Biomolecular and Computational Frameworks for Genetic Circuit Design

by

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Forest M. White Chair, Department Committee on Graduate Theses *For mom and dad*

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Preface

The work described in this thesis was the result of collaborations with many talented researchers at MIT, Boston University, the National Institute of Standards and Technology. **I** am privileged to have worked alongside some of the sharpest and most creative biological engineers, and **I** am especially grateful to Prof. Christopher Voigt and the extremely talented members of his group.

Parts of Chapter 1 were published as a review in *Current Opinion in Chemical Biology* in December of **2013.** I co-authored this review with fellow graduate student Thomas Segall-Shapiro, and it provides a useful overview of recent advances in genetic parts and circuit design.

Parts of Chapter 2 were published in *Nature Chemical Biology* in February of 2014. Brynne Stanton initiated this project as a postdoc and took me on as a lowly rotation student. She planned and developed many aspects of this work, including the repressorbinding operator discovery microarray assay central to the project **-** the details of which are not provided in this thesis, but are available in the original publication. **I** would also like to acknowledge Alvin Tamsir for his insights into the practicalities of genetic circuit design, and for laying the foundation for much of the work present in this thesis.

Chapter **3** was published in *Molecular Systems Biology* in November of 2014. I started this project on the heels of Wendell Lim's group's seminal publication, "Repurposing CRISPR as an RNA-guided platform for sequence-specific control of gene expression". **I** am grateful to Samira Kiani, Fahim Farzadfard, Sam Perli, and Lior Nissim in Prof. Timothy Lu's and Prof. Ron Weiss's groups for their early contributions to CRISPRbased genetic regulation and for fruitful discussions.

Chapter 4 was published in *Science* in April of **2016.** It represented the culmination of several years of effort, and would not have been possible without the contributions of

Bryan Der, Jonghyeon Shin, Prashant Vaidyanathan, and Doug Densmore. **I** would also like to thank David Ross, Vanya Paralanov, and Elizabeth Strychalski at the National Institute for Standards and Technology for working tirelessly to perform the single molecule **FISH** experiments under the pressure of a tight deadline and remote interactions with the rest of the paper's authors.

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I would also like to thank my thesis committee members. Ron Weiss, whose PhD thesis is the closest thing to a spiritual predecessor and guiding light for **my** own, was the first synthetic biologist whose research **I** was exposed to as an undergrad. His work continues to inspire, and I'm honored to have interacted with him over the course of my PhD. **My** thesis chair and head of the Biological Engineering department, Doug Lauffenburger, is a scientific heavyweight who has been an excellent resource for research insight and career advice. He has also managed to create one of the most collaborative and respected departments on the planet. BE grad students seem happier than most, and that is in large part due to Doug's tireless efforts to engage students and improve the system in which they inhabit.

The other grad students and postdoes of the Voigt lab are unreasonably talented, and **I** had the good fortune of being trained **by** some of the best synthetic biologists in the world. **I** would like to extend a special thanks to those who **I** consider technical mentors-Brynne Stanton, Mike Smanski, and Brian Caliando. Working with others in the area of genetic circuits was a daily pleasure, including Chunbo Lou, Bryan Der, Jonghyeon Shin, Thomas Gorochowski, YongJin Park, Thomas Segall-Shapiro, Adam Meyer, Jenn Brophy, Felix Moser, Shuyi Zhang, and Lauren Woodruff. Thanks to my skilled collaborators at Boston University (Doug Densmore and Prashant Vaidyanathan), **NIST** (David Ross, Vanya Paralanov, and Elizabeth Strychalski), and MIT Media Lab (Will Patrick, Steven Keating, Neri Oxman, and David Kong).

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Lastly, thank you to my family. **I** love you so much. That **I** was born to parents so encouraging and loving is the luckiest aspect of my existence. Thank you for helping me to pursue my dreams. To my mother, the kindest and most caring person **I** know, **I** owe everything to you having raised me. To my father, who imbued me with a fascination for the natural world, you are deeply missed. Thanks to Sandy, Kim, and Kraig for being a wonderful addition to my family, and continuing to play a huge role in my life. And thanks to my little brother, Nate-I couldn't ask for a better bro. You inspire me, **I** look up to you, and **I** love you.

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Abstract

Living cells naturally use gene regulatory networks termed "genetic circuits" to exhibit complex behaviors such as signal processing, decision-making, and spatial organization. The ability to rationally engineer genetic circuits has applications in several biotechnology areas including therapeutics, agriculture, and materials. However, genetic circuit construction has traditionally been time- and labor-intensive; tuning regulator expression often requires manual trial-and-error, and the results frequently function incorrectly. To improve the reliability and pace of genetic circuit engineering, we have developed biomolecular and computational frameworks for designing genetic circuits.

A scalable biomolecular platform is a prerequisite for genetic circuits design. In this thesis, we explore TetR-family repressors and the CRISPRi system as candidates. First, we applied 'part mining' to build a library of TetR-family repressors gleaned from prokaryotic genomes. **A** subset were used to build synthetic **'NOT** gates' for use in genetic circuits. Second, we tested catalytically-inactive dCas9, which employs small guide RNAs (sgRNAs) to repress genetic loci via the programmability of **RNA:DNA** base pairing. To this end, we use dCas9 and synthetic sgRNAs to build transcriptional logic gates with high on-target repression and negligible cross-talk, and connected them to perform computation in living cells. We further demonstrate that a synthetic circuit can directly interface a native **E.** coli regulatory network.

To accelerate the design of circuits that employ these biomolecular platforms, we created a software design tool called Cello, in which a user writes a high-level functional specification that is automatically compiled to a **DNA** sequence. Algorithms first construct a circuit diagram, then assign and connect genetic "gates", and simulate performance. Reliable circuit design requires the insulation of gates from genetic

context, so that they function identically when used in different circuits. We used Cello to design the largest library of genetic circuits to date, where each **DNA** sequence was built as predicted **by** the software with no additional tuning. Across all circuits **92%** of the output states functioned as predicted. Design automation simplifies the incorporation of genetic circuits into biotechnology projects that require decisionmaking, control, sensing, or spatial organization.

Thesis supervisor: Christopher **A.** Voigt Title: Professor Department of Biological Engineering

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Chapter 1

1 Introduction

Cells naturally control gene expression using a variety of RNA, protein, and **DNA**modifying regulators (Ptashne, **1986b;** Ideker et *a],* 2001; Alon, **2007).** It was recognized early that interactions between these regulators could lead to computational operations that are analogous to electronic circuits (Monod **&** Jacob, **1961;** Ptashne, 1986a; McAdams **&** Shapiro, **1995).** Genetic engineers have attempted to build synthetic circuits that would implement artificial programs of gene expression. This could have a revolutionary impact on biotechnology, such as programming bacteria to individually respond to transient conditions in a bioreactor (Moser *et al.* 2012a), designing therapeutic cells to sense and respond to diseased states within the human body (Ruder et *a],* 2011; Chen **&** Smolke, 2011; Ghosh et *a],* 2012; Huh et a], **2013;** Hasty, 2012), or smart plants that can respond to changing conditions in the environment (Bowen *et al*, 2008). However, building synthetic circuits remains one of the greatest challenges in the field, where even simple circuitry is labor intensive to build and lacks the performance of its natural counterparts. As a result, synthetic genetic circuits have been slow to appear in practical applications (Purnick **&** Weiss, 2009a).

There are several reasons why genetic circuit design has been challenging compared to other areas in genetic engineering. First, functional genetic circuits require precise tuning in the expression levels of their component regulators (Ang et *a,* **2013).** This is less essential when engineering cells to make small molecules or individual proteins, where genes tend to be maximally expressed. Second, regulators are prone to being toxic and, even when slight, can inhibit growth and lead to evolutionary instability and a reduction in performance. Third, the regulatory interactions comprising a circuit all occur within the cell and crosstalk between them or with the host can impact circuit behavior (Andrianantoandro et *a,* **2006).** Fourth, there are few design rules for the systematic improvement of circuit performance (speed, dynamic range, robustness, and cell-to-cell variability). Finally, the physical construction of circuits requires the assembly of many parts, which until recently, has been technically challenging (Czar et *a],* 2009a; Gibson et al, **2009;** Engler et *a],* **2009).** Often, these parts appear in genetic contexts that are different than that for which they were characterized and this can lead to interference (Moser et al, 2012a).

In this review, we focus on recent advances in synthetic circuit design for bacteria. There have been other reviews looking at circuit design for eukaryotes and higher organisms (Keasling, **2008;** Purnick **&** Weiss, 2009a; Ellis et *a],* **2009;** Greber Fussenegger, **2007;** Wang et *a],* **2013b;** Mukherji **&** van Oudenaarden, **2009).** In section **1.1,** we describe new approaches to identifying how to assemble and tune regulators to produce a desired circuit function. In section 1.2, we describe how the toolbox of regulators has expanded, both in increasing the number of characterized regulators from different families, as well as the discovery of new biochemistries that can be harnessed for circuit design. Finally in section **1.3,** we review new approaches to obtain precision expression control and its potential impact on building sophisticated circuitry.

1.1 Advanced circuit designs

To date, most of the genetic circuits that have been constructed are so small that there has been little need to utilize advanced concepts or algorithms in their design. As they get more sophisticated however, it will become more difficult to identify a pattern of regulatory interactions that can produce a desired function. To this end, approaches for digital and analog circuit design from electrical engineering have begun to be applied, and are described below. Realizing these designs requires that regulators be functionally connected. This will require better control over their response functions (how each regulator converts different levels of input signal to output signal) as well as handling of other circuit characteristics such as retroactivity and instability. New approaches for these concerns also reviewed in this section.

1.1.1 Layered Digital Circuits

Digital circuits produce signals at discrete levels (most commonly, high and low or 1 and **0),** as opposed to operating in a continuous range. Their advantage is in their designability; there are many design tools that can abstract a desired circuit function into a large assembly of logic gates (Clancy **&** Voigt, 2010). This comes at a cost of size and power requirements. Many more digital gates may be needed to produce a computational function than what would be required if continuous variables were allowed. In terms of genetic circuits, this manifests as more **DNA,** regulators, and energetic resources (Lu et *a],* **2009;** Qian **&** Winfree, 2011; Moon et al, 2012a).

Many genetic circuits have been built that produce Boolean logic functions or 'logic gates' (Tamsir et *a],* 2011a; Anderson et al, **2007;** Guet et *a],* 2002). Note that while these are often described as being digital, all of these circuits exhibit analogue features (so-called fuzzy logic), where there is a continuous change in output. This can be used as the basis for the construction of analog circuitry (next section).

If genetic logic gates are designed to have inputs and outputs that have the same signal, they can be layered to produce more complex computational operations. In practice, this has been on the level of transcription, where the inputs and outputs are promoters. This approach is modular, but it is also slow, with each layer requiring a step of transcription and translation with a timescale of 20 minutes (Hooshangi *et* al, 2005). Further, if one of the signals skips a layer, this can produce a fault where the output is transiently incorrect. Such faults have been exploited in the construction of pulse-generating genetic circuits, in the form of incoherent feed-forward loops (Mangan **&** Alon, **2003;** Entus *et a],* **2007;** Basu *et al,* 2004).

There have been several studies to layer logic gates to produce more complex functions. This is closely related to work to build cascades through the connection of gates in a linear series (Hooshangi *et a],* **2005;** Pedraza **&** Oudenaarden, **2005;** Rosenfeld *et a],* **2005).** As a proof-of-principle, a 4-input **AND** gate was built **by** layering three 2-input **AND** gates along with additional layers that contain the 4 sensors and an output **(Moon** *et a],* 2012a) (Figure 1a). It has also been shown that a set of orthogonal NOR gates can be layered to form different logic operations **by** permuting the input and output promoters to reproduce different wiring diagrams (Stanton *et al*, 2013). Both of these examples perform relatively simple computations that could be designed **by** hand and required more gates than the minimal set that could be imagined to generate each of these functions. It would require significantly larger circuits to realize the benefits of digital gates and computational design automation (Beal *et a],* 2012; Bilitchenko *et al,* 2011; Clancy **&** Voigt, 2010).

1.1.2 Analog Circuits

Analog circuits operate with continuous signals. In electronic circuits, they are used when there are limitations in the number of components or power that can be used (e.g., in medical devices) (Sarpeshkar, 2010). This comes at a cost of designability, where each circuit has to be individually designed and simulated, which limits the size and flexibility of the circuits. In practice, every genetic circuit **-** natural or synthetic **-** is analog to some degree and this needs to be accounted for in their design. The question is to what extent the design of genetic circuits can benefit from the principles used for building analogue electronic circuits.

The value in considering analogue circuit design was recently demonstrated in work by Lu and co-workers (Daniel *et al*, 2013a). In this work, analog circuits were implemented to solve mathematical functions that would otherwise require many digital gates, including logarithm and power-law functions, and continuous addition and division (Figure **1b). A** circuit was built that generates a wide dynamic range response function using a positive feedback loop and a means to titrate away the activator. This design computes a logarithm and the introduction of a second positive feedback loop produces a circuit that computes log-domain addition of two inducers. **A** log-domain division circuit was further engineered **by** having the two feedback loops compute the ratio between the two inducers. Remarkably, all of these arithmetic functions could be computed using only two transcription factors.

1.1.3 Recombinase-based Memory and Logic

Logic gates based on transcription factors often exhibit analogue features, with high off-states and graded switch transitions. In contrast, more digital switches can be built using recombinases that catalyze a sequence-specific change the orientation of a unit of **DNA,** where each orientation corresponds to a different signal level. Recombinases have been used as the basis for a number of synthetic circuits (Moon et *a],* **2011;** Ham et *a],* **2008, 2006)** and have been layered to form a cascade (Friedland et *a],* **2009).** Previously, the recombinases used were either irreversible (where the inversion is unidirectional) or reversible (where the same recombinase catalyzes both directions). Recently, a rewriteable switch has been built based on a system where an integrase catalyzes the switch in one direction and an integrase/excisionase pair catalyzes the reverse reaction (Bonnet *et al.*, 2012). This is a significant improvement in that it allows the signal to both hold permanently and be able to switch back to the initial state.

Multiple recombinases have been built into circuits that function as "memory logic" devices, where the rearrangement of **DNA** is conditional to two input inducers (Siuti et *a],* **2013;** Bonnet et *a],* **2013).** In one paper, two recombinases (Bxb1 and phiC31) irreversibly invert promoters, unidirectional terminators, and **GFP.** Only when transcription initiation, termination, and **GFP** are in the correct orientation is fluorescent output seen, and memory circuits for all irreversible 2-input logic functions were successfully constructed (Siuti et *a],* **2013)** (Figure 1c). In a second paper, two recombinases (Bxbl and TP901-1) irreversibly invert or excise terminators and promoters to implement six irreversible 2-input logic functions (Bonnet et *a],* **2013).**

There are several advantages to this approach in building logic gates. The gate response has a larger dynamic range that is easier to connect to downstream gates and the signal levels are more easily distinguishable (two different **DNA** orientations versus the presence or absence of a regulator). The hold state is also permanent, surviving over many generations and even after cell death. These gates could be layered as with those based on transcription factors and the size of the **DNA** per gate is about the same. However, there are two disadvantages with using recombinases. First, they are not true logic in that a transient but temporally separate induction of the two signals leads to a permanent change in the output. Also, they tend to be slow, with each layer requiring between up to eight hours (Moon *et al,* 2011) to complete.

1.1.4 Control of the Response Function

Building genetic circuits **by** connecting logic gates requires that their response functions match, that is, the output range of upstream gates matches the input range of downstream gates. In Section **1.3,** we look at methods based on changing the expression levels of the regulators. Here, we look at new approaches to change the shape of their response functions, including the basal level of the off state, dynamic range, and cooperativity (Ang *et al*, 2013). These approaches could be applied to digital or analogue circuits and those based on different regulator families.

One of the biggest practical problems in constructing complex circuits is that the basal level of activity from the off-state of regulators ("leak") can often be sufficient to trigger the next layer of a circuit. This has been difficult to control, but there are several promising new approaches. First, leakage can be minimized using riboregulation to suppress translation. This has been used effectively to minimize the uninduced activity of toxic proteins (Callura *et a],* 2010). **A** similar approach is to use small RNAs (sRNAs) to bind an RNA chaperone Hfq and the target mRNA to both inhibit translation and also target the mRNA for destruction **by** RNase **E** (Aiba, **2007).** Second, in natural prokaryotic genetics, leakiness is controlled using 5'-terminators that come directly after a promoter to attenuate transcription (Naville **&** Gautheret, 2010). **A** similar strategy could be used in synthetic systems to reduce leaky transcription of mRNA.

Increasing the nonlinearity of a response curve can also be important in circuit design. Nonlinearity occurs naturally via cooperativity, but this can be challenging to engineer *de novo.* An easier approach is to incorporate interactions that sequester the regulator at the **DNA** (Lee **&** Maheshri, **2012b),** RNA, or protein level (Buchler Louis, **2008).** The level of effector must exceed the binding capacity of the competitively sequestering partner to pass the threshold, bind the cognate partner, and take action. Examples of competitive binding partners include anti-sigmas sequestering sigma-factor (Chen **&** Arkin, 2012a), sRNA sequestering mRNA (Levine et *a,* **2007),** and decoy operators sequestering DNA-binding proteins (Lee **&** Maheshri, **2012b).**

1.1.5 Buffering retroactivity

Genetic gates within a cell inevitably share resources; for example, they utilize the host RNA polymerase and ribosomes. Shared resources can cause coupling between gates that are otherwise unconnected and can cause a downstream gate to affect the behavior of an upstream one (Del Vecchio et al, 2008; Jayanthi et al, 2013). It has been experimentally shown that increasing the number of downstream operators can impact the response time and threshold of a gate (Jayanthi et *a],* **2013).** Since the size of genetic circuits has been small, retroactivity has not yet emerged as a significant problem, but this is expected to worsen ascircuit size increases and when the output of a gate is connected to many downstream circuits or actuators ("fan-out").

An interesting approach for insulating modules from retroactivity has been mathematically investigated (Del Vecchio et *a],* **2008).** While the general solution is well known from control theory (high input amplification and high negative feedback), the authors of this study looked at specific biological mechanisms that could **fill** the role. Surprisingly, simple circuit modifications like a non-leaky input promoter (for high input amplification) and rapid degradation of the transcription factor (for negative feedback) effective insulate retroactivity in mathematical models.

1.1.6 Engineering evolutionary stability

The selection of a particular circuit topology and genetic implementation also impacts its evolutionary stability. Recent work has begun to illuminate the design choices that lead to instability, which can in turn be used to guide future designs. It has been observed that if the resting state of a gate requires the expression of an active regulator, the gate is more evolutionarily unstable (Canton et al, 2008a). Thus, selecting an architecture that minimizes the number of regulators that have to be expressed at a given time could increase stability (Sleight **&** Sauro, **2013).** The modes **by** which cells reject circuits are also becoming better understood. Unsurprisingly, the use of plasmids and the repetition of **DNA** sequences in a design leads to instability (Sleight **&** Sauro, **2013;** Sleight et *al,* 2010; Moser et *a],* 2012a). The re-use of strong double terminators has been found to be particularly bad and their diversification dramatically increases the number of generations before a circuit is lost due to homologous recombination (Chen et al, 2013; Sleight et al, 2010).

Additionally, a recent large-scale effort to ascertain which heterologous genes are toxic in **E.** coli has begun to shed light on how synthetic constructs affect host fitness (Kimelman et *al,* 2012). **By** examining cloning gaps in over **9.3** million sequencing clones from **393** microbial genomes, more than **15,000** were found to have toxic expression products. Through subsequent validation and analysis, new restriction enzymes, toxin-antitoxic systems, and toxic small RNAs were discovered. Toxic **DNA**binding motifs were also observed that likely titrate away DnaA and inhibit normal replication. This wealth of information about toxic **DNA** elements is a fantastic resource for predicting how genes may affect host systems, and could guide which regulators can be effectively used in circuits.

1.2 Classes of regulators

The last few years has seen an explosion in the number of well-characterized regulators that are available for building genetic circuits. Before this, there were relatively few that were available (e.g., LacI, TetR, AraC, and CI) and these were reused in many designs. **A** goal has been to expand the number of variants within each family that are orthogonal, that is, do not cross react with each other such that they can be used together in a circuit (Lucks et *a],* **2008;** Rao, 2012). This has been achieved via two approaches. First, bioinformatics and whole gene **DNA** synthesis has been used to access regulators from the sequence databases ("part mining") (Bayer *et al*, **2009).** Second, families of regulators have been characterized that are conducive to the rational design of orthogonal sets (zinc finger proteins, TALEs, and CRISPR-Cas9). Computational methods have played a role both to predict the orthogonality of regulators identified in databases as well as in structure-guided design. Collectively, this has resulted in 100s of regulators that could theoretically be used together in a single large circuit in a bacterium.

Despite efforts to standardize and collect data surrounding biological parts (Canton et *a],* **2008b;** http://parts.igem.org/), the majority of the information is buried in individual papers, making direct comparisons difficult. In Table **1,** we show data comparing **15** common regulator families along with the properties of each family. For the families, the number of characterized orthogonal regulators are shown (with a metric of crosstalk), along with the size in basepairs of the potential gate, and dynamic range that has been achieved with that regulator. Note that the table focuses on bacteria and there is more data for some families in eukaryotic cells.

1.2.1 Protein Regulators of Transcription

Proteins that directly bind **DNA** to regulate transcription make up the majority of the regulatory parts available for use in bacteria (Figure 2a). One way in which proteins can regulate transcription is **by** initiating transcription at promoters. The native *E. coli* RNAP can be directed to new promoters **by** expressing sigma factors from other organisms (Chen **&** Arkin, 2012a; Rhodius *et* al). **A** large set of orthogonal sigma factors has been generated through part mining, in which sigma factors from many organisms were synthesized and their activities characterized (Rhodius *et a).* Alternatively, the phage RNAP from **T7** is often used and the promoter specificity of this polymerase has been changed through rational design and part mining (Temme *et a],* 2012; Raskin *et a],* **1993;** Shis **&** Bennett, **2013)** as well as random mutagenesis (Chelliserrykattil *et al,* 2001; Esvelt *et a],* 2011).

Activators upregulate transcription **by** binding to a promoter to recruit RNAP. Classically, there are a number of natural activator proteins that have been used in genetic engineering, such as λ *cI* and *luxR*. A small library of *crp* activators was built **by** using bioinformatics to direct mutations at residues responsible for operator specificity (Desai *et al.* 2009). Part mining has been applied to identify activators that require a second chaperone protein for activity and this has been used as the basis for building AND gates (Moon *et al*, 2012a).

Repressors block transcription **by** blocking the binding or progression of RNAP. Recently, there have been efforts to increase the number of orthogonal repressors available for circuit design. To expand the LacI family, mutations were made to specific **DNA** residues in the binding site and **DNA** binding residues in the protein and a set of orthogonal repressors was selected (Zhan *et al,* 2010). Part mining has been applied to expand the number of available TetR homologues and this led to the identification of an orthogonal set of **16** repressors (Stanton *et a,* **2013).**

There are several modular classes of transcription factors that have modular protein structures that facilitate their engineering to target particular **DNA** sequences. Zinc finger proteins (ZFPs) and transcription activator like effectors (TALEs) have such a structure and have been particularly successful in being used in eukaryotic cells (Desjarlais **&** Berg, **1992;** Moscou **&** Bogdanove, **2009;** Boch *et a,* 2009a; Beerli Barbas, 2002a; Morbitzer *et al.* 2010a; Garg *et al.* 2012b). It has been surprisingly difficult to get these regulators to work in bacteria, but there examples of ZFPs being used as activators and '(Lee *et a,* **2008)** a **TALE** as a repressor in *E. coli* (Politz *et a],* 2013a).

1.2.2 RNA Regulators of Translation

RNA parts that regulate translation take advantage of fact that RNA base pairing follows a simple code that is computationally predictable (Markham **&** Zuker, **2008)** (Figure **2b).** Two parts families of this type are variants of riboregulators, which alter the accessibility of the ribosome binding site (RBS) controlling translation initiation. **RNA-IN/OUT** parts consist of a modified natural system (Kittle *et al*, 1989) in which an RNA molecule base pairs to the **5'** end of an mRNA (including the RBS) such that the ribosome cannot initiate translation (Mutalik *et a],* 2012a). The orthogonal set of these regulators was increased through computational design and experimentally confirmed. **A** second part family uses trans-activating RNAs that work **by** disrupting a secondary structure that blocks the RBS **by** default, leading to translational activation (Isaacs *et al,* 2004; Callura *et al,* 2010, 2012). Finally, it has been shown that the expression of modified **16S** RNA that has been engineered to bind a noncanonical Shine Delgarno sequence can recruit ribosomes and this has been used as the basis to build gates (Chubiz **&** Rao, **2008;** Rackham **&** Chin, **2005;** An **&** Chin, **2009).**

When designing gates, the challenge with using RNA that acts on the level of translation is that it is difficult to convert an RNA input to an RNA output of the same form. Therefore, the resulting gates are not layerable. An approach to this problem is to use a *cis* element that converts translation into transcription (Liu *et a],* 2012). This component utilizes a modified sequence from the tnaCoperon (Gong *et a],* 2001) and makes transcription of a downstream region dependent on translation **of** a short peptide, effectively linking the two. It has been successfully applied to both classes of riboregulators.

1.2.3 RNA Regulators of Transcription

An exciting development over the last year has been in the development of RNAbased systems that can directly regulate transcription **by** behaving as a repressor (Figure **2b).** This is based on Cas9, which is a protein that uses a small guide RNA to target a **DNA** sequence as part of the CRISPR/Cas bacterial immunity system (Horvath **&** Barrangou, 2010). Normally, Cas9 functions as a nuclease and cleaves **DNA,** but it was shown that if the nuclease activity is mutated, then the complex blocks RNAP (Figure **1d).** This either can be used as a repressor or as an activator **by** fusing an activation domain to Cas9 (Qi *et al,* **2013;** Bikard *et a],* **2013).** An advantage of this system is the potential to design vast numbers of orthogonal regulators **by** building guide RNAs that target different "operator" sequences. The cross reactions that may result from this approach are just beginning to be characterized and understood (Fu *et al*, 2013a; Hsu *et al*, 2013a). Once it is shown that the Cas9-based systems can be layered, this will become a powerful toolbox for circuit engineering. However, a practical challenge with using this system is the acute toxicity of Cas9 when expressed in many organisms.

A more developed approach for RNA to control transcription is based on the **PT181** attenuation system (Takahashi **&** Lucks, **2013;** Lucks et *a],* 2011; Brantl Wagner, 2000). When an antisense RNA is present and binds a target sequence on a transcript RNA, the nascent transcript folds into a transcriptional terminator and attenuates the message. This part family was expanded both through both part mining and random mutagenesis, including utilizing some of the orthogonal RNA pairs from the **RNA-IN/OUT** system. These attenuators have been shown to be fully compostable into cascades and logic gates (Lucks *et al*, 2011).

1.2.4 Proteins that Modify DNA

Thus far, **DNA** modification has been built in bacteria **by** using recombinases to invert segments of **DNA** (Figure **2d).** This mechanism is commonly found in bacteria, phages, and mobile genetic elements, providing a diversity of natural parts to exploit in synthetic systems (Hirano *et al*, 2011).

The current parts for engineering **DNA** flipping are all natural recombinases, which vary in a number of ways. The most commonly used recombinases in genetic engineering are the simple tyrosine recombinases Cre and **Flp** (Nagy, 2000). Tyrosine recombinases are bidirectional **-** they can flip the region between their recognition sites in both directions, leading to an even distribution of orientations. Additionally, if their recognition sites are oriented in the same direction, they catalyze **DNA** excision. These two recombinases have been used in bacteria, and shown to function properly and orthogonally (Friedland *et al*, 2009). The invertases FimB and Hin have also been used together in a bacterial system (Ham et *a!,* **2008).** These invertases are similarly bidirectional, but they lack the capability for excision. Finally, phage integrases are a class of recombinases that catalyze unidirectional flipping **-** leading to the accumulation of a specific **DNA** orientation (Groth **&** Calos, 2004). Three integrases

(BxBI, **ypC3,** and TP901-1) have been characterized and used to build bacterial systems (Siuti *et a],* **2013;** Bonnet *et a], 2013).* Additionally, a number of these integrases have matching excisionases, which allow for the reversal of **DNA** flipping (Groth **&** Calos, 2004; Bonnet *et a],* 2012).

In addition to part mining natural recombinases, there has been progress in generating new families of recombinase parts through modifications. One such approach was to iteratively make mutations to the **DNA** binding region in the recombinase and select for proteins with new specificities (Santoro **&** Schultz, 2002; Gaj *et al.* 2011). Another promising method is to generate new parts by creating recombinase fusions with zinc-finger and **TALE DNA** binding domains (Mercer *et a],* 2012).

Finally, while current efforts have focused on recombinases, other mechanisms of **DNA** modification may also hold promise for building circuitry. Recently, there have been successful efforts to selectively methylate **DNA** in bacteria (Chaikind *et a],* 2012), and mammals (Konermann *et a],* **2013)** using modular zinc-finger and **TALE** designs. An *in vivo* means of reading methylation state would open up these parts for use in gene circuits. This seems feasible, as bacteria are known to contain many regulatory systems that respond to DNA methylation (Løbner-Olesen *et al*, 2005; Casadesús & Low, **2006).**

1.3 Precision gene expression

Building, tuning, and connecting genetic circuits require the ability to engineer precise changes in gene expression. Further, when gates are combined to build a complex circuit, the genetic context changes, which can impact their function (Lou *et* **al,** 2012a). There have been many recent advances in the development of "tuning

knobs" that allow for the fine-tuned control of transcription and translation (Figure **3).** These can take the form of part libraries or computational tools. Further, insulator parts have been developed that decouple the contribution of various parts to expression. This has led to a redefinition of the classical expression cassette.

1.3.1 Tuning knobs for expression

Promoters. Libraries of constitutive promoters for different species have been built **by** mutating the **-10** and **-35** RNAP binding regions of the promoter or the region affecting **DNA** melting **(-10** to +2) (Kosuri et *a],* **2013;** Mutalik et *a],* **2013b;** Mey et a, **2007;** Jensen **&** Hammer, **1998;** Rud et *a],* **2006;** Seghezzi et *a],* 2011). Advances in oligonucleotide synthesis have enabled these libraries to become very large. For example, **>10,000** combinations of promoters and 5-UTR's were built from a pooled oligonucleotide library and screened **by** combining cell sorting and deep sequencing (flow-seq) (Kosuri et *a],* **2013).** Computational models of promoters have also been developed that are based on the free energy of RNAP binding to the **-10/-35** sites and promoter melting (Rhodius et *a],* 2012; Brewster et *a],* 2012). These show promise in predicting promoter strength, however, a complete model that balances all contributions has yet to be built.

Ribosome Binding Sites. The RBS is a part that is relatively simple to tune to achieve different expression levels. As a result, it has been broadly applied to tuning response functions for building genetic circuits (Stanton et a], **2013;** Moon et *a],* 2012a; Chen *et al*, 2012; Gardner *et al*, 2000a; Basu *et al*, 2004; Egbert & Klavins, 2012). The ribosome makes contacts with the Shine-Delgarno sequence and start codon and binding is influenced **by** RNA base-pairing, the spacing between these regions and the mRNA secondary structure. The RBS Calculator is a computational tool based on a biophysical model that balances these contributions (Salis *et al*, 2009; Voigt, 2011).

There are additional terms that influence the strength of the RBS and several of these, including the role of the standby site, have been characterized and incorporated into new versions of the software (de Smit **&** van Duin, **2003;** Voigt, 2011). There is much to be learned from non-canonical RBSs (Boni et *a],* 2001) including leaderless RNAs (Laursen et *a],* **2005)** and a better understanding of these processes could improve the model. Libraries of $5'-UTRs$ that include the RBS have been measured (Kosuri *et al.*) **2013;** Mutalik et *a],* **2013b).** Additionally, a recent technique to tune RBS strength using hypermutable sequence repeats between the Shine-Dalgarno region and start codon was used to explore expression parameters for a bistable switch (Egbert $\&$ Klavins, 2012).

Terminators. During transcription, mRNA is released when the RNAP reaches a terminator. Terminators are important in circuit design for three reasons. First, they offer a means to tune expression **by** modulating read-through and could potentially decrease leaky expression. Second, many terminators are required when gates are combined to build circuits. These circuits can have many transcription units, each of which needs strong termination to avoid interference with other circuit elements. The terminators have to be sequence diverse to avoid recombination. Finally, the recombinase-based memory circuits utilize unidirectional terminators as a core part of their design. To address these needs, there have been several major efforts to use part mining to build large libraries of terminators gleaned from the genomes of bacteria (Cambray et a], **2013;** Chen et **al, 2013).**

Origins. To finely control plasmid replication beyond the standard plasmid systems, tunable-copy-number plasmids can be used. Increasing the expression of trans-acting replication factors (repA and pir) increases the plasmid copy number (for ColE2 and R6K origins, respectively). Using this system, a library of **"DIAL"** strains that constitutively express replication factors from the genome has been constructed that can yield between 1 and **250** plasmid copies **by** transforming the corresponding plasmids into the different strains (Kittleson *et al*, 2011).

1.3.2 Insulators to buffer the impact of genetic context

Part function is impacted **by** their genetic context, in other words the sequences of the neighboring parts (Lou et a], 2012a; Qi et al, 2012; Davis et *a],* 2011; Mutalik et al, 2013a; Kosuri *et al*, 2013). In turn, this can impact the response function of the entire genetic circuit. Context effects can have two forms. First, there is a direct interference of one part type on another. For example, the strength of a RBS is influenced **by** the promoter and the first codons of the expressed gene. Second, when two parts are combined a new function can appear at their interface. For example, promoters have been inadvertently constructed **by** the assembly of two parts containing an LVA-degradation tag, a **DNA** barcode, and a BioBrick scar (Yao et a], **2013).** To overcome this issue, insulator parts have been developed to diminish the effect of genetic context. Figure **3** shows a conceptual re-visiting of the expression cassette, where insulators are strategically placed between key parts (Mutalik et al, 2013a).

The first insulators are based on bidirectional terminators, which flank the expression cassette to reduce transcriptional read through in or out of the expression cassette (Chen et *al,* **2013).** Typically, the promoters that are used in synthetic biology are too small and only capture the **-35** and **-10** regions. This can cause the promoter to have different strengths depending on the up and downstream sequence. Longer promoters should be used that at least encompass the **UP** element **(-35** to -64) that binds the \boxtimes -subunit of RNAP (Rhodius *et al*, 2012; Estrem *et al*, 1998). Taking this further, it has been shown that the addition of upstream sequences (up to **-105)** and downstream sequences (down to **+55)** will further insulate promoter activity (Davis et **al, 2011).**

The transcription start site of promoters is not always known and a "promoter part" is rarely annotated to end at the **+1** position. This can be further complicated **by** the observation that there is sometimes a distribution of mRNA produced from the same promoter and single mutations to the promoter can change the start site. The RBS is particularly sensitive to changes in the **5'-UTR,** even **by** a single nucleotide. Both selfcleaving ribozymes (Lou *et al*, 2012a) and CRISPR RNA-processing (Qi *et al*, 2012) have been used to physically cut and detach the variable **5'-UTR** from the mRNA, thereby shortening and making constant the 5'-mRNA context. These tools are particularly important when combining gates to build a circuit, where the promoter inputs and output of each gate occur in new contexts.

A bicistronic RBS sequence has been shown to reduce the impact of the secondary structure of the **5'-UTR** on the RBS (Mutalik et *a],* 2013a). **A** small 'leader' peptidecoding sequence with its own RBS is positioned upstream from the gene of interest such that the peptide sequence overlaps the RBS for the downstream gene and the peptide's stop codon ends at the gene of interest's start codon. The natural helicase activity of ribosomes loaded at the first RBS unfolds the mRNA secondary structure near the second RBS that controls gene expression, decoupling the translation initiation rate of the second RBS from the downstream coding sequence.

Lastly, the variability in gene expression when coupled with various terminators can be reduced **by** encoding an RNase **III** site in the 3'-UTR of the mRNA (Schmeissner et *a],* 1984). Post-transcriptional processing of mRNAs **by** RNase **III** standardizes the 3'-end of the mRNA, such that the sequence and secondary structure of the cleaved RNA can no longer contribute to mRNA stability and degradation.

1.4 Discussion

Genetic circuit design is at an inflection point regarding the size and sophistication of computational operations that can be implemented within living cells. The first phase of the field involved the construction of individual circuit functions (e.g., an oscillator or a gate) **by** piecing together the necessary biochemistries. For an extended period, the complexity of these circuits remained relatively flat as the rules for composing a circuit were explored (Purnick **&** Weiss, 2009a). After this, there have been tedious efforts to build out the number of available regulators. During this time, there has been **highly** technical work to better understand how to control and insulate expression **by** revisiting old paradigms, like the expression cassette. These efforts have yielded large sets of regulators that have been thoroughly characterized and for which the rules of assembly are better understood. This is expected to lead to a period, over the next few years, where there is sudden scale-up in the complexity of circuits. Ultimately, this will lead to circuit design as a regular component of genetic engineering projects, along with protein, pathway, and strain engineering. In this thesis, we explore TetR-family repressors and CRISPRi-based repression as platforms for scalable genetic circuit design. Further, we create a genetic circuit design software tool called Cello that automates the construction of genetic circuits using libraries of characterized parts. The goal of Cello is to accelerate and improve the reliability of genetic circuit design.

Figure **1-1:** Advanced genetic circuit designs. Recent progress in building more complex genetic circuits has been enabled through development of new part families, and more sophisticated circuit architectures. **(A)** An intracellular 4-input **AND** gate built **by** layering three 2-input logic gates. Each 2-input logic gate works **by** expressing an activator from one input and a chaperon from the other output that complex and activate the output. The entire **AND** gate's output is high only when all four inputs (arabinose, IPTG, AHL, and aTc) are present. Adapted from (Moon *et al*, 2012). (B) An analog circuit that computes log-domain addition of arabinose and AHL concentrations was built using two wide dynamic input range feedback loops (AraC and LuxR) that express a common output. The dynamic input ranges for each feedback loop were extended **by** providing a "shunt" plasmid with a promoter that titrates away the transcription factor from the feedback loop. Adapted from (Daniel et al, **2013). (C)** Recombinase memory circuits effect stable inversions of genetic regulatory elements.

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An irreversible 2-input **AND** memory circuit was built **by** expressing recombinases Bxbl and phiC31 with AHL and aTc, such that two unidirectional terminators are flipped into a non-terminating orientation when both recombinases are expressed. This circuit stably maintains its output state for several days. Adapted from (Siuti et al, **2013). (D)** CRISPR-based gene regulation uses a catalytically-inactive Cas9 protein (dCas9) and a targeting short guide RNA (sgRNA) to guide the sgRNA-dCas9 complex specific **DNA** loci. **By** targeting various regions of a bacterial promoter, dCas9 was shown to repress transcription initiation using a highly-programmable targeting mechanism. Adapted from (Qi et al, **2013).**

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Figure 1-2: The diversity of genetic regulatory parts available for building bacterial genetic circuits. Schematics and representative data for a selection of different circuitbuilding mechanisms are shown. The colored regions in the schematic indicate the variable regions that make up each part. **A** solid line surrounding a part type indicates that there is a well-characterized, orthogonal set of parts of this type available for circuit building. **A** dashed line indicates that there is a proof-of-concept part. The data shown either demonstrates the orthogonality and size of a parts family, or if that is not available, it shows proof-of-concept activity. **(A)** Protein parts that act on transcription include natural repressors and activators, phage polymerases, sigma factors, and repressors and activators based on programmable **DNA** binding proteins. Data shown is from: Natural repressors (Zhan et al, 2010), Phage polymerases (Temme et al, 2012), Natural activators (Moon et al, 2012), Sigma factors (Rhodius et al), Programmable repressors (Politz *et al.*, 2013b), Programmable activators (Lee *et al.*, **2008).** (B) RNA parts that act on translation include orthogonal ribosomes, the **RNAIN/OUT** system of repressing riboregulators, and activating riboregulators. Data shown is from: Orthogonal ribosomes (Chubiz **&** Rao, **2008), RNA-IN/OUT** (Mutalik et al, 2012), Activating riboregulators (Callura et al, 2012). (C) RNA parts that act on transcription include riboregulators converted to affect transcription, transcription attenuation using a PT181-like hairpin, $dCas9$ repression, and $dCas9-\omega$ activation. Data shown is from: Converted regulators (Liu et *a,* **2012), PT181** attenuation (Takahashi & Lucks, **2013),** dCas9 repression (Qi et *a,* **2013),** dCas9 activation (Bikard et *al,* **2013). (D)** Natural recombinases have been used to modify **DNA** and implement logic. Data shown is from (Siuti et al, **2013).**

Figure **1-3: A** modern expression cassette comprising genetic tuning knobs and insulators. **(A) A** cassette is shown for precise expression of a gene of interest (GOI). Insulating parts at the junctions are highlighted in blue. The cassette is shown using symbols from the synthetic biology open language visual (SBOLv). (B) Biophysical models of transcription based on the RNAP binding energy have been constructed to compliment empirically-characterized promoter libraries. Data is from (Brewster et al, 2012). **(C)** The RBS Calculator provides a computational framework for designing RBS sequences of a given strength based on a thermodynamic model of translation initiation. Data is from (Salis et al, **2009). (D)** Terminator strength is partially informed from a biophysical model relating various aspects of the terminator sequence. Data is from (Chen et *al,* **2013). (E)** Tunable copynumber plasmids allow for a wide range of gene expression based on the repA/ColE2 and pir/R6K plasmid systems. Data is from (Kittleson et al, 2011).(F) Promoter-insulating

sequences have been shown to reduce the change in promoter activity when upstream and downstream sequences are introduced to the flanking promoter context. Data is from (Davis et *al,* 2011). **(G)** Ribozymes have been used to improve the predictability of gene expression **by** reducing promoter-5'UTR coupling effects. Data is from (Lou et *al,* 2012). (H) Bicistronic RBS designs cause the rank order of expression constructs to be more predictable compared to single RBSs. Data is from (Mutalik et *a],* **2013). (I)** RNase **III** sites in the 3'UTR reduce the variability in gene expression for reporters coupled with libraries of promoters. Data is from (Cambray et al, **2013).**

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Table **1-1:** Characteristics of part families currently available for constructing genetic circuits in bacteria.

This table presents a brief comparison of a number of regulatory part families that have been characterized and are available for use in building genetic circuits in bacteria. Each part is defined as a trans-acting element and the target of this element: for example a transcriptional repressor and its binding site. Part families were chosen to either have at least three characterized members or be based on a technology proven to be extendable **(TALE,** zinc finger, and CRISPR-based parts).

Characterized family size indicates the number of parts of this type that have been characterized for crosstalk. **A '+'** indicates that this parts family is based off of a technology proven to enable orthogonal, programmable **DNA** binding and so the parts set may be predictably extendable.

Maximum dynamic range is the largest reported fold change between the on and off states (i.e. with the trans-acting element present and absent) of a single member of the part family.

The largest tested parts sets show the largest number of parts in each family that have been shown to function above specific thresholds of orthogonal range. Orthogonal range is a conservative measurement of the orthogonality of a parts set; it represents the fold change between the on-target effect of a part and the worst off-target effect on that part. For example, the **'T7** polymerases' family has a **3** part set that functions above 10x orthogonal range, meaning that there is a group of three polymerases where each activates its target promoter to a level more than 10x the level that either of the other two polymerases activate it.

a Numerical data was used from this reference for the part family in this row.

b Data computed from bar or line plots in this reference was used in this row.

c Data was read from colored orthogonality grids in this reference. Note that the numbers in this row may be less accurate because of uncertainties in this method.

d While only two recombinases have been tested together at a time, at least seven have been used in genetic circuits in bacterial systems (Ham et al, **2008, 2006;** Friedland et al, 2009; Bonnet et al, 2012; Siuti et al, 2013; Bonnet et al, 2013).

e TAL repressors and activators are much more widely used in eukaryotes. **A** set of **8** orthogonal TAL activators has been tested in mammalian cells, and it is predicted that many more could be built (Garg et al, 2012).

f Zinc fingers have also been widely used in eukaryotes (Beerli **&** Barbas, 2002).

g CRISPR repression and activation is being widely adopted in eukaryotes. Crosstalk data from these organisms suggests that many orthogonal variants could also be made in bacteria (Farzadfard et al, 2013; Fu et al, 2013; Hsu et al, 2013).

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Chapter 2

2 Genomic mining of prokaryotic repressors for orthogonal logic gates

2.1 Background

Living cells can be programmed **by** incorporating integrated genetic gates into their **DNA** (Weiss **&** Jr, 2000). These gates rely on biochemical interactions to perform computational operations, including switches, logic and memory (Khalil **&** Collins, 2010; Weber **&** Fussenegger, 2011). Gates can be connected to each other when they are designed to be extensible, meaning that the form of their input and output signals are the same. For example, if both the inputs and outputs are promoters, then this signal is defined as the flux of RNA polymerase on **DNA** (Endy, **2005).** To date, the complexity of circuits has been low, consisting of the few available gates based on the transcription factors reused across labs and projects (Purnick **&** Weiss, **2009b).** Increasing the number of available gates will enable the construction of larger circuits to encode more sophisticated algorithms (Moser et al, **2012b).** The challenge has been that all of the gates within a circuit need to be orthogonal; in other words, the biochemical interactions on which they are based cannot cross-react (Thompson et al, 2012). It becomes increasingly difficult to add gates because the number of potential cross-reactions grows quickly as N^2 -*N*.

NOT and NOR gates are simple and broadly useful functions. **A** transcriptional **NOT** gate (the output is OFF when the input is **ON)** can be implemented **by** using an input promoter to drive expression of a repressor, which turns off expression of an output promoter (Fig. 2-1a) (Yokobayashi et *a],* 2002a). Even these simple gates can perform signal-processing functions, for example, converting a dark sensor into a light sensor (Tabor et *a],* 2011) and a male sensor into a female sensor (Fu et *a],* 2010). **A** NOR gate is a logic function where the output is **ON** only when both inputs are OFF. NOR gates are Boolean complete, meaning that they can be combined to generate any computational operation. **A** genetic NOR gate can be built **by** adding a second input promoter in series to the **NOT** gate so that both input promoters drive the expression of the repressor (Tamsir et *a],* **2011b).** Two gates are orthogonal if their repressors do not bind each other's promoters. Obtaining more gates that can be used as part of the same circuit requires having a set of repressors that bind different operator sequences.

There are a number of biochemical mechanisms that could be used to produce the repressing function required **by** a **NOT** gate. The most common is to use a proteinbased repressor, which binds an operator **DNA** sequence within its target promoter. **NOT** gates have been built using different classes of natural repressors including phage repressors (e.g., cI), LacI-family and TetR-family repressors (Yokobayashi et al, 2002a; Gardner *et al*, 2000b; Elowitz & Leibler, 2000a). Several modular scaffolds, such as zinc finger proteins (ZFPs) (Hurt et *a],* **2003)** and transcription activator-like effectors (TALEs) (Boch et *a],* **2009b),** have a domain architecture that allows proteins to be designed to bind target sequences. ZFPs and TALEs have been used to control expression in eukaryotic cells (Khalil et *a],* 2012; Garg et *a],* 2012a; Zhang et *a],* 2011) and to a lesser degree in prokaryotes (Politz et al, 2013b; Durai et al, 2006).

Recently, it has been shown that transcription can be repressed with a CRISPR-Cas system ('CRISPRi') that uses a nuclease-null Cas9 protein and an RNA guide sequence to block transcription at a specific site (Qi *et al,* **2013).** Because of the programmability of the **RNA-DNA** interaction, this system holds promise for building orthogonal repressors; the use of CRISPRi to build layerable gates has the potential to be a powerful tool in the construction of circuits.

In this paper, we decided to target TetR homologs for several reasons. First, TetR is one of the earliest and most pervasive transcription factors used in biotechnology and has appeared in numerous applications (Ramos *et a],* **2005).** As an inducible system, it is part of a classic multi-plasmid system (Lutz **&** Bujard, **1997)** and has been used in a broad range of host organisms, including bacteria and archea (Guss *et al,* 2008), fungi (Dingermann *et al,* 1992), insects (Lycett *et al,* 2004), plants (Gatz **&** Quail, **1988, 10),** mammalian cells (Gossen **&** Bujard, **1992),** and live animals (Saez *et a],* **1997).** Second, it has been used in many genetic circuits in synthetic biology, including a toggle switch (Gardner *et a,* **2000b)** and oscillator (Elowitz **&** Leibler, 2000a) in *Escherichia coli.* It has also been used to build a time-delay circuit in mice (Weber *et a],* **2007)** and a **NOT** gate in mosquitoes (Fu *et a],* 2010). Third, TetR and most homologs have a simple mode of repression where dimers bind a promoter and physically block RNA polymerase (Orth *et a,* 2000). Fourth, they are able to achieve specificity with relatively short operator sequences (Ramos *et a],* **2005).** Finally, tens of thousands of homologs are available from many host organisms, and there is evidence that they exhibit sequence specific binding to disparate operator sequences (Lutz **&** Bujard, **1997).** Small differences in the amino acid sequence and operator nucleotides have been shown to yield high-affinity, orthogonal interactions (Helbl *et* al, 1998; Krueger *et al*, 2007). The potential for orthogonality is also large; coding theory predicts that there is an upper limit of **130** helix-turn-helix repressors that could function in one cell without exhibiting cross-talk (Itzkovitz *et a],* **2006).**

To increase the number of available gates, we used **DNA** synthesis to access repressors selected from the sequence database and screened them to identify an orthogonal subset. Using an *in vitro* microarray assay, the **DNA** binding preferences for individual repressors were comprehensively examined, from which well-defined motifs were obtained. This information, together with previously identified operator sequences, was used to construct synthetic promoter libraries to identify those that were **highly** repressed. The resulting repressor-promoter pairs were systematically converted into **NOT** gates, their cross-reactions were measured in all combinations and then they were used to construct composite circuits *in vivo.* Overall, this work represents a large set of compatible, orthogonal components from which user-defined circuits can be constructed **by** simply changing the pattern of input and output promoters between a set of conserved gates.

2.2 Characterization of a TetR homolog library

We developed a pipeline to expand the number of available TetR family repressors, to exhaustively measure their activity and orthogonality and to characterize them in the context of genetic gates (Fig. **2-1b).** TetR homologs encompass one of the largest families of transcription factors, with **82,017** members currently annotated in EMBL-EBI (Hunter *et al,* 2012). To build a library of homologs, we started with 73 repressors obtained from a collated list of TetR homologs with known regulatory functions from diverse organisms (Ramos *et al,* **2005)** (Fig. 2-1c). Redundant sequences and incomplete entries were excluded from the list. This set contains homologs from 45 distinct prokaryotic species and has an average amino acid identity of 21%. Genes were codon optimized for expression in a set of target organisms and built using **DNA** synthesis.

For the majority of repressors in the library, operators were determined using an assay based on cognate site identifier array analysis (Stanton *et al*, 2013). The operators for McbR, PsrA, QacR and ScbR had been previously identified, and the array data closely matched sequences from the literature. Substantial diversity exists among the operator sequences bound **by** different repressors within the library.

2.3 Synthetic promoter design and orthogonality characterization

Synthetic promoters were designed to contain operator sequences that were either identified using the array or obtained from the literature (Methods). **A** strong constitutive *E. coli* promoter (BBa J23119) was used as a backbone into which an operator was placed (Kelly *et a],* 2009a). Promoter libraries were constructed to determine the optimal placement and sequence of the operators. The data from the array were used to determine an 'operator motif' that captures the functional diversity of the operator sequence (Fig. 2-2a). Sequences consistent with the motif were constructed using degenerate oligonucleotides and inserted into various positions in the promoter around and between the **-35** and **-10** sequences. The promoter libraries were then screened in the presence and absence of their cognate repressor **by** eye or using flow cytometry (Fig. **2-2b).** From each library, the promoter that generated the highest dynamic range was identified, sequenced and then confirmed. At the end of this process, we identified promoters that were responsive to 20 repressors (Fig. 2-2c). This set consists of ten promoters whose operators were obtained from the **CSI** array and ten that were obtained from the literature (Table **2-6).**

To measure all of the possible cross-reactions, we assayed the activity of each repressor against the set of 20 promoters. Repressor expression was controlled **by** the HSL-inducible PLux promoter in a colEl plasmid (Fig. **2-3).** The promoters were fused to YFP in a **p15A** plasmid (Fig. 2-14). The repressor and promoter plasmids were cotransformed in all combinations. The resulting 400 strains were grown in the presence of inducer, the promoter activity was measured using cytometry and the fold repression was reported as the ratio between the non-repressor-containing control plasmid and the induced repressor. These data were used to construct an orthogonality matrix that shows the specificity of each promoter and repressor (Fig. **2-2d).** The repressors are remarkably orthogonal, and a core set of **16** have minimal cross-reactions (TetR, IcaRA, AmtR, BetI, SrpR, Orf2, BM3R1, ButR, PhlF, AmeR, QacR, LmrA, PsrA, HlyIIR, McbR, ScbR, TarA, LitR, HapR, and SmcR). Among this orthogonal set, the sequence diversity of the DNA-binding region is noteworthy (Fig. **2-8)** (Orth *et a],* 2000). Previous work shows that within the recognition region of the **DNA**binding domain (residues 25-44 in TetR), residues **28** and **37** are particularly important for binding specificity (Orth *et al,* 2000; Krueger *et a],* **2007).** Out of the set of **16** orthogonal repressors, **11** and **9** different amino acids are represented at these positions, respectively.

Several groups of repressors are not orthogonal, and this corresponds to amino acid similarity in their DNA-binding domain (Fig. **2-9).** The HapR, LitR, and SmcR repressors (all from *Vibrio* species) interact with each other's promoters and have similar patterns of cross-talk. Similarly, the HlyIIR and PsrA repressors share amino acid identity and bind similar operators. Unexpectedly, the converse is not true, where similarity between promoters is not predictive of cross-talk. This is largely a result of the variability observed in the acceptable spacing distance between the 6-mer repeat of the operator. For example, the LitR and HapR promoters have spacers of **11 bp** and **3 bp,** but the repressors cross-react equally well with both.

2.4 Design and measurement of genetic NOT gates

The repressors and their synthetic promoters were used to build a library of **NOT** gates. To measure the response as a function of the activity of an input promoter, the IPTG-inducible **PTac** promoter was connected to each gate. The output was measured **by** having the repressible promoter drive the expression of YFP. Each **NOT** gate consists of a **5'** UTR, repressor gene, terminator and synthetic promoter. These parts, along with the P_{Tac} -inducible system and YFP, were assembled into a p15a plasmid (Fig. $2-14$).

Ensuring repressor expression is within the appropriate range to generate a large output response represents a challenge in converting repressors into gates. Expression levels cannot be changed **by** varying the dynamic range.of the input promoter because, for circuit construction, inputs must be swapped without further modification. Thus, we define the beginning of each gate to be the transcription start site and vary the repressor level **by** changing the strength of the ribosome binding site (RBS). Each repressor has unique properties that influence their absolute protein levels (e.g., codon usage, mRNA and protein stability and binding affinity). Hence, the RBS of the repressors had to be individually tuned to maximize the dynamic range. To accomplish this, we used the RBS calculator (Methods) to design a set of sequences that systematically vary the predicted expression from medium-high to low (because the optimal desired expression is not known a priori). These were used to design a degenerate oligonucleotide, from which an RBS library was constructed for **19** out of the 20 gates (Table 2-4). These libraries were screened, and the RBS that produced the highest dynamic range was selected (Table **2-5).**

The response function of a gate captures how the activity of the output promoter changes as a function of the input promoter. This information is critical in determining how gates will operate when connected in a circuit. It is also important that the inputs and outputs are reported in the same units (Endy, **2005).** As such, we reported these values as relative expression units (REUs) (Fig. **2-15)** (Kelly et *a],* 2009a). REUs are calculated **by** normalizing the YFP output values **by** that measured from a reference standard and **by** separately measuring the activity of the PTac input promoter as a function of IPTG (Fig. **2-16),** using the same reference standard. With these data, it is theoretically possible to know whether the range of the output of one gate is sufficient to serve as an input to the next gate in series.

Each gate produces a unique response function (Fig. **2-3).** The dynamic ranges of the gates vary from 207-fold (SrpR) to 5-fold (SmcR and ButR), with an average of 51.3-fold (Table 2-1). Cytometry distributions are shown for the **ON** and OFF states, which are narrow and have good separation, even for those that have a smaller dynamic range (Fig. **2-5).** The response functions can be fit to a Hill equation:

$$
y = f(x) = y_{\min} + (y_{\max} - y_{\min}) \frac{K^n}{K^n + x^n}
$$

where y is the activity of the output promoter, y_{min} is the minimum output, y_{max} is the maximum output, n is the Hill coefficient and K is the threshold level of input where the output is half-maximal. The Hill equation was used to fit the data for each gate, and the parameters are shown in Table 2-1.

The thresholds for the gates are similar with an average of $K = 0.4$ REU and a range of **0.1 REU** (TarA) to **1.3 REU** (ButR). Considering this, all of the **NOT** gates have sufficiently high **ON** states (between **3 REU** and **70 REU)** to achieve full repression **by** crossing the threshold required **by** a downstream circuit. However, the OFF states range between **0.1 REU** and 2.1 **REU.** Because the OFF states are similar in magnitude to the thresholds, this can be problematic when connecting gates and can lead to a degradation in the signal as the number of layers in the circuit increases (Yokobayashi *et a],* 2002a).

Gates that exhibit ultrasensitivity generate a large output response with little change in the input signal. This also comes at a cost: it becomes increasingly difficult to balance the input to span the range required to achieve the maximum response. The cooperativity for the majority of gates is $n \approx 2$, which is consistent with that measured for TetR, and a mechanism of dimers binding to a single operator (Elowitz & Leibler, 2000a). Five of the repressors yield gates with $n > 3$, with the largest being **6.1** for Orf2. This has been observed before with TetR homologs, which can bind with higher cooperativities **by** assembling as multimers or multiple dimers within a single operator (Grkovic *et al*, 2001).

Transcription factors can be toxic and exhibit slow growth when expressed above a critical threshold (Kittleson *et al,* 2012). We measured the impact on cell growth **by** recording the OD_{600} 6 hours after induction for each NOT gate at various levels of induction (Fig. **2-6).** The majority of repressors are nontoxic, even when maximally expressed. Six repressors showed toxicity at high input levels: TarA, ScbR., ButR, SmcR, Orf2 and HapR (with toxicity defined as **>25%** reduction of growth) (Fig. **2-7).** In each case, the toxicity occurs after the output promoter has been repressed. The quantification of regions of toxicity enables a designer to build circuits that avoid expression above these levels. Further, it enables a comparison between different biochemistries that can be used for the construction of integrated circuits.

2.5 Connecting gates to create layered genetic circuits

The **NOT** gates can be converted into multi-input NOR gates **by** connecting multiple promoters in series to drive repressor expression (Tamsir et al, **2011b).** Logic minimization algorithms, such as **ESPRESSO** (Rudell, **1986),** can convert any arbitrary user-defined truth table into a wiring diagram composed of layered NOR gates (Brown **&** Vranesic, **2013).** The wiring diagram can then be replicated as a genetic circuit through assembling a particular pattern of input and output promoters connected to the gates (Fig. 2-4). **By** changing this assembly pattern, the same set of underlying orthogonal gates can be used to build any desired circuit.

To demonstrate the assembly of gates, we constructed two simple circuits that perform the **AND** (the output is **ON** exclusively in the presence of both inputs) and **NAND** (the output is OFF exclusively in the presence of both inputs) logic functions through different permutations of the **NOT** and NOR gates. The inputs to the circuits consist of different combinations of inducible promoters: **PTac (IPTG), PLux (HSL)** and **PTet** (aTc) (Fig. 2-12). The **NAND** gate consists of two **NOT** gates (based on PhlF and LmrA), which invert the two input signals **(Fig.** 2-4a). The output of the **NOT** gates are assembled in series to form an OR gate, which then serves as the output of the circuit. The circuit produces the correct **NAND** function, with a sixfold difference between the OFF state $(+/+)$ and the lowest ON state. The OFF state is high, which is consistent with the leakiness of the LmrA promoter.

The **AND** circuit was constructed **by** combining three gates (Fig. 2-4b). The PhlF **NOT** gate (the same as that used for the **NAND** circuit) serves to invert one of the input promoters. The other input promoter is inverted **by** the QacR **NOT** gate. The output promoters of these gates are connected to BetI to form a NOR gate, the output of which drives the expression of YFP. This circuit produces a 4.4-fold response when the ON state $(+/+)$ and the highest OFF state are compared. Flow cytometry histograms for each circuit and the terminal gates are illustrated in Figure 2-10.

To determine whether individually measured response functions of gates (Fig. **2-3)** can be used to predict their combined response as a circuit, we developed a simple model of the **NAND** and **AND** circuits. This model simply adds the response functions of the inducible inputs and the gates to obtain the response of the circuit as a whole, with no additional fit parameters. The OFF and **ON** states of inducible promoters that serve as inputs $(P_{Tac}, P_{Lux}$ and P_{Tet}) were measured independently and converted into **REU.** The **(OFF-ON)** states of the inducible promoters are: PTac(0.06-6.2), **PLux (0.7- 8.2)** and **PTet (0.07-9.8).** To determine the predicted function of a circuit, we tracked the combinations of signals from the input promoters through the gates using their response functions. This process is visualized in Figure **2-13.**

To model the NAND circuit, the range of P_{Tac} is inserted into the PhIF response function, yielding outputs of **16 REU** and **0.1 REU** (Table **2-3).** Similarly, the range of the **PLux** input is converted to **61 REU** and 1.4 **REU by** the LmrA response function. The output of the OR gate is treated as the simple sum of the outputs of the tandem promoters. The predicted values for the four combinations of input states closely match the experimental data (Fig. 5a).

To model the AND circuit, the output of P_{Tac} connected to the PhlF gate is the same as reported above **(16 REU** and **0.1 REU),** and the output of **PTet** connected to the QacR gate is 20 **REU** and 0.4 **REU** (Table 2-2). To model the NOR gate, the outputs of these promoters are summed as $x = x_1 + x_2$ and serve as the input to the BetI response function. As with the **NAND** circuit, the predicted response closely matches the experimental measurements (Fig. 2-4b). Both circuits have some quantitative differences between the predictions and experimental data. This is most

likely due to the simplicity of the model, which does not account for changes in genetic context, promoter interference between tandem promoters, plasmid copy number variation (Moser et *a],* 2012b; Lou et *a],* **2012b)** or the growth phase under which the outputs were measured (Fig. 2-11).

2.6 Discussion

The ability to manipulate gene regulation is one of the last frontiers in genetic engineering. The implementation of computing in cells has the potential to affect many applications in biotechnology. However, the field has been limited in the size and sophistication of circuits that could be constructed from a small number of characterized transcription factors. Here, we substantially expand the number of repressors that are available for circuit c

onstruction. Further, we have rigorously measured the cross-reactions to identify a core orthogonal set. Each member of this set is converted into' a gate and fully characterized. Finally, we introduced a generalized method **by** which circuits can be assembled **by** changing the pattern of input and output promoters to reproduce a wiring diagram composed of **NOT** and NOR gates. For simplicity, we demonstrate this **by** building two circuits that perform digital Boolean logic operations. Notably, the same approach could be applied to build analog (Daniel *et al*, 2013b) and dynamic (Elowitz **&** Leibler, 2000a) circuits.

The mining effort described here started with **73** homologous repressors and ended with a set of **16** orthogonal gates. **By** considering all of the possible ways that these gates can be combined, one can imagine a 'circuit space' that consists of all of the possible wiring diagrams. The size of this space can be estimated **by**

$$
N = \sum_{k=0}^{n} \frac{n!(3k+1)^{2k}}{k!(n-k)!}
$$

where *n* is the size of the orthogonal set, and *k* is the number of repressors in the circuit. This takes into account that (i) there are up to **2k** sensor inputs to the circuit as a whole; (ii) only **NOT** and 2-input NOR gates are considered; (iii) for a gate, each input can comprise one of the circuit inputs or an output from another gate or can be unconnected, yielding $(3k + 1)$ possibilities; and (iv) functionally redundant or isomorphic circuits are not removed from the set. This estimates that $n = 16$ orthogonal gates can be used to build $N>10^{54}$ possible circuits. This set includes feedback loops and is not limited to digital logic. Each of these circuits can be accessed **by** permuting the input and output promoters into a particular pattern.

The challenge now becomes achieving a degree of reliability where the gates can be assembled into any of these circuits with a reasonable chance of functioning properly. Although we demonstrate this mapping with a few circuits, accessing the potential of the space remains a challenge. The first generation of gates presented here was designed to be simple and consist of a single operator in a constitutive promoter. This simplicity leads to gates that exhibit low cooperativity, a high OFF state and sensitivity to genetic context (Lou *et al,* 2012). Further, each gate uses the same pair of terminators, which can lead to evolutionary instability for large circuits (Chen *et al,* **2013;** Sleight **&** Sauro, **2013).** Analyzing the gates in different contexts and identifying the failure modes could lead to second-generation designs that are engineered to be faster, tunable and robust **by** implementing design rules that have emerged from control theory and systems biology (Lou *et al,* **2012b;** Lee **&** Maheshri, 2012a; Buchler **&** Cross, **2009;** Bintu *et a],* **2005).**

We selected TetR homologs because of their high specificity, stability and proven capability to operate in synthetic circuits. Other biochemistries could be used to expand the number of orthogonal gates in our library. To be compatible, the only constraint is that the inputs and outputs of each gate must be promoters, thus allowing the gates to be layered. The repressors could be other classes of proteins that bind **DNA,** such as TALEs, ZFPs or the guide RNA that directs Cas9 as part of CRISPRi; a single large circuit could contain mixtures of these biochemistries. Indeed, this may be a mechanism to expand the gate library beyond the informatic limit of any one family. For example, our TetR library already covers **15%** of the predicted upper limit on helix-turn-helix repressors (Itzkovitz et al, **2006).**

The set of orthogonal gates we present is sufficiently large to implement nontrivial circuits of direct relevance to applications in biotechnology, which includes multi-input logic control for environmental or metabolite sensing, timers to control when different genes are expressed, multiple toggle switches for memory and simple algorithms from control theory. However, now that parts are no longer limiting, it remains a challenge to build large circuits. To this end, computational tools will most likely play a more central role in design. Changing the inputs and outputs to gates **by** rearranging the pattern of input and output promoters is a sufficiently simple operation to be performed **by** a computer. The co-development of simple schemes for genetic programming, as well as gates designed specifically to be compatible with these schemes, will enable the broader application of genetically encoded algorithms to program cells.

Figure 2-1: **A** large repressor library is compiled using genome mining. (a) **A** genetic **NOT** gate (symbol shown) can be built using a repressor (pink arrow) that binds an operator (pink box) in an output promoter. **(b)** The pipeline for the discovery and characterization of orthogonal repressors is shown. The second panel depicts a portion of the **CSI** microarray used to determine the operator sequence. (c) The complete library of **73** synthesized repressors (plus TetR) are organized into a phylogenetic tree diagram, where carets indicate repressors that appear in the final orthogonality matrix illustrated in Figure **2-3d.** The tree was aligned on the basis of respective repressor protein sequences, and branch lengths correspond to relative divergence in amino acid sequence. The two IcaR orthologs originate from two distinct host organisms where **A** indicates Staphylococcus aureus and **E** indicates Staphylococcus epidermidis.

Figure 2-2: Design and screening of orthogonal promoters. (a) Degeneracy in operator sequences (Stanton et *a],* 2014) is converted into a single motif. The LitR motif is shown (W is A/T , H is $A/T/C$, Y is T/C , K is G/T , M is C/A , R is A/G and D is **A/T/G).** The degenerate operator is placed in the **BBaJ23119** constitutive promoter spanning either the **-35** or **-10** element (right panel). **(b)** The results of screening the LitR promoter library are shown. The fold repression is calculated as the ratio of fluorescence from the promoter alone and that obtained when the repressor is present and uninduced for a single replicate. (c) The best promoters identified in the screens are shown for each repressor that are part of the final set of 20 repressors. The operator sequence is shown in capital red letters, and the Shine-Dalgarno sequence is in bold letters. Those promoters lacking the Shine-Dalgarno sequence contain this sequence adjacent to the 3' end of the sequence listed; when not shown, the sequence up to the **ATG** start is identical. **(d)** The promoters driving YFP expression are carried on a p15a plasmid, and the repressors are under 3OC6-N-(β -ketocaproyl)-L-homoserine lactone-inducible control on a ColEl plasmid (Figs. **2-8** and **2-9).** The matrix has been sorted **by** eye such that the most orthogonal promoters appear at the top and the least at the bottom, and similar patterns of cross-reactivity are clustered together. Repressor expression is induced by $20 \mu M$ HSL (except in the case where such concentrations of **HSL** are toxic, including HapR, Orf2, ScbR and SmcR, which were induced with 2 μ M, 0.02 μ M, 0.2 μ M and 0.2 μ M HSL, respectively). The data represent the average of three replicates collected on different days.

Figure **2-3:** Response function measurement. The response functions are measured using the IPTG-inducible P_{Tac} promoter as an input and measuring the response of the output promoter. The activity of the input promoter is measured separately using YFP. The activities of the input and output promoters are converted to **REU.** The response functions of the **NOT** gates are shown. From left to right, the concentration of IPTG is: **0** piM, **5** riM, **10** pM, 20 pM, **30** VM, 40 VM, **50** pM, **70** jiM, **100** pM, **150** pM, 200 pM, **500** VM and **1,000** pM. As a guide to the eye, the highest (LmrA) and lowest (BM3R1) response functions are shown on each plot, with the region between them in gray. The dashed regions indicate the levels of expression beyond which toxicity is observed (Figs. **2-15** and **2-16).** The data represent the average of three replicates collected on different days, and error bars correspond to the s.d. between these measurements.

Figure 2-4: Construction and characterization of integrated circuits. (a) The process of promoter mapping for the assembly of gates into a desired circuit is shown for the NAND circuit. The measured data are grown under conditions of no inducer $(-/-)$, 1 mM IPTG $(+/-)$, 20 μ M HSL $(-/+)$ and 1 mM IPTG and 20 μ M HSL $(+/+)$. The bar graph details the measured output levels under all of the input combinations. Small black bars indicate the predicted output value for the indicated input. The data represent the average of three replicates collected on different days, and error bars correspond to the s.d. between these measurements. **(b)** The design, construction and characterization of the **AND** circuit is illustrated. Note that when multiple promoters are placed upstream of a repressor, the gate is converted from the **NOT** to NOR function. The measured data are grown under conditions of no inducer $(-/-)$, 1 mM IPTG **(+/-), 100** ng/mL aTc **(-/+),** and **1** mM and **100** ng/mL aTc **(+/+).** The bar graph details the measured output levels under all input combinations. Small black bars indicate the predicted output value for the indicated input. The data represent the average of three replicates collected on different days, and error bars correspond to the s.d. between these measurements.

Figure **2-5:** Flow cytometry data for each **NOT** gate. Fluorescence histograms correspond to representative single cytometry replicates for induced (black) and uninduced (green) states. The induced state corresponds to the highest IPTG concentration before toxicity was observed $(200 \mu M)$ for ButR, 150 μ M for TarA, 100 pM for HapR, **70** 1M for ScbR, **70** jiM for SmcR, **70** VM for Orf2, and **1** mM IPTG for all other repressors). Each histogram comprises **>10000** cells.

 \mathcal{L}

Figure **2-6:** Growth measurements for **NOT** gate response functions. The optical density at **600** nanometers was measured for all **NOT** gates at each of the twelve inducer concentrations: **0, 5, 10,** 20, **30,** 40, **50, 70, 100, 150,** 200, **1000** VM IPTG in an analogous manner to the response functions (Figure **2-3).** The x-axis values are converted to the **REU** values measured for the response function assay. Toxicity is indicated **by** the hash-marked region, and begins when the cell growth falls below **75** percent of the uninduced cell growth. Each data point was measured in triplicate on three separate days, and the data represent mean values \pm 1 standard deviation.

Figure **2-7:** Toxic induction threshold versus decrease in cell growth.' The highest input level before toxicity is observed is plotted versus the percent decrease in cell growth. For most repressors, toxicity is not observed, and is indicated **by** the horizontal black line at the top of the graph. HlyIIR and LitR exhibit a **10** percent decrease in growth at high induction levels. The cross-section of the toxicity trajectories at **25%** decrease in cell growth for TarA, ButR, HapR, SmcR, Orf2, and ScbR is reflected in the toxic regions of Figure **2-3** and Figure **2-6.** Threshold data (y-axis) represents mean maximum induction levels before the growth decreases beyond a mean percentage (xaxis) from three separate experiments.

Figure **2-6:** DNA-binding domain recognition region diversity. The recognition regions of the DNA-binding domains for all 20 repressors were aligned, and the number of different residues at each position across the set was counted. The wild-type sequence of TetR is shown below the plot for reference, along with the secondary structure of the protein.

Figure 2-9: Fold-repression versus percent pairwise identity of the recognition region. The fold-repression values of all repressor-promoter pairings are the mean repression values from triplicate orthogonality measurements (Figure **2-2d).** These data are plotted versus the corresponding percent pairwise sequence identity of the recognition regions of the repressors' DNA-binding domains.

Figure 2-10: Flow cytometry data for logic circuits and terminal gates. Upper panel: Representative fluorescence histograms that correspond to the average fluorescence values in Figure 2-4a, **b.** For the **NAND** circuit, the black line corresponds to no inducer, green to 1 mM IPTG, red to 20 μ M 3OC6HSL, and blue to the presence of both IPTG and **30C6HSL.** For the **AND** circuit, the black line corresponds to no inducer, red to **1** mM IPTG, green to **100** ng/mL aTc, and blue to the presence of both IPTG and aTc. Lower panel: Representative fluorescence histograms for repressors connected to circuit outputs. The **output** distributions for the terminal repressors were taken from response function characterization data, and input levels were chosen such that they approximate the predicted levels seen within the circuits. Each histogram comprises **>10000** cells.

Figure 2-11: Growth phase robustness of repressors and **AND** gate. Left panel: Response functions for AmtR (blue squares), BM3R1 (red squares), PhIF (orange squares), and SrpR (green squares) measured in exponential phase (top) and stationary phase (bottom) and grown in LB media. Data points represent the geometric mean of a fluorescence histogram at each data point. Right panel: Output values for **AND** gate measured in exponential phase and stationary phase in LB media. The measured data are grown under conditions of no inducer $(-/-)$, 1 mM IPTG $(+/-)$, 100 ng/mL aTc $(-$ **/+),** and **1** mM IPTG and **100** ng/mL aTc **(+/+).** Bars corresponding to the **ON** and OFF states are colored black and gray, respectively. Data was collected in triplicate on three different days and points represent mean values \pm 1 standard deviation.

Figure 2-12: Characterization of inducible promoters. Promoters PTac, **PLux,** and PTet drive yellow fluorescent protein expression and were induced with 1 mM IPTG, 20 μ M **30C6-HSL,** and **100** ng/mL aTc, respectively. Cells grown under maximum inducing and non-inducing conditions were measured via cytometry; fluorescence values were normalized **by** an in vivo reference standard to obtain the promoters' outputs in **REU** (Figure **2-16).** Data was collected in triplicate on three different days and points represent mean values \pm 1 standard deviation.

Figure **2-13:** Modeling of genetic circuits. For the first layer of gates, experimentally characterized input promoter values (red lines) are mapped onto Hill-equation fits of **NOT** gate response functions (dashed lines), resulting in predicted output values (blue lines) that feed into the next logic layer. For the **NAND** gate, the individual **NOT** gate output values from the first layer are summed to yield the final circuit output. For the **AND** gate, the individual **NOT** gate outputs from the first layer are summed to yield the BetI inputs (red lines) that drive the final NOR gate output.

 $\overline{\mathbf{u}}$

 $\bar{\alpha}$

Figure 2-14: **NOT** gate plasmid maps. These plasmids are used to calculate the response functions shown in Figure **2-3.** The Response Function vectors (pRF-) contain an individual repressor, whose expression is controlled **by** the PTac inducible promoter (which corresponds to a version of Ptaci that has been modified to contain a perfect inverted repeat sequence for the Lac operator). Each **NOT** gate also contains the cognate promoter for the repressor, which controls expression of the YFP output. The terminator present after the repressor coding sequence corresponds to BBa_B0015, a double terminator consisting of both BBa_B0010 and BBa_B0012 (partsregistry.org). The wild type promoter of the Lac Repressor (labeled Pconst) constitutively expresses both LacI and LuxR. These components are maintained on a lower copy number plasmid that was derived from the expression plasmid **pEXT20.** Activation of repressor expression **by** IPTG results in repression of the promoter driving YFP (Figure **2-3).**

Figure **2-15:** Response function input measurement plasmid. To report the response function input as **REU,** the activity of the input promoter is measured separately.

Figure **2-16:** The reference plasmid is shown for converting fluorescence units to **REU.** The fluorescent measurements are normalized **by** the fluorescence produced from a constitutive promoter (BBa **J23101).** The corresponding output, defined as a single **REU,** serves as the unit to which all other fluorescence values are normalized (Methods).

 $\hat{\mathcal{C}}$

 $\overline{\mathcal{E}}$

Figure **2-17:** Orthogonality measurement plasmids maps. Orthogonality measurements were obtained using two plasmids: one expresses the repressor and the second contains the promoter reporters. In this way, the two sets of plasmids can be co-transformed to build all of the strains required for the orthogonality screen. For the repressor library, each repressor is placed under the control of a **30C6HSL** inducible system (the pOrtho set of plasmids). For the reporters, the same plasmids are used as were built to measure the response functions (Figure 2-14), but the repressors encoded **by** these plasmids are not induced.

 $\bar{\mathcal{A}}$

Table 2-1: **NOT** gate response function parameters

a. Fold-change was calculated as the ratio of the maximum and minimum output values from the Hill-equation.

Table 2-2: **AND** circuit modeling

Input ^a		Internal ^a		Output ^a	
P_{Tac}	P_{Tet}	P_{PhIF}	$P_{\rm QacR}$	P_{Bett}	
0.06	0.07	16	20	0.4	
6.2	0.07	0.1	20	0.4	
0.06	9.8	16	0.4	0.4	
6.2	9.8	0.1	0.4	1.7	
	α All values are in RFII				

a. All values are in REU.

Table **2-3: NAND** circuit modeling

Input ^a			Output ^a
P_{Lux}	P_{PhIF}	P_{LmrA}	P _{PhiF} -P _{LmrA}
0.7	16	61	78
0.7	0.1	61	62
8.2	16	1.4	17
8.2	0.1	1.4	1.4
			Internal ^a

a. All values are in REU.

Table 2-4: Degenerate **NOT** gate repressor RBS sequences

Repressor	RBS Library Sequence ^a
AmeR	CTATGGACTATGTTTTCACANANGANGNGGATTAGATG
AmtR	CTATGGACTATGTTTGANAGANANAATACTAGATG
Betl	GCTACGACTTGCTCATTTGANAGAGGANAANTACTAGTG
BM3R1	CTATGGACTATGTTTNAANTACTAGATG
ButR	CTATGGACTATGTTTTCASASRGGARRTACTASGATG
HapR	CTATGGACTATGTTTAAAGAGGANANNTACTAGATG
HyllIR	CTATGGACTATGTTTGAAAGAGGGANAAANACTANATG
lcaR	CTATGGACTATGTTTTCACACAGGGSCYSGATG
LitR	CTATGGACTATGTTTTCACACAGGTTTTCACACAGRARARRCCTCGATG
LmrA	CTATGGACTATGTTTTCACACAGGAAAGGNCTCGATG
McbR	CTATGGACTATGNAGGANAANTACTAGATG
Orf2	CTATGGACTATGTTTTGAAAGAGGAGAAANNCTAGATG
PhIF	CTATGGACTATGTTTGANANGGANAANTACTAGATG
PsrA	CTATGGACTATGTTTSAMASAGGATACRAMMTACTAGATG
QacR	GCCATGCCATTGGCTTTTCACACAGGACACCGGTTAGTACTAGATG
ScbR	CTATGGACTATGTTTAMASAGGARAMSTACTAGATG
SmcR	CTATGGACTATGTTTSAMASAGGARRRRWWYTMGATG
SrpR	CTATGGACTATGTTTTSAMASAGGAAMTACMAGSATG
TarA	CTATGGACTATGTTTTTSAMASAGGARAMMTACTAGATG
TetR	CTATGGACTATGTTTTCACACAGGAAAGGCCTCGATG
	a. Codes are defined as $N = A$, T, G, or C, S = G or C, R = A or G, Y = T or C, M = A

or C , $K = G$ or T , and $W = A$ or T .

 κ

Table **2-5: NOT** gate repressor RBS sequences

Repressor	RBS sequence
AmeR	CTATGGACTATGTTTTCACATACGAGGGGGATTAGATG
AmtR	CTATGGACTATGTTTGAAAGAGAGAATACTAGATG
Betl	GCTACGACTTGCTCATTTGACAGAGGATAACTACTAGTG
BM3R1	CTATGGACTATGTTTTAACTACTAGATG
ButR	CTATGGACTATGTTTTCACACAGGAAATACTACGATG
HapR	CTATGGACTATGTTTAAAGAGGACACATACTAGATG
HyllIR	CTATGGACTATGTTTGAAAGAGGGACAAACACTAAATG
lcaR(A)	CTATGGACTATGTTTTCACACAGGGGCCGGATG
LitR	CTATGGACTATGTTTTCACACAGGGTTTTCACACAGGAGAAACCTCG ATG
LmrA	CTATGGACTATGTTTTCACACAGGAAAGGCCTCGATG
McbR	CTATGGACTATGTAGGAGAAATACTAGATG
Orf ₂	CTATGGACTATGTTTTGAAAGAGGAGAAACACTAGATG
PhIF	CTATGGACTATGTTTGAAAGGGAGAAATACTAGATG
PsrA	CTATGGACTATGTTTGAAAGAGGATACGAACTACTAGATG
OacR	GCCATGCCATTGGCTTTTCACACAGGACACCGGTTAGATG
ScbR	CTATGGACTATGTTTAAAGAGGAAAAGTACTAGATG
SmcR	CTATGGACTATGTTTGAAAGAGGAGAAATACTAGATG
SrpR	CTATGGACTATGTTTTCACACAGGAAATACCAGGATG
TarA	CTATGGACTATGTTTTCAAAGAGGAGAAATACTAGATG
TetR	CTATGGACTATGTTTTCACACAGGAAAGGCCTCGATG

Table **2-6:** Native operator sequences

Repressor	Operator Sequence		
AmtR	TTTCTATCGATCTATAGATAAT		
Betl	ATTGATTGGACGTTCAATATAA		
BM3R1	CGGAATGAACGTTCATTCCG		
HapR	TTATTGATTTTTAATCAAATAA		
HIVIIR	ATATTTAAAATTCTTGTTTAAA		
lcaR(A)	TTCACCTACCTTTCGTTAGGTTA		
ImrA	GATAATAGACCAGTCACTATATTT		
PhIF	ATGATACGAAACGTACCGTATCGTTAAGGT		
SmcR	TTATTGATAAATCTGCGTAAAAT		
TetR	TCCCTATCAGTGATAGA		

Chapter 3

33 Multi-input CRISPR/Cas genetic circuits that interface host regulatory networks

3.1 Background

Genome editing has been revolutionized **by** the RNA-guided endonuclease Cas9 *from Streptococcus pyogenes* due to its ability to target **DNA** sequences adjacent to **'NGG'** motifs using a guide RNA (Cong *et a],* **2013;** Jiang *et a],* **2013;** Wang *et al,* 2013a; Esvelt *et al,* **2013;** Zhou *et a],* 2014; Shalem *et a,* **2013).** This programmability has been harnessed for gene regulation using a Cas9 double mutant that eliminates nuclease activity (dCas9) so that guide RNAs cause it to bind tightly to the corresponding **DNA** sequence without cleaving it (Jinek *et a],* 2012). This complex can serve as a repressor **by** blocking RNAP binding to a promoter or **by** terminating transcription (Qi *et a],* **2013;** Bikard *et al,* **2013;** Esvelt *et a],* **2013). A** chimeric small guide RNA (sgRNA) is sufficient to drive Cas9 to a target (Jinek *et a,* 2012), and it comprises a complementary domain that binds to the **DNA** followed **by** a "handle" that is bound **by** Cas9. Considering the programmability of **DNA:RNA** interactions and the existence of a "seed" region at the 3'-end of the sgRNA's complementary region, this system could yield **~107** orthogonal sgRNA:DNA pairs. This is a potentially versatile
platform for building genetic circuits, which have been limited in size and sophistication **by** the number of available orthogonal transcription factors.

Extensible circuits, whose inputs and outputs are of an identical form, can be connected in different ways in order to perform user-defined computational operations (Nielsen *et al*). For genetic circuits, the simplest way to achieve this is to design gates whose inputs and outputs are both promoters (Moon *et al*, 2012b; Tamsir *et al*, 2011a; Stanton *et al,* 2014). In this formalism, the common signal carrier is RNAP flux and gates are connected **by** having the output of one serve as the input to the next. The majority of transcriptional gates have been built using DNA-binding proteins. The challenge has been to obtain large sets of orthogonal proteins that do not cross-react with each other's binding sites. These sets can be obtained either **by** part mining, where bioinformatics is applied to search databases for classes of regulators that are synthesized and screened (Moon et *a],* **2012b;** Stanton et *a],* 2014; Rhodius et *a],* **2013),** or **by** building variants of modular DNA-binding proteins whose domains can be engineered to target different operators (e.g., ZFPs (Beerli **&** Barbas, **2002b;** Miller et al, **2007)** and TALEs (Morbitzer et *a,* **2010b;** Miller et *a],* **2011)).** For both approaches, cross-reactions are prevalent and many variations have to be screened to obtain an orthogonal core set. Another challenge is that within a regulator class, some can be non-toxic whereas others exhibit extreme toxicity (Kimelman et *al,* 2012; Stanton et *al*, 2014). Collectively, restrictions on function, orthogonality, and toxicity reduce the size of the libraries dramatically; for example, an initial set of **73** TetR homologues was reduced to 16 repressors (Stanton *et al*, 2014).

Here, we build a set of transcriptional gates based on sgRNA-guided repression of a synthetic *E. coli* σ_{70} promoter (Figure 3-1a). The input to the sgRNA NOT gate is a promoter that contains a precise transcription start site $(+1)$ so that additional nucleotides are not added to the 5'-end of the sgRNA, which has been shown to reduce activity (Larson et *a],* **2013).** The sgRNA includes a guide region that targets dCas9 to the cognate bacterial promoter. **A** strong terminator (Qi et *a],* **2013;** Chen et a], **2013)** is placed after the sgRNA to stop transcription. The output is an **E.** coli constitutive promoter (BBa J23101) that has been modified to include both forward and reverse **'NGG'** PAMs (for targeting either the template or non-template strands of the promoter), and a unique 13bp "operator" region between the -35 and -10 \boxtimes_{70} binding sites (Figure 3-2c). The entire transcription unit (promoter, sgRNA, and terminator) can be constructed from a pair of 5200nt single-stranded **DNA** oligonucleotides that are annealed and extended at the dCas9 handle region. These ssDNA oligos also encode Type Ils restriction enzyme recognition sites that flank the transcription unit. The resulting dsDNA modules can then be combined into a final circuit plasmid using a one-pot Golden Gate assembly reaction (Engler et al , 2009) (Figure **3-1b).**

Multi-input NOR and **NAND** gates are "Boolean complete" and are each sufficient to build any user-defined computational operation (Katz **&** Boriello, 2004). Transcription factor-based NOR gates have previously been built **by** placing two input promoters in series upstream of a repressor gene (Tamsir et *a],* 2011a; Stanton et a], 2014). Without additional RNA processing, this design does not work for sgRNAcircuits because of the detrimental influence of 5'-mismatches (Larson et al, **2013)** and the 'roadblocking' effect of CRISPRi (small for template-targeting sgRNAs, substantial for non-template-targeting sgRNAs) (Qi et *a],* **2013).** Hammerhead ribozymes and endoRNase cleavage of 5'-mismatches have both been shown to effectively remove extraneous $5'$ -RNA from sgRNAs (Gao & Zhao, 2014; Nissim *et al*, 2014) and could be employed in multi-input dCas9 circuits. Instead, our design is based on two transcription units, each of which contains a different input promoter. When either promoter is active, the sgRNA is transcribed and represses the output promoter. This

design allows larger circuits to be constructed simply **by** changing the pattern of input and output promoters around the sgRNAs. This approach requires that the sgRNAs be able to be layered into a cascade, which has been shown to work in mammalian cells (Kiani *et a],* 2014; Nissim *et a],* 2014).

Linking the output(s) of a genetic circuit to regulate host genes provides control over cellular responses. For example, cells could be programmed to sense the cell density in a fermenter and respond **by** expressing enzymes to redirect flux through global metabolism (Nielsen *et a],* 2014). Similarly, the cell phenotype could be controlled, like the ability to swim or associate into biofilms. Various approaches have been taken to link synthetic circuits to endogenous genes. Church and co-workers used **MAGE** to insert **T7** RNAP promoters upstream of genes participating in lycopene biosynthesis and upregulated production **by** expressing the polymerase as a circuit output (Wang *et a],* **2009).** Natural and synthetic sRNAs have been used to knockdown endogenous genes involved in motility (Sharma *et a],* **2013),** iron metabolism (Kang *et* al, 2012), acetone-formation (Tummala *et al*, 2003), β -glucuronidase (Man *et al*, 2011), membrane porin and flagellin genes (Sharma *et a],* 2012), and to increase tyrosine and cadverine production (Na *et a],* **2013).** Finally, strains have been constructed that express a protein that can be targeted to the genome (ZFP (Beerli **&** Barbas, **2002b), TALE** (Zhang *et a],* 2011; Morbitzer *et al,* **2010b),** or dCas9 (Gilbert *et a],* **2013;** Farzadfard *et al*, 2013; Qi *et al*, 2013)) to upregulate or knockdown endogenous genes. Here, we link the synthetic dCas9-based circuits to the native *E. coli* regulatory network **by** designing the final sgRNA in a circuit to target a transcription factor on the host genome. This provides a generalizable mechanism **by** which the same biochemistry is used to both perform computation and also actuate host phenotype in response to conditions defined **by** the circuitry (Figure 3-1c).

3.2 Orthogonal NOT gates based on *dCas9* **and sgRNAs**

A three-plasmid system was built to measure sgRNA orthogonality and characterize their performance in the context of a gate (Figure 3-2a). The first plasmid controls the expression of *S. pyogenes* $dCas9$ from an aTc-inducible P_{Tet} promoter. The sgRNA is carried on a high-copy plasmid and transcribed using a variant of the arabinoseinducible P_{BAD} promoter that is truncated to end at the transcription start site $(+1)$. Finally, the output promoter repressed **by** the dCas9-sgRNA is transcriptionally fused to red fluorescent protein (RFP) and carried on a low-copy plasmid.

dCas9 can exhibit toxicity when overexpressed. To reduce background expression, we selected an aTc-inducible P_{Tet} variant that exhibits low leakiness and added the strong L3S3P21 terminator (Chen *et al.* 2013) upstream to block read-through transcription. As the expression of dCas9 is increased, higher fold-repression is observed but this comes at the cost of reduced cell growth (Figure **3-2b).** These effects are balanced at **0.625** ng/ml aTc, which elicits near-full repression with a growth impact of less than **15** percent (after **6** hours, an **OD6oo** of 0.44 versus **0.51).** This induction level is used for all subsequent experiments.

A set of five synthetic promoters **(PA1-PA5)** were designed to be targeted **by** corresponding sgRNAs. An *E. coli* constitutive promoter (BBa J23101) was chosen as a scaffold and the operator that is recognized **by** the sgRNA was inserted between the **-35** and **-10** consensus sites where the housekeeping **070** binds (Figure 3-2c). The region between these sites is **17bp,** the center of which contains a unique **13 bp** sequence that is bound **by** the "seed" of the sgRNA complementary region, which is less tolerant of **RNA-DNA** mismatches (Jinek *et a,* 2012). This is flanked **by** forward and reverse **'NGG'** protospacer adjacent motifs (PAMs), which are required for dCas9 binding (Marraffini **&** Sontheimer, 2010). When dCas9 is directed to this region **by** a corresponding sgRNA, the promoter is repressed **by** sterically blocking the binding of *E. coli* RNAP. The orthogonal sgRNAs were designed **by** selecting a set of five distinct **13bp** seed sequences that have no matches to PAM-proximal sequences in the *E. coli* genome. Two variants of each sgRNA were built that target the non-template **(-NT)** and template $(-T)$ strands of each promoter. Each of the sgRNAs strongly represses its target promoter **(56-** to 440-fold), with no preference for the non-template or template strand, as observed previously (Bikard *et* al, **2013).** The orthogonality of the promoters and sgRNAs are near-perfect, with essentially no off-target interactions (Figure **3-2d).** In addition, we observe only a small amount of toxicity when the sgRNAs are **highly** expressed, and no growth differences between the sgRNA variants.

The response function of a gate captures how the output changes as a function of input. This is critical in predicting how gates can be connected to form larger circuits. To characterize the gates, the **PBAD** promoter serves as the input, which we characterized separately as a function of arabinose concentration. This is used to rescale the data to report it as a function of promoter activity, as opposed to inducer concentration (Figure 3-2e). The log-linear shape of this response curve is approximated well **by** a power law, and is very different from those observed from similar gates based on transcription factors, which saturate as a Langmuir isotherm. This log-linearity is also evident when observing the relationship between the intermediate and output promoters of an sgRNA cascade (Figure **3-3b,** right).

The dynamics of repression were also measured (Figure **3-2f).** After induction, there is an initial delay of 1.5 hours corresponding to the activation of $\text{Pr}_{ct}/\text{P}_{BAD}$ and the accumulation of $dCas9/sgRNA$. After this delay, there is a consistent exponential decline in RFP $(t_{1/2} = 33 \text{ min})$ over seven hours, which is consistent with the dilution rate of the reporter expected from cell division.

3.2.1 Measurement of NOT gate response functions

The response function of a **NOT** gate captures how the output promoter changes as a function of the input promoter. Because the gate is measured using an inducible promoter (in our case arabinose-inducible **PBAD),** the concentration of inducer has to be exchanged for the activity of the inducible promoter(Anderson et al, **2007).** To do this, the activity **of PBAD** is measured as a function of [arabinosel and this is used to rescale the input (x-axis of the function). For example, to generate the response function for sgRNA-1T (Figure 3-2e), we induced cells harboring $pAN-P_{BAD-Sg}RNA-$ **AlT, pAN-PA1-RFP,** and pAN-PTet-dCas9 in **0.625** ng/mL aTc and various arabinose concentrations, and then performed flow cytometry (Figure **3-5,** bottom panel). Additionally, in order to determine what the underlying activity of P_{BAD} was in these experiments, we induced cells harboring **pAN-PBAD-YFP** in an identical manner (Figure **3-5,** top panel).

A plot **of** PBAD-YFP as a function of arabinose shows the plateaus of the promoter at low and high arabinose concentrations (Figure 3-6a). Similarly, a plot **of** PA1-RFP as a function of arabinose shows a similar plateauing at high and low concentrations due to the underlying **PBAD** saturation (Figure **3-6b).** In order to visualize the relationship between **PBAD** activity and **PAl** activity, we convert the x-axis of Figure **3-6b** to units **of** PBAD-YFP (Figure **3-6c).** The response functions for all sgRNAs with their cognate promoters are shown in Figure **3-7.**

3.2.2 Cytometry data for sgRNA orthogonality

The programmability of **RNA-DNA** interactions potentially allows for a large number of orthogonal sgRNAs and cognate promoters to be designed. Figure **3-8** shows the raw data for the full orthogonality grid shown in Figure **3-2d.** Although each template sgRNA shares its six 5'-nucleotides with every other template sgRNA in order to bind the $-35 \sigma_{70}$ -binding site of the promoter (similarly for the non-template sgRNAs and the $-10\sigma_{70}$ -biding site), the subsequent twelve 3'-nucleotides are unique and comprise a "seed" region that does not tolerate mismatches.

3.2.3 Design of sgRNA sequences

Each sgRNA was designed so that the first eight nucleotides of the guide region bind the **-35** or **-10** sites (for template and non-template targeting sgRNAs, respectively) followed **by** a **'CC'** for the opposite strand's PAM. The subsequent twelve nucleotides of the guide region bind the promoter-specific sgRNA operator for each promoter PA1 through **PA5.** Tables **3-1** and **3-2** list the sequences and fold-repression values for sgRNA **NOT** gates. Fold-repression values were calculated from the orthogonality grid experiment, and represent the RFP output for the uninduced state (no aTc, no arabinose) divided **by** the RFP output of the fully induced state **(0.625** ng/mL aTc and 2 mM arabinose).

3.2.4 Comparison of response functions from gates based on sgRNA and TetR-family repressors

Figure **3-9** shows a comparison of response functions. Previously, we measured the response functions for a library of **NOT** gates based on TetR-family repressors. The average of 14 response functions is shown in Figure **3-9** (green line) along with the highest (LmrA) and lowest (BM3R1) individual response functions (Stanton et al, 2014). The average line was generated **by** calculating the average of a set of parameters (half-max threshold, Hill coefficient, maximum and minimum) and then generating a line corresponding to these parameters. The purple line is the power law fit to the sgRNA response function from Figure **3-3b.** In Figure 3-9a, the average line, LmrA,

and BM3R1 y-axis values are scaled **by** the maximum output value of the average line. Simiarly, the sgRNA output values are scaled **by** its maximum output value. The xaxis values are scaled **by** maximum values measured for the input promoter. In Figure **3-9b,** both the y-axis and x-axis are scaled so that input and output range for both lines spans from 10^{-3} to 10^{0} . This is done to both show the difference in dynamic range and overall shape of the response functions.

3.2.5 Toxicity of sgRNA expression

High expression of dCas9 can be very toxic to the host cell (Figure **3-2b).** To determine the toxicity of sgRNA expression, we induced the expression of sgRNAs at various levels and measured the optical density after six hours. Both dCas9 and RFP were expressed in the cells as well. Two sgRNAs were tested: **1)** an sgRNA that targets an operator in an otherwise functionless region of the high-copy sgRNA plasmid (blue squares), and 2) a scrambled sgRNA that does not target any **DNA** sequence in the cell (red squares). Only a slight decrease in the growth is observed and both the functional and scrambled sequence have identical behaviour (Figure **3-10).**

3.3 Circuits based on layered sgRNA gates

The advantage of transcriptional gates is that they can be easily interconnected in order to build more complex circuit functions. Gates where repression is based on a non-coding RNA (ncRNA) can be challenging to connect in series for three reasons. First, they require more precision in the promoter start site or additional RNA processing due to sensitivities in the addition or removal of nucleotides at the 5'-end. Second, changing the ribosome binding site (RBS) has been an important lever for functionally connecting protein-based gates. The RBS is not relevant for an ncRNA-

based gate and matching gate responses **by** promoter tuning is more challenging. This is exacerbated **by** the shape of the response functions for the sgRNA-based gates, which do not plateau at high or low input promoter levels (Figure 3-2e); therefore the input to any gate needs to have a very wide dynamic range in order to avoid signal degradation at each layer. However, despite these challenges, sgRNA-mediated repression has desirable properties that other ncRNA technologies do not possess, such as high dynamic range, specificity, and the ability to be composed into cascades ($Qi \&$ Arkin, 2014).

The layering of two **NOT** gates based on sgRNAs has been previously demonstrated in mammalian cells (Kiani *et al.* 2014; Nissim *et al.* 2014). We started **by** building a similar circuit architecture **by** connecting two of our sgRNA-based gates in series in *E. coli* (Figure 3-3a). These were connected simply **by** combining the parts from the sgRNA-A2NT and sgRNA-A4NT gates in the appropriate order with no additional tuning. dCas9 is induced from a low-leakage variant **of** PTet, as was done for the characterization of individual gates. In the absence of dCas9, the background activity of the output promoter (PA4) is 1040 au (arbitrary units, Figure **3-3b,** leftmost bar). When dCas9 and the input to the circuit (P_{PhIF}) are both induced, this lead to a 98-fold repression of the circuit output (PA4) compared to no sgRNA production (Figure **3-3b,** left). When the input promoter is induced with **DAPG,** the output state recovers completely to the level of the dCas9 **(-)** control. **By** observing the middle promoter (P_{A2}) in the cascade in a separate experiment, the trade-off between P_{A2} and PA4 expression can be seen at intermediate sgRNA induction levels (Figure **3-3b,** right). The log-linearity of the curve spans almost three orders of magnitude.

In addition to layering, the construction of more complex circuits requires that gates be able to receive multiple inputs. So-called "Boolean complete" logic gates NOR and **NAND** functions **-** are particularly useful because they can be connected to build any computational operation. Genetic NOR gates have proven to be particularly easy to build using transcriptional regulation where two input promoters drive the expression of a repressor that turns off an output promoter. The capacity for the orthogonality of sgRNA:promoter interactions has the potential to enable a very large number of NOR gates, which could be used to realize large integrated circuits. However, to date, it has not been shown that dCas9-based gates can be designed to respond to more than one input promoter.

To build a simple NOR gate, we connected two input promoters to the transcription of independent copies of sgRNA-2NT (Figure 3-3c), either of which will repress a single output promoter **(PA2).** These two input promoters are responsive to small molecule inducers: **DAPG (PPh1F)** and arabinose **(PBAD).** In the presence of dCas9, but neither arabinose nor **DAPG,** the NOR gate output from promoter **PA2** remains high at only 2.3-fold reduction compared to the $dCas9$ $(-)$ control due to leaky sgRNA production. When both inducers are added, there is 100-fold repression of the output promoter (Figure **3-3d,** left), which is on par with the best gates that use protein-based repressors. The OFF state is ~3-fold higher when only arabinose is added, which is likely due to the lower maximum activity from the P_{BAD} promoter as compared to **PPh1F.** While this does not significantly degrade the function of the NOR gate alone, it is representative of the sensitivity of sgRNA-based gates to the dynamic range of the inputs and is potentially problematic when building longer cascades.

Next, we connected multiple NOR and **NOT** gates to build larger layered circuits. First, we built a simple circuit that inverts the output of the NOR gate to make an OR gate (Figure 3-3e). The **PA2** output of the NOR gate is used to drive the transcription of sgRNA-A4NT, which in turn represses the PA4 output promoter. **A** challenge that emerged from building these circuits is transcriptional readthrough, which occurs because the output promoters are strong and the sgRNAs short. To

mitigate this, strong unique terminators (Chen *et al.*, 2013) are placed after each sgRNA, immediately downstream from the dCas9 handle and *S. pyogenes* terminator regions of the sgRNA (Qi *et al,* **2013).** For the OR gate, the TrrnB and **L3S2P55** terminators (terminator strengths, *Ts =* 84 for TrrnB and *Ts =* **260** for **L3S2P55,** respectively (Chen *et a],* **2013))** are placed after the two sgRNA-A2NT sequences and L3S2P21 $(T_s = 380)$ is placed after sgRNA-A4NT. The output of the OR gate is strongly repressed >100-fold in the absence of both inducers (Figure **3-3f).**

We then built a larger circuit **by** connecting three gates based on four sgRNAs. **A** cascade with two branches is formed **by** the **A2NT** and A4NT sgRNAs, which invert the output of the arabinose- and **DAPG-** inducible systems, respectively (Figure **3-3g).** The output promoters from these **NOT** gates then connect to a NOR gate **by** using each to drive a different copy of sgRNA-A1NT. The computing portion of the circuit requires 1234nt to encode. This circuit should produce an **AND** logic operation and, indeed, there is a 107-fold difference between the OFF and **ON** states when both inducers are absent and present (Figure **3-3h).** There is some leakiness when either input is induced alone and these states show **2.6-** to 5.0-fold activity above the OFF state observed in the absence of both inducers. Four versions of this circuit were designed with varied sgRNA positions and orientations. Other versions were slightly less functional, with higher OFF states and lower **ON** state; the best version is presented here. This circuit can be compared to a similar **AND** gate design built from TetR homologues. That circuit generated a ~5-fold response and required 2577nt to encode (Stanton *et a],* 2014).

3.3.1 Cytometry data for genetic circuits

Representative fluorescence histograms corresponding to the five input states for the genetic circuits of Figure **3-3b (NOT-NOT), 3d** (NOR), **3f** (OR), **3h (AND)** and Figure 3-4b (NOR from OR-MalT-3NT) are shown (Figure **3-11).** Black histograms correspond to no induction of dCas9 and reflect the "maximum output" achievable. Colored histograms each have dCas9 induced and correspond to the four digital induction conditions for expressing input promoters.

3.4 Interfacing a circuit with a native *E. coi* **regulatory network**

Guide RNAs can be designed to knock down genes encoded in the host genome (Qi *et a],* **2013).** In this way, native cellular processes can be easily actuated as an output of an sgRNA-based circuit using the same biochemistry. To demonstrate this, we started with the OR circuit (Figure 3-3e) and substituted the sgRNA used for the **NOT** gate with one designed to target the *malT* gene in the *E. coli* genome (Figure **3-** 4a). MalT is a positive regulator of the maltose utilization operons. **A** knockdown would alter sugar utilization and has additional impacts on the cellular phenotype (Boos **&** B6hm, 2000; Tchetina **&** Newman, **1995).** Notably, it decreases the production of LamB **-** the lambdaphage receptor **-** resulting in decreased susceptibility of *E. coli* to lambdaphage infection (Thirion **&** Hofnung, **1972).** To target *ma]T,* we designed sgRNA-MalT-3NT to target the non-template strand of the protein coding sequence from the 110^{th} to the 117^{th} codon. By targeting the nontemplate strand, the roadblock formed **by** dCas9 would disrupt any transcription from upstream promoters (Qi *et al*, 2013; Bikard *et al*, 2013).

Cells harboring this circuit exhibit a 240-fold reduction in lambda plaque formation in the absence of both inducers (Figure 3-4c). When either or both inducers are present, the cells show wild-type phage infectivity. In addition, we can separately report the activity of an internal state of the circuit **by** using PA2, which is the output of the NOR gate alone, to drive the transcription of a fluorescent reporter (RFP). This results in a NOR gate that is repressed 120-fold when either inducer is present (Figure 3-4b). These experiments demonstrate that a heterologous output (knockdown of RFP) and an endogenous response (knockdown of MalT) can be simultaneously co-regulated according to different logic operations using the same underlying circuit.

3.5 Discussion

Extensible NOR and **NOT** gates are fundamental logic operations from which more complex circuitry can be built. Previously, these gates have been based transcription factors that bind to DNA, such as phage repressors, LacI, and TetR homologues. Gates based on dCas9 and guide RNAs offer several advantages. The most significant is the ease **by** which new sgRNA:promoter pairs can be designed and the orthogonality that they exhibit with each other. While there has been much discussion regarding offtarget Cas9 interactions and several efforts seeking to reduce it (Fu et al, 2013b; Cradick et a], **2013;** Pattanayak et a], **2013;** Hsu et al, **2013b;** Mali et al, **2013;** Ran et al, 2013; Guilinger et al, 2014; Tsai et al, 2014; Fu et al, 2014; Kuscu et al, 2014; Wu et al, 2014), this is not as relevant for synthetic circuits because sgRNAs can be designed to be maximally different from each other and the host genome. Indeed, no designed sgRNAs had to be discarded from the orthogonal set that we built, either for activity, orthogonality, or growth defects. Further, one transcriptomic analysis of CRISPR interference revealed no off-target signatures (Qi et a], **2013).** This is a major improvement over the protein-based gates, which have problems in all of these areas. The "operator" that corresponds to the sgRNA is also relatively small **(13bp)** and can be easily inserted between the **-10** and **-35** region of a promoter (TetR homologue operators range from **20-50bp).** In addition, the gates are small and can be easily

synthesized as oligos, including in pooled libraries (Kosuri *et a],* **2013).** The gates also reliably produce >50-fold dynamic ranges. This is akin to the best protein-based gates, but those exhibit far more diversity with such gates in the leakiness, dynamic range, and shape of the response function.

Toxicity is observed from dCas9, where high levels reduce cell growth in *Escherichia coli.* While the mechanism of toxicity is still unclear, it has been reported to be more severe in other species. This may reduce the long-term evolutionary stability of dCas9 in engineered cells, as has been observed for other toxic genetic circuits (Sleight *et a],* 2010; Sleight **&** Sauro, **2013;** Chen *et a],* **2013).** However, we find that the toxicity can be managed **by** controlling the level of expression while still eliciting a substantial circuit response. Also, once dealt with, we do not observe substantial toxicity as more sgRNAs are transcribed. This is in contrast to protein-based gates, which may have less toxicity individually, but can be problematic if multiple repressors are used in a design because their growth defects often stack and can become severe.

There are also some challenges in working with dCas9 that are unique compared to protein-based gates. The shape of the response function, where no saturation is observed at high or low levels, poses a problem when layering gates. Without nonlinearity, the signal is degraded at each layer. Indeed, we attempted to add another layer to the **AND** gate and this yielded a non-responsive circuit likely for this reason. Because there is no RBS to tune, it is difficult to fix this problem through the rational modification of the gate. No cooperativity also impedes the use of these gates for dynamic and multistable circuits, such as bistable toggle switches, pulse generators, or oscillators. Adding cooperativity could potentially be accomplished through dCas9 dimerization to effect promoter looping, sgRNA feedback latching motifs, or sequestration-based techniques such as "decoy operators" to titrate sgRNA away from cognate promoters. While the graded response could be of value for analog circuit

construction, an inability to change its shape could remain problematic. It may be possible to change the position of the response function **by** engineering specific mismatches to reduce the effectiveness of repression (Farzadfard *et al,* **2013).** In addition, it is more difficult to connect input promoters upstream in series before an sgRNA, which has been a valuable design strategy for protein-based gates. Doing this would both require processing to remove the 5'-mismatch from the sgRNA, and also minimization of transcriptional roadblocking, which could occur at the downstream promoter. Finally, because all of the gates require the same dCas9, this could impose retroactivity in the system where the activity state of upstream gates impacts the performance of downstream gates. An approach to circumvent this for larger circuits may be to use multiple orthogonal Cas9 homologues in a design (Esvelt *et a],* **2013).**

It has been challenging to build genetic circuits that are as robust or capable as their natural counterparts. The potential for dCas9 to address this problem is vast. Synthetic sgRNAs can be designed to target a large number of sequences—synthetic and natural-and the sgRNA circuit architecture can be encoded in compact genetic constructs. This could allow the paradigm of analog and digital computing to be applied *in vivo* without requiring large and cumbersome constructs. dCas9 circuits also offer a mechanism whereby the same biochemistry can be used to both build circuitry that is orthogonal to the host and to directly interface host processes **by** design.

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Figure **3-1:** Schematic of dCas9 logic circuit design and construction. **(A)** CRISPR/Cas-based **NOT** gates comprise a catalytically-dead dCas9 protein, an input promoter that transcribes a small guide RNA (sgRNA), and a synthetic output promoter with an sgRNA operator between the **-35** and **-10** sigma factor binding sites. When the dCas9 handle of the sgRNA (dark green) complexes with dCas9 (blue), the sgRNA binds the operator (light green) and a sigma factor binding site (gray), causing steric repression of transcription initiation at the output promoter. (B) CRISPR/Cas genetic circuits are easily constructed from pairs of ssDNA oligonucleotides \leq 200nt long that encode the necessary genetic parts (promoter, sgRNA, terminator, assembly scars, and restriction enzyme recognition sites). These oligos are annealed to each other at the dCas9 handle and extended. The resulting dsDNA modules are assembled in a one-pot Golden Gate assembly reaction (colored diamonds are assembly scars). **(C)** Complex genetic circuits that respond to chemical input signals can be constructed from simple **NOT-** and NOR-gate motifs. In these circuits, dCas9 (blue) mediates repression of synthetic promoters **by** programmable sgRNAs (visualized as solid colored rectangles from here on). Both heterologous and endogenous genes can be regulated at circuit outputs **by** expressing sgRNAs tailored to target transcription initiation or elongation.

Figure **3-2:** Characterization of dCas9 and orthogonal sgRNA **NOT** gates. **(A)** The inducible dCas9 and sgRNA system comprises a medium-copy plasmid with P_{Tet} inducible dCas9, a high-copy plasmid with PBAD-inducible sgRNAs, and a low-copy plasmid encoding a synthetic sgRNA-repressible promoter driving RFP. (B) When sgRNA-A2NT is induced, increasing dCas9 expression causes greater repression **of** PA2 (lower panel), at the cost of decreased cell growth (upper panel). **All** samples were grown in the presence of 2 mM arabinose. Concentrations of aTc used from left to right (ng/mL): **0.0391, 0.313, 0.625, 1.25, 5,** and **10. A** single intermediate expression value for dCas9 was used for the remaining experiments **(0.625** ng/mL aTc, dashed lines). **(C)** Synthetic repressible promoters designed **by** modifying the sequence of promoter BBa J23101. The -35 and $-10 \sigma_{70}$ binding sites flank forward and reverse **'NGG'** protospacer adjacent motifs (PAMs) and a promoter-specific **13bp** sgRNA operator. An sgRNA bound to dCas9 will base-pair with either the template or nontemplate strand of a promoter's sgRNA operator and one of the σ_{70} binding sites,

causing steric repression of transcription initiation. In the absence of repression, transcription of the downstream RNA begins at the $+1$ site. **(D)** The cross-talk map for all combinations of sgRNAs and synthetic promoters is shown. The heat map indicates the amount of RFP observed for that sgRNA-promoter pair. Only cognate pairs of sgRNAs and promoters exhibit significant repression, whereas non-cognate pairs interact negligibly. Samples were grown in the presence of **0.625** ng/mL aTc and 2 mM arabinose. **(E)** The response function for sgRNA-A1T measured **by** expressing intermediate levels of sgRNA-A1T reveals a non-cooperative, log-linear relationship between the input and output promoters. The solid line visualizes a power law fit to the data points. Error bars represent the standard deviation of fluorescence geometric mean for three independent experiments on different days. The reporter expression when dCas9 is not induced is shown (dashed line), and all other samples were grown in the presence of **0.625** ng/mL aTc. Concentrations of arabinose used from left to right (mM): **0, 0.0313, 0.0625, 0.125, 0.25, 0.5, 1,** and 2. Inset: the power law fits for each of the **10** sgRNAs and their cognate promoters (data presented in Figure **S3);** axes values are the same as the encompassing figure. (F) The temporal dynamics of dCas9 and sgRNA induction are shown. Red squares indicate induction of both dCas9 $(0.625 \text{ ng/mL} \cdot \text{aTc})$ and sgRNA-A2NT (2 mM arabinose) commencing at $t = 0$ hrs. Blue squares indicate uninduced cultures. After a **~90** minute delay, fluorescence decreases concomitantly with cell dilution-occurring at a rate of **33** minutes per doubling.

Figure 3-3: Design and characterization of synthetic circuits. (A) The wiring diagram and genetic schematic for a double inverter circuit is shown. The sgRNA-A2NT/PA2 pair is shown in orange, the sgRNA-A4NT/PA4 pair is shown in magenta, dCas9 is shown in blue, positive regulation is indicated by arrows, and negative regulation is indicated by flat-headed arrows. (B) The digital RFP response of the NOT-NOT gate is shown for the two input inducer states (dCas9 induced with 0.625 ng/mL aTc): no DAPG and $25 \mu M$ DAPG. Also shown is the RFP output without dCas9 induction (leftmost column), which represents the maximum achievable output. Gray columns are expected to be OFF and black columns are expected to be ON (left). The tradeoff in expression between the middle and output promoters $(P_{A2}$ and P_{A4} , respectively) is shown for intermediate sgRNA induction levels (right). DAPG concentrations from left to right (μ M) are: 0, 2.42, 3.39, 4.74, 6.64, 9.30, 13.0, 18.2, 25.5, 35.7, and 50. Dashed lines are uninduced dCas9 control experiments and represent the maximum output for each promoter. Error bars represent the standard deviation of three independent experiments on different days. **(C)** The wiring diagram and genetic schematic for a NOR(A,B) gate is shown. The $sgRNA-A2NT/P_{A2}$ pair is shown in orange, and dCas9 is shown in blue. (D) The NOR gate digital REP response is shown (left) for the four input inducer states (with dCas9 induced by **0.625** ng/mL aTc): no arabinose or DAPG, arabinose (2 mM) , DAPG $(25 \mu M)$, and arabinose and DAPG (2 m) mM and 25 μ M). Also shown is the output without dCas9 induction (leftmost column). In addition, the circuit response to intermediate inducer values **is shown** to the right. **(E)** The wiring diagram and genetic schematic for a layered $NOT(NOR(A,B))$ gate (i.e., an OR gate) is shown. The sgRNA-A2NT/P_{A2} pair is

shown in orange, the sgRNA-A4NT/PA4 pair is shown in magenta, and dCas9 is shown in blue. (F) The OR digital RFP response is shown (left) for five input inducer states (as in **D).** Intermediate values are also shown (right). **(G)** The wiring diagram and genetic schematic for a four sgRNA circuit with **NOR(NOT(A),NOT(B))** functionality (i.e., an **AND** gate) is shown. The sgRNA-A2NT/PA2 pair is shown in orange, the sgRNA-A4NT/PA4 pair is shown in magenta, the sgRNA-A1NT/PA1 pair is shown in green, and dCas9 is shown in blue. (H) The **AND** gate digital RFP response is shown (left) for five input inducer states (as in **D).** Intermediate values are also shown (right). For graded induction of circuits in **(D),** (F), and (H), aTc was added to **0.625** ng/mL; arabinose was added to the following final concentrations **(mM):** 0, **.00391, .00781, .0156, .0313, .0625, 0.125, 0.25, 0.5, 1,** and 2; 2,4 diacetylphloroglucinol was added to the following final concentrations **(pM): 0,** 0.0244, **0.0488, 0.0977, 0.391, 0.781, 1.56, 3.13, 6.25, 12.5,** and **25.**

Figure 3-4: Interfacing logic circuits with host physiology. **(A)** The wiring diagram and genetic schematic for a $NOT(NOR(A,B))$ gate is shown (i.e., an OR gate). The $sgRNA-A2NT/P_{A2}$ pair is shown in orange, the $sgRNA-A4NT/P_{A4}$ pair is shown in magenta, dCas9 is shown in blue, and both sgRNA-MalT-3NT and the MalT gene are shown in yellow. (B) The NOR gate digital RFP response is shown for the four input inducer states (with dCas9 induced **by 0.625** ng/mL aTc): no input inducer, arabinose (2 mM) , DAPG (25 µ) , and arabinose and DAPG (2 mM) and $25 \text{ µ})$. Also shown is the output without dCas9 induction (leftmost column). Gray columns are expected to be OFF and black columns are expected to be **ON.** Error bars represent the standard deviation of three independent experiments on different days. **(C)** The OR gate digital lambdaphage infectivity response is shown for five input inducer states (as in B), where infectivity is measured **by** the number of lambdaphage plaques formed on a bacterial lawn on an agar plate. Error bars represent the standard deviation of three independent experiments on different days.

Figure **3-5:** Cytometry data used to rescale the response function of the **NOT** gate based on sgRNA-A1T. (A) YFP histograms for the inducible promoter control, P_{BAD} driving YFP (plasmids pAN-P_{Tet}-dCas9 and pAN-P_{A1}-RFP). All samples were grown in the presence of **0.625** ng/mL aTc to induce dCas9 and the stated amount of arabinose. (B) The raw data for the response function of the **NOT** gate based on sgRNA-A1T is shown. **All** samples were grown in the presence of **0.625** ng/mL aTc to induce dCas9 and the stated amount of arabinose, except for the right-most histogram which was grown in the absence of both inducers and provides a maximum achievable reporter output for PA1-RFP. Plasmid maps are shown in Figure **S8.**

Figure **3-6:** Creation of the response function for the **NOT** gate (sgRNA-A1T). **(A)** The data shown is for the induction **of** PBAD and is calculated using the geometric mean of the cytometry data in Figure **Si** (top). (B) The activity **of** PA1-RFP output as a function of arabinose. Dashed lines indicate the maximum achievable RFP output, determine from an experimental treatment where dCas9 was not induced (Figure **S1** bottom, rightmost panel). (C) The x-axis of the P_{A1}-RFP plot is transformed to P_{BAD}-YFP units to visualize the relationship between the input promoter that drives sgRNA-**AlT** and the cognate repressible promoter that drives RFP. Data points represent the average and standard deviation of three experiments.

Figure **3-7:** Response functions for all of the **NOT** gates based on orthogonal sgRNAs repressing their cognate -promoters. Dashed lines indicate the maximum achievable RFP output, determine from an experimental treatment where dCas9 was not induced. Solid lines are power law fits to the data and correspond to the lines shown in the Figure 2e inset. Data points represent the average of the geometric means of three experiments on different days.

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Figure 3-8: Representative cytometry data corresponding to the values used for the cross-talk map in Figure 2d. Histograms are for RFP produced from $pAN-P_{A(X)}-RFP$ while being repressed by sgRNAs produced from $pAN-PBAD-SgRNA-A(X)(T/NT)$. Cells also harbor pAN-P_{Tet}-dCas9. Black histograms correspond to $dCas9$ induction with aTc, but no sgRNA induction. Gray histograms correspond to dCas9 and sgRNA induction with 0.625 ng/mL aTc and 2mM arabinose, respectively. Red boxes indicate cognate sgRNA-promoter pairs.

Figure **3-9:** Comparison of **NOT** gate response functions generated **by** sgRNAs versus TetR-family repressors. Purple lines: Power law fit to the sgRNA cascade relationship from Figure **3b.** Green lines: Hill-function generated from the average Hill-equation parameters of 14 TetR homologues $(K, n, max, min)²$. Black lines: Hill-function fits to the highest and lowest response curves, LmrA and BM3R, respectively. **(A)** For dynamic range comparison, all input and output values are re-scaled so that their maxima equal **1** (except for the black line outputs, which are scaled using the green line maximum). (B) Same as in **A,** except the y-axis is also normalized **by** the minimum value to compare the shape of the curves.

Figure **3-10:** Toxicity of sgRNA expression from an arabinose-inducible promoter. Blue squares: expression from pAN-P_{BAD}-sgRNA-VR, which binds an operator on its highcopy plasmid backbone. Red squares: expression from pAN-PBAD-sgRNA-scramble, a "scrambled" sgRNA that does not target any genetic locus in the cell. **All** samples had dCas9 induced with **0.625** ng/mL aTc, and RFP constitutively expressed.

Figure **3-11:** Histograms for genetic circuits encoded on **pAN-NOT-NOT, pAN-NORpAN-OR, pAN-AND,** and pAN-OR-MalT-3NT. The black histograms indicate cultures without inducer and correspond to the maximum value achievable for the output promoters, blue is with **0.625** ng/mL aTc, orange is with **0.625** ng/mL aTc and 2mM arabinose, green is with **0.625** ng/mL aTc and **25** pM **DAPG,** and red is with **0.625** ng/mL aTc, 2mM arabinose, and **25 pM DAPG.** The plasmid maps are shown in Figure **S8** and **S9.**

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Figure 3-12: Plasmids encoding basic circuit components. The pAN-P_{Tet}-dCas9 plasmid **(p15A,** KanR) encodes the insulated, tight-off aTc-inducible dCas9 used for all experiments. The pAN-PA(x)-RFP series of reporter plasmids **(pSC101,** AadA) encode one of five synthetic sgRNA-repressible promoters that express mRFP1. The $pAN-P_{BAD}-sgRNA-A(X)(T/NT)$ and $pAN-P_{PhIF}-sgRNA-A(X)(T/NT)$ series of plasmids (ColE1, AmpR) drive one of ten sgRNAs from either the arabinose- or DAPG-inducible promoters, respectively. The pAN-P_{Tet}-YFP and pAN-P_{BAD}-YFP plasmids were used to characterize the promoter activities of P_{Tet} and P_{BAD}, respectively, for dCas9 and sgRNA response functions.

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Figure **3-13:** Plasmids encoding genetic circuits. The **pAN-NOT-NOT, pAN-NOR, pAN-OR,** and **pAN-AND** plasmids encode the sgRNA circuits from Figure **3.** The pAN-OR-MalT-3NT encodes the MalT knockdown logic circuit from Figure 4. These plasmids were co-transformed with pAN-PTet-dCas9 and the appropriate **pAN-PA(X)-** RFP plasmids to implement complete systems.

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Table **3-1.** Sequences and fold-repression values for template-targeting sgRNAs

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		Region that binds Region that binds the	Fold-
		-10 and forward promoter-specific	repressio
Name	PAM	operator	n
$sgRNA-$			
A1NT	AUAAUACC	UAGGACUGAGCU	94
$sgRNA-$			
A2NT		AUAAUACC CGUGUGACCCGU	250
$sgRNA-$			
A3NT		AUAAUACC AUGCUCCAUUUC	340
$sgRNA-$			
A4NT	AUAAUACC	AGCUAGUUGUGG	56
$sgRNA-$			
A5NT	AUAAUACC	CUCCGAGUGUUU	270

Table **3-2.** Sequences and fold-repression values for non-template-targeting sgRNAs

 \mathcal{M}_c

 $\mathcal{L}(\mathcal{C})$

 $\mathcal{L}(\mathcal{A})$

 \mathcal{S}

 $\mathcal{R}=\mathcal{R}$

 $\sim 10^{-11}$

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Chapter 4

4 Genetic circuit design automation

4.1 Background

Electronic design automation **(EDA)** software tools aid engineers in the design and analysis of semiconductor-based electronics (Hasty et *a],* 2002). Prior to **EDA,** integrated circuit design was a manual process performed **by** hand. This was accelerated **by** the development of hardware description languages (e.g., Verilog) that enabled a user to design an electronic system through textual commands that are transformed to a circuit patterned on silicon. We applied this approach to genetic circuits, so that a Verilog design is transformed to a linear **DNA** sequence that can be constructed and run in living cells. The design environment, referred to as Cello (Cellular Logic), implements algorithms that derive the detailed physical design from the textual specification (Fig. 4-1). Cello requires genetic logic gates that are sufficiently modular and reliable such that their interconnection can be automated.

Moving computing into cells enables programmable control over biological functions (Hasty et a], 2002; Sprinzak **&** Elowitz, **2005;** Drubin et a], **2007;** Endy, 2011; Gibson *et al.* 2010). This is crucial for fully realizing the potential of engineering biology, where applications require that different sets of genes be active under different conditions (Weber & Fussenegger, 2012; Ruder *et al*, 2011; Boyle & Silver, 2012; Holtz

& Keasling, 2010). Cells are naturally able to respond to their environment, make decisions, construct intricate structures, and coordinate to distribute tasks. These functions are controlled **by** a regulatory network of interacting proteins, RNA, and **DNA.** Patterns of such interactions generate computational operations analogous to those used in electronic circuits (McAdams **&** Arkin, **1998;** McAdams **&** Shapiro, **1995;** Ptashne, 1986a; Alon, **2007;** Buchler et *a],* **2003),** and regulators can be combined to build synthetic genetic circuits (Elowitz **&** Leibler, **2000b;** Stricker et *a],* **2008;** Basu et al, 2005 ; Lim, 2010). This approach has led to digital logic gates (Moon *et al.* $2012b$; Tamsir et *a],* 2011a; Stanton et *a],* 2014; Anderson et *a],* **2007;** Aushinder et *a],* 2012; Teo **&** Chang, 2014), memory devices (Siuti et *a],* **2013;** Bonnet et *a],* **2013,** 2012; Yang et *a],* 2014; Kramer **&** Fussenegger, **2005),** analog computation (Daniel et *a],* 2013c) and dynamic circuits (e.g., timers and oscillators) (Elowitz **&** Leibler, **2000b;** Stricker et *a],* **2008;** Danino et *a],* 2010; Basu et *a],* 2004; Tigges et *a],* **2009).** These have begun to be integrated into biotechnological applications (Lo et al, 2013; Ellis et al, 2009), for example, to implement feedback control in a metabolic pathway (Zhang *et al.*) 2012). However, the construction of simple circuits consisting of only a few regulators remains a time consuming task and this has limited their widespread implementation.

Genetic circuit design is challenging for several reasons (Kwok, 2010; Purnick $\&$ Weiss, 2009a). First, circuits require precise balancing of regulator expression (Yokobayashi et *a],* **2002b;** Anderson et *a],* **2007).** Second, many parts are combined to build a circuit and their function can vary depending on genetic context, strain, and growth conditions (Kosuri et a], **2013;** Goodman et a], **2013;** Lou et *a],* 2012a; Mutalik et al, 2013a; Moser *et al*, 2012a; Yordanov *et al*, 2014; Cardinale *et al*, 2013). Third, circuits are defined **by** many states (their response to different inputs or how they change over time) and this can be cumbersome to characterize (Rosenfeld *et al*, 2005; Elowitz & Leibler, 2000b; Gardner *et al*, 2000a; Balagaddé *et al*, 2005). Finally, many

regulators are toxic when overexpressed and even mild effects can combine to drive negative selection against the circuit (Arkin **&** Fletcher, **2006).** Balancing these issues is difficult to do **by** hand. Thus, computational tools have been developed for the study of natural networks and to aid circuit design **by** predicting how parts or devices will perform when connected (Chandran et al, **2009;** Myers et *a],* **2009;** Beal et al, 2011; Czar et *a],* **2009b;** Marchisio **&** Stelling, **2011;** Sauro et a., **2003;** Rudge et **a,** 2012).

We developed Cello to accelerate circuit design, allow increased complexity of circuits, and enable non-experts to incorporate synthetic gene regulation into genetic engineering projects (Fig. 4-1). The focus is on the design of a circuit that performs a desired computational operation, which connects to cell-based sensors and cellular functions (actuators). **A** user provides three specifications to Cello. The first are the **DNA** sequences for the sensors: the sequences of their output promoters and data for their ON/OFF signal strengths in standardized units (see below) (Kelly *et al.* 2009b). The second is the "user constraints file" **(UCF),** which contains the functional details of the gate library, the layout of the genetic system, the organism and strain, and the operating conditions for which the circuit design is valid. The third is Verilog code that captures the desired computational operation. Cello uses this information to automatically design a **DNA** sequence encoding the desired genetic circuit **by** connecting a set of simpler gates that implement Boolean logic to the sensors and each other. The output of the circuit can be connected to cellular processes **by** directing the output promoter to control a cellular function (e.g., a metabolic pathway), either directly or through an intermediate $(e.g., a phase RNA polymerase)$ (Segall-Shapiro et al. 2014; Wang et al. 2012). The sensors, circuit, and actuator are inserted into specific genetic locations and transformed into a strain, both of which are defined in the **UCF** (Fig. 4-1b).

Cello builds circuits **by** connecting transcriptional gates, whose common signal carrier is RNA polymerase (RNAP) flux on DNA (Canton *et al.* 2008a). This conversion allows gates to be layered **by** having the output promoter from one gate serve as the input to the next. This modularizes the design, so that a circuit is defined **by** a pattern of promoters in front of regulators on a linear **DNA** strand (Fig. 4-2a). Within this paradigm, the regulators performing the gate biochemistry could be transcription factors (Weiss, 2001; Stanton *et al*, 2014), RNA based regulation (Green et *a],* 2014; Mutalik et *a!,* **2012b;** Chappell et *a,* **2015),** protein-protein interactions (Moon et *a!,* **2012b;** Chen **&** Arkin, **2012b),** CRISPR-Cas based regulation (Qi et al, **2013;** Bikard et *a!,* **2013;** Nielsen **&** Voigt, 2014; Esvelt et *a!,* **2013),** or recombinases (Siuti et *a],* **2013;** Bonnet et *a],* **2013;** Ham et *a],* **2008).** In this manuscript, we develop a set of insulated **NOT** and NOR gates based on prokaryotic repressors (Stanton et a, 2014). These repressor-based gates were characterized in isolation as **NOT** gates. To facilitate the connection of gates and sensors, we adopt the BBa J23101 constitutive promoter as a standard (Kelly et *a],* **2009b).** The output of an insulated version of this promoter (The standard differs from the Kelly standard and contains: an insulating upstream terminator, a different spacer upstream of the promoter (as opposed to a BioBricks prefix), RiboJ, RBS B0064, a different terminator, and three silent mutations to **yfp.)** is defined as **1** RPU and, working with National Institute of Standards and Technology **(NIST)** collaborators, this was measured to correspond to 24.7 ± 5.7 mRNAs per cell, which is approximately 0.02 RNAP/s-promoter (Fig. 4-**38).** These data were used **by** Cello to automatically generate a large set of circuits. The sequences were built as specified **by** the software output with no additional tuning, which facilitates the iterative improvement of the quality of the gates and design rules.

4.2 Cello design environment

Verilog is a commonly used hardware description language for electronic system design (Thomas **&** Moorby, 2002). It is hardware-independent, meaning that a circuit can be described **by** abstract textual commands and then transformed to different physical implementations *(i.e.,* chip types). Verilog is often accompanied **by** a simulation package that aids the evaluation of a design *in silico* before building the system. Verilog code has a hierarchical organization centered on modules that communicate through wires to propagate signals. In our implementation, circuit function can be defined **by** *case, assign, or structural* statements within modules (Fig. 4-28). Initially, our focus with Cello is on the creation of asynchronous combinational logic without feedback. This is useful in the design of genetic circuits that can process multiple environmental sensors in order to choose amongst different cellular functions. However, Verilog provides the framework to extend the designs to include more complex circuits, including those with specified timing and signal strengths as well as analog (Verilog-AMS) functions.

The philosophy behind Cello is to generate circuits for highly specified physical systems and operating conditions. This is defined **by** the User Constraint File **(UCF),** which specifies:

- **(1)** The gate technology, including **DNA** sequences and functional data,
- (2) Defined physical locations for the circuit *(e.g.,* plasmid or genomic locus),
- **(3)** The organism, strain, and genotype,
- (4) Operating conditions where the circuit design is valid,
- **(5)** Architectural rules to constrain the part arrangement,
- **(6)** Preferred logic motifs to be incorporated during logic synthesis.

The **UCF** follows the **JSON** (JavaScript Object Notation) standard \sim (<douglas@crockford.com>), which is both human- and machine-readable and is convertible with SBOL (Synthetic Biology Open Language) (Galdzicki *et al,* 2014). We developed the Eco1C1GiT1 **UCF** for *E. coli* **(NEB** 10-beta) and gate technology based on a set of 12 prokaryotic repressors (Stanton *et al,* 2014). The development of additional UCFs would enable a circuit design to be transferred to other organisms, conditions, or gate technologies.

When a user selects a **UCF** and synthesizes a circuit from Verilog code, the corresponding **DNA** sequence is designed in three steps (Fig. 4-1). First, the textual commands are converted to a circuit diagram. Algorithms parse the Verilog code and derive a truth table (Fig. 4-28), which is converted to an initial circuit diagram **by** the logic synthesis program **ABC** (Brayton & Mishchenko, 2010) and subsequently modified to only contain logic operations for gates available in the **UCF** (Fig. 4-30). The second step is to assign specific regulators to each gate in the diagram. Functionally connecting gates requires that the outputs from the first gate span the input threshold of the second gate (Fig. 4-2b). Because gates based on different regulators have different response functions, not all pairs can be functionally connected (Fig. 4-2c). Identifying the optimal assignment is an NP-complete problem (Fig. 4-2d) (Roehner **&** Myers, 2014; Yaman *et a,* 2012; Rodrigo **&** Jaramillo, **2013;** Huynh Tagkopoulos, 2014). We implemented a Monte Carlo simulated annealing algorithm to rapidly identify an assignment that produces the desired response (Fig. 4-2e and 4- **33).** The third step is to create the linear **DNA** sequence based on the circuit diagram and gate assignment. The assignment is converted to a set of parts and constraints between the parts (written with the Eugene language (Oberortner *et a],* 2014)). The **UCF** can also include additional constraints on the genetic architecture, for example, to forbid a particular combination of parts. **A** combinatorial design algorithm (Smanski *et al,* 2014), is used to build a genetic construct that conforms to the constraints (Fig. 4-34). This allows a user to design multiple constructs containing the same circuit function and genetic constraints, while varying unconstrained design elements to build a library that can be screened.

Cello then simulates the performance of the genetic circuit. When flow cytometry data is provided in the **UCF** for the gates, this provides the cell-to-cell variation in the response for a population of cells. We developed a computational approach to quantify how population variability propagates from the sensors, through the gates, to the output promoters (Fig. 4-35). Cello applies a simple algorithm to determine how signals propagate from the sensors through the gates to the output promoters. This generates predicted cytometry distribution for all combinations of input states, which can be directly compared to experiments. Finally, for each gate, the load on the cell for carrying the gates is estimated based on their impact on growth ($\%$ reduction of OD₆₀₀) as a function of the activity of the input promoter (Methods). For any combination of inputs, if the predicted growth reduction exceeds a threshold, this information can guide multi-objective circuit optimization or be provided as a warning to the user (Fig. 4-32).

4.2.1 Specification: Verilog hardware description language

The Cello software provides a design automation environment whose input is a high-level specification from a hardware description language (Verilog). The first step is to parse the Verilog code to compute the truth table. The truth table is the starting point for logic synthesis, which generates the circuit diagram.

A subset of Verilog is synthesizable, meaning the program can be directly mapped to a physical implementation in hardware. Synthesizable Verilog is transformed to a netlist (a list of connected primitive gates that can be mapped to a hardware technology), which is functionally equivalent to the Verilog code. The subset of Verilog used in Cello is described in this section.

Verilog module. Verilog is written using modules, where each module has a name, and the line defining the module name also requires input definitions and output definitions. The following box defines a module named "example" with output **"x",** and. inputs "a" and **"b".** Keywords are shown in blue.

```
module example (output x, input a, b);
endmodule
```
Assign statement. Within a Verilog module, Cello accepts and parses assign statements, case statements, and structural statements. An assignment provides a concise way to specify a combinational logic function. Assign statements use an $=$ operator to set the value of a wire on the left-hand side based on the wire values and logic operators on the right-hand side.

```
module example(output x, input a, b);
  assign x = a \& b;endmodule
endmodule
```
Additional Verilog operators that can be used in assign statements are:

The following statement uses multiple operators.

```
module example (output x, input a, b, c);
  assign x = a \& b \in \neg c;
endmodule
erdmodu Le
```
The order of operations proceeds from left to right. Parenthesis can be used to specify a different order of operations to implement a different function.

```
module example (output x, input a, b, c)
  assign x = a \& (b + \infty);endmrodu le
endmoduile
```
More complex assign statements can use internal wires to carry values within the module. To use internal wires, the names must be defined, and they must be assigned (appearing on the left-hand side of the equation) before they can be used as an operand on the right-hand side. The function above can also be implemented using internal wires.

```
module example (output x, input a, b, c)
  wire wl, w2;
  assign wl - ~C;
  assign w2 = b | w1;\text{assign } x = w1 \& w2;andmodule
```
Case statement. A case statement provides a way to specify a truth table in Verilog. Since all combinational logic functions can be represented as a truth table, the case statement can be used to specify any combinational logic function as input to Cello. **A** case statement is placed within an "always" block. An always block contains a "sensitive list", meaning the always block executes the code within the begin/end keywords whenever a value changes for a member of the sensitive list. The sensitive list below contains inl and in2.

```
module example (output out, input inl, in2);
always@(inl, in2)
    beain
    end.
endnodule
```
The case statement is placed within the begin/end lines within the always block. The line case($\{\text{in1}, \text{in2}\}\$) indicates that the argument of the case statement is $\{\text{in1}, \text{in2}\}.$ In Verilog, the brackets indicate concatenation, meaning the argument for the case statement is one value that is the concatenation of inl and in2. **If** in1 is **0** and in2 is **1,** the argument would be **01.**

```
module example (output out, input inl, in2);
always@ (inl, in2)
    begin
      case (\{in1, in2)\})endcase
    end
endmcduie
```
The actual cases within the case statement are specified using a bit-wise numbering system: **2'bOl:** {out} **=** 1'bO. This individual case executes when the argument is a 2-bit number in binary notation **(2'b)** equal to **01.** When this case executes, the value **0** for a 1-bit number in binary notation **(1'b)** is assigned to the wire named "out". **By** **specifying all combinations of input values as individual cases, a complete truth table can be specified. The following example specifies the truth table for a 2-input AND operation.**

```
module example (output out, input inl, in2);
alwavs@(inl, in2)
    begin
      case ( inl, in2})
        2'bOO: {out} 1'bO;
         2'bOl: {out} l'bO;
         2'blQ: {out} I'bC;
        2'bll: {out} = 1'bl;
      endcase
    e nd
endmodule
```
More complex case statements can be used to specify n-input m-output truth tables,

such as the multiple output truth table for the priority circuit (Figure 4-4a).

```
module example (output x, y, z, input a, b, c);
always@ (a, b, c)
    begin
      case({a,b,c})3'bOOO: {x,y,z} = 3'bOQO;
         3'b001: \{x, y, z\} = 3'b001;
         3'b010: \{x, y, z\} = 3'b010;
         3'bOll: {x,y,z} 3'bOlO;
         3'blOO: {x,y,z} 3'bi00;
         3'bl0l: {x,y, z}= 3'blGQ;
         3'bllO: {x,y,z} 3'blGO;
         3'bl11: \{x, y, z\} = 3'b100;
      endcase
    end
endmodule
```
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The names of multiple output wires are concatenated within brackets, so the concatenated value of xyz equals **000** in the first case, equals **001** in the second case, and so on. Due to concatenation within brackets, the order of names matters in ${a,b,c}$ and $\{x,y,z\}$. However, the order of names in the sensitive list does not matter.

always@(a, **b,** c) is the same as always@(c, **b,** a)

{x, **y,** z} is different than {z, **y,** x}

case({a, **b,** c}) is different than case({c, **b,** al)

Structural statement. Assign statements and case statements are forms of "behavioral" Verilog, meaning that the function is specified without considering a gatelevel schematic. Structural Verilog can be used to directly specify the desired circuit topology using the same form as a netlist, which specifies a gate type, the output wire name, followed **by** the input wire names.

nor (x, a, **b) ;**

The above example specifies the function $x = a$ nor b. Note that gate types are specified in lowercase in Verilog. Each gate can only have a single output, but can have multiple inputs. Allowed gate types include: not, or, nor, and, nand, xor, xnor, buf. For example, the following specifies the function $x = a$ and b and c.

and (x, a, **b, c);**

To use structural elements within a Verilog module, the above lines just need to be written within a Verilog module:

```
module example (output x, input a, b, c)
  and (x, a, b, c)
endmodule
```
Internal wires can be used to build up more complex structural statements. The next example also implements 3-input **AND** logic, but uses a combination of four **NOT** gates and two NOR gates:

```
module example (output x, input a, b, c);
  wire wl, w2, w3, w4, w5;<br>not (wl, c);
  not (w1, c);<br>not (w5, b):
  not (w5, b);<br>not (w4, a);
        (w4, a);nor (w3, w4, w5);
  not (w2, w3);
  nor (x, wl, w2);
endimodule.
```
Even though structural Verilog can be used to specify a wiring diagram, logic synthesis is used to convert certain primitive gate types might not be available in the genetic gates library and to minimize number of gates in the circuit, if possible.

Combining Verilog statements. Explanations and examples of Verilog case statements, assign statements, and structural statements provided above were limited to one type of statement per module. However, these forms can also be combined in a module to build more complex programs. An example is provided below that combines the following commands:

Define a module name, input wire names, and output wire names:

module example(output out, input a, **b,** c);

Initialize the internal wire names that will be required to carry values within the module: wire w1, w2, w3, w4;

Assign: Let w1 carry the value of the logical operation a AND c:

assign $w1 = a & c$;

Assign: Let w2 carry the value of the logical operation **(NOT** a) **AND (NOT** c):

assign $w2 = a \& c;$

Structural: Define a NOR gate with output wire w3 and input wires **wi** and w2:

nor ($w3$, $w1$, $w2$);

Structural: Define a **NOT** gate with output wire w4 and input wire w3:

not (w4, w3);

Case: Use a case statement to define a truth table for a 2-input **AND** function with inputs w4 and **b,** and output out. Members of the sensitive list are w4 and **b,** so the begin/end block will execute when w4 or **b** changes value. The argument for the case statement is the concatenated value of w4 and **b.** Only set the value of wire out to **1** when the concatenated value of w4 and **b** equals **11.**

End the Verilog module:

endmodule

```
module example (output out, input a, b, c);
wi:re wl, w2, w3, w4;
assign w1 = a % c;<br>assign w2 = \sima & \simnor (w3, wl, w2);
not (w4, w3);
always@(w4, b)
     begin
       case({w4,b})2'bOO: {out} = l'b0;
          2'bOl: {out} = l'bO;
2'blO: {out} = l'bO;
          2'bll: {out} l'bl;
       endcase
     end
endmodul e
```
4.2.2 Parsing Verilog to generate a truth table

Section V.A explained the syntax for writing Verilog code. **All** combinational logic functions can be expressed in the form of a truth table, which is the entry point to logic synthesis. In this section, we describe how the Verilog program is parsed to a nafve netlist (list of connected gates), and how the naive netlist is used to generate a truth table.

The first Verilog line is the module definition, which is parsed to obtain the input names and output name (s) . From there, individual assign, structural, and case statements are parsed from the Verilog file. Each individual statement is converted to a logic node that can contain a single gate, multiple gates, or a truth table.

Assign. **A** line starting with the assign keyword indicates an assign statement, which is parsed to a tree data structure in which input wire names are the leaf nodes, the output wire name is the root node, logic operators **(~, 1, &)** are the internal nodes, and parentheses inform the branching. This tree is functionally equivalent to a circuit diagram, which is used as a logic node with one or more logic gates.

Structural. **A** line starting with the lowercase name of a gate type (not, nor, or, and, nand, xor, xnor) indicates a structural statement, which is parsed to a single-gate logic node of that type, where the first argument indicates the node's output wire name, and all subsequent arguments indicate input wire names.

Case. An always block containing a case keyword is parsed to a truth table, where the wire name within curly brackets (for example, {out}) is the output wire name of the node, and the case argument (for example, $\{w4,B\}$) indicates the input wire names. Gate types are not used in the logic node parsed from a case statement; instead, the truth table is used to relate output values to the input values of the node.

Connecting all nodes according to the input/output wire names results in a graph that can be used to propagate logic through each node to calculate the truth table specified **by** the input Verilog (Figure 4-28).

Nested Verilog modules. The above example used different types of Verilog statements in the same module. However, Verilog modules can also be nested to form more complex programs. In the module hierarchy, the referencing module is called the parent module, and the referenced modules are called child modules (Figure 4-29). This nesting implements the reuse of previously written modules, which is helpful when scaling up to larger logic programs.

4.2.3 Logic synthesis

The previous section describes how the Verilog code is parsed to create a truth table. This section focuses on the next step, which is to convert the truth table to a circuit diagram. This is a process known as logic synthesis and our approach relies on algorithms that are typically applied to electronic circuits, with additional steps to incorporate constraints that arise from working with a limited set of genetic gates.

Logic synthesis is performed in several steps (Figure 4-30). First, the truth table is converted to a NOR-Inverter Graph **(NIG).** Second, logic motifs can be swapped for equivalent subcircuits to reduce circuit size. Logic motifs can be stored and retrieved from the **UCF** to biasing the circuit toward particular motifs that are desirable given the biochemistries of the gates in the library.

To convert a truth table to a NOR-Inverter Graph **(NIG),** an intermediate step uses the logic synthesis tool **ABC** (Brayton **&** Mishchenko, 2010) to generate an **AND-**Inverter Graph **(AIG)** built exclusively from 2-input **AND** and **NOT** gates. **ABC** minimizes the number of gates (nodes) and layers (longest path) in the **AIG.** The **AIG** is converted to an **NIG** containing 2-input NOR and **NOT** gates. This conversion is

done **by** replacing **(A AND** B) with the equivalent **(NOT A)** NOR **(NOT** B) according to DeMorgan's rule.

As an alternative to **ABC,** we also developed a path to the circuit diagram using Espresso (Brayton et al, 1984), another commonly used tool for logic synthesis. This approach differs in that it first converts a truth table to a minimized Product of Sums **(POS),** which we then convert to an **NIG.** Both the **ABC** and Espresso routes are implemented in Cello and the one that produces the circuit diagram with the minimum number of gates is selected. In approximately **95%** of the cases, the number of gates after the **ABC** route is less than or equal to the number of gates after the Espresso route.

The user may have preferred logic motifs that they would like to have in the circuit diagram, if possible. These could represent optimized combinations of gates (both **ABC** and Espresso are not guaranteed to find the global minimum) or motifs that are particularly robust for a given biochemistry. For example, the **UCF** we developed has a list of small 3-input 1-output motifs generated from brute-force enumeration (Methods). Additionally, this is a simple mechanism to introduce non-NOR logic functions for which genetic gates may be available. The EcolC1G1T1 **UCF** motif library contains: (1) a 2-input OUTPUT OR motif to replace a NOR-NOT subcircuit at an output, (2) a 2-input 1-output optimal XNOR motif, and **(3)** small 3-input **1** output **NOR/NOT** motifs.

An attempt to incorporate the user-defined circuit architecture motifs into circuit diagrams occurs during the final step of logic synthesis. Starting with an initial **NOR/NOT** circuit diagram, subcircuits are replaced with a set of user-defined motifs, if possible. This is performed **by** the following steps. First, all possible subcircuits in the initial circuit diagram with ≤ 4 input wires and 1 output wire are enumerated. This is done **by** visiting each gate's output wire, then performing a breadth-first search on the incoming wires and gates, proceeding until the circuit inputs are reached. During this search, unique subcircuits are added to a list. Second, the truth table for each subcircuit and each user-defined motif is evaluated. **If** a subcircuit and a motif have Boolean equivalence (also checking permuted input wire order), then the motif is substituted in place of the subcircuit. **If** multiple subcircuit/motif matches are found, the motif that reduces the number of circuit gates the most is used. Finally, each time a motif replacement is made, the replacement algorithm is performed again until no more replacements can be made.

Motifs in the library can use gate types other than **NOR/NOT,** such as **AND, NAND,** OR, XOR, or XNOR. To constrain the logic gates according to the number and types of gates available in the genetic gates library, a cost function is used during subcircuit substitution. The cost is the total number of gates in the circuit that exceed the gates available in the library. For example, if there are **6 NOR/NOT** gates and **¹ AND** gate in the library, and the circuit has **7 NOR/NOT** gates and 2 **AND** gates, the cost would evaluate to $(7-6) + (2-1) = 2$. If there are enough available gates in the library to cover the gates in the circuit, the cost is **0. A** substitution is rejected if the cost increases, and is accepted if the cost decreases or does not change. This cost evaluation guides logic synthesis to produce a circuit that can be covered **by** the gates library. However, after subcircuit substitution converges and no more substitutions are possible, if the cost is still greater than **0,** the circuit is reported as "not synthesizable".

4.2.4 Repressor assignment

The previous section describes how the circuit diagram is generated. The next step is to assign genetic regulators to the gates in the diagram. Each gate is based on a unique biochemistry and thus generates a different response function. The assignment

problem is to identify the optimal way to select and connect these gates to generate the maximum overall dynamic range for the circuit. In this section, we first describe how we score a particular repressor assignment. Next, the search algorithm is described that optimizes the assignment.

One approach to the assignment problem would be to permute all possible combinations of gates and identify the one that generates the best circuit. This would guarantee the identification of the global optimum. However this method becomes intractable as circuit size and library size grow. The number of unique assignments (with a single RBS variant per gate) is given by $\frac{A}{r-g}$, where g is the number of gates in the circuit and *r* is the number of repressors in the library. With our library of repressors (including RBS variants), a 9-gate circuit has $\sim 10^{11}$ permutations. A search algorithm needs to be implemented to scale to larger circuits and libraries, but often comes with the tradeoff of introducing stochasticity into the search and can converge on local optima.

Calculating the circuit score. The circuit score **S** captures how closely the logic function generated **by** a repressor assignment matches the desired truth table for the circuit. Because the output of genetic circuits is not digital, the **ON** and OFF states have numerical values and a larger difference between these values (the dynamic range) is desirable. Calculating **S** requires two steps. First, the output is calculated for all combinations of input states. An example is shown in Figure 4-31, where there are two sensors and four input states. The activity of the sensors feeds into the gates and their response functions are used to calculate how the signal propagates through the circuit. Then, **S** is calculated **by** comparing the lowest output for a state that should be **ON** and the highest output for a state that should be OFF:

$$
S = \frac{\min(ON)}{\max(OFF)}
$$

Calculation of predicted circuit toxicity. For each gate, normalized cell growth is measured as a function of input promoter activity (Figure 4-15). For a circuit, certain input states can lead to the expression of multiple repressors and this can lead to toxicity. For each gate in a circuit, the input RPU is calculated, and the cell growth value is interpolated from the two nearest experimentally-measured normalized cell growth values from the **UCF.** The toxicity of the whole circuit for a particular input combination is calculated as the product of normalized cell growth for each of the individual gates. There is no theoretical basis for this; rather, it was chosen to strongly bias against circuits where any repressors are expressed beyond their empirical toxicity threshold. After the toxicities of all the input states are calculated, the toxicity of the circuit as a whole ("growth score") is taken as the worst input state.

As shown in Figure 4-32 for the Majority circuit, there is a trade-off between the circuits with the highest circuit score (S) and those that are at risk of reducing growth, creating a Pareto-optimal curve. The current algorithm applies a cutoff **(0.75)** with respect to the growth score and only allows circuit assignments that fall above the cutoff.

Sinulated Annealing Assignment Algorithm. The goal of repressor assignment is to find the combination of gates that maximizes the circuit score, *S.* The repressor assignment problem has a large discrete search space for which we implemented a Monte Carlo simulated annealing algorithm (Aarts et al, **2005;** Metropolis **&** Ulam, 1949) to identify an optimum assignment. The search initializes with gates from the library being randomly chosen and assigned to a gate in the circuit. Any gate can be assigned to any position in the circuit. Each iteration of the Monte Carlo algorithm swaps the assignments of two gates. This is done **by** randomly selecting one gate in the circuit, randomly selecting a second gate either in the circuit or in the gate library,

and then performing the swap. After the swap, the circuit score for the new assignment S' is calculated and the move is accepted with a probability based on the score change and the temperature factor *T*

$$
P = e^{-\left(\frac{S-S'}{T}\right)}
$$

After calculating the probability, a random number R between **0** and **1** is generated: if $R < P$, the swap is accepted, and if $R > P$, the swap is rejected. If the swap improved S, then $P > 1$, and the move is always accepted. After the first assignment is initialized, the probability of accepting a move decreases as the temperature anneals with exponential decay:

$$
T_i = T_{max} \cdot e^{-C_i}
$$

where *i* is the current iteration, T_{max} is the starting temperature, and *C* is a constant that determines the rate of cooling. After reaching the end of annealing, the run continues at $T = 0$ until 10,000 steps progress with no additional improvement. The simulated annealing results in Figure 4-33 show convergent solutions for the circuits ranging from 5 to 9 gates, where $T_{max} = 100$, and C is 5 x 10⁻⁵.

Several modifications were made to the basic algorithm described above to allow for additional constraints that do not appear in the **S** calculation. Some gates have multiple RBS options, but a repressor cannot be used more than once in a circuit. To prevent illegal swaps that reuse a repressor, a list of gates that can be legally swapped is generated. Gates with the same repressor as the selected gate are allowed in the list, because this swap simply replaces the RBS for the gate. Gates with a different repressor are only allowed in the list if another gate from the circuit does not use the same repressor. To avoid repressor reuse, gate group names are also specified in the **UCF** (gates collection). The group name will typically be the repressor name, but different repressors can also be grouped if they exhibit cross-talk.

Additional constraints can be applied to reject assignments that would otherwise be accepted based on **S.** For example, we have implemented the rejection of assignments whose growth score is below a threshold (previous sub-section) or when two "roadblocking" promoters have to be connected as inputs to a gate.

4.2.5 Combinatorial design of circuit layouts

After a gate assignment has been found for a circuit diagram, a linear **DNA** sequence that contains the complete circuit is generated. This is done using combinatorial design (Smanski et al, 2014; Bhatia et al), which has been applied to build **DNA** sequences using a set of parts, constraints between parts, and organizational rules. The assignment algorithm leads to a list of parts in the circuit as well as constraints between parts (e.g., due to roadblocking). The **UCF** can also contain additional organization rules, such that the repressors have to appear in a specified order and orientation. After the assignment algorithm, the parts and rules for a circuit are automatically used to build a Eugene file. From this Eugene file, combinatorial algorithms described previously(Smanski et **al,** 2014; Bhatia et *al)* are used to build the **DNA** sequence, which is the output of Cello. The Eugene file itself is also an output of Cello so that it can be run at a later time to generate additional constructs (https://cidar.bu.edu/EugeneLab/).

One of the advantages of using combinatorial design is that many constructs can be built that preserve the same underlying rules-and therefore produce the same circuit function-but unconstrained aspects of the design are allowed to vary. Before the user runs Cello, an option is available to specify the number of desired constructs. Building and testing a library of designs instead of a single design can help identify a functional variant. Additionally, identifying failed and successful designs provides a data set for learning new organizational rules (Smanski et al, 2014). An example of this are the Majority circuits in Figure 4-5e, where multiple constructs are shown.

This section describes how gates and their component parts are organized in Eugene as well as the impact of adding organizational constraints to the **UCF. A** hierarchical design is used to describe circuits in Eugene (Level **1:** Parts, Level 2: Gates, and Level **3:** Circuit).

In Level **1,** part types are defined, and individual parts with those types are defined. Parts in Eugene require a type and a name, while other attributes such as **DNA** sequence can be added optionally. Below are examples of part definitions for a promoter, ribozyme, RBS, **CDS** and terminator that make up a gate.

Level 1: Part type definitions

```
PartType Promoter;
PartType Ribozyme;
PartType RBS;
PartType CDS;
PartType Terminator;
```
Level 1: Part definitions

```
Promoter pTac;
Ribozyme RiboJ53;
RBS P3;
CDS PhiF;
Terminator ECK120033737;
```
In Level 2, we assemble parts into gate devices (a device is defined as a collection of parts). The gate device contains the ribozyme insulator, RBS (sometimes multiple variants are allowed), repressor, and terminator. For a NOR gate, there can be two additional undefined promoters. For example, the device for the PhlF gate (with the P3 RBS) is as follows.

Level 2: Gate device

```
Device PhIF_device(
   Promoter, Promoter, RiboJ53, P3, PhlF, ECK120033737
\mathcal{C}
```
We then define a set of rules that act on the P3_PhIF device. These rules define the promoters that drive PhiF according to the circuit diagram, and an enforced order of those promoters (e.g., to avoid roadblocking). The ALL FORWARD rule just orients all parts in the forward direction (this gate will be allowed in the reverse direction in a later step). Note that rules on different lines must be joined with the **AND** keyword.

Level 2: Gate rules

```
Rule PhlF_rules<br>(ON PhlF_device:
     CONTAINS pBM3R1 AND
    CONTAINS pHlyIIR AND
    pBM3R1 BEFORE pHlyIIR AND<br>ALL_FORWARD
);
```
Given the devices and rules for each gate, an enumeration of variants for each device is performed using the 'product' function. The PhlF device shown above only allows a single device variant.

Level 2: Design of gate variants

In Level **3,** gate device variants will be combined into the circuit device. First, we must initialize the circuit device and each gate device, where each gate is named by the repressor to allow rules from the UCF to be applied according to that name.

Level 3: Initializing the circuit device, and its component devices.

```
Device circuit();
Device gate PhlF();
Device gate SrpR();
Device gate_BM3R1();
Device gate HlyIIR();
Device gateBetI();
Device gate = \text{Amtr}(x);
```
Rules are applied to the circuit device before enumerating circuit variants. The EXACTLY 1 counting rule ensures that each gate appears once and only once in the circuit. Additional rules can also be specified, for example requiring the PhlF gate to be in the first position and in the forward orientation, and requiring each gate to alternate orientation, as follows.

Level 3: Circuit device rules

```
Rule circuit rules
(ON circuit:
     gate PhIF EXACTLY 1 AND
     gate<sup>-</sup>SrpR<br>gate-BM3R1
                       EXACTLY 1 AND<br>EXACTLY 1 AND
     gate_HlyIIR EXACTLY<br>gate_BetI EXACTLY
     gate<sup>-</sup>BetI EXACTLY 1 AND<br>gate<sup>-</sup>AmtR EXACTLY 1 AND
                       EXACTLY 1 AND
     STARTSWITH gate_PhlF AND
      FORWARD gatePhlF AND
     ALTERNATE_ORTENTATION
);
```
Now that we have specified the circuit rules, the combinatorial design step can be performed. Nested for-loops iterate through all gate device variants from Level 2 (there might only be a single variant for each gate, or there might be variants with different promoter orders). In the innermost loop, the current set of gate device variants is used to build the circuit device in Level **3** in the 'permute' function. Each set of designs in the inner loop is appended to an array called 'allResults'.

Level 3: Design of circuit variants

```
Array allResults;
for(num i0=0; i0<sizeof(PhlF_devices); i0=i0+1)<br>for(num i1=0; i1<sizeof(BetI<sup>-</sup>devices); i1=i1+1)
for(num il=0; il<sizeof(BetI<sup>-</sup>devices); il=il+1)<br>for(num i2=0; i2<sizeof(SrpR<sup>-</sup>devices); i2=i2+1)
for(num i2=0; i2 <sizeof(SrpR<sup>-</sup>devices);
for(num i3=0; i3<sizeof(HlyITR devices); i3=i3+1)<br>for(num i4=0; i4<sizeof(AmtR devices); i4=i4+1)
for(num i4=0; i4<sizeof(AmtRdevices); i4=i4+1) {<br>for(num i5=0; i5<sizeof(OacRdevices); i5=i5+1) {
for(num i5=0; i5<sizeof(QacR<sup>-devices);</sup>
gate PhlF = PhilFdevices [iO];
gate BetI = BetI devices[il];
gateSrpR = SrpR devices [i2];
gate HlyIIR = HlyITR devices[i3];<br>gate AmtR = AmtR devices[i4];
gate AmtR = AmtR devices [i4];
                 = QacR<sup>-</sup>devices [i5];
Device circuit(
    gate PhlF,
    gate_BetI,
    gate_SrpR,
    gate_HlyIIR,
    gate AmtR,
    gate<sup>-</sup>QacR
\mathbf{1}:
result = permute(circuit);
allResults = allResults + result;
}}}}}
```
Next, we explain how Eugene rules specify the design space of allowed circuit layouts (Figure 4-34). At the gate device level (Level 2), the only degree of freedom is promoter order within each gate. **NOT** gates can only have 1 variant. NOR gates can have two variants, where either promoter order is allowed. This degree of freedom allows 2^N variants, where N is the number of 2-input gates. Enforcing roadblocking rules (STARTSWITH) constrains promoter order, but for tandem non-roadblocking promoters, either promoter order is still allowed (Figure 4-34, Gate devices).

In addition to promoter order, gate order/orientation is the other degree of freedom. At the circuit device level (Level **3),** if the repressor order is constrained, and all gates are in the forward orientation (as specified in EcolCIGITI), then the only degree of freedom is promoter order from Level 2. In the example circuit assignment, repressor order and all forward rules result in 4 solutions (Figure 4-34, Panel **1).**

Additional variants can be generated **by** removing order/orientation rules. For example, removing the FORWARD gate PhlF rule allows the reverse orientation of the PhlF gate and results in 8 solutions (Panel 2). Removing a second rule, gate PhlF BEFORE gate BetI, now allows the PhIF gate in any position and results in 40 solutions (Panel **3).** Removing all remaining gate order rules (a BEFORE **b)** allows unconstrained shuffling of gate order and results in **960** solutions (Panel 4). Removing all remaining FORWARD rules allows all gate orders and orientations and results in **15,360** solutions (Panel **5).**

The Eugene rules specified in the **UCF** *(eugene rules* collection) include roadblocking rules in Level 2 gate devices, and repressor order and all forward rules in the Level **3** circuit device. As described above, these rules can be removed to unconstrain the layout design space. Furthermore, any additional rules from the Eugene language (Oberortner et al, 2014) can be added to the **UCF** for user-specified constraints to the design space. The number of desired variants can be specified in the Options tab of the Cello web application. After layout design using Eugene, the Cello output has three forms. The first output is a file containing an ordered list of part names and part orientations **(+, -)** for each variant. The second output is a file containing an ordered list of gate names and gate orientations for each variant. The third output is a separate plasmid file for each variant in which the circuit module is inserted into the specified genetic location (Section VII, *genetic locations* collection).

4.2.6 Predictions of circuit performance

Qualitative predictions of the circuit output distributions can be computed for each input combination. This is performed as a final step in Cello, after the gate assignment search has converged. In order to perform this step, each gate in the circuit must have experimental cytometry distributions added to the **UCF,** with fluorescence values converted to RPU.

As a first step, the experimentally-measured gate output RPU histograms are normalized to have a total of **10,000** events in evenly log-spaced bins (one bin every **100.024x** RPU). At least **8** experimentally-measured output RPU histograms at various input RPU levels are required (the gates in this work use 12 input levels). Histograms $Y(x)$ are generated at intermediate input levels x by positioning their medians, $\langle Y(x) \rangle$, on the gate's response function. Once the medians are in place, the counts *f* for each bin are interpolated from the counts $(f_L \text{ and } f_R)$ of the experimentallymeasured histograms that lie to either side of **x.** The experimentally measured histograms have input values, *XL* and *xR.* The parameter m is the bin relative to the median, $y \ll Y$. These relationships are captured by the equations:

$$
\langle Y(x) \rangle = y_{min} + \frac{(y_{max} - y_{min})K^n}{x^n + K^n}
$$

$$
f(m) = f_L(m) + (f_R(m) - f_L(m))\frac{x - x_L}{x_R - x_L}
$$

In this way, histograms at intermediate inputs are generated with medians on the response function, and shapes interpolated from the nearest experimental histograms.

Once all the gate distribution response functions are computed, the qualitative predictions for output distributions can be computed. For a particular input combination, sensor values feed into the first layer of gate distribution response functions (dashed vertical lines, Figure 4-35). This input value takes a vertical "slice" of the distribution response function to create the output histogram. Next, those gate output histograms become input histograms for the second layer of gates.

Input histograms can be viewed as **10,000** individual input events, each of which produces its own output histogram-all of which are averaged to produce a histogram containing **10,000** events. At NOR and OR gates, input histograms are combined **by** first summing the histogram medians (or summing the histogram median and the sensor input value if a sensor promoter is an input), then shifting both histograms to be centered at that new median, and then averaging the counts in each bin to create a histogram with **10,000** events.

Sensor input signals are propagated through gate distribution response functions in the circuit until the output histograms are produced for each input row in the truth table (Figure 4-35c).

Input threshold analvsis. Genetic gates output a continuous range of values as opposed to digital Os and Is. This is similar to electronic systems, where output voltages also take continuous values. For digital abstraction in electronic design, a maximum value for low-inputs and a minimum value for high-inputs specify the input ranges that produce outputs considered to be **ON** and OFF (Hauser, **1993). If** an input signal falls between a gate's low/high thresholds, this can lead to an intermediate output or an incorrect **ON/OFF** output if the input is perturbed slightly. This section describes how we define and use input thresholds in Cello.

For two **NOT** gates connected in series, the low and high output levels of the first gate *(OL* and *OIJ)* must map onto either side of the low and high input thresholds of the second gate *(IL* and *H).* The difference between *IL* and *OL* is the low margin *(ML)*, and the difference between *OH* and *IH* is the high margin *(MH)*. Both margins must be positive to satisfy the input threshold criteria. **A** negative margin indicates

an input that falls in the sensitive intermediate zone, the region between *IL* and *IH* (Figure 4-36a, diagonal hatching).

In electronic design, the low and high input thresholds are identical for all gates in a circuit. However, each genetic gate has unique thresholds due to their different response functions. Each gate's *IL* and *IH* thresholds are calculated from its response function using the input levels that cause the gate output to be 0.5x the maximum and 2x the minimum output, respectively (Figure 4-36a, black dots). ML and MH must be positive values for a gate connection to be valid, and all gate connections must be valid for the circuit as a whole to be valid. As an example, in the Majority circuit (Figure 4-5) the assignment had a good predicted circuit score, but the assignment did not satisfy all input margins. Specifically, the PhlF gate has a predicted input RPU that falls in the intermediate region (Figure **4-36b).** Experimentally, the initial design for this circuit (Figure 4-20) had one high OFF state caused **by** the PhlF gate input falling in the sensitive intermediate region.

4.3 Characterization of sensors and gates for use with Cello

Different sensors and actuators can be connected to the circuits built **by** Cello. To make use of this, a user has to characterize the output promoter of their sensor(s) in the genetic context defined for the circuit (in the **UCF).** The sensor is characterized in two states, **ON** and OFF, under the conditions defined **by** the user. For example, it could be two different concentrations of a small molecule or the presence and absence of an environmental stimulus. This measurement has to be provided to Cello in standard units (RPUs). The **DNA** containing any regulators necessary for sensor function (referred to as the "sensor block") could either be uploaded to appear in the circuit plasmid or separately inserted into a different context *(e.g.,* the genome). Sensor blocks are not necessarily required; for example, when the promoter depends only on native regulators. The connection of the output to a new actuator is more straightforward, where it simply requires knowing whether its dynamic range is sufficient to trigger a phenotypic response. **A** step-by-step guide for the characterization of new sensors such that they can be used with Cello is provided in this section.

Similarly, building new UCFs requires the characterization of new gates and/or gate libraries in different organisms or operating conditions. The procedure is similar to characterizing sensors and is also provided in this section. The details of the data organization for the gate library in the **UCF** are provided in the Appendix.

4.3.1 Measurement of RPU plasmid

Sensor and gate fluorescence characterization data must be converted into relative promoter units (RPUs) for incorporation into Cello. To convert characterization data to RPUs, an RPU standard plasmid must first be measured along with an autofluorescence control.

Transform the RPU plasmid to create an RPU standard strain and a non- YFP plasmid to create an autofluorescence control strain. Following work **by** Kelly et al. (Kelly *et al,* **2009),** the promoter activities must be reported to Cello in standard units. The standard plasmid used for the EcolC1G1T1 **UCF** is shown in Figure 4-37. New UCFs may define different standards. This is the same backbone as the circuit plasmid (Figure 4-1b) and the gate measurement plasmid (Figure 4-41), and contains the same YFP expression cassette. Note that while the standard constitutive promoter (BBaJ23101 (Part:BBa **J23101 -** parts.igemn.org)) is the same, this plasmid is different from the Kelly standard (Kelly *et al,* **2009;** Stanton *et al,* 2014), including an upstream

insulating terminator, an upstream promoter spacer, and a different RBS. Our RPU plasmid produces 4.2x the YFP signal as the Kelly standard. The plasmid should be transformed into the strain defined **by** the **UCF,** which for the Eco1C1GIT1 **UCF** is *E. coli* NEB 10-beta (New England Biolabs, MA, C3019).

Measure the fluorescence of the RPU standard strain and the autofluorescence control strain. For each set of inducer conditions to be applied to a circuit, gate, or sensor, YFP fluorescence measurements are collected for the RPU strain and the autofluorescence strain. Fluorescence can be measured using flow cytometry, a plate reader, or any instrument capable of measuring YFP fluorescence. The measurements should be made under media and growth conditions that are as close as possible to that defined in the **UCF.**

We performed additional characterization of the RPU standard to estimate the RNAP flux on the promoter **J23101.** The RPU standard plasmid was measured using smFISH (Raj *et al*, 2008) to obtain the rate of mRNA transcription from the P_{Tac} promoter. **A** background control and a measurement plasmid with an inducible promoter were also measured to generate a standard curve to determine the steady state number of yfp mRNAs per cell. We quantified the steady state number of *yfp* mRNA copies per cell at mid-exponential growth using single-molecule fluorescence *in situ* hybridization (smFISH) (Raj *et al*, 2008) following the method given in (Skinner *et al,* 2013), which we adapted for counting *yfp* mRNA in *E. coli* at single-transcript resolution. Briefly, we designed a set of **25** oligonucleotide probes, fluorescently labeled with TAMRA, each 20 bases in length, against the *yfp* transcript (Table 4-10) using Stellaris Probe Designer version **4.1.** The mean *yfp* mRNA copy number for the RPU standard plasmid (pAN1717) strain was found to be 24.7 ± 5.7 molecules per cell (Figure 4-38). The half-life for *gfp* mRNA in *E coli* has been determined to be approximately 2 minutes (Smolke *et a],* 2000), and the average plasmid copy number

for the **p15A** origin of replication has been determined to be approximately **15** per cell (Hiszczyfiska-Sawicka **&** Kur, **1997).** Therefore, the estimated mRNA production rate is 0.30 ± 0.07 mRNAs per second per cell or 0.02 ± 0.005 mRNAs per second per plasmid for the **pAN1717 J23101** promoter. Stated errors are the standard deviation from replicate measurements and do not include any estimate of systematic bias of the measurement. For comparison, the mRNA production rate for the **J23101** promoter was estimated to be approximately **0.03** mRNA per second per **DNA** copy in (Kelly *et* al. 2009).

4.3.2 Sensor characterization

Sensors convert signals (small molecules, light, etc.) into **a** transcriptional output. This section provides the steps required to characterize **a** sensor and report its output in standard units (RPUs). First, the output promoter needs to be cloned into the circuit plasmid defined **by** the **UCF.** Next, the sensor responses are characterized in the strain of interest and parallel measurements of the RPU standard's fluorescence and the strain's autofluorescence are made (previous section). These data are used to calculate sensor output RPU values, which are input into Cello along with the sequence of the output promoter and sequence of the sensor block.

Construct the plasmid to measure the sensor output promoter. The sensor is characterized in the same backbone as the circuit in Figure 4-lb (Figure 4-39, bottom). A version is provided that contains a P_{Lac} -lacZ α module used for blue/white screening (Figure 4-39, top). The sensor output promoter is used to drive a YFP expression cassette, which matches the RPU standard. This cassette includes a ribozyme insulator (RiboJ) and the same RBS-YFP-terminator set as the RPU standard plasmid. The transcriptional fusion between the promoter and expression cassette should be scarless (note that a 4 **bp** scar is defined at the 5'-end of each ribozyme insulator that can be used for cloning). To clone the entire cassette into the plasmid, BbsI Golden Gate sequences flanking the P_{Lac} -lac $Z\alpha$ module simplify cloning, but do not have to be used.

Transform the sensor plasmid from #1 into the strain defined by the UCF._The Eco1C1G1T1 **UCF** defines the strain as *E coli* **NEB** 10-beta (New England Biolabs, MA, **C3019).**

Characterize the ON/OFF state of the sensors. For each set of conditions, fluorescence measurements are made for three strains containing different plasmids: the sensor, the RPU standard, and empty plasmid for autofluorescence. The measurements should be made under media and growth conditions that are as close as possible to that defined in the **UCF.** The following equation converts the median YFP fluorescence to RPU:

$$
RPU = \frac{\langle YFP \rangle - \langle YFP \rangle_0}{\langle YFP \rangle_{RPU} - \langle YFP \rangle_0}
$$

where *<YFP>* is the median fluorescence of the cells containing the sensor, $\langle YFP\rangle_{RPU}$ is the median fluorescence of the cells containing the standard plasmid, and $\langle YFP \rangle$ is the median autofluorescence.

Example: Characterization of sensors (IPTG, aTc, arabinose). We demonstrate the characterization of the three sensors used in this manuscript. Three plasmids were constructed (Figure 4-40) to individually test the output promoters that respond to IPTG (P_{Tac}), aTc (P_{Tet}), and arabinose (P_{BAD}). The same sensor block was used containing the necessary regulators (LacI, TetR, and AraC*). We measured each of these sensors in response to "low" and "high" input signals: the absence or presence of **¹**mM IPTG, 2 ng/mL aTc, and **5** mM L-arabinose respectively. The extraction of median fluorescence from the cytometry plots and conversion into RPUs are shown in Table 4-6.

4.3.3 Characterization of gates to be included in the UCF

Characterizing gates is similar to sensors, with three differences. First, both the input and output of the gate are promoter activities. This requires a separate characterization of the input promoter that is used to characterize the gate. Second, a full response function is required for the gate, as opposed to simpler **ON/OFF** values. Finally, in order to qualitatively predict population behavior, Cello requires RPU distributions and these are more complicated to normalize to RPUs. The protocol for gate measurement is below.

Clone the gate into the measurement plasmid. For the Eco1C1G1TI **UCF,** the input promoter to the gate is P_{Tac} and a LacI expression cassette is provided in the backbone of the same plasmid used to characterize sensors and the circuits (Figure 4-1b). The output is the same YFP expression cassette used for the RPU standard plasmid. The gate-which consists of a ribozyme insulator, RBS, gene, terminator, and the output promoter-is cloned between P_{Tac} and the standard YFP expression cassette on the circuit backbone that encodes a constitutively expressed LacI (Figure $4-41$). The resulting construct allows the gate to be induced with IPTG, and the output to be measured **by** quantifying YFP with cytometry.

Transfoim the gate plasmid from #I, the RPU standard plasinid, the autofluorescence measurement plasmid, and input promoter- YFP plasmid. Transform the gate plasmid (Figure 4-41), the same RPU standard plasmid and autofluorescence measurement plasmid for sensor measurement (Figure 4-37), and the $P_{Tac}-YFP$ plasmid (Figure 4-42). The IPTG-inducible P_{Tac} promoter is used as the input to the gate. This allows the gate's response to different input promoter activities to be measured. The EcolC1G1TI **UCF** defines the strain as **E.** coli **NEB** 10-beta.

Characterize the fluorescence of cells carrying the gate plasinid, the input promoter-YFP plasmid, the RPU standard plasmid, and autofluorescence under a series of inducer *concentrations.* Grow the cells according to the **UCF** growth specifications. Induce the input promoter with various concentrations of inducer; at least six inducer concentrations should be used so that the gate output evenly spans the entire output range. For each inducer treatment, calculate the median fluorescence for the sensor, RPU plasmid, and empty cells. The RPU equation in the previous section is used to convert the median YFP fluorescence to RPU.

Fit the input-output gate data to an equation capturing the response function. Step **#3** results in a series of data generated **by** different concentrations of inducer that can be used to generate the response function of the gate. This is done **by** plotting the activity of the input promoter (using the plasmid in Figure 4-42) versus the activity of the output promoter of the gate (using the plasmid in Figure 4-41) at each concentration of inducer. Both of these measurements are first normalized to RPUs. Then, an equation describing the gate response is fit to the data to generate the response function used **by** Cello. This response function has the form of a Hill equation when the regulator is a repressor,

$$
y = y_{min} + (y_{max} - y_{min})\frac{K^n}{x^n + K^n}
$$

where *n* is the Hill coefficient, *K* is the threshold, y_{max} and y_{min} is the maximum and minimum activity of the output promoter, and x is the activity of the input promoter.

(Optional) Convert the response function cytometry distributions to RPU. Fluorescence histograms can also be converted from arbitrary fluorescence units to RPU. This can be accomplished in a single step **by** taking the gate output histogram and multiplying all the fluorescence-axis values **by** the constant *c:*

$$
c = \frac{\langle YFP \rangle - \langle YFP \rangle_0}{\langle YFP \rangle (\langle YFP \rangle_{RPU} - \langle YFP \rangle_0)}
$$
Effectively, this rescaling performs two transformations of the data: **(1)** multiplying the x-axis by $\frac{\langle \angle YFP \rangle - \langle \angle YFP \rangle}{\langle \angle YFP \rangle}$ shifts the median of the gate's fluorescence distribution down in log-space **by** the autofluorescence median; and (2) division **by** *<YFP>RPu-<YFP>o* normalizes the x-axis values to the RPU standard. These operations are visualized in Figure 4-43.

This section provides an example for the measurement of the PhlF gate with RBS-P2. We measured the YFP expression from the PhlF(RBS-P2) gate and the P_{Tac} -YFP plasmid in the following IPTG concentrations: **0, 5, 10,** 20, **30,** 40, **50, 70, 100, 150,** 200, and **1000 pM.** We also measured cellular autofluorescence and YFP expression using the RPU standard **(pAN1717).** The median fluorescence value for the RPU standard $\langle YFP\rangle_{RPU} = 1540$ and the median autofluorescence value $\langle YFP\rangle_0 = 17.4$. The median fluorescence values for the PhIF gate and P_{Tac} -YFP were converted to RPU for each concentration of IPTG, and then the PhlF output RPU values were plotted against the P_{Tac} -YFP RPU values to generate the gate's response curve (Figure 4-44). Using values $y_{max} = 4.1$ RPU and $y_{min} = 0.017$ RPU, a Hill equation was fit to the data points and resulted in the fitted parameters $K = 0.13$ RPU and $n = 0.92$.

4.4 Initial gate assembly and failure modes

We constructed a gate library based on a set of **16** Tet repressor (TetR) homologues that are orthogonal; that is, they do not bind to each other's promoters (Stanton *et* al, 2014). These can be converted into simple NOT/NOR gates by having the input promoter(s) drive the expression of the repressor, after which there is a terminator and output promoter. Due to a lack of strong terminators when these gates were built, the same terminator (BBa B0015) was reused for each one. Each repressor had a different ribosome binding site (RBS), chosen to maximize the dynamic range.

These gates can be connected to form simple functional circuits; however, in each case additional tuning was required and the dynamic range of the output was low (Stanton et al, 2014). We tested the ability of the response functions of the gates to predict circuit behavior as a whole with no additional tuning. We designed a set of **8** simple circuits from these gates that required between one and four repressors (Fig. 4- 3a and (Methods)). Nearly all of the circuits generated an incorrect response. Only the **(A** NIMPLY B) gate functioned properly and **6** out of **8** circuits had their output states either all OFF or all **ON** for every input condition. Across all the circuits, **13** out of **32** output states were correct, which is comparable to what would be expected from a process that generates random outputs.

We used this test set to determine common causes for circuit failure (Figs. 4-11 through 4-15). When paired with different promoters, gates often generated an unpredictable response and this was apparent even for circuits based on a single repressor (Lou et al, 2012a). The promoters generated transcripts with different untranslated regions (5'-UTRs), which can strongly influence gene expression (Kosuri et *a],* **2013;** Salis et *a],* **2009). A** second problem was that some promoters in the downstream "position 2" of a NOR gate (Fig. 4-2c) can reduce transcription from the upstream promoter, a phenomenon we refer to as "roadblocking". Third, some circuits had growth defects, which were caused **by** repressors that become toxic when expressed past a threshold (Fig. 4-3d). Fourth, several circuits were genetically unstable because of homologous recombination of parts re-used in the same circuit (Sleight & Sauro, **2013;** Chen et al, **2013).**

4.4.1 Non-insulated gates: predicted and measured outputs

Originally, the simple circuits (Figure 4-3a, left data column) were build based on non-insulated gates taken directly from a subset of the repressors previously

characterized (Stanton et *a],* 2014). We allowed a library of **16** members, each of which used the same terminator (BBa_B0015). Response functions for these gates were determined as the activity of the output promoter versus the activity of the input promoter (in RPU). The response function of each gate was fit to a Hill equation, the parameters of which are in Table 4-5.

The non-insulated gates were assembled to form the wiring diagrams shown in Figure 4-5. The gate assignments differ from those built with the insulated gates (indicated **by** color). The detailed parts are also different and shown in this figure. The genetic circuits were inserted into the same plasmid backbone as the insulated gates (Figure 4-1c) and included YFP on the same plasmid as the circuits (no output plasmid).

The assembly strategy used for the non-insulated circuits differed slightly from the insulated circuits. Golden Gate assembly was used to assemble the final circuits, but we used different 4 **bp** scars than for the insulated circuits. We also used a two-tier assembly where intermediate constructs with 1-4 transcription units were assembled first and then assembled to build the final circuit. The sensor block was also assembled with gate modules into intermediate constructs. This is in contrast to the insulated circuits where the sensor block was cloned into the plasmid before circuit assembly, and then all circuit modules were cloned into the backbone in one step.

4.4.2 Characterization of error modes

The circuits built from non-insulated gates were almost entirely non-functional. We identified several failure modes in these circuits, which when corrected fixed the circuit function. We describe the design solutions for five primary error modes in this section: mismatched response functions, promoter/5'-UTR contextual effects, promoter interference, homologous recombination, and toxicity.

Mismatched response functions. In the construction of the non-insulated gates, several of response functions were mismatched. The outputs from one gate frequently did not map onto either side of the threshold of the downstream gate (Figure 4-11). For example, in the initial construction of the XNOR circuit from non-insulated gates (Figure 4-11a), the outputs from the LmrA NOR gate (red gate) is very high, even in its repressed OFF state. These high OFF-state outputs map onto to the downstream response functions to the right of the threshold point. This causes the signal to deteriorate after the first layer. For subsequent circuit designs, the selection of repressor assignments based on the circuit's output dynamic range ensured that the response functions of gates connected to each other in a functional manner. For example, the XNOR circuit built from insulated gates (Figure 4-11b) has good predicted separation between **ON** and OFF promoter levels after each gate in the circuit.

Promoter 5'-UTR context effects. The response function of a **NOT** gate can change when connected to different input promoters (Lou *et a],* 2012). In addition, for NOR gates the connection of two promoters in series can lead to contextual effects as they create transcripts of different length (Figure 4-12), which changes the length of the **5'-** UTR-a sensitive region for controlling expression (Goodman *et al,* **2013;** Kosuri *et a],* **2013;** Mutalik *et a],* **2013;** Salis *et al,* **2009).** This manifested as an error mode, where gates that functioned properly as **NOT** gates fail when converted to NOR gates. The promoter context and **5'-UTR** effects can be mitigated through the inclusion of a ribozyme after the promoter, which cleaves the mRNA at a defined nucleotide. This makes the transcripts identical, whether they are produced **by** the upstream or downstream promoter.

Terminator recombination. The evolutionary stability of a genetic circuit is dependent on several factors. Repeated genetic sequences undergo homologous recombination at a frequency that increases with the repeat length and the number of repetitions (Lovett *et a],* 2002; Shen **&** Huang, **1986).** Initially, we designed genetic circuits that each contained the **129 bp** double terminator BBa_B0015. The largest such circuit, XNOR, underwent rapid homologous recombination that resulted in a non-functional circuit (Figure 4-13). We sequenced the plasmid and found that the AmtR transcription unit had looped out of the plasmid **by** homologous recombination between two instances of the BBa_B0015 double terminator. This caused constitutive expression of SrpR and BM3R1 which lead to an always ON output from the circuit. To mitigate homologous recombination, we used a library of sequence-diverse strong terminators (Table 4-2) to terminate gene expression.

Roadblocking. Genetic NOR gates contain tandem promoters that drive expression of repressors. Our initial assumption was these promoters would function independently, where the activity of a downstream promoter would not impact the activity of an upstream promoter, and vice versa. In practice, we found that some promoters in the downstream position (position 2 of Figure 4-2c) could interfere with the upstream promoter when in the repressed state. We refer to this effect as "roadblocking" (the name is not intended to imply mechanism). We developed a simple system to measure the propensity of each promoter to roadblock when in the downstream position (Figure 4-14a). YFP is measured from a single promoter (P_{Tac} or **PTet) by** cytometry. Next, we insert a second promoter downstream from this promoter (position 2) and the impact on the upstream promoter was quantified (Figure 4-14b). We incorporated this roadblocking data into Cello by forbidding PBAD, P_{Tac}, P_{PhIF}, **PBM3R1, PSrpR,** and **PQacR** from occupying the second position in a tandem promoter. This appears as Eugene rules in the **UCF** and impacts the repressor assignment **by** disallowing multiple gates with output promoters that exhibit roadblocking to both serve as inputs to a downstream gate.

Toxicity. Certain repressors can be toxic when overexpressed, causing slow cell growth. For example, we constructed an **AND** gate from the PhiF, BM3R1, and QacR gates, and did not expect to see an impact on growth. However there was a growth defect when the cells were induced with 2 $\frac{ng}{m}$ aTc (which expresses QacR from P_{Tet}). When the repressors were initially characterized (Stanton *et al*, 2014), their toxicity was measured **by** inducing their expression from **PTac** using various concentrations of IPTG. However, we later found that repressors that were initially not measured to be toxic impacted cellular growth when expressed from promoters stronger than P_{Tac} , as in the case of QacR being expressed from P_{Tet} . To determine whether genes expressed at higher levels could exhibit toxicity, we cloned the repressors downstream from a tandem inducible promoter $(P_{Tac}-P_{Tet})$ and measured the impact on growth at various IPTG and aTc concentrations (Figure 4-15).

4.5 Insulated gates

A second generation of gates was constructed to address the observed failure modes (Fig. 4-3b). Changes took two forms: (i) new parts were added to gates to insulate them from genetic context, and (ii) rules were included in the **UCF** that disallow certain parts, positions, and part combinations that lead to unpredictable behavior. Transcriptional insulation was achieved for gates **by** adding a different strong terminator with sufficiently diverse sequences to avoid homologous recombination (Table 4-2) (Chen *et al,* **2013).** The output promoters were also insulated on both sides from changes to their up- and down- stream context. Insulators consisting of a hammerhead ribozyme and downstream hairpin (RiboJ) ensure that a promoter generates the same response function irrespective of the downstream gene (Lou *et al,* 2012a). As with the terminators, to avoid recombination we had to create a library of RiboJ variants that are functionally identical but sequence-diverse so that each gate had a unique insulator sequence (Fig. 4-8 and Table 4-1). To insulate the promoter from the upstream sequence, we added **15** nt of randomly generated **DNA** to extend the promoters to **-50** to include regions that impact strength (Table 4-8) (Rhodius et $a, 2012$. Finally, the propensity for repressible promoters to roadblock was measured (Fig. 4-14) and these data were used to create Eugene rules in the **UCF** that disallow these promoters from position 2 in NOR gates (Fig. 4-2c).

The response functions were then experimentally measured for all the gates (Fig. 4-3c, 4-9, and Table 4-4). Several of the first version gates had response functions that were difficult to connect functionally to sensors or other gates (Fig. 4-2b). To increase the likelihood of finding a connection, we made versions of the gates with different RBSs that shift the response threshold (Table 4-3). The growth impact of each gate was then measured as a function of the input promoter activity to determine whether there is a toxicity threshold that should be avoided (Fig. 4-3d and 4-15). To eliminate toxic or cross-reacting repressors, the original set of **16** was reduced to 12. Only four of these caused a growth defect at high inputs and this could be avoided **by** the assignment algorithm (Fig. 4-32).

The **8** simple circuits were redesigned with the new gate library (Methods). The sequences were constructed as designed with no post-design tuning. **All** of the circuits functioned correctly, corresponding to a total of **32/32** correct output states (Fig. 4- 3a).

4.5.1 Insulators of promoter context: design of ribozymes and spacers

The function of a genetic part can depend on its local genetic context; that is, the identity of up- and downstream parts (Bennett, 2010). Previously, we found that the inclusion of the RiboJ insulator ensured that the response function of a gate would not

be impacted **by** the identity of the input promoter (Lou et al, 2012). RiboJ is composed of two elements: (i) a hammerhead ribozyme derived from the satellite RNA of tobacco ringspot virus (sTRSV) that cleaves the **5'-UTR** at a defined point and thereby removes upstream sequences that derive from the promoter, and (ii) an additional hairpin at the 3'-end of the ribozyme that helps expose the Shine-Dalgarno sequence of the RBS (Figure 4-5b). The entire RiboJ **DNA** sequence is **75** base pairs **(bp),** which is large enough to undergo homologous recombination if used more than once in a genetic circuit (Lovett et al, 2002; Sleight et al, 2010; Sleight **&** Sauro, **2013;** Chen et al, 2013). Thus, each gate needs its own insulator with the same functionality of RiboJ but with a sequence that is different enough to prevent homologous recombination. To address this, we built and tested natural and engineered RiboJ variants and characterized both their cleavage activity and insulator functionality.

Two approaches were taken to identify ribozyme sequences that have diverse sequences but still function as insulators. First, "part mining" was performed to identify other hammerhead ribozymes derived from plant viroids and plant virus satellite RNAs. We built and tested sixteen hammerhead ribozymes (Khvorova *et al.* 2003; Dufour *et al.* 2009) (including RiboJ) and others that had been previously tested as insulators (Lou et *a],* 2012). This approach ultimately led to the characterization of nine functional natural ribozyme-based insulators (Fig. 4-5a, Table 4-1).

A second approach to library expansion was taken **by** diversifying the sTSRV scaffold. This was aided **by** a number of structural studies detailing ribozyme function (Khvorova et *a,* **2003;** Dufour et *a],* **2009;** Ruffner et *a],* **1990;** Haseloff **&** Gerlach, **1988;** Pley et *a],* 1994). Three design rules were implemented (Figure 4-5b). First, the sequences of the catalytic core residues **(CTGATGA** and **GAAA)** and two loops **(GTGC** and **GTGA)** were conserved (Dufour et *a],* **2009;** Khvorova et a], **2003).** Second, the total number of nucleotides and the hammerhead secondary structure were kept intact. This was achieved **by** only mutating three stem regions: **5 bp** of stem **1,** 4 **bp** of stem 2, and **3 bp** of stem **3.** These mutated sequences were generated using the Random **DNA** Generator (http://www.faculty.ucr.edu/~mmaduro/random.htm; **50%** GC-content). RNA secondary structures were predicted using mFold (Zuker, **2003)** and were found to maintain their hammerhead structure when simulated in isolation from flanking sequences (conditions: 37°C, 1M NaCl). We built and tested 45 engineered ribozymes, of which seven were functional and used to insulate gates (Table 4-1). For both the natural and engineered RiboJ variants, the downstream hairpin sequence was held constant due to its short size **(23** nucleotides), which is short enough that it should not lead to homologous recombination.

The natural and synthetic ribozymes were examined in two assays to measure cleavage activity and functional insulation. To measure cleavage, Rapid Amplification of Complementary **DNA** End (5'-RACE) was used to generate cDNA from mRNA **by** reverse-transcription for PCR amplification (Methods). Acrylamide gel analysis shows two bands: one from full-length, uncleaved mRNA and another from cleaved mRNA. The ratio between cleaved and total cDNA is used to calculate the efficiency (Figure *4-7).* Several ribozymes, both engineered and natural, failed to achieve **>75%** cleavage efficiency. **A** set of **16** catalytically-active ribozymes is shown in Figure 4-7c.

A second assay was performed to determine the insulation functionality of each RiboJ variant. Following an assay developed **by** Lou *et a].* (Lou *et a],* 2012), we compared the expression of two genes (gfp *and cI-gfp)* from two different inducible promoters, Prae *and PLiacO-l* (Figure 4-8a). The *cI-gfp* fusion gene saturates when induced **by** pLlacO-1, whereas this saturation is not observed from the pTac promoter (Lou *et a],* 2012) (Figure **4-8b).** The RiboJ insulator was originally selected because its inclusion between the pLlacO-1 promoter and the RBS ameliorated this saturation and caused the outputs from both promoters to converge onto the same line. Further,

the slopes of these lines are approximately constant, indicating that the two genes are expressed proportionally at different promoter activities. Thus, this assay is a direct measurement of insulation; in other words, the context effects that occur for particular promoter-gene combinations are reduced. **All 16** RiboJ variants (including the original RiboJ) were tested via this assay and insulation was demonstrated for each (Figure 4- 8c).

4.5.2 Terminator selection for transcriptional insulation

Strong terminators are needed for genetic circuits to prevent transcriptional readthrough between gates. In addition, these terminators must be sequence-diverse to prevent homologous recombination (Sleight et *a],* 2010; Sleight **&** Sauro, **2013).** For the later circuits discussed in this work, we used strong terminators that were measured previously (Chen et *a],* **2013)** (Table 4-2). These replaced double terminator BBa_B0015 used in earlier circuits.

4.5.3 RBS selection to tune the response threshold

The strength of the RBS controlling repressor expression is one determinant of the threshold of a gate. When the ribozyme insulators were added to each gate, this impacted RBS strength and the thresholds shifted (or the response was completely eliminated). To alter the threshold of the insulated gates, we built and screened RBS libraries. For some gates, multiple RBSs were found that generated different thresholds. These were kept and included in the library so that there would be more ways in which the gate could be connected to others in the circuit.

The RBS libraries were built using PCR to amplify the gate plasmid with primers containing degenerate nucleotides in the region in and around the RBS (Methods). The resulting PCR products were ligated and transformed in **E** coli **NEB** 10-beta. Individual clones from the gate RBS library were screened **by** growing them in the presence and absence of inducer. Clones with the largest dynamic range were chosen for further characterization. The full response functions of these gates were measured. Representative cytometry histograms and Hill equation fits to the data are given in Figure 4-9. The final RBS sequences are given in Table 4-3, and the response function parameters and toxicity threshold are listed in Table 4-4.

4.5.4 Response functions and cytometry data for insulated gates

Production of YFP from the insulated gates' outputs were measured at various inducer concentrations **by** cytometry and converted to output relative expression units (RPU). For each of these gates, IPTG was used to induce gate expression from the P_{Tac} promoter. Additionally, inducer concentrations were converted to input promoter activity **by** measuring expression of YFP from **PTac** at those inducer concentrations (Figure 4-9a). The median input and output RPU values were plotted for each inducer concentration to create the experimental response function (Figure 4-9b).

4.5.5 Insulated gates: predicted and measured outputs

The circuits constructed from non-insulated gates were rebuilt using insulated gates and design rules extracted from the previous section. These repressor assignments were found using a MATLAB script that was developed prior to the complete Cello software (Methods). For each circuit, we started with the circuit diagram (Figure 4- 3a) and a subset of repressors from Figure 4-3b. We enumerated all possible repressor assignments for every gate, with the exception of assignments that would result in a

promoter roadblock. For each gate assignment, we propagated sensor input signals through the gate response functions to the circuit output, summing promoter activities at NOR and OR gate inputs. Each circuit assignment was scored as the ratio between the lowest **ON** state and the highest OFF state. The highest scoring assignment was selected for construction and testing (Methods). For these circuits, the only promoters forbidden from being in position 2 of the NOR gates were P_{SrpR} and P_{Tac} . Figure 4-16 shows the experimental data from Figure 4-3a alongside the simulated outputs for the circuits.

4.6 Circuit design automation using Cello

Cello was used to design a large set of **52** additional circuits based on the insulated gates (Fig. 4-4). These circuits include a Priority Detector (that prioritizes the inputs and selects which output is **ON** based on the highest priority input that is **ON),** wellknown functions (e.g., a multiplexor), as well logic underlying cellular automaton pattern formation (e.g., "Rule **30")** (Wolfram, 2002). Additional 3-input 1-output logic circuits are built that demonstrate the ability to integrate inputs in different ways. This could be applied to turn a cellular function on or off in response to an environment defined **by** multiple signals. Each of the **52** circuits was specified either **by** using behavioral Verilog (and Cello performs the logic minimization step) or **by** performing a separate enumeration to identify the global minimum number of gates and specifying the circuit diagram using structural Verilog (This was done for OxOE, 0x19, Ox1C, $0x38, 0x3D, 0x6E, 0x81, 0xB9, 0xC6, 0xC7, 0xBD, and 0xC8$). Subsequently, the global minimum 3-input logic gates were included in the **UCF** so that they could be incorporated as motifs in larger circuits in future designs (Fig. 4-30). For each circuit, the sensor promoters and **ON/OFF** values were specified, the Eco1C1G1T1 **UCF**

selected, and a **DNA** sequence was automatically generated **by** Cello. **DNA** synthesis (Kosuri **&** Church, 2014) and assembly was used to build each sequence, which contained up to **10** regulators and **55** parts. The output states of each circuit were measured **by** flow cytometry and compared with the Cello predictions. No additional tuning was done to diverge from the Cello-predicted sequence.

37 of the **52** circuits functioned as predicted, such that all of the output states matched desired **ON** and OFF levels (Fig. 4-4a). Further, the predicted cytometry distributions closely matched those measured experimentally. Out of 412 output states across all circuits we built, **92%** were correct. The Consensus circuit (output is **ON** only when all three inputs agree) is the largest, containing **10** regulatory proteins **(7** repressors from **NOT/NOR** gates and **3** from the inducible systems) and **55** genetic parts. Two of the circuits with 4 layers $(0x3D \text{ and } 0x8E)$ were selected to characterize the switching dynamics between states (Fig. 4-4b). Interestingly, Ox8E shows a transient incorrect state, known as a "fault" in electronics, when the inputs are changed from **-/-/-** to **+/-/+.** This is consistent with the last NOR gate transiently receiving **ON/OFF** inputs until one of the signals transits two layers.

Of the **52** circuits, **7** were incorrect in one state, 2 were incorrect in two states, and **5** had **>3** failures (Figs. 4-17 through 4-19 and 4-25). As more gates were included in a design, there was a higher probability of failure (Fig. 4-5a). Two circuits were found to cause a growth defect (Fig. 4-5b). The circuits that failed in a few states tended to match the remaining states closely, so the initial design can be used as the basis for further rounds of optimization. Debugging experiments were performed to determine which gates fail as a means to focus optimization. This was done **by** creating a set of plasmids that contain each gate's output promoter fused to YFP. These plasmids were transformed with the circuit in lieu of the output plasmid and the response of the internal gate was measured for all combinations of inputs. An example of this is shown

in Fig. 4-5c and several other examples are shown in Fig. 4-26. From this analysis, most of the circuit failures point to unexpected behavior from the aTc sensor **(7** circuits) or AmtR gate (2 circuits).

Screening design variants has the potential to increase the probability of success, particularly for larger circuits. To do this, Cello outputs a Eugene file that contains architectural rules from the **UCF** as well as constraints to enforce the circuit diagram and repressor assignments (Fig. 4-34). The user can specify the size of the library and a combinatorial design algorithm (Smanski *et al.* 2014) generates the target number of constructs. Although all of the systems should be functionally equivalent, subtle changes in their composition may impact circuit function through hidden effects (e.g., transcriptional read-through or promoter interference). We tested this approach **by** designing a Majority circuit (Fig. 4-5d), whose output is **ON** when a majority of its inputs are **ON.** We built a small library of six constructs that maintained the same circuit diagram and repressor assignments, but in which the order and orientation of genes was allowed to vary (Fig. 4-5e). Several of these circuits functioned correctly and the response of the best is shown in Fig. **4-5f.**

4.6.1 Complete circuit data

We constructed **a** library of 3-input, 1-output genetic circuits using Cello. **All** the fully functional circuits are shown with data and predictions in Figure 4. The remaining circuits are shown in Figures 4-17 through 4-19. Experimental/predicted distributions and replicates for the Majority circuit variants are shown in Figures 4-20 and 4-21. Experimental/predicted distributions and replicates for three alternate circuit assignments are shown in Figure 4-22 and 4-23. Replicates for the circuit library are shown in Figures 4-24 and 4-25.

4.6.2 Majority circuit variants

The original design for the Majority circuit produced an output that was higher than expected for input state $2 (+IPTG, -aTc, and -arabinose)$. We constructed an additional five layouts that retained the same repressor assignments to test whether we could fix that output state (Figure 4-5e). We hypothesized that subtle contextual effects might arise in different layouts (terminator read-through, part interference, cryptic promoters, etc.), and that these effects could improve the circuit's performance.

For the original circuit (Design **#1),** we used the default Cello layout where all transcription units point in the forward orientation and the repressors have a defined order (PhlF, SrpR, BM3R1, BetI, HlyIIR, AmtR). Design #2 reverses the order of all transcription units, keeping them pointed in the forward orientation. Design **#3** clusters the three **NOT** gates together in the first half of the **DNA** sequence, and the three NOR gates together in the second half. Design #4 clusters one three gate subcircuit (AmtR, BetI, SrpR) in the first half of the **DNA** sequence, and a second three gate sub-circuit (BM3R1, PhlF, HlyIIR) in the second half. Design **#5** scrambles the order of the transcription units, keeping them pointed in the forward orientation. Design **#6** uses the default transcription unit positions, but alternates their orientation so that the first transcription unit points backward, the second points forward, the third points backward, and so on. Each of these genetic layouts was physically constructed **by** simply changing the 4 **bp** Golden Gate scars that occur between transcription units.

The precise rules that govern the layout of these circuits were converted to Eugene code (Data File **S3).** Each variant used a different Eugene file, and the only differences are a small set of rules in the "circuit device". The different rule sets only use three different Eugene keywords, but in different combinations: ALLFORWARD, ALTERNATE_ORIENTATION, and BEFORE (e.g. gate_PhlF BEFORE gate SrpR). The promoter order was also fixed due to roadblocking constraints in "gate devices".

In principle, if all the gates were perfectly modular and exhibited no contextual behavior differences, then all six layouts should function identically. Instead, we observed slight shifts in the output distributions for each circuit. The alternating orientation layout (Design **#6)** produced the greatest fold-change between the lowest **ON** state and the highest OFF state; furthermore, the high OFF state from Design **#1** was decreased to more closely match the predictions. Representative experimentallymeasured histograms and the predicted outputs are shown in Figure 4-20.

4.6.3 Alternate repressor assignments

In addition to testing different layouts for **a** single gate assignment, we constructed three of the circuits (Multiplexer, Consensus, and Majority) using alternate repressor assignments predicted **by** Cello (Figure 4-22). The alternate Multiplexer circuit replaces only the terminal PhlF NOR gate from the original assignment (Figure 4-4a) with a BM3R1 NOR gate. The outputs are correct for all of the assignments. The alternate Consensus circuit swaps two gate assignments (HlyIIR and PhlF) from the original circuit. This swap results in two failed output states, whereas the original version had all states correct (Figure 4-4a). The alternate Majority circuit changes the assignment for every gate, except for the HlyIIR **NOT** gate connected to the Prac input. While most of the repressors are present in the same circuit layer in both circuits, BM3R1 is absent in the alternate assignment and AmeR is present. The alternate Majority circuit's output behaves correctly for every input state.

4.6.4 Debugging genetic circuits

We developed a strategy for "debugging" a malfunctioning circuit to determine which gate is causing the failure. This was done **by** creating a series of plasmids that transcriptionally fuse the output promoter of each gate to **yfp.** These constructs are carried on a plasmid with a **pSC101** origin of replication and a spectinomycin resistance marker. This is co-transformed with the circuit plasmid (the plasmid containing the output promoter of the circuit is not included) and the cells are grown and assayed in the same way that the circuit is characterized (Methods). This is done in two steps. First, a single screen is performed on all gates and all combinations of input conditions. From this, it can be seen which gates are failing to respond as expected. Then, the screen is followed up with more detailed measurements including replicates that focus on the failed gate. **A** summary of these experiments is shown in Fig. 4-26, which shows the subset of data highlighting the failure discovered. From these data, the gate where the problem originates can be deduced and the impact as the error propagates through the circuit observed. The most prevalent failure mode appears linked to the P_{Tet} promoter, an effect we observed in seven cases (OxF9, Ox06, Ox9F, OxB9, 0x19, 0x36, and OxC1). We also saw a repeated failure associated with the use of the AmtR gate (Figure 4-26: 0x98 and Figure 4-5c: OxC9).

4.7 Discussion

The design of synthetic regulatory networks has been dominated **by** manual trialand-error tinkering at the nucleotide level. Cello automates the selection and concatenation of parts and balancing the associated constraints. **By** doing this, it enables more rapid design of larger multi-part systems; the circuits that we present here are larger and more complex than most that have been built **by** hand. Out of **60** circuits designed automatically, 45 functioned as designed (Figs. 4-2a, 4-4, 4-5 and 4- 22). Our largest circuit has 12 regulated promoters, doubling a plateau first noted in **2009** (Purnick **&** Weiss, 2009a). The **DNA** sequence output represents a testable prediction that either validates the underlying theory or reveals failure modes that can be addressed in the gate design. Experiments in which repressors were used to build synthetic logic gates showed that this often led to nonsensical functions that could not be predicted from the known interactions (Cox et *a],* **2007).** Quantifying why predictions fail, where systems break, and how the host evolves can be addressed through engineering. Iterative co-development of robust gates and software converged on genetic systems that are **highly** repetitive and modular, in stark contrast to the encoding of natural networks.

The future of engineering biology will require integrated design across many subcellular systems, including the creation of sensors that can process many stimuli, management of resources and metabolites, and control over multiple cellular functions (communication, stress response, chemotaxis, etc.). Within this greater framework, our approach is to separate the design and construction of synthetic circuits from engineering considerations for other cellular processes. Working with transcriptional circuits establishes a discrete boundary that other methods can engage to create a desired circuit to specification. For, example could build circuits for which the sensors had been designed using all-atom biophysical models (Dahiyat **&** Mayo, **1997;** Looger et *a],* **2003;** Tinberg et al, **2013)** and the outputs used to control enzyme expression levels, as determined via metabolic flux models (Henry *et al*, 2007). Integration with amorphous computing would enable spatial and community design (Rudge $et al$, 2012; Jang et *a],* 2012; Blanchard et *a],* 2014). Integrating across these computer aided design **(CAD)** tools in a way that automates design choices and balances constraints will be critical to advance the complexity of genetic engineering projects.

Figure 4-1: Overview of Cello. **(A)** Cello users write Verilog code and select or upload sensors and a **UCF.** Based on the Verilog design, a truth table is constructed, from which a circuit diagram is synthesized. Regulators are assigned from a library to each gate (each color is a different repressor). Combinatorial design is then used to concatenate parts into a linear **DNA** sequence. SBOL Visual (Quinn et al, **2015)** is used for the part symbols. Raised arrows are promoters, circles with dashed stems are ribozyme insulators, hemispheres are RBSs, large arrows are protein coding sequences, and "T"s are terminators. Part colors correspond to physical gates. (B) The physical specification for the EcolC1G1T1 **UCF** is shown. The circuit and sensors are inserted into one plasmid, whereas the other contains the circuit output promoter, which can be used to drive the expression of a fluorescent protein or other actuator. Both plasmids must be present in the specified strain for the design to be valid.

Figure 4-2: Assignment of genetic gates to the circuit diagram. **(A) A** set of four gates based on different repressors (colors) connected in various permutations to build different circuit functions. The inputs **(A,** B, and **C)** are sensor input promoters and the circuit output promoter (X) controls the actuating gene. (B) The shapes of the gate response functions determine whether they can be functionally connected. The orange gate (PhlF) has a large dynamic range (dashed lines) that spans the threshold of the purple gate (BetI). However, in the reverse order, the gates do not functionally connect. **(C)** Combinatorial relations of repressors from the insulated gate library are shown in the up- (Gate **A)** and down- (Gate B) stream position. Colors indicate whether the gates can be connected (yellow) or not (black). Fold-change (normalized) is calculated as the maximum output range that can be achieved **by** connecting Gate **A** to Gate B. Numbers indicate different RBSs. The left graph shows when Gate **A** regulates position **1** and the right graph when it regulates position 2. Gates that are excluded from position 2 due to roadblocking are shown in black (Fig. 4-14). **(D)** The probability of finding a functional circuit versus the number of logic gates. The probability of a functional circuit is defined as the likelihood that a random assignment passes input threshold analysis (Fig. 4-35) and has no roadblocking combinations (Fig. 4-2c). **(E)** The convergence of the simulated annealing gate assignment algorithm (Fig. 4-33). Inset: black bars should be **ON,** gray bars should be OFF; the y-axis is the output in RPU on a log scale and the x-axis is the input states (from left to right: **000, 001, 010, 011, 110, 101, 110, 111).** The circuit score **(S)** is defined as the ratio of the lowest predicted **ON** state to the highest predicted OFF state (Fig. 4-31 and Equation **S2).** An example search is shown for the circuit diagram in the inset; colors correspond to repressors assigned to each gate (Fig. 4-3b).

Figure 4-3: Impact of gate insulation. **(A)** The logic function, circuit diagram, and **DNA** construct are shown for each genetic circuit. Only the insulated circuit schematics are shown; the equivalent information for the non-insulated circuits is shown in Fig. 4-10. The expected output for each circuit is shown at the bottom of each bar graph as a 1 for

ON and **0** for OFF. The numbers are colored whether the state is predicted correctly (green) or incorrectly (red). For non-insulated circuits, inputs correspond to the absence or presence of 1 mM IPTG (right $-/-$) and 20 μ M **3OC6HSL** (left $-/-$). For insulated circuits, inputs correspond to the absence or presence of 1 mM IPTG (right $-\ell$ +) and 2 ng/mL aTc (left **-/+)** Methods). (B) The architectures of the insulated gates. Some gates have multiple versions with different RBS sequences. The gate **DNA** sequences are provided in Table 4-8. **(C)** An example of a response function is shown for a **NOT** gate based on the PhlF repressor. The change in the threshold for the three RBSs is shown. Data for all insulated gates are shown in Fig. 4-9. **(D)** The impact of each gate on cell growth as a function of its input promoter activity. Cell growth was measured as OD_{600} and normalized **by** the growth of the no-inducer control six hours after induction (Methods). The four gates that reduced growth >20% are indicated **by** red arrows. Error bars are one standard deviation of normalized cell growth (y-axis: part **d)** and the median (y-axis: parts a and c; x-axis: parts c and **d)** for three independent experiments performed on the same day.

Figure 4-4 (part 4): Automated design of circuits **by** Cello. **(A)** An example of the code along with the input states (in RPU) is shown for the Priority Detector circuit. **All** circuits designed **by** Cello that had correct output states are shown along with their genetic schematics, output predictions, and experimental measurements. The inputs **A,** B, and **^C** correspond to the PTac, PTet, and PBAD sensor promoter activities; their corresponding regulators (LacI, TetR, and AraC^{*}) are not shown in the schematics. The outputs (X, Y, Y) and Z) correspond to YFP driven from output promoters in separate experiments. Solid black distributions are experimental data, and blue/red line distributions are computational predictions from Cello (Fig. 4-35). The number of parts for each circuit includes all functional **DNA** parts in the circuit (promoters, ribozymes, RBSs, protein

coding sequences, and terminators), plus **8** parts for the sensor block and 2 parts for the plasmid backbones. Inputs correspond to the absence or presence of **1** mM IPTG (top **/+),** 2 ng/mL aTc (middle **-/+),** and **5** mM L-arabinose (bottom **-/+).** Replicates are provided in Fig. 4-24. When the circuit does not have a common name $(e.g.,$ Priority Detector), a hexadecimal naming system is used (e.g., 0x41). The names starting with "Rule" refer to Wolfram's cellular automaton convention (Wolfram, 2002). (B) Timecourse data are included for two circuits. The circuits are maintained in the **-/-/-** state for three hours prior to induction and then switched to the other eight possible states at time **= 0** hr. Error bars are one standard deviation of RPU median performed on three separate days.

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Figure 4-5: Analysis of circuit failures and the design of multiple constructs **by** combinatorial design. **(A)** For the library of **60** circuits (Figs. 4-3a, 4-4, 4-17 through 4- **19,** and 4-22), the fraction of correct states (black) and the fraction of fully correct circuits (gray) are shown versus the number of repressors in the circuit. (B) The impact on cell growth is shown for the two circuits that fail due to toxicity. The control bar is for cells containing the RPU standard plasmid only. The average of three experiments performed on different days and the error bars represent the standard deviation. **(C)** An example of circuit debugging is shown. **All** combinations of inputs for all wires were tested; for clarity, only a subset of debugging for the failed state $\left(\frac{+}{+}\right)$ is shown. The data is normalized to **10,1]** to correct for the dynamic range across gates. In this case, the failure originates when the AmtR gate produces an intermediate response that then propagates through the circuit. **(D)** The circuit diagram for a "Majority" circuit is shown with colors corresponding to repressors. **(E)** Six layouts were designed for this circuit that maintain the same repressor assignments, but allow the order and orientation of the gates to vary. The circuit score **(S)** is defined as the ratio of the lowest **ON** state's median to the highest OFF state's median. Error bars are one standard deviation for two experiments performed on different days. Cytometry distributions for each design are shown in Fig. 4-20. The dashed line marks the lowest circuit score in the library. (F) The predictions and cytometry distributions for the final design are shown. The format and inducer concentrations are as described in Fig. 4-4.

Figure 4-6: Expanding a library of hammerhead ribozymes. **(A)** Phylogenetic tree of functional hammerhead ribozyme-based insulators. "Ribo" is the sequence used to build RiboJ. (B) Secondary structure of a hammerhead ribozyme-based insulator including the downstream hairpin. Conserved sequence regions are shown as defined nucleotides and mutable regions are shown adjacent to orange lines **(1,** 2, and **3).**

Figure 4-7: Cleavage activity of **16** ribozyme insulators. **(A)** Schematic of ribozyme activity and measurement using 5'-RACE (Methods). Post-transcription, the hammerhead ribozyme folds and cleaves itself at its 5'-end. The measurement plasmids are **pJS1-pJS68.** (B) Quantifying ribozyme cleavage activity using acrylamide gel electrophoresis and image processing. Full-length and cleaved cDNA products are separated and visualized, and then the band intensities (area under the curve, inset) are quantified using ImageJ. The intensity ratio of cleaved product (shorter band, filled circle) to the full-length product (longer band, empty circle) plus cleaved product yields the cleavage efficiency. **(C)** Acrylamide gel electrophoresis images and cleavage efficiencies of **16** ribozyme insulators.

Figure 4-8: Insulating functionality of **16** ribozyme-based insulators. **(A)** Schematics of genetic constructs used to determine insulating functionality of ribozymes. Two genes **(cI-**GFP and GFP) are each induced from one of two promoters $(P_{\text{LlacO-1}})$ and P_{Tacl} with various IPTG concentrations. The plasmids used for this study are **pJS1-pJS68.** (B) Expression of cI -GFP versus GFP for $P_{LlacO-1}$ (red line) and P_{Tac} (blue line) when no ribozyme insulators are present. This experiment was performed to recapitulate the experiment in ref (Lou et al, 2012). Plasmids used are **pJS1-pJS4. (C)** Expression of cI-GFP versus GFP for $P_{LlacO-1}$ (red line) and P_{Tac} (blue line) when various ribozyme insulators are used between the promoter and $5'-UTR$. The slopes of the $P_{LLa}O_{-1}$ and P_{TaC} lines for each ribozyme are as follows: ScmJ $(P_{LaCO-1} = 2.8, P_{TaC} = 2.2)$; AraJ $(1.8,$ **1.6);** BydvJ (2.0, 2.2); CchJ **(1.1, 1.3);** ElvJ (1.4, **1.6);** LtsvJ **(0.60, 0.65);** PlmJ **(1.9,** 2.2); SarJ (2.2, **2.3);** RiboJ **(1.5, 1.5);** RiboJl0 (1.4, **1.6);** RiboJ51 **(1.8, 1.5);** RiboJ53 (2.1, **1.8);** RiboJ54 (2.0, **2.3);** RiboJ57 **(5.7, 5.0);** RiboJ60 (1.4, **1.6);** and RiboJ64 (4.9, **3.5).** For panels (B) and **(C),** error bars are one standard deviation of the median for three experiments performed on different days.

Figure 4-9: Distributions and response functions for insulated gates. **(A)** Representative YFP fluorescence histograms for each gate are each normalized to RPU. IPTG concentrations used were: **0, 5, 10,** 20, **30,** 40, **50, 70, 100, 150,** 200, and **1000** pM. (B) The response functions are fit to Equation **S1** (black lines). Error bars are one standard deviation of the median for three experiments performed on different days. Hill equation parameters are given in Table 4-4.

Figure 4-10: Circuit diagrams and genetic schematics for simple circuits built from noninsulated gates. This corresponds to the "non-insulated" data shown in Figure 4-3a. Gate colors correspond to the repressors in the genetic construct. **All** the terminators are the same (BBa_B0015) and are shown as a black "TT". Plasmids used were pAN901-908.

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Figure 4-11: Response function matching in circuits. **(A)** XNOR circuit built from noninsulated gates. Assuming the response functions behave the same in the context of a circuit, the circuit is still predicted to be non-functional because all the output states from the first gate map onto the next gate's response function to the right of the threshold. Experimental data from Figure 4-3a shown at right. Inputs correspond to the absence or presence of 1 mM IPTG (right $-\prime$ +) and 20 μ M **30C6HSL** (left $-\prime$ +). (B) XNOR circuit built from insulated gates (Figure 4-3a). The repressor assignment algorithms cause the outputs from the first gate to span the threshold of each gate. Experimental data from Figure 4-3a shown at right. Inputs correspond to the absence or presence of 1 mM IPTG (right **-/+)** and 2 ng/mL aTc (left **-/+).** For both panels, error bars are one standard deviation of the median for three experiments performed on different days.

Figure 4-12: Comparison of non-insulated and insulated **NOT/NOR** gates. **NOT** and NOR gates without ribozymes contain promoter sequence in the mRNA transcript that can affect translation (left panel). Black bars are expected to be high and gray bars expected to be low. Cells were grown measured with the presence and absence of inducers: 1 mM IPTG and 20 μ M **3OC6HSL** (Methods). Error bars are one standard deviation of the median for three experiments performed on the same day. The plasmids used are: $pAN215$ = non-insulated NOT gate, $pAN216$ = non-insulated NOR gate, $pAN412$ = insulated **NOT** gate, and **pAN413 =** insulated NOR gate.

Figure 4-13: Repeated terminators cause high rates of homologous recombination. The top construct is the original design. The bottom construct was identified **by** sequencing, where the AmtR gate was deleted **by** recombination.

Figure 4-14: Measuring the roadblocking ability of various repressors. The ability of a repressed promoter in position 2 to reduce YFP expression from a promoter in position **¹** was tested. (A) Promoter 1 alone (either P_{Tac} or P_{Tet}) was induced to express YFP and was measured by cytometry. Next, a second promoter was inserted downstream from P_{Tac} or PTet. The upstream promoter was induced, and the downstream promoter was repressed (inactivated in the case of LuxR and AraC). The decrease in YFP expression compared to the P_{Tac} or P_{Tet} -only case was used to calculate roadblocking. Plasmids used are **pAN1250** and **pAN1681-pAN1697.** (B) The fold-decrease caused **by** each repressed (or unactivated) promoter when in the downstream position. The upstream promoter is P_{Tet} in all cases, except for when the ability of P_{Tet} to roadblock is being measured, in which case the upstream promoter is P_{Tac} . Error bars are one standard deviation of the median for three experiments performed on different days (Methods).

Figure 4-15: Toxic circuits and gate measurements. We induced expression of each repressor from the tandem promoter with seven IPTG concentrations: **0, 9.5, 19,** 47.5, **95,** 285, and 950 μ M; for an additional five samples, we induced with 950 μ M IPTG along with aTc at concentrations: **0.0095, 0.095, 0.285, 0.95,** and **1.9** ng/mL (Methods). After a period of growth, we measured the cultures' absorbances at **600** nm and normalized the values to the uninduced sample. For x-axis values, YFP was measured from the same tandem promoter at the same inducer concentration and fluorescence was converted to RPU. Error bars are one standard deviation of absorbance (y-axis) and the median (xaxis) for three experiments performed on the same day. Plasmids used were **pJS0101 pJS0109.**

Figure $4-16$: Predicted and measured outputs for simple circuits built from insulated gates. Experimentally measured outputs (black bars) for the circuits in Figure 4-3a, alongside predicted outputs (white bars) generated from sensor input levels and gate response functions. Inputs are the absence or presence of **1** mM IPTG (bottom **-/+)** and 2 ng/mL aTc (top **-/+).** Error bars are one standard deviation of the median for three experiments performed on different days. Plasmids used were **pAN901-pAN908.**

Figure 4-17: Circuits with **1** failed output state. Representative experimentally measured fluorescence histograms (black) and predicted distributions (blue and red lines) are shown for circuits with a single failed output state. Inputs correspond to the absence or presence of **1** mM IPTG (top **-/+),** 2 ng/mL aTc (middle **-/+),** and **5** mM L-arabinose (bottom $/+)$.

Figure 4-18: Circuits with 2 failed output states. Representative experimentally measured fluorescence histograms (black) and predicted distributions (blue and red lines) are shown for circuits with two failed output states. Inputs correspond to the absence or presence of **¹**mM IPTG (top **-/+),** 2 ng/mL aTc (middle **-/+),** and **5** mM L-arabinose (bottom **-/+).**

Figure 4-19: Circuits with **3** or more failed output states. Representative experimentally measured fluorescence histograms (black) and predicted distributions (blue and red lines) are shown for circuits with three or more failed output states. For the demultiplexer circuit, inputs correspond to the absence or presence of **1** mM IPTG (top **-/+)** and 2 ng/mL aTc (bottom **-/+).** For all other circuits, inputs correspond to the absence or presence of **1** mM IPTG (top **-/+),** 2 ng/mL aTc (middle **-/+),** and **5** mM L-arabinose $(\text{bottom} -/+).$

Figure 4-20: Majority circuit variants. Representative experimentally measured fluorescence histograms (RPU, black) and predicted distributions (blue and red lines) are shown for the Majority circuit variants in Figure 4-5.The simplified genetic schematics from Figure 4-5e are shown above the full, labeled schematics. Inputs correspond to the absence or presence of 1 mM IPTG (top $-\prime$ +), 2 ng/mL aTc (middle $-\prime$ +), and 5 mM Larabinose (bottom **-/+).**

Figure 4-21: Replicates of majority circuit variants. Average output (RPU) for alternate repressor assignments circuits (Figure 4-20). Outputs are predicted to be high (black bars) or low (gray bars). Error bars are one standard deviation of the median for two experiments performed on different days. Inputs correspond to the absence or presence of 1 mM IPTG (top **-/+),** 2 ng/mL aTc (middle **-/+),** and **5** mM L-arabinose (bottom **-/+).**

Figure 4-22: Alternate repressor assignments. Representative experimentally measured fluorescence histograms (black) and predicted distributions (blue and red lines) are shown. Inputs correspond to the absence or presence of 1 mM IPTG (top **-/+),** 2 ng/mL aTc (middle $-$ / $+$), and 5 mM L-arabinose (bottom $-$ / $+$).

Figure 4-23: Replicates of alternate assignment circuits. Average output (RPU) for alternate repressor assignments circuits (Figure 4-22). Outputs are predicted to be high (black bars) or low (gray bars). Error bars are one standard deviation of the median for two experiments performed on different days. Inputs correspond to the absence or presence of 1mM IPTG (to **-/+),** 2ng/mL aTc (middle-/+), and 5mM L-arabinose $(bottom -/+).$

Figure 4-24: Replicates of functional circuits. Average output (RPU) for all functional **3** input circuits from the circuit library (Figure 4-4). The ordering of the circuits in panels **(A)-(D)** matches the four pages of circuits in Figure 4-4. Outputs (X, Y, and Z) correspond to YFP driven from output promoters in separate experiments, and are predicted to be high (black bars) or low (gray bars). Error bars represent one standard deviation of the median for two experiments performed on different days. Inputs correspond to the absence or presence of 1 mM IPTG (top **-/+),** 2 ng/mL aTc (middle **-/+),** and **5** mM L-arabinose $(\text{bottom} -/+).$

Figure 4-25: Replicates of circuits with failed output states. Average output for circuits with **(A)** 1 failed output state (Figure 4-17), (B) 2 failed output states (Figure 4-18), or **(C) 3** or more failed output states (Figure 4- **19).** The ordering of the circuits matches the corresponding figures. Outputs (W, X, Y, and Z) correspond to YFP driven from output promoters in separate experiments, and are predicted to be high (black bars) or low (gray bars). Error bars are one standard deviation of the median for two experiments performed on different days. For 3-input circuits, inputs correspond to the absence or presence of **1** mM IPTG (top $/+)$, 2 ng/mL aTc (middle $-/-)$), and **5** mM L-arabinose (bottom **/+).** For the Demultiplexer circuit (Demux), inputs correspond to the absence or presence of **1** mM IPTG (top $/+)$ and 2 ng/mL aTc (bottom - $(+)$.

Figure 4-26: Experiments to determine gate failures internal to a circuit. Data are shown for **8** of the non-toxic circuits that show at least one failed state. In each case, an initial screen was performed where the debugging plasmids are substituted for the output plasmid (shown under the cytometry plot) and screened under all eight combinations of inputs. The bar graphs correspond to the activity of each promoter for the failed state under investigation (e.g., $+/-$ for 0xC1, red arrow). To account for the dynamic range

differences of the gates, the fluorescence measured is normalized **by** the minimum and maximum fluorescence observed for the debugging plasmid across all circuits and states. This allows the reporting of the gate activity in the range **[0,1].** The dashed red box shows where the error initiates and the thick black line shows how it propagates to the circuit output.

Figure 4-27: Overview of the Cello software. The Cello input is a high-level logic specification written in Verilog, a hardware description language. The code is parsed to generate a truth table, and logic synthesis produces a circuit diagram with the genetically available gate types to implement the truth table. The gates in the circuit are assigned using experimentally characterized genetic gates. In assignment, a predicted circuit score guides a Monte Carlo simulated annealing search. The assignment with the highest score is chosen, and this assignment can be physically implemented in a combinatorial number of different layouts. The Eugene language is used for rule-based constrained combinatorial design of one or more final **DNA** sequence(s) for the designed circuit.

Figure 4-28: Flow of Verilog parsed to a truth table. **A** Verilog file is parsed into individual assign, structural, and case statements. Each statement is converted into a logic node, which can contain one or more gates, or a truth table. Logic nodes are connected **by** matching input/output wire names, and Boolean logic is propagated through each node to compute the truth table of the circuit output.

Figure 4-29: Nested Verilog modules for module reuse. The same logic function shown in Figure 4-28 is rewritten using a parent module that references child modules. In the same **flow,** each statement is converted to logic nodes, which are used to generate the truth table specified **by** the full program. In Cello, the parent and child modules would appear as a single long file.

Figure 4-30: Logic synthesis workflow. The starting point is a truth table. The **AIG** is converted to an NIG using DeMorgan's rule: **(A AND** B) equals **(NOT A)** NOR **(NOT** B), and removing double **NOT** gates. Subcircuits in the initial circuit diagram can be substituted for user-defined logic motifs specified in the **UCF.** The black dashed box highlights one subcircuit from the initial circuit, and the red dashed box indicates a functionally equivalent motif from the library, which is substituted into the circuit. This process is done iteratively until no more substitutions are identified. The logic constraints are determined **by** the gate types available in the **UCF,** and the number of instances of each gate type in the **UCF.** In this example, there are a maximum of 12 **NOR/NOT** gates, and any number of **OUTPUT_OR** gates.

Figure 4-31: Circuit score calculation. **(A)** Circuit diagram for an XOR circuit with gate assignments AmtR (blue), IcaRA (magenta), and PhlF (orange). (B) Visualization of signal propagation for each of four input states. Colored curves are gate response functions (Equation **Si)** with the same coloring scheme from **(A).** Dashed vertical lines represent promoter input levels for the gate. Dashed horizontal lines represent promoter output levels. The **"+"** symbol indicates promoter outputs from the IcaRA and PhlF gate are summed at the terminal OR gate. **(C)** Predicted output levels for each of the four input combinations. The Os and is at the top of the graph indicate the desired truth table behavior for each output. The lowest **ON** state and highest OFF state are marked, and the ratio of these values is the circuit score, **S.**

Figure 4-32: Tradeoff between circuit score and predicted cell growth. For the Majority circuit (Figure 4-5), each assignment has a circuit score **(S)** and a growth score (represented as a point on the scatter plot). The Pareto frontier is shown as a red line. **A** threshold is defined to eliminate toxic assignments from consideration (shaded region in center plot). Left (assignment highlighted yellow in center plot): Prediction of assignment with high **S** but toxic expression of IcaRA. Assigned gates: P2-PhlF, H2-HlyIR, **A2-** AmtR, B3-BM3R1, I1-IcaRA, S4-SrpR. Right (assignment highlighted yellow in center plot): Prediction of assignment with normal cell growth but low **S.** Assigned gates: B3- BM3R1, Fl-AmeR, S4-SrpR, A2-AmtR, P2-PhlF, H2-HlyIIR.

Figure 4-33: Simulated annealing search algorithm for repressor assignment. Each plot shows **100** trajectories, and as the number of steps increases for each trajectory, the highest **^S**up to that point is plotted (black lines). The temperature factor annealed according to the schedule listed above.

Figure 4-34: Example sets of Eugene rules for the Majority circuit. Parts (Level **1)** are used to build gate devices. Promoter order rules are used to disallow roadblocking promoters in the downstream position. The resulting gate devices (Level 2) can be composed in to a circuit device (Level **3).** The rules in this figure defined for a circuit device would be specified in "circuit rules" block in Eugene file, in addition to the EXACTLY **1** gate assignment rules. Depending on the set of rules, the design space for this 5-gate circuit ranges from 4 to **15,360** layouts.

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Figure 4-35: Circuit distribution calculation. **(A)** Circuit diagram for an XOR circuit with gate assignments AmtR (blue), IcaRA (magenta), and PhIF (orange). (B) Visualization of distribution propagation for each of four input combinations. Colored curves are gate distribution response functions with the same coloring scheme from **(A).** Dashed vertical lines represent sensor input levels for the gate. Vertical histograms to the right of each response function are the output histograms for the gate. The **"+"** symbol indicates the output histograms from the IcaRA and PhiF gate are summed at the terminal OR gate. **(C)** Predicted output histograms for each of the four input combinations. The Os and Is at the top of the graph indicate the desired truth table behavior for each output. Black and gray histograms are expected to be high and low, respectively.

Figure 4-36: Input threshold analysis. **(A) A** low threshold and high threshold for a gate (IL, IH) are used to determine valid levels for inputs to that gate. In this example, the outputs from the previous gate (OL, OH) result in positive margins (ML, MH, horizontal arrows). **A** negative margin would indicate an input level in the forbidden zone (diagonal hatching). (B) Input threshold analysis for the Majority circuit (output of Cello). Yellow regions indicate positive margins that pass input threshold criteria. The red margin for PhlF (P3 RBS) indicates a negative input margin that fails the IH threshold criterion.

Figure 4-37: RPU standard plasmid and autofluorescence control. Part sequences are provided in Table 4-9. The RPU plasmid (top) promoter is **J23101** (Part:BBa **J23101** parts.igem.org, **23101).** The RiboJ sequence is the same as published previously (Lou et al, 2012), with an additional upstream cloning scar. The RBS is B0064 (Part:BBa B0064 **-** parts.igem.org). The YFP is as published previously (Cormack et *al,* **1996),** with three synonymous mutations: **C153A, C564A,** and **G606T.** The YFP terminator is **L3S2P21** (Chen et al, **2013).** There is a **15 bp** spacer upstream from **J23101,** and the upstream terminator **L3S3P21** (Chen et al, **2013)** insulates the YFP cassette from transcriptional readthrough from the plasmid backbone. Cells transformed with **pAN1201** (bottom) are used to measure autofluorescence.

Figure 4-38: smRNA-FISH measurement of the RPU standard. **(A)** Merged fluorescent and brightfield micrographs of background $(pAN1201)$, P_{Tac} -YFP $(10 \mu M IPTG)$ **pAN1818),** PTac-YFP **(100** iM IPTG, **pAN1818),** and the RPU standard **(pAN1717).** (B) Histograms of spot heights for the strains shown in **(A).** Y-axis units are number of spots per **1000** pixels. Histograms were fit to a sum (solid line) of two log-normal distributions (dashed lines). **(C)** Number of bright spots per cell area vs. **FISH** signal per cell area for one example replicate experiment. X-axis and y-axis units are both per **1000** pixels. Number of bright spots was estimated from the integrated area of the 2nd (brighter) lognormal distribution fit from (B). The error bars are the standard errors from that estimate. The dashed line is the fit result using a Poisson filling process model (Methods). **(D)** Histograms of estimated mRNA copy number per cell for the strains shown in **(A).** Estimates were obtained from the RNA-FISH signal for each cell using the linear extrapolation of the fit curve shown in **(C). (E)** Estimated mean mRNA copy number per cell vs. IPTG concentration for P_{Tac} -YFP (filled diamonds), background (open triangle), and RPU standard (open square). Plotted values and error bars are the averages and standard deviations of three replicate measurements of the mean mRNA copy number. Dotted and dashed lines represent copy number estimates for background and the RPU standard strains, respectively. The estimated mRNA copy number per cell for background is consistent with zero and the estimated mRNA copy number per cell for the RPU standard is 24.7 ± 5.7 .

Figure 4-39: Constructing a sensor measurement plasmid. **A** sensor promoter (red) is positioned in front of the YFP RPU cassette (RiboJ-B0064-YFP-L3S2P21, green) to create a sensor measurement plasmid (bottom). This module is inserted into **pAN1201,** optionally using BbsI restriction enzyme recognition sites (triangles) and ligation into the insertion scars "gctt" and "aatg". The entire LacZoa module (blue) is replaced upon successful insertion.

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Figure 4-40: Fluorescence data for IPTG-, aTc-, and arabinose-sensors, the RPU standard, and autofluorescence. **DNA** sequences for these sensor measurement plasmids and RPU standard can be found in Table 4-9 (PTac: **pAN1718,** PTet: **pAN1719,** PBAD: **pAN1720,** RPU standard: **pAN1717).**

Figure 4-41: Constructing a **gate** measurement plasmid. **A gate** comprising a ribozyme insulator, RBS, protein coding sequence, terminator, and output promoter is inserted between P_{Tac} and the YFP expression cassette with constitutively expressed LacI. The gate is inserted at nucleotide position **129** on **pAN1818.**

Figure 4-42: Plasmid to characterize the IPTG-inducible P_{Tac} input promoter. The P_{Tac} promoter with symmetric LacO **(71 bp,** sequence as previous published (Lou et al, 2012), with an upstream spacer from **-51** to **-37)** is positioned in front the standard YFP cassette with constitutively expressed LacI **(pAN1818).** The LacI promoter, RBS, and **CDS** are the same as in the **E.** coli genome (Durfee et al, **2008),** except the **"GTG"** start codon is replaced with **"ATG".** The LacI terminator is the genomic AraC terminator (TaraC) from the **E.** coli genome (Durfee et al, **2008).**

Figure 4-43: Converting a fluorescence histogram to RPU. Beginning with a raw fluorescence histogram (black histogram, left panel; gray histogram, middle panel), shift it left (black arrow) by the autofluorescence median value $\langle YFP \rangle_0 = 15.0$ au to generate the autofluorescence-corrected histogram (black histogram, middle panel). Next, divide the x-axis units by the corrected median RPU standard fluorescence <YFP>RPU- \langle YFP >0 = 460 au to convert the x-axis to RPU (right panel). The resulting RPU histogram can then be incorporated into a **UCF.**

Figure 4-44: Measuring the response function for a gate. RPU measurements at different IPTG concentrations for a gate PhIF(RBS-P2) (upper left) and the input promoter P_{Tac} -YFP (lower left) are plotted against each other to create the response function (right). **A** Hill equation is fit to the response curve (Equation **Si,** solid line). IPTG concentrations used were: **0, 5, 10,** 20, **30,** 40, **50, 70, 100, 150,** 200, and **1000 pM.**

Figure 4-45: Overview of the Eco1C1GIT1 User Constraint File. **All** data objects in the **UCF** are organized **by** collection name (shaded gray).

Figure 4-46: Genetic circuit assembly. Final circuit plasmids are constructed from one or more submodule plasmids inserted into the circuit backbone containing the sensor effectors. Submodule plasmids comprise transcriptional units containing different genes (colored shapes correspond to genes). Each overhang is a **4bp** sticky end scar generated in the Golden Gate assembly that connects the submodules together. The assembled circuit replaces a P_{Lac} -lac $Z\alpha$ cassette (black shape) between the insertion scars "gctt" and "aatg".

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Figure 4-47: Plasmid backbones for measuring circuits. Top: output plasmid. Middle: 2 input circuit backbone. Bottom 3-input circuit backbone.

Figure 4-48: Gate characterization plasmids. Top: roadblocking test plasmids. Second from top: Insulated gate measurement plasmids. Third from top: toxicity measurement plasmids. Bottom: Ribozyme test plasmids.

Figure 4-49: Sensor measurement and RPU plasmids. Top: RPU standard plasmid. Middle: P_{Tac} activity plasmid. Bottom: Sensor measurement plasmids.

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1 avie 4-1.	rupozyme sequences
Name	Sequence ^a
RiboJ (Lou et al. 2012; Khvorova et al, 2003)	AGCTGTC ACCGGATGTGCTTTCCGGTCTGATGAGTCCGTGAGGACGAAACAGCCTCTACAAATAATTTTGTTTAA
Natural AraJ (Dufour et al, 2009)	
BydvJ (Khvorova	AGTGGTC GTGATCTGAAACTCGATCACCTGATGAGCTCAAGGCAGAGCGAAACCACCTCTACAAATAATTTTGTTTAA
<i>et al</i> , 2003) CchJ	AGGGTGTC TCAAGGTGCGTACCTTGACTGATGAGTCCGAAAGGACGAAACACCCCTCTACAAATAATTTTGTTTAA
(Khvorova et al, 2003) ElvJ (Dufour et	AGTTCCAGTC GAGACCTGAAGTGGGTTTCCTGATGAGGCTGTGGAGAGAGCGAAAGCTTTACTCCCGCACAAGCCGAAACT GGAACCTCTACAAATAATTTTGTTTAA
al, 2009) LtsvJ (Lou et al, 2012; Khvorova et	AGCCCCATA GGGTGGTGTGTACCACCCCTGATGAGTCCAAAAGGACGAAATGGGGCCTCTACAAATAATTTTGTTTAA
al, 2003) PlmJ (Lou et al. 2012; Khvorova et	AGTACGTC TGAGCGTGATACCCGCTCACTGAAGATGGCCCGGTAGGGCCGAAACGTACCTCTACAAATAATTTTGTTTAA
al, 2003) SarJ (Lou et al. 2012; Khvorova et	AGTCATAAGTC TGGGCTAAGCCCACTGATGAGTCGCTGAAATGCGACGAAACTTATGACCTCTACAAATAATTTTGTTTAA
al, 2003) ScmJ (Khvorova	AGACTGTC GCCGGATGTGTATCCGACCTGACGATGGCCCAAAAGGGCCGAAACAGTCCTCTACAAATAATTTTGTTTAA
<i>et al.</i> 2003) Engineered	AGCGCTGTC TGTACTTGTATCAGTACACTGACGAGTCCCTAAAGGACGAAACACCGCCTCTACAAATAATTTTGTTTAA
RiboJ10	AGCGCTC AACGGGTGTGCTTCCCGTTCTGATGAGTCCGTGAGGACGAAAGCGCCTCTACAAATAATTTTGTTTAA
RiboJ51	AGTAGTC ACCGGCTGTGCTTGCCGGTCTGATGAGCCTGTGAAGGCGAAACTACCTCTACAAATAATTTTGTTTAA
RiboJ53	AGCGGTC AACGCATGTGCTTTGCGTTCTGATGAGACAGTGATGTCGAAACCGCCTCTACAAATAATTTTGTTTAA
RiboJ54	AGGGGTC AGTTGATGTGCTTTCAACTCTGATGAGTCAGTGATGACGAAACCCCCTCTACAAATAATTTTGTTTAA
RiboJ57	AGAAGTC AATTAATGTGCTTTTAATTCTGATGAGTCGGTGACGACGAAACTTCCTCTACAAATAATTTTGTTTAA
RiboJ60	AGTCGTC AAGTGCTGTGCTTGCACTTCTGATGAGGCAGTGATGCCGAAACGACCTCTACAAATAATTTTGTTTAA

Table 4-1: Ribozyme sequences

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Table 4-2: Terminator sequence alignment

a. Strength values reproduced from ref (Chen et al, **2013).**

b. The **"C"** at nucleotide 45 from was mutated to **"A"** to eliminate a Bsal recognition site.

						Toxicity
Repressor	RBS	<u>Ymin^a</u>	y max ^a	Ka	n	(RPU) ^b
AmeR	F1	0.2	3.8	0.09	1.4	
AmtR	A1	0.06	3.8	0.07	1.6	4.1
Betl	E1	0.07	3.8	0.41	2.4	
BM3R1	B1	0.004	0.5	0.04	3.4	
	B ₂	0.005	0.5	0.15	2.9	
	B ₃	0.01	0.8	0.26	3.4	
HlyllR	H1	0.07	2.5	0.19	2.6	
IcaRA	1	0.08	2.2	0.10	1.4	1.7
LitR	L1	0.07	4.3	0.05	1.7	0.2
LmrA	N ₁	0.2	2.2	0.18	2.1	
PhIF	P1	0.01	3.9	0.03	4.0	
	P ₂	0.02	4.1	0.13	3.9	
	P3	0.02	6.8	0.23	4.2	
PsrA	R1	0.2	5.9	0.19	1.8	
$\sf QacR$	Q1	0.01	2.4	0.05	2.7	N.D.
	Q2	0.03	2.8	0.21	2.4	1.7
SrpR	S1	0.003	1.3	0.01	2.9	
	S2	0.003	2.1	0.04	2.6	
	S3	0.004	2.1	0.06	2.8	
	S4	0.007	2.1	0.10	2.8	

Table 4-4: Insulated gate response function parameters

a. In units of RPU.

b. Highest input RPU achieved before cell growth was reduced >20% compared to a control (Methods). Dashes indicate no toxicity observed at the highes inducer levels. **N.D.** means no data collected.

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Name	Кp	n	y _{max} b	y min ^b
AmeR	0.11	1.4	3.9	0.40
AmtR	0.06	1.8	2.2	0.08
Betl	0.05	2.4	3.1	0.09
BM3R1	0.13	4.5	0.61	0.02
ButR	0.30	2.4	2.9	0.44
HIVIIR	0.12	2.7	3.9	0.08
lcaR(A)	0.10	1.8	3.0	0.09
LitR	0.03	1.9	3.9	0.12
LmrA	0.29	3.1	17	0.27
McbR	0.10	1.6	3.8	0.27
PhIF	0.09	4.5	3.8	0.02
PsrA	0.10	2.0	4.7	0.11
QacR	0.11	1.4	5.0	0.05
SrpR	0.07	32	6.0	0.03
TarA	0.02	1.8	3.0	0.05

Table 4-5: Non-insulated gate parameters^a

a. The 0.02 **1** RPU standard in ref (Stanton et al, 2014) differs from this manuscript (Figure 4-37). These values were recalculated based on the new standard.

b. In units of RPU.

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		$<$ YFP $>$	<yfp>RPU</yfp>	$<$ YFP >0	RPUs
Pr_{ac}	OFF	16.6	475	15	0.0034
	OΝ	1300	475	15	2.8
Pr_{et}	OFF	15.6	475	15	0.0013
	ON	2020	475	15	4.4
P _{BAD}	OFF	18.8	475	15	0.0082
	OΝ	1170	475	15	2.5

Table 4-6: Calculation of Sensor **OFF/ON** activities

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Part name	Type	DNA sequence ^a
AmeR (RBS-F1) gate	gate	CTGAAGGGGTCAGTTGATGTGCTTTCAACTCTGATGAGTCAGTGATGACGAAACCCCCTCTACAAATAATTTTGTTT AACTATGGACTATGTTTTCACATACGAGGGGGATTAGATGAACAAAACCATTGATCAGGTGCGTAAAGGTGATCGTA AAAGCGATCTGCCGGTTCGTCGTCGTCCGCGTCGTAGTGCCGAAGAAACCCGTCGTGATATTCTGGCAAAAGCCGAA GAACTGTTTCGTGAACGTGGTTTTAATGCAGTTGCCATTGCAGATATTGCAAGCGCACTGAATATGAGTCCGGCAAA TGTGTTTAAACATTTTAGCAGCAAAAACGCACTGGTTGATGCAATTGGTTTTGGTCAGATTGGTGTTTTTGAACGTC AGATTTGTCCGCTGGATAAAAGCCATGCACCGCTGGATCGTCTGCGTCATCTGGCACGTAATCTGATGGAACAGCAT CATCAGGATCATTTCAAACACATACGGGTTTTTATTCAGATCCTGATGACCGCCAAACAGGATATGAAATGTGGCGA TTATTACAAAAGCGTGATTGCAAAACTGCTGGCCGAAATTATTCGTGATGGTGTTGAAGCAGGTCTGTATATTGCAA CCGATATTCCGGTTCTGGCAGAAACCGTTCTGCATGCACTGACCAGCGTTATTCATCCGGTTCTGATTGCACAAGAA ACTTGACAACTCATCACTTCCTAGGTATAATGCTAGC
AmtR (RBS-A1) gate	gate	CTGAAGGGTGTCTCAAGGTGCGTACCTTGACTGATGAGTCCGAAAGGACGAAACACCCCTCTACAAATAATTTTGTT TAAAATGTTCCCTAATAATCAGCAAAGAGGTTACTAGATGGCAGGCGCAGTTGGTCGTCGCGTCGTAGTGCACCGC GTCGTGCAGGTAAAAATCCGCGTGAAGAAATTCTGGATGCAAGCGCAGAACTGTTTACCCGTCAGGGTTTTGCAACC ACCAGTACCCATCAGATTGCAGATGCAGTTGGTATTCGTCAGGCAAGCCTGTATTATCATTTTCCGAGCAAAACCGA AATCTTTCTGACCCTGCTGAAAAGCACCGTTGAACCGAGCACCGTTCTGGCAGAAGATCTGAGCACCCTGGATGCAG GTCCGGAAATGCGTCTGTGGGCAATTGTTGCAAGCGAAGTTCGTCTGCTGCTGAGCACCAAATGGAATGTTGGTCGT CTGTATCAGCTGCCGATTGTTGGTAGCGAAGAATTTGCAGAATATCATAGCCAGCGTGAAGCACTGACCAATGTTTT TCGTGATCTGGCAACCGAAATTGTTGGTGATGATCCGCGTGCAGAACTGCCGTTTCATATTACCATGAGCGTTATTG AAATGCGTCGCAATGATGGTAAAATTCCGAGTCCGCTGAGCGCAGATAGCCTGCCGGAAACCGCAATTATGCTGGCA GATGCAAGCCTGGCAGTTCTGGGTGCACCGCTGCCTGCAGATCGTGTTGAAAAAACCCTGGAACTGATTAAACAGGC AGATGCAAAATAACTCGGTACCAAAGACGAACAATAAGACGCTGAAAAGCGTCTTTTTTCGTTTTGGTCCCTTGTCC AACCAAATGATTCGTTACCAATTGACAGTTTCTATCGATCTATAGATAATGCTAGC
BM3R1 (RBS-B1) gate	gate	CTGAAGACTGTCGCCGGATGTGTATCCGACCTGACGATGGCCCAAAAGGGCCGAAACAGTCCTCTACAAATAATTTT GTTTAACTATGGACTATGTTTTAACTACTAGATGGAAAGCACCCCGACCAAACAGAAAGCAATTTTTAGCGCAAGCC TGCTGCTGTTTGCAGAACGTGGTTTTGATGCAACCACCATGCCGATGATTGCAGAAAATGCAAAAGTTGGTGCAGGC GTGTATTGAAAGCGGTCTGGCAAATGAACGTGATGGTTATCGTGATGGCTTTCATCACATTTTTGAAGGTATGGTGA CCTTTACCAAAAATCATCCGCGTGCACTGGGTTTTATCAAAACCCATAGCCAGGGCACCTTTCTGACCGAAGAAAGC CGTCTGGCATATCAGAAACTGGTTGAATTTGTGTGCACCTTTTTTCGTGAAGGTCAGAAACAGGGTGTGATTCGTAA TCTGCCGGAAAATGCACTGATTGCAATTCTGTTTGGCAGCTTTATGGAAGTGTATGAAATGATCGAGAACGATTATC TGAGCCTGACCGATGAACTGCTGACCGGTGTTGAAGAAAGCCTGTGGGCAGCACTGAGCCGTCAGAGCTAACTCGGT ACCAAATTCCAGAAAAGAGACGCTTTCGAGCGTCTTTTTCGTTTTGGTCCAATCCGCGTGATAGGTCTGATTCGTT
BM3R1 (RBS-B2) gate	gate	ACCAATTGACGGAATGAACGTTCATTCGATAATGCTAGC CTGAAGACTGTCGCCGGATGTGTATCCGACCTGACGATGGCCCAAAAGGGCCGAAACAGTCCTCTACAAATAATTTT GTTTAACTATGGACTATGTTTTTCAAAGACGAAAAACTACTAGATGGAAAGCACCCCGACCAAACAGAAAGCAATTT TTAGCGCAAGCCTGCTGCTGTTTGCAGAACGTGGTTTTGATGCAACCACCATGCCGATGATTGCAGAAAATGCAAAA TGAATTTCTGCAGTGTATTGAAAGCGGTCTGGCAAATGAACGTGATGGTTATCGTGATGGCTTTCATCACATTTTTG AAGGTATGGTGACCTTTACCAAAAATCATCCGCGTGCACTGGGTTTTATCAAAACCCATAGCCAGGGCACCTTTCTG ACCGAAGAAAGCCGTCTGGCATATCAGAAACTGGTTGAATTTGTGTGCACCTTTTTTCGTGAAGGTCAGAAACAGGG TGTGATTCGTAATCTGCCGGAAAATGCACTGATTGCAATTCTGTTTGGCAGCTTTATGGAAGTGTATGAAATGATCG AGAACGATTATCTGAGCCTGACCGATGAACTGCTGACCGGTGTTGAAGAAAGCCTGTGGGCAGCACTGAGCCGTCAG AGCTAACTCGGTACCAAATTCCAGAAAAGAGACGCTTTCGAGCGTCTTTTTTCGTTTTGGTCCAATCCGCGT6ATAG
BM3R1 (RBS-B3) gate	gate	GTCTGATTCGTTACCAATTGACGGAATGAACGTTCATTCCGATAATGCTAGO CTGAAGACTGTCGCCGGATGTGTATCCGACCTGACGATGGCCCAAAAGGGCCGAAACAGTCCTCTACAAATAATTTT GTTTAACCAAACGAGGCCGGGAGGATGGAAAGCACCCCGACCAAACAGAAAGCAATTTTTAGCGCAAGCCTGCTGCT GTTTGCAGAACGTGGTTTTGATGCAACCACCATGCCGATGATTGCAGAAAATGCAAAAGTTGGTGCAGGCACCATTT ATCGCTATTTCAAAAACAAAGAAAGCCTGGTGAACGAACTGTTTCAGCAGCATGTTAATGAATTTCTGCAGTGTATT GAAAGCGGTCTGGCAAATGAACGTGATGGTTATCGTGATGGCTTTCATCACATTTTTGAAGGTATGGTGACCTTTAC CAAAAATCATCCGCGTGCACTGGGTTTTATCAAAACCCATAGCCAGGGCACCTTTCTGACCGAAGAAAGCCGTCTGG CATATCAGAAACTGGTTGAATTTGTGTGCACCTTTTTTCGTGAAGGTCAGAAACAGGGTGTGATTCGTAATCTGCCG GAAAATGCACTGATTGCAATTCTGTTTGGCAGCTTTATGGAAGTGTATGAAATGATCGAGAACGATTATCTGAGCCT GACCGATGAACTGCTGACCGGTGTTGAAGAAAGCCTGTGGGCAGCACTGAGCCGTCAGAGCTAACTCGGTACCAAAT TCCAGAAAAGAGACGCTTTCGAGCGTCTTTTTTCGTTTTGGTCCAATCCGCGTGATAGGTCTGATTCGTTACCAATT
BetI (RBS-E1) gate	gate	GACGGAATGAACGTTCATTCCGATAATGCTAGC CTGAAGAAGTCAATTAATGTGCTTTTAATTCTGATGAGTCGGTGACGACGAAACTTCCTCTACAAATAATTTTGTTT GAAGCAATTAATGAAGTTGGTATGCATGATGCAACCATTGCACAGATTGCACGTCGTGCCGGTGTTAGCACCGGTAT CAGTTCTGAATCGTCTGCATGCACTGCCGCAGGGTAGCGCAGAACAGCGTCTGCAGGCAATTGTTGGTGGTAATTTT GTATCGTCTGCAGCAGGTTAGCAGTCGTCGTCTGCTGAGCAATCTGGTTAGCGAATTTCGTCGTGAACTGCCTCGTG TGAACACCCTTCGGGGTGTTTTTTTGTTTCTGGTCTACCAGCGGGGTGAGAGGGATTCGTTACCAATTGACAATTG
HlylIR (RBS-H1) gate	gate	ATTGGACGTTCAATATAATGCTAGC CTGAAGTAGTCACCGGCTGTGCTTGCCGGTCTGATGAGCCTGTGAAGGCGAAACTACCTCTACAAATAATTTTGTTT AAACCCCCGAGATGAAATACATCCTGTTTGAGGTGTGCGAAATGGGTAAAAGCCGTGAACAGACCATGGAAAATATT CTGAAAGCAGCCAAAAAGAAATTCGGCGAACGTGGTTATGAAGGCACCAGCATTCAAGAAATTACCAAAGAAGCCAA AGTTAACGTTGCAATGGCCAGCTATTACTTTAATGGCAAAGAGAACCTGTACTACGAGGTGTTCAAAAAATACGGTC TGGCAAATGAACTGCCGAACTTTCTGGAAAAAAACCAGTTTAATCCGATTAATGCCCTGCGTGAATATCTGACCGTT TGTTTCACTTTTTTAGCATCAACCATACCATCCATTGGATTACCAGCATTGTTCTGTTTCCGAAATTCAAAAAATTC ATCGATAGCCTGGGTCCGAATGAAACCAATGATACCAATCATGAATGGATGCCGGAAGATCTGGTTAGCCGTATTAT TAGCGCACTGACCGATAAACCGAACATTTAAAACGCATGAGAAAGCCCCCGGAAGATCACCTTCCGGGGGCTTTTTT

Table 4-8: Sequences of insulated gates and sensor modules used in this work

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(red), terminators (black), output promoters (orange), and sensor transcription units (purple).

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1 apie 4-9:	Genetic part sequences							
Part name	Type	DNA sequence ^a						
BBa J23101	promoter	tttacagctagctcagtcctaggtattatgctagc						
BBa J23105	promoter	tttacggctagctcagtcctaggtactatgctagc gcggcgcgccatcgaatggcgcaaaacctttcgcggtatggcatgatagcgcccggaagagagtcaattcag						
P_{Lacl}	promoter	ggtggtgaat						
P _{Tac}	promoter (Boer <i>et al</i> , 1983)	aacgatcgttggctgtgttgacaattaatcatcggctcgtataatgtgtggaattgtgagcgctcacaatt						
Pr_{et}	promoter (Stanton et al, 2014)	tactccaccgttggcttttttccctatcagtgatagagattgacatccctatcagtgatagagataatgagc ac						
P _{BAD}	promoter (Moon <i>et al</i> , 2011)	acttttcatactcccgccattcagagaagaaaccaattgtccatattgcatcagacattgccgtcactgcgt cttttactggctcttctcgctaaccaaaccggtaaccccgcttattaaaagcattctgtaacaaagcgggac caaagccatgacaaaaacgcgtaacaaaagtgtctataatcacggcagaaaagtccacattgattatttgca cggcgtcacactttgctatgccatagcatttttatccataagattagcggatcctacctgacgctttttatc gcaactctctactgtttctccatacccgtttttttgggctagc						
P_{AmeR}	promoter (Stanton <i>et al</i> , 2014)	tcgtcactagagggcgatagtgacaaacttgacaactcatcacttcctaggtataatgctagc						
P _{AmtR}	promoter (Stanton <i>et al</i> , 2014)	cttgtccaaccaaatgattcgttaccaattgacagtttctatcgatctatagataatgctagc						
P_{Bett}	promoter (Stanton et al. 2014)							
P _{BM3R1}	promoter (Stanton <i>et al</i> , 2014)	aatccgcgtgataggtctgattcgttaccaattgacggaatgaacgttcattccgataatgctagc						
PHIVIIR	promoter (Stanton et al. 2014)	accaggaatctgaacgattcgttaccaattgacatatttaaaattcttgtttaaaatgctagc						
PIcaRA	promoter (Stanton <i>et al</i> , 2014)							
P_{LitR}	promoter (Stanton <i>et al</i> , 2014)	cgagcgtagagcttagattcgttaccaattgacaaatttataaattgtcagtataatgctagc						
P_{LmrA}	promoter (Stanton <i>et al</i> , 2014)	cgctcattcactaggtctgattcgttaccaattgacaactggtggtcgaatcaagataatagaccagtcact atattt						
P _{Phif}	promoter (Stanton <i>et al</i> , 2014)	cgacgtacggtggaatctgattcgttaccaattgacatgatacgaaacgtaccgtatcgttaaggt						
P _{PsrA}	promoter (Stanton et al, 2014)							
PQacR	promoter (Stanton et al, 2014)	ggtatggaagctatacgttaccaattgacagctagctcagtcctactttagtatatagaccgtgcgatcggt ctata						
P _{SrpR}	promoter (Stanton <i>et al</i> , 2014)	gtttgtaaac						
RiboJ	insulator (Lou et al. 2012)	agctgtcaccggatgtgctttccggtctgatgagtccgtgaggacgaaacagcctctacaaataattttgtt taa						
RiboJ54	Insulator	aggggtcagttgatgtgctttcaactctgatgagtcagtgatgacgaaaccccctctacaaataattttgtt taa						
BydvJ	Insulator	agggtgtctcaaggtgcgtaccttgactgatgagtccgaaaggacgaaacacccctctacaaataattttgt ttaa						
RiboJ57	Insulator	agaagtcaattaatgtgcttttaattctgatgagtcggtgacgacgaaacttcctctacaaataattttgtt taa						
SarJ	insulator (Lou et al, 2012)	gactgtcgccggatgtgtatccgacctgacgatggcccaaaagggccgaaacagtcctctacaaataatttt gtttaa						
RiboJ51	Insulator	agtagtcaccggctgtgcttgccggtctgatgagcctgtgaaggcgaaactacctctacaaataattttgtt taa						

Table 4-9: Genetic part sequences

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a. Underline indicates the upstream promoter spacer.

b. The "C" at nucleotide 45 from was mutated to "A" to eliminate a Bsal recognition site.

Probe name	Size (nt)	%GC	DNA sequence
eYFP 1	20	60	TCCTCGCCCTTGCTCACCAT
eYFP ₂	20	50	GCTGAACTTGTGGCCGTTTA
eYFP3	20	65	CAGGGTCAGCTTGCCGTAGG
eYFP4	20	55	TGCCTGTGGTGCAGATGAAC
eYFP ₅	20	60	GTAGCCGAAGGTGGTCACGA
eYFP ₆	20	60	TAGCGGGCGAAGCATTGCAG
eYFP 7	20	60	GTGCAGCTTCATGTGGTCGG
eYFP 8	20	55	GCATGGCGGACTTGAAGAAG
eYFP 9	20	65	CGCTCCTGGACGTAGCCTTC
eYFP 10	20	50	GTCGTCCTTGAAGAAGATGG
eYFP 11	20	65	CGGCGCGGGTCTTGTAGTTG
eYFP ₁₂	20	60	GTGTCGCCCTCGAACTTCAC
eYFP 13	20	55	TTCAGCTCGATGCGGTTCAC
eYFP ₁₄	20	55	CGTCCTCCTTGAAGTCGATG
eYFP 15	20	55	AGCTTGTGCCCCAGGATGTT
eYFP 16	20	45	GTGGCTGTTGTAGTTGTACT
eYFP 17	20	50	TGTCGGCCATGATATAGACG
eYFP ₁₈	20	50	ACCTTGATGCCGTTCTTCTG
eYFP ₁₉	20	50	TGTTGTGGCGGATCTTGAAG
eYFP 20	20	55	TGTTCTGCTGGTAGTGGTCG
eYFP 21	20	55	CTAAGGTAGTGGTTGTCGGG
eYFP ₂₂	20	65	CTTTGCTCAGGGCGGACTGG
eYFP ₂₃	20	60	TGATCGCGCTTCTCGTTGGG
eYFP 24	20	60	CACGAACTCCAGCAGGACCA
eYFP ₂₅	20	45	TACTTGTACAGCTCGTCCAT

Table 4-10: FISH probe sequences

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5 Appendix: Methods

5.1 Methods for genomic mining of prokaryotic repressors for orthogonal logic gates

5.1.1 Strains and media

E. coli strain DH10B (F mcrA Δ (mrr-hsdRMS-mcrBC) Φ 80lacZ Δ M15 Δ lacX74 recA1 endA1 ara Δ 139 Δ (ara, leu)7697 galU galK λ -rpsL (StrR) nupG) was used for all experiments, except in logic gate measurement where $DH5\alpha$ (fhuA2 lac(del)U169 phoA glnV44 D80' lacZ(del)M15 gyrA96 recAl relAl endAl thi-1 hsdRl7) was used and in protein expression and purification where $BL21$ ($DE3$) $pLysS$ (F^- ompT gal dcm lon hsdS_B $(r_B \, m_B \, \bar{\hspace{0.2cm}}) \lambda(DE3)$ pLysS (cm^R)) was used. Cells were grown in LB Miller Broth, M9 minimal medium $((6.8 \text{ g/L Na}_2) \text{HPO}_4, 3 \text{ g/L KH}_2 \text{PO}_4, 0.5 \text{ g/L NaCl}, 1)$ **g/L NH4Cl;** Sigma), 2 mM MgSO4, **100** LM CaCl2, 0.4% glucose, 0.2% casamino acids, 340 mg/L thiamine (vitamin B1)) or Super Optimal Broth (SOB). Ampicillin **(50** μ g/ml), kanamycin (25 μ g/ml) and/or chloramphenicol (37 μ g/ml) were used where appropriate. Isopropyl P-D-1-thiogalactopyranoside (IPTG) or **30C6-N-(1** ketocaproyl)-L-homoserine lactone **(HSL)** inducers were used as inducers for the various repressor constructs. Each of the newly constructed plasmids was made **by** the one-step isothermal **DNA** assembly method or inverse PCR (see below). In all cases, YFP (Cormack *et al*, 1996) was used as the reporter.

5.1.2 Codon optimization and gene synthesis

Repressor coding sequences were optimized for production in *E. coil,* chloroplasts and *Bacillus subtilis* using multiparameter gene optimization methods (Fath *et al,* 2011). Optimized sequences were synthesized **by** GeneArt, are contained within a pET21a-derived plasmid (where each repressor contains an N-terminal His6 tag) and were sequence verified.

5.1.3 Calculation of REU

REUs were calculated through use of a strain harboring **pJ23101-YFP** (Fig. **2-16),** which contains a constitutive promoter (BBa_J23101) followed **by** a **5'** UTR (BBa_B032) and YFP. **A** plasmid containing the reference standard was transformed into DH10B cells, resulting in the *in vivo* reference strain. The reference strain was grown under conditions identical to an experimental strain (in this work, strains harboring NOT gates or genetic circuits). The mean reference fluorescence of three replicates minus white cell fluorescence was set to 1 **REU.** The mean fluorescence from experimental strains was divided **by** the reference standard to obtain their output in **REU.**

5.1.4 Repressor expression and purification

Plasmids encoding the synthesized repressor were transformed into BL21(DE3)pLysS cells. Single colonies were selected for **by** growth on LB Miller medium containing ampicillin andchloramphenicol. Cells were inoculated in SOB containing ampicillin and chloramphenicol and grown overnight at **37 *C.** The following morning, cells were diluted back to an OD_{600} of 0.1 in 50 mL fresh SOB medium without antibiotics and were induced using **1** mM IPTG once cells reached an ODo(between **0.6-0.8.** Cells were grown for **6** h at **37 *C** at **250** r.p.m. in a shaking incubator and spun down at 4,000 r.p.m. at 4 **'C,** the supernatant was discarded and pellets were stored at -80 °C.

Cell pellets were resuspended on ice in **5** mL binding buffer **(0.5** M NaCl, 20 mM **HEPES (pH 8), 5** mM imidazole, **50** mM phenylalanine, **50** mM isoleucine, **10%** glycerol and **0.1** iM DTT) containing protease inhibitors and **0.1%** Igepal detergent. Resuspended cells were lysed **by** sonication at room temperature with a setting of 20% duty cycle and 0.1-s pulses, using two 20-s cycles, followed **by** a final 10-s cycle, with icing in between. Lysates were clarified **by** centrifugation at 4 C at **10,000** r.p.m. for **30** min. Clarified extracts were then filtered and applied to **0.5** ml Nickel resin (that had been equilibrated with binding buffer for **30** min at room temperature using a Nutator), and the resin was collected using a gravity flow column. The repressor-bound resin was washed with **5** ml binding buffer and **10** ml wash buffer **(0.5** M NaCl, 20 mM **HEPES (pH 8), 25** mMimidazole, **50** mM phenylalanine, **50** mM isoleucine, 10% glycerol and $0.1 \mu M$ DTT) and was eluted in 0.5 ml elution buffer **(0.5** M NaCl, 20 mM **HEPES (pH 8), 0.5** M imidazole, **50** mM phenylalanine, **50** mM isoleucine, 10% glycerol and $0.1 \mu M$ DTT). Binding buffer (3.5 mL) was added to the eluate, and it was applied to a 15-ml microconcentrator and spun down at **4,000g** for 20 min at 4 **'C.** The concentrated eluate was stored on ice, the concentration was determined using Bradford reagent, distributed into approximately 150-µg aliquots, flash frozen in liquid nitrogen and stored at **-80** *C.

5.1.5 Library screening to identify repressible promoters

A single-letter, degenerate code was defined for each position within an arrayidentified motif on the basis of MEME-identified consensus sequences (Stanton et al, 2014) to generate an operator motif (Fig. 2-2a). Degenerate oligonucleotides representing the resulting operator motif were designed to insert the operator motif into a strong, constitutive synthetic BioBricks BBA J23119 standard promoter (Kelly et *a],* **2009b).** Operator motifs were inserted, in various positions, between or around the **-35** and **-10** elements of the **BBAJ23119** promoter using inverse PCR. Specifically, vector sequences were PCR amplified using Phusion **DNA** polymerase **(NEB)** along with the degenerate, operator motif-containing oligonucleotides. The resulting product was run on an agarose gel, extracted and digested with DpnI. The blunt-ended, DpnI-digested product was phosphorylated (T4 Polynucleotide Kinase) and ligated (T4 **DNA** ligase) in a single reaction at room temperature, transformed into chemically competent DH1OB cells and plated on selective LB medium. Libraries containing individual sequence variants of an operator motif were screened for fluorescence using a blue light transilluminator to ensure that the resulting promoters containing operator motifs retained activity. Those operator motif variants that promoted fluorescence were also screened for repression **by** transformation together with the cognate repressor (Fig. **2-2b).** Briefly, DH10B cells containing a repressor plasmid expressing the cognate repressor were made competent using the Z-competent cell kit (Zymo Research). Plasmid **DNA** was prepared, in 96-well format, from individual fluorescent operator motif variants. The resulting plasmid **DNA** was transformed into Z-competent DH10B cells containing the cognate repressor. Overnights were made from cells containing the fluorescent operator motif reporters only and from cells containing the reporter co-transformed with the cognate repressor. Overnight culture (1μ) was diluted into 200 μ l 1× PBS, and flow cytometry was carried out to quantify fluorescence in the presence and absence of repressor for the LitR and McbR repressors (and then assessed **by** eye for all other repressor or reporter screens using a blue light transilluminator). The promoter variant associated with the largest difference in fluorescence in the absence and presence of repressor was selected to be the cognate promoter for a given repressor. Promoters were also constructed using the previously identified operator sequences for the AmtR, BetI, BM3R1, HapR, HlyIIR, IcaR(A), LmrA, PhLF, SmcR, and TetR repressors listed in Table **2-6.** Individual operator sequences were inserted into the BioBricks **BBAJ23119** standard promoter in various positions surrounding either or both the **-- 35** and **-10** elements. Those promoters that retained constitutive activity were screened for repression **by** their cognate repressor using the methods outlined above.

5.1.6 Construction and tuning of repressor expression

The reverse engineering feature of the RBS calculator (Salis *et a],* **2009)** (https://salis.psu.edu/software/reverse/) was used to identify a weak and a strong RBS sequence for each individual repressor, with the following settings: free energy model, v1.1; organism (16s rRNA), *Escherichia colistr.* K12 substr. DH10B **ACCTCCTTA.** Specifically, RBS sequences were reverse engineered using the following four RBS sequences to obtain their translation initiation rate for an individual repressor: B0034 **GAAAGAGGAGAAATACTAGATG,** rbsl **TCACACAGGAAACCGGTTCGATG,** rbs2 **TCACACAGGAAAGGCCTCGATG** or rbs3 **TCACACAGGACGGCCGGATG.** Successive single-base substitutions were made until RBSs of the desired strength were obtained. This strategy was used to identify both a weak and strong RBS for a given repressor. The two respective strength RBS sequences were aligned and combined into a single, degenerate RBS (except in the case of TetR, where a single RBS was used; Table 2-4). The sequence content based on the alignment and relative translation initiation strength information for each sequence variant were taken into account when assigning degenerate codes to each position within an RBS. Oligonucleotides were designed to encode the degenerate RBS,

which was inserted upstream of the repressor coding sequence, to generate an RBS library. The repressor ORF, reporter fragment and vector backbone were PCR amplified using Phusion **DNA** polymerase **(NEB)** and fused into a single vector using Gibson assembly to generate a single response function vector (Fig. 2-14). The entire 20-VI Gibson reaction was transformed into chemically competent DH10B cells and plated onto LB-selective medium containing ampicillin. Single colonies were inoculated and grown for **6** h at **37 *C** in SOB medium containing ampicillin, in 96-well format, in the presence and absence of **1** mM IPTG. Fluorescence was quantified using flow cytometry to deduce the fold change of the induced and uninduced clones as outlined above. Those clones demonstrating high fluorescence in the absence of inducer and low fluorescence in the presence of inducer were selected. The RBSs that give rise to the highest fold change are shown in Table **2-5** and were used for the orthogonality measurements and in the construction of **NOT** gates.

5.1.7 Measurement of orthogonality matrix

Competent *E. coli* DH10B cells were made using the Z-competent cell kit **(Zymo** Research) that contained individual **NOT** gates (pRF-; Fig. 2-14), which serve as the reporter. Cells were transformed with an additional vector containing the repressor (pOrtho-; Fig. **2-17),** whose expression was controlled **by** the HSL-inducible PLux promoter (Urbanowski *et a],* 2004), in all possible combinations. Specifically, **10- 50** ng of plasmid **DNA** were incubated with 10-20 jil Z-competent cells on ice for **10** min in a 96-well plate. **SOC** broth **(150** 4l) was added, and cells were outgrown at **37 'C** for **1** h with shaking at **1,000** r.p.m. in an ELMI shaker (ELMI Ltd) and plated on LB agar. Plated cells were inoculated into LB containing ampicillin and kanamycin, and grown overnight at **37 "C** with shaking at **1,000** r.p.m. The following morning, stationary-phase cultures were diluted 1:200 into LB-containing antibiotics and grown in a 96-well shaking incubator for 4 h at **37 *C** with shaking at **1,000** r.p.m. The cultures were diluted $1:100$ into LB-containing antibiotics and 20 μ MHSL, except in the cases of HapR, Orf2, ScbR and SmcR, where $2 \mu M$, 20 nM, 200 nM and 200 nM **HSL** were used, respectively, owing to toxicity. The induced cells were grown at **37 'C** for **6** h with shaking at **1,000** r.p.m., and then fluorescence was measured **by** diluting the induced culture 1:40 in PBS and carrying out flow cytometry as described below. Induction assays were run in triplicate for each repressor-reporter combination, and a control plasmid for the orthogonality assays (that corresponds to the pOrtho vector lacking a repressor coding sequence) was used as a normalization control to signify the unrepressed state for individual reporters. The data represent the average of three replicates collected on different days.

5.1.8 Measurement of NOT gate response functions

E. coli DH10B cultures containing **NOT** gate constructs were grown overnight for **16** h in liquid SOB medium containing ampicillin. The cells were grown in a 96-well shaking incubator at **37 *C** and **1,000** r.p.m. The next day, stationary-phase cultures were diluted 1:200 into antibiotic-containing minimal M9 medium supplemented with glucose and grown in the 96-well shaking incubator for **3** h using the same shaking and temperature settings as the overnight growth. Subsequently, the cultures were diluted **1:700** into antibiotic-containing minimal M9 medium supplemented withglucose containing different concentrations of IPTG and then grown for **6** h in the shaking incubator to obtain sufficient exponential-phase cell density for cytometric analysis. The IPTG concentrations used were 0 μ M, 5 μ M, 10 μ M, 20 μ M, 30 μ M, 40 pM, **50** jM, **70** 4M, **100** jM, **150** VM, 200 4M and **1,000** jM. At the end of the final growth period, cultures were diluted **1:5** into PBS. Strains containing the plasmids for the measurement of input promoter activity (Fig. **2-15)** and the conversion to **REU**

(Fig. **2-16)** were grown and measured concurrently with these strains. Flow cytometry was performed as described below. The data represent the average of three replicates collected on different days, and error bars correspond to the s.d. between these measurements.

5.1.9 Measurement of genetic circuits

 $E.$ *coli* DH5 α cultures containing the plasmids encoding the circuits were grown overnight in liquid SOB medium containing kanamycin and ampicillin (for the 2 plasmid **NAND** circuit) or kanamycin(for the 1-plasmid **AND** circuit) in a 96-well incubator at **37 *C** shaking at **1,000** r.p.m. After **16** h of growth, cultures were diluted 1:200 into LB medium with antibiotics and grown in the 96-well shaking incubator for **3** h using the same shaking and temperature settings as the overnight growth. Subsequently, the cultures were diluted **1:700** into LB medium with inducers and then grown for **6** h in the shaking incubator. The inducer concentrations used are: **¹** mM IPTG, 20 μ MHSL and 100 ng/mL aTc. Cultures were diluted 1:20 into PBS, and fluorescence was measured **by** flow cytometry as described below.

5.1.10 Cytometry measurement experiments

At the end of growth, cultures were diluted into PBS with 2 mg/mL kanamycin to arrest cell growth. Cells were analyzed **by** flow cytometry, using a BD Biosciences LSRII flow cytometer with a blue **(488** nm) laser. An injection volume of **10** jiL and the flow rate of $0.5 \mu L/s$ were used.

Cytometry data analysis 5.1.11

Cells were analyzed using FlowJo (TreeStar Inc., Ashland, OR), and populations were gated on the forward scatter area from **100** to **50,000,** and on the side scatter area from **50** to **50,000.** The gated population consisted of thousands of cells. The fluorescence geometric mean of the gated population was calculated, and the mean autofluorescence of a 'white cell' control sample was subtracted from the experimental sample's mean. Fold change is calculated **by** dividing the mean fluorescence of the **ON** state **by** the mean fluorescence of the OFF state (Table **2-5).** The data represent the average of three replicates collected on different days, and error bars correspond to the s.d. between these measurements.

5.1.12 Cellular growth and toxicity assay

Repressor toxicity was assessed **by** comparing the growth of induced, **NOT** gatecontaining cells to the growth of uninduced cells (Fig. **2-6).** Cells were grown identically to the response function assay. A 100 - μ L culture aliquot was placed into an optically clear-bottom 96-well plate, and absorbance was measured at **600** nm using a BioTek Synergy H1 Hybrid Microplate Reader. Repressors were considered toxic under conditions where cell growth is less than **75%** of the uninduced culture growth. The final nontoxic induction point occurs at 200 μ M, 150 μ M, 100 μ M, 70 μ M, 70 μ M and **70** 4M IPTG for ButR, TarA, HapR, ScbR, SmcR and Orf2, respectively. **If** the threshold for toxicity is redefined to a different number, a plot of the maximum induction levels **(REU)** for a given toxicity threshold is provided (Fig. **2-7).** The data represent the average of three replicates collected on different days, and error bars correspond to the s.d. between these measurements.

5.2 Methods for multi-input CRISPR/Cas genetic circuits that interface host regulatory networks

5.2.1 Strains and media

E. coli DH10b (F- *mcrA* Δ(*mrr-hsdRMS-mcrBC*) Φ801acZΔM15 *AlacX74 recAl endAl* araD139 *A(ara leu) 7697 gaJ galK ipsL nupG* X-)(Durfee *et al,* **2008)** was used for cloning (New England Biolabs, MA, **C3019).** *E.* coli K-12 **MG1655*** $(F - \lambda - i\text{lv}G - r\text{fb-50 mph-1 }\Delta(\text{ar}CBAD) \Delta(\text{Lac}I))$ (Blattner *et al.* 1997) was used for measurement experiments. Cells were grown in LB Miller broth (Difco, MI, **90003-350)** for overnight growth and cloning, and MOPS EZ Rich Defined Medium (Teknova, **CA, M2105)** with 0.4% glycerol carbon source for measurement experiments. Ampicillin **(100** pg/ml), kanamycin **(50** pg/ml), and spectinomycin sulfate **(50** pg/mL) were used to maintain plasmids. Arabinose (Sigma Aldrich, MO, **A3256),** 2,4 diacetylphloroglucinol (Santa Cruz Biotechnology, TX, **CAS 2161-86-6)** and anhydrotetracycline (aTc) (Sigma Aldrich, MO, **37919)** were used as chemical inducers. The fluorescent protein reporters YFP(Cormack *et a],* **1996)** and mRFP1(Campbell *et a],* 2002) were measured with cytometry to determine gene expression.

5.2.2 Flow cytometry analysis

Fluorescent protein production was measured using the LSRII Fortessa flow cytometer (BD Biosciences, San Jose, CA). Between 10^4 and 10^5 events were collected for subsequent analysis with the software tool FlowJo v10 (TreeStar, Inc., Ashland, OR). From the resulting fluorescence histograms for YFP and RFP, we calculated the geometric means of each sample, and then corrected for cellular autofluorescence **by** subtracting the geometric mean of a strain harboring only $pAN-P_{Tet}-dCas9$ that was grown in an identical manner.

5.2.3 Computational design of sgRNA-promoter pairs

DNA sequences of **13** nucleotides in length were generated using the Random **DNA** Sequence Generator (www.faculty.ucr.edu/~mmaduro/random.htm), with a GC content probability parameter of **0.5.** The resulting sequences were flanked **by** forward and reverse PAMs and the **-35** and **-10** sigma factor binding sites to generate sgRNA repressible promoters. **If** the forward sequence for the promoter contained any stretches with more than three guanine nucleotides, the promoter design was discarded due to the difficulty in synthesizing oligos with G-quadruplexes (Burge *et a],* **2006).** Next, the 12 nucleotides adjacent to either the forward or reverse PAM were searched for in the genome of *E. coli* strain K-12 substrain **MG1655** (taxid: 511145) using Standard Nucleotide BLAST (blast.st-va.ncbi.nlm.nih.gov/Blast.cgi?PROGRAM=blastn) (Altschul *et al,* 1990) to search for somewhat similar sequences (blastn). The following parameters were used: short queries was enabled; expect threshold **= 10;** word size **= 11;** match/mismatch scores **= 2,-3;** gap costs **=** existence: **5,** extension: 2; and low complexity regions unmasked. **Of** the ten sgRNAs designed, no 12nt seed regions had complete homology to a PAM-adjacent locus in the *E coli* genome. **If** the resulting 20 nucleotide sgRNAs had **GC** content less than **35%** or greater than **80%,** the sequence was discarded and redesigned.

5.2.4 Induction endpoint assays

E. coli **MG1655*** cells were transformed with three plasmids encoding **(1)** inducible dCas9, (2) one or more sgRNAs, and **(3)** a fluorescent reporter. Cells were plated on LB agar plates with appropriate antibiotics. Transformed colonies were inoculated into MOPS EZ Rich Defined Medium with 0.4% glycerol and appropriate antibiotics, and

were then grown overnight in V-bottom 96-well plates (Nunc, Roskilde, Denmark, 249952) in an ELMI Digital Thermos Microplates shaker incubator (Elmi Ltd, Riga, Latvia) at **1000** RPM and **37*C.** The next day, cultures were diluted 180-fold into EZ Rich Medium with antibiotics, and grown with the same shaking incubator parameters for three hours. At three hours, cells were diluted 700-fold into EZ Rich Medium with antibiotics and inducers. The cells were grown using the same shaking incubator parameters for six hours. For cytometry measurements, 40 jiL of the cell culture was added to **160** pL of phosphate buffered saline with **0.5** mg/mL kanamycin to arrest cell growth. The cells were placed in a 4*C refrigerator for one hour to allow the fluorophores to mature prior to cytometry analysis.

5.2.5 Toxicity measurements

For dCas9 toxicity measurements, cells were grown identically to the induction endpoint assays until the second dilution after the three hour growth. From here, the cultures were diluted 360-fold into EZ Rich Defined Medium with 0.4% glycerol with antibiotics and inducers in 2 mL 96-deep well plates **(USA** Scientific, FL, **1896-2000)** and were grown for six hours in a Multitron Pro shaker-incubator (In Vitro Technologies, **VIC,** Australia) at **37'C** and **1000** RPM. At this point, cultures were transferred to 1 cm optical cuvettes and the cultures optical density at **600** nm was measured for the cell cultures, after a blank measurement with EZ Rich Medium. For sgRNA toxicity measurements, cells were grown identically to the induction endpoint assays.

5.2.6 Induction timecourse assays

Timecourse experiments were performed identically to endpoint assays, with the exception that cells were grown in 14 mL round-bottom polystyrene culture tubes (VWR, PA, **60819-524).** After the second dilution into inducers, culture samples were taken every **30** minutes for seven hours and were added to phosphate buffered saline with 0.5 mg/mL kanamycin for subsequent cytometry analysis.

5.2.7 Inducer concentrations

For dCas9 toxicity measurements, arabinose was added to 2 mM, and aTc was added to the following final concentrations (ng/mL): **0, 0.3125, 0.625, 1.25, 5,** and **10.** For sgRNA response curve experiments, aTc was added to **0.625** ng/mL and arabinose was added to the following final concentrations (mM): **0, 0.03125, 0.0625, 0.125, 0.25,** and **0.5.** For timecourse and orthogonality experiments, aTc was added to **0.625** ng/mL and arabinose was added to 2 mM. For digital genetic circuit measurements and lambdaphage infection experiments, inducers were either absent or added to the following final concentrations: **0.625** ng/mL aTc, 2 mM arabinose, and **25** pM 2,4 diacetylphloroglucinol. For the intermediate genetic circuit measurements, aTc was added to **0.625** ng/mL; arabinose was added to the following final concentrations **(mM): 0, .00391, .00781, .0156, .0313, .0625, 0.125, 0.25, 0.5, 1,** and 2; 2,4 diacetylphloroglucinol was added to the following final concentrations (piM): **0,** 0.0244, **0.0488, 0.0977, 0.391, 0.781, 1.56, 3.13, 6.25, 12.5,** and **25.**

5.2.8 Lambdaphage infection assay

E. coli **MG1655*** cells were grown from colonies overnight in EZ Rich Defined Media with antibiotics. The next day, cultures were diluted 180-fold into EZ Rich

Medium with 0.4% glycerol and antibiotics, and grown at **37'C** shaking at **250** RPM in culture tubes for three hours. Next, cells were diluted 180-fold once again into five different tubes of 4 mL of EZ Rich Medium with antibiotics and containing the five different inducer conditions. These cells were grown for six hours using the same shaking incubator conditions in culture tubes. After six hours, each culture was pelleted at 4000 **g** and then resuspended in **100** 1iL of **10** mM **MgSO4.** Half of each resuspension **(50 pL)** was diluted into **950 pL** of **10** mM **MgSO4** and the optical density at 600 nanometers was measured. The remaining **50** pL of each cell resuspension were diluted to an **OD600** of **3.0** in **10** mM **MgSO4.** Next, **1 pL** of lambdaphage was added to **100 pL** of each cell resuspension, vortexed lightly, and then allowed to incubate at **37*C** for one hour. Finally, all **100 pL** of cells were plated onto **1.5%** agar LB Miller plate and allowed to grow overnight at **370C.** The next day, phage plaques were counted on each plate.

5.3 Methods for genetic circuit design automation

5.3.1 Circuit induction and measurement guide.

A step-by-step guide to transforming, inducing, and measuring circuits is provided below. The OxF6 circuit is used as a specific example.

Co-transform the OxF6 plasmid (pAN3938) and the PPhE-PAmtR-YFP output plasmid (pAN4044) into chemically competent NEB 10-beta (New England Biolabs., MA, C3019). Add 1 ul of each purified plasmid to 50 ul of thawed chemically competent cells. Incubate mixture on ice for half an hour, and then heat shock at 42'C for **30** seconds. Incubate on ice for 2 more minutes, and then add **1** mL room temperature **SOC** media. Incubate at **37*C** for one hour. Plate serial dilutions of recovered cells on LB agar plates with **50** pig/mL kanamycin (Gold Biotechnology, MO, K-120-5) and **50** pg/mL spectinomycin (Gold Biotechnology, MO, S-140-5). Grow plates at **37'C** overnight.

The day after transformation, pick single colonies and inoculate into 200 **pI** of M9 glucose with antibiotics in a V-bottom 96-well plate (Nunc, Roskilde, Denmark, 249952). M9 glucose media is composed of M9 media salts $(6.78 \text{ g/L} \text{ Na}_2\text{HPO}_4, 3 \text{ g/L})$ KH2PO4, 1 **g/L NH4Cl, 0.5 g/L** NaCl; Sigma-Aldrich, MO, **M6030),** 0.34 **g/L** thiamine hydrochloride (Sigma-Aldrich, MO, T4625), 0.4% D-glucose (Sigma-Aldrich, MO, **G8270),** 0.2% Casamino acids (Acros, **NJ, AC61204-5000),** 2 mM **MgSO4** (Sigma-Aldrich, **MO, 230391),** and **0.1** mM CaCl2 (Sigma-Aldrich, MO, 449709). Antibiotic concentrations in M9 glucose media are **50** pg/mL kanamycin and **50** pg/mL spectinomycin.

Grow single colonies in V-bottom 96-well plates overnight **(16** hours) at **370C** and **1000** RPM in an ELMI Digital Thermos Microplates shaker incubator (Elmi Ltd, Riga, Latvia).

The next day, dilute the overnight cultures 178-fold **by** adding **15** pL of culture into **185 pL** of M9 glucose media, and then **15 pL** of that dilution into **185 pL** of M9 glucose media with **50** pg/mL kanamycin and **50** pg/mL spectinomycin in a V-bottom 96-well plate.

Grow the diluted cultures in an ELMI shaker incubator at **37 "C** and **1000** RPM for three hours.

Dilute the cultures **by** adding **15 pL** of culture into **185** pL of M9 glucose media.

Take 3 uL aliquots of that dilution and distribute into eight wells with 145 pL of inducer-containing M9 glucose media with 50 μ g/mL kanamycin and 50 μ g/mL spectinomycin in a V-bottom 96-well plate. The eight wells correspond to the inducer conditions $(-/-/-)$, $(-/-/+)$, $(-/+/-)$, $(-/+/+)$, $(+/-/-)$, $(+/-/+)$, $(+/+\sqrt{-})$, and $(+/+\sqrt{+})$. Each – or + corresponds to the absence or presence of 5

mM L-arabinose (Sigma-Aldrich, MO, **A3256),** 2 ng/mL aTc (anhydrotetracycline hydrochloride; Sigma-Aldrich, MO, **37919),** and **1** mM IPTG (isopropyl **P-D-1** thiogalactopyranoside; Sigma-Aldrich, MO, 16758).

Grow the cultures containing inducer in an ELMI shaker incubator at **37*C** and **1000** RPM for five hours. Note: at the end of five hours, the cultures should still be in exponential-growth phase, and not in stationary phase.

Aliquot 10 µL of cell culture into 190 µL of phosphate buffered saline (PBS) containing 2 mg/mL kanamycin to arrest protein production and cell growth. Incubate this mixture for one hour at room temperature.

Measure the fluorescence of **>1000** cells per inducer condition using flow cytometry (see Flow cytometry analysis).

5.3.2 Circuits library measurement and time-courses.

For 2-input circuits, the protocol was as above except that the four inducer combinations were the presence or absence of **1** mM IPTG and 2 ng/mL aTc. For all 3-input circuits, the protocol was identical to above. For time-course measurements, we took an initial sample for cytometry before dilution into inducer-containing medium. Next, we performed **10** sets of parallel circuit inductions (all eight states) for a given circuit, and removed **50 pL** from a consecutive set every **30** minutes for cytometry analysis.

5.3.3 Circuit analysis.

After fluorescence measurement **by** flow cytometry (see Flow cytometry analysis), the medians of the YFP histograms were calculated and converted to RPU. Individual states were deemed "successful" if the experimental distributions were near the predicted distributions, as measured **by** eye. Because the output plasmid is lower copy than the gate measurement plasmid, the amount of YFP produced is lower. We measured PTac induction of the YFP RPU cassette on the circuit plasmid and output plasmid, and observed a 2.5-fold decrease in the amount of YFP produced from the output plasmid. We used the conversion factor to downscale all predicted output values; it is stored in the "genetic_locations" collection of the EcolC1G1T1 **UCF,** as the "unit conversion" attribute in "output module location".

5.3.4 Strain, media, and inducers.

E. coli NEB 10-beta Δ *(ara-leu) 7697 araD139 fhuA* Δ *lacX74 galK16 galE15 e14p86U1acZAM15 recAl relAl endAl nupG rpsL (StrR) rph spoTi A(mnrr-hsdRMSmcrBC), a DH10B derviative*(Durfee *et al.* 2008), was used for cloning and measurements (New England Biolabs, MA, **C3019).** Cells were grown in LB Miller broth (Difco, MI, **90003-350)** for harvesting plasmid. Cells were grown M9 glucose media for measurements. M9 glucose media was composed of M9 media salts **(6.78 g/L** Na2HPO4, **3 g/L** KH2PO4, 1 **g/L NH4Cl, 0.5 g/L** NaCl; Sigma-Aldrich, MO, **M6030),** 0.34 **g/L** thiamine hydrochloride (Sigma-Aldrich, MO, T4625), 0.4% D-glucose (Sigma-Aldrich, MO, **G8270),** 0.2% Casarnino acids (Acros, **NJ, AC61204-5000),** 2 mM **MgSO4** (Sigma-Aldrich, MO, 230391), and 0.1 mM CaCl₂ (Sigma-Aldrich, MO, 449709). Chemical inducers used as inputs for sensor promoters were isopropyl β -D-1thiogalactopyranoside (IPTG; Sigma-Aldrich, MO, **16758),** anhydrotetracycline hydrochloride (aTc; Sigma-Aldrich, MO, **37919),** and L-arabinose (Sigma-Aldrich, MO, **A3256).** Antibiotics used to select for the presence of plasmids were **100** pg/ml ampicillin (Gold Biotechnology, MO, **A-301-5), 50** pg/ml kanamycin (Gold Biotechnology, MO, K-120-5), and **50** pg/ml spectinomycin (Gold Biotechnology, MO, S-140-5).

5.3.5 Design and assembly of 2-input circuits.

The circuits in Figure **3** based on non-insulated gates were constructed **by** using the **DNA** sequences previously described(Stanton *et al,* 2014) and patterning the promoters in front of the repressors consistent with the desired circuit diagram (Figure **S5).** The insulated circuits in Figure **3** were constructed automatically, but using software developed in MATLAB that was the precursor to Cello. In this program, all possible gate assignments were exhaustively checked and their performance scored as $\min(\text{ON})/\max(\text{OFF})$. Promoter activities (in RPU) were propagated through a circuit using the response functions of the insulated gates. The activity of tandem promoters was taken as the sum of the activities of the individual promoters. An early version of roadblocking rules was included to disallow certain promoters in downstream positions.

5.3.6 Ribozyme cleavage assay.

For *in vitro* quantification of cleavage, we performed the Rapid Amplification of cDNA End (RACE) assay(5' RACE System for Rapid Amplification of cDNA Ends). For each sample, one colony was inoculated into **1** mL LB Miller broth with 20 pg/mL chloramphenicol and then grown for **16** hours at **37 *C** shaking at **250** rpm. The next day, the liquid culture was diluted 1000-fold into M9 glucose media (1 µL into 1 mL) with chloramphenicol and 1 mM of IPTG , and then grown until an OD₆₀₀ of 0.2. Cells were then harvested and total mRNA was extracted using the RiboPure bacteria kit (Ambion, **CA,** AM1924). To ligate a unique RNA adaptor to the 5'-end of the mRNA, three enzymatic steps were performed sequentially. First, **15 pg** of purified mRNA was treated with **10 U** of T4 polynucleotide kinase **(NEB,** MA, **M0201S)** in a total volume of **50** pl 1X T4 **DNA** ligase buffer and incubated for one hour at **37 *C** to phosphorylate the end of the cleaved mRNA. Second, the mRNA was purified **by** phenol/chloroform extraction **(USB, CA, 75831)** and ethanol precipitation (VWR, PA, **V1016)** and then treated with **10 U** of Tobacco acid pyrophosphatase (TAP, Epicenter, **T19250)** in **50** pl of IX TAP buffer for two hours at **37 *C** to convert the triphosphate of uncleaved mRNA to monophosphate. The treated mRNA was phenol/chloroform extracted and ethanol precipitated once again. Next, **1 pL** of **100 pM** RNA adaptor **(5'- GAGGACUCGAGCUCAAGC-3')** was ligated to all extracted mRNA using **15 U** of T4 RNA ligase (Ambion, **CA,** AM2140) in **30 pl** of 1X RNA ligase buffer for 2 hours at **37 *C.** The mRNA was phenol/chloroform extracted and ethanol precipitated one final time. Next, we reverse transcribed the mRNA using 200 **U** of SuperScript **III** (Invitrogen, **CA,** 18080-044) with a gene specific primer **(GSP1, 5'- ATCCCCATCTTGTCTGCGACAG-3')** in 20 **pl** of 1X SuperScript **III** buffer. In each previous enzymatic step, 20 **U** of RNasin (Promega, WI, **N2611)** or 40 **U** of RNaseOUT (Invitrogen, **CA,** 100000840) was added to inhibit RNase activity. After reverse transcription, 2 **U** of RNase H (Invitrogen, **CA,** 18021-014) was added directly to the 20 **pl** volume to remove RNA from any **RNA/DNA** duplex. The cDNA was used as a template for PCR amplification using two primers (the first being the **DNA** version of the RNA adapter: **5'-GAGGACTCGAGCTCAAGC-3',** and the second being the genespecific primer named **GSP2: 5'-TCCTGGGATAAGCCAAGTTC-3').** We performed the PCR using **5** pmol each primer, 2 **pl** of cDNA template, and Phusion Hi-Fi **DNA** polymerase **(NEB,** MA, **M0530L)** with a **58 *C** annealing temperature and **10** second elongation time for **29** cycles. The resulting PCR product comprises multiple sized bands that correspond to cleaved and uncleaved mRNA fragments. These were separated **by** gel electrophoresis on a **15%** acrylamide gel (Bio-Rad, **CA, 456-5053)** for **¹**hour at **100** V. The band corresponding to the cleaved mRNA was excised and placed into **50** pl of water, allowing the **DNA** to diffuse into the water over 24 hours. This

aqueous **DNA** solution was used as template for a second PCR (performed identically to above). This PCR product was submitted for Sanger sequencing using primer **GSP2.** To quantitate ribozyme cleavage efficiency, the **15%** acrylamide gel with PCR products separated **by** gel electrophoresis was imaged using a ChemiDoc MP (Biorad, **CA, 170- 8280).** The band intensity of each fragment was integrated using ImageJ 1.47v (National Institute of Health, MD, http://imagej.nih.gov/ij/). The "rectangular selection tool" was used to select the region surrounding both the cleaved and uncleaved bands between **150 bp** and **250 bp.** Using the "gel analysis tools", band intensity was plotted, and background was subtracted to obtain a single value corresponding to the intensity of the cleaved and uncleaved band. The intensity of cleaved band was divided **by** the total sum intensity of both bands to obtain the fraction of cleaved mRNA.

5.3.7 In vivo ribozyme insulation assay.

The four ribozyme-insulator constructs (Figure **S3)** were transformed into separate aliquots of *E. coli* **NEB** 10-beta (New England Biolabs, MA, **C3019).** One colony from each transformant was inoculated into $1 \text{ mL of LB with } 20 \text{ kg/mL}$ chloramphenicol in a culture tube and grown for **16** hours at **37 0C** shaking at **250** rpm. The next day, the culture was diluted 178-fold (two serial dilutions of $15 \mu L$ into $185 \mu L$) into M9 glucose media with chloramphenicol in a V-bottom 96-well plate (Nunc, Roskilde, Denmark, 249952) and grown for three hours at **37 *C** shaking at **1000** rpm in an ELMI Digital Thermos Microplates shaker incubator (Elmi Ltd, Riga, Latvia). Next, the cells were diluted 658-fold (two serial dilutions of **15 pL** into **185** piL, then **3 pL** into 145 11L) into M9 glucose media with chloramphenicol and IPTG. IPTG concentrations used for the P_{Tac} constructs were: 0, 0.12, 0.48, 1.9, 7.6, 30.4, and 121.6 μ M; IPTG concentrations used for the P_{LlacO-1} were: 0, 1.9, 7.6, 30, 120, 490, and 1900 μ M. Cells were grown in

the same shaking-incubator conditions for six hours, and then 40 µL of culture was added to **160 pL** of phosphate buffered saline (PBS) with 2 mg/mL kanamycin to halt protein production. Cells were incubated in PBS for one hour to allow YFP to mature, and then flow cytometry was performed. The fluorescence values were white-cell subtracted, and then plots of **CI-GFP** production versus **GFP** production were created for both PTac and **PLlacO-1** (see Section **I.A.).**

5.3.8 Construction and screening of RBS libraries.

Mutations in the ribosomal binding site of several gates were introduced to shift the threshold of the gates' response curves. These RBS libraries were created using oligonucleotide primers containing multiple degenerate nucleotides in the **18** bases immediately upstream from the start codon. These primers were used to amplify the entire gate characterization plasmid using two primers diverging from each other at the gate's RBS. **100** ng of linear dsDNA PCR product was phosphorylated and ligated in a one-pot reaction using **0.5** pL of T4 **DNA** ligase (New England Biolabs, MA, **M0202S)** and **0.5** 1iL of T4 polynucleotide kinase (New England Biolabs, MA, **M0201S)** in **10 pL** IX T4 ligase buffer, and then transformed into **E.** *coli* **NEB** 10-beta (New England Biolabs, MA, **C3019).** Individual clones from the gate RBS library were screened **by** growing them in the presence and absence of 1 mM IPTG. Clones with the highest **ON/OFF** range were chosen for further characterization. The full response functions of these gates were measured (Methods), and a subset of the gates that had unique threshold values were kept (see Section **I.C).**

5.3.9 Gate construction and characterization.

To characterize gate response functions, the IPTG-inducible promoter **PTac** was positioned directly upstream from a gate expression cassette on the circuit backbone (without the 5'-insulating terminator L3S3P21). Following the P_{Tac} -driven gate expression cassette, the cognate promoter for the gate was positioned upstream from the standard RPU cassette. The plasmid backbone also encoded the sensors LacI and TetR in an operon driven from a constitutive promoter. These gate measurement plasmids were transformed into *E. coli* **NEB** 10-beta, and then a colony was inoculated into 200 **pl** of M9 glucose media with **50** pg/mL kanamycin in a V-bottom 96-well plate (Nunc, Roskilde, Denmark, 249952) and then grown for **16** hours at **37 *C** shaking at **1000** rpm in an ELMI Digital Thermos Microplates shaker incubator (Elmi Ltd, Riga, Latvia). The next day, liquid culture was diluted 178-fold (two serial dilutions of **15** 1iL into **185 pL)** into M9 glucose media with kanamycin and grown for three hours in the same shaking-incubator conditions. Subsequently, the culture was diluted 658-fold (two serial dilutions of **15** pL into **185** 11L, then **3 pL** into 145 pL) into M9 glucose media with kanamycin and IPTG to induce the gate. The IPTG concentrations used were used were: **0, 5, 10,** 20, **30,** 40, **50, 70, 100, 150,** 200, and **1000 pM.** Cells were grown for five hours in the same shaking-incubator conditions, and then 40 pL of culture was added to **160 pL** of phosphate buffered saline (PBS) with 2 mg/mL kanamycin to halt protein production. These cells were incubated in PBS for one hour to allow YFP to mature, and then flow cytometry was performed (see Flow cytometry analysis), the data was converted to RPU (see Conversion of fluorescence to RPU, below). In addition to the gate characterization, we also measured a strain containing a similar plasmid that contained **PTac** driving the YFP RPU cassette directly; we converted its fluorescent output to RPU. Three independent replicates were performed on three separate days for each measurement, and the average RPU was calculated.

We next plotted the average gate output RPU versus the average P_{Tac} -YFP RPU output to visualize the response of the gate output promoter activity as a function of **PTac** input promoter activity. This relationship was fit to a Hill equation using the Solver add-in for Microsoft Excel.

5.3.10 Characterization of gate impact on cell growth.

To quantify how growth is impacted **by** expression of various repressors, we constructed tandem inducible gate measurement plasmids to achieve higher levels of gate expression **(pJS101-109).** These plasmids are identical to the gate measurement plasmids ($p[Gate-RBS\#]$), with the exception that a tandem $P_{Tac}P_{Tet}$ promoter drives the gate expression cassette. We inoculated and grew these strains in an identical manner to the gate characterization experiments, except we used different inducer concentrations to span the wider inducible range of the tandem promoter. For each construct, we induced with seven IPTG concentrations: **0, 9.5, 19,** 48, **95, 290,** and **950 pM;** for an additional five samples, we induced with **950 pM** IPTG along with aTc at concentrations: **0.0095, 0.095, 0.29, 0.95,** and **1.9** ng/mL. These induced cells were grown for six hours in the same shaking-incubator conditions. After the induction experiment, 200 pl of cells were added to an optically clear bottom **96** well plate. The optical density of the cultures was measured at **600** nm using a BioTek Synergy H1 Hybrid Microplate Reader. We also measured 200 pl of blank media to determine the background absorbance of the media. For each gate, the final absorbance measurements were normalized to the absorbance of the first sample that had no inducer added (Figure **3d).**

Flow cytometry analysis. 5.3.11

Fluorescence was measured using an LSRII Fortessa flow cytometer (BD Biosciences, San Jose, **CA)** run **by** the BD FACSDiva software. An **FSC** voltage of 437 **V, SSC** voltage of **289** V, and a green laser **(488** nm) voltage of 425 V were used. An **SSC** and **FSC** threshold of >200 was used to limit collection to cell-sized particles. Between 10^3 and 10^5 gated events were collected for analysis. To calculate YFP fluorescence values for bar graphs, we used the flow cytometry software FlowJo (TreeStar, Inc., Ashland, OR), and used the median statistical tool. For conversion of the cytometry data to RPU, we used MATLAB to perform the fluorescence-axis transformations and to normalize the distributions.

5.3.12 Conversion of fluorescence to RPU.

The raw fluorescence from measurement of a sensor, gate, or circuit using the measurement protocol must be converted to relative expression units (RPU). The RPU standard used in this study differs from the Kelly standard (Kelly et *a,* **2009)** in that we use an upstream insulating terminator, a 5'-promoter spacer, and a ribozyme insulator to reduce contextual variations. We also maintain an identical RBS, YFP, terminator, and plasmid backbone to the circuit measurement constructs **(pAN1717). E.** coli **NEB** 10-beta (New England Biolabs, MA, **C3019)** were transformed with the RPU standard plasmid and plated on LB agar with 50 μ M kanamycin. Transformed colonies were inoculated into **1** mL M9 glucose media with kanamycin and grown for **16** hours at **37 'C** and shaking at **250** rpm. Next, the cells were diluted **178-fold** (two serial dilutions of **15** pL into **185 pL)** into M9 glucose media with kanamycin and grown for three hours in the same shaking-incubator conditions. Next, cells were diluted 658-fold (two serial dilutions of **15** pL into **185** pL and then **3 pL** into 145 pL) M9 glucose media and grown for six hours in the same shaking-incubator conditions.
At this point 40 11L of cells were added to **160 pL** of phosphate buffered saline (PBS) with 2 mg/mL kanamycin to halt protein production. Cells were incubated in PBS for an hour to allow YFP to mature, and then flow cytometry was performed. Additionally, un-transformed *E. coli* **NEB** 10-beta cells ("white cells") were grown in an identical manner alongside the RPU standard-harboring strain, but without any antibiotics. These cells' autofluorescence were measured using flow cytometry as well. After flow cytometry as performed, the median of YFP fluorescence was calculated for the both the RPU standard and the white cells.

The median fluorescence measurements of sensors, gates, and circuits were converted to RPU using the following procedure. The median autofluorescence value from the white cells was first subtracted from all fluorescence values to correct for this non-YFP derived signal. In our experiments with our cytometer settings, the white cell fluorescence was approximately **15** au. The median fluorescence of the RPU standard was also subtracted **by** the white cell fluorescence. Next, the experimental sample (sensor measurement, etc.) as divided **by** the median fluorescence of the RPU standard (after autofluorescence correction). In our experiments, our corrected RPU standard fluorescence is 460 au. To return values to corrected arbitrary units, multiply the RPU numbers **by** the RPU standard's median (460 au for our measurements).

5.3.13 Genetic circuit assembly.

The genetic circuits in this research comprise codon optimized repressors and their cognate promoters (from ref (Stanton *et a],* 2014)) with additional 5'-promoter spacers, hammerhead ribozyme-based insulators (from ref (Lou *et al*, 2012) and this work), ribosomal binding sites (from this work), and transcriptional terminators (from ref (Chen *et al.* 2013)). The sensors used include a truncated AraC (AraC-C280^{*}, referred to as AraC* in this work) that has reduced cross-talk with IPTG(Lee *et a],* **2007)** and its output promoter **PBAD** which is induced using L-arabinose; LacI and its output promoter with a symmetric lac-operator P_{Tac} which is IPTG-inducible(Dykxhoorn et al, 1996); and TetR with its output promoter $P_{Tet}(Lutz & Bujard, 1997)$. LacI and TetR are transcribed from the native **PLacI** promoter. AraC* is transcribed from BBa_J23105 and terminated **by** L3S3P22(Chen et *a],* **2013).** The circuit measurement backbone harbors a medium-copy **p15A** origin of replication and kanamycin resistance gene (from ref (Lutz **&** Bujard, **1997)).** The circuit insertion site is flanked **by** an upstream insulating terminator L3S3P21(Chen et *al,* **2013),** and a downstream insulating terminator the native AraC terminator TaraC. The actuator used in this research is a variant of yellow fluorescent protein (YFP)(Cormack et *a!,* **1996).** The output plasmid harbors a **pSC101** origin of replication(Lutz **&** Bujard, **1997)** and encodes the spectinomycin resistance gene, aadA. The output insertion site is flanked **by** an upstream insulating terminator L3S2P44(Chen et *a],* **2013)** and a downstream insulating terminator L3S2P21 (Chen et al, 2013). Each transcription unit for a circuit was cloned into a submodule plasmid with the ampicillin-resistance gene, ampR, and flanked on either side **by 4bp** scars and BbsI restriction enzyme recognition sites. To assemble a final circuit plasmid, submodule plasmids and the circuit measurement plasmid (with sensors already inserted) were mini-prepped prior to assembly (Qiagen, Limburg, 27104) and their concentration was measured using a NanoDrop **1000** spectrophotometer (Thermo Fisher Scientific, MA). In one tube, 40 fmol of each **DNA** plasmid were combined. In addition, 2 pL of ligase buffer, **0.5 pL** of T4 **DNA** ligase **HC** (Promega, WI, M1794), and 2 11L of BbsI (New England Biolabs, MA, R0539L) were added to the tube (Figure S41). Lastly, filtered, deionized water was added to the tube to a total volume of 20 µL. This mixture was heated and cooled in a thermocycler repeatedly: **37 'C** for 2 min, then **16 *C** for **5** min, repeated for **10-100** cycles, depending on the number of pieces of **DNA** being assembled **(10** cycles per piece of **DNA).** After the cycling, the reaction was heated to **50 *C** for **10** minutes to inactivate the ligase, and then 80° C to inactivate the restriction enzyme. Then, 10 μ L of assembly mixture was then transformed into **50** IiL of **NEB** 10-beta chemically competent *E.* coli, allowed to recover for an hour, and then plated on agar with antibiotics.

5.3.14 Hexadecimal and Wolfram Rule naming conventions.

The convention for naming 3-input circuits is to first order the input states so that P_{Tac} activity is the least significant input bit, P_{Tct} is the middle significance input bit, and **PBAD** is the most significant input bit. The corresponding expected output states for all inputs from **000** to **111** are converted to hexadecimal-four binary bits are converted to a single hexadecimal digit. The resulting two-digit hexadecimal number is listed after the hexadecimal indicator "Ox" to create a name of the form "OxNN". This is similar to the Wolfram Rule naming system, where the input rows are arranged **111, 110, ... , 001, 000** and then the binary output vector is converted to decimal (e.g., "Rule **110"** has binary output vector *01101110).*

5.3.15 Software tools.

The following software, languages, and libraries were used in this work. The Cello source code is written in Java (version **1.8.0_31)** with software project management **by** Apache Maven (version **3.2.1).** Constrained combinatorial designs of genetic architectures are produced using Eugene (version 2.0) (Oberortner et *al,* 2014), and the synthetic biology open language library **(libSBOLj** version **1.1)** is used to store circuit designs in a hierarchy of annotated **DNA** components (Galdzicki *et al,* 2014). Logic minimization uses Espresso (Brayton et *a],* 1984) (version **2.3)** and ABC(Brayton & Mishchenko, 2010) **(UC** Berkeley, version **1.01** March 2014).

Several figures for data visualization are generated during a Cello design run. Directed graphs are produced using Graphviz (version 2.34.0). Data plots for response function calculations and predicted output distributions are produced using Gnuplot (version 4.6). Part-based circuit representations are produced using Dnaplotlib, which uses the python matplotlib **2D** plotting library for programmable rendering of **highly** customizable genetic diagrams. **A** static plasmid image is produced using **EMBOSS** cirdna (version **6.6.0.0).**

The Cello web application is hosted using the Amazon Web Service (AWS) and is deployed using the Jetty web server (version **8.1.13).** The browser (client-side) sends data to and retrieves data from the Amazon server (server-side) using **AJAX** (Asynchronous JavaScript and XML). The web interface uses JavaScript, jQuery, and jQuery **UI** (version 1.10.2) for user-interactive event handling and dynamic interface manipulation. **CSS** Bootstrap (version **2.3.1)** is used to style the content, and CodeMirror (version **3.13)** is used for Verilog syntax highlighting.

For parameterizing Hill equations to response functions, the fit was performed **by** minimizing the sum of relative error magnitudes between the trend line and the data points using the Excel Solver add-in with the GRG Nonlinear solving method. The initial version of Cello that performed gate assignments **by** simulating input signal propagation through response functions was implemented using MATLAB version R2012a **(7.14.0.739).** Design of the Cello circuits library used the distribution propagation to screen for circuits, and used the simulated annealing algorithm with a temperature of **0.** Additionally, assignments using QacR, LitR, IcaRA, PsrA, and LmrA repressors were disallowed.

Ribozyme secondary structure was simulated using RNA mFold (Zuker, **2003)** (http://mfold.rna.albany.edu/?q=mfold/RNA-Folding-Form) using the following parameters: **37*C,** IM NaCl, **5** percent suboptimality folds computed, **50** maximum computed foldings, maximum interior bulge/loop size **= 30,** maximum asymmetry of an interior bulge/loop **= 30,** no limit for maximum distance between paired bases. Sequence alignments were performed with Clustal Omega (1.2.1) multiple **DNA** sequence alignment using the default parameters (http://www.ebi.ac.uk/Tools/msa/clustalo/). The ribozyme phylogenetic tree was also generated using Clustal Omega using the default tree format, distance correction **off,** exclude gaps off, the **UPGMA** clustering method, and the "real" phylogram branch length setting.

5.3.16 Precomputing 3-input 1-output NOR circuit diagrams.

In the library of user-defined circuit motifs (Section **V.C),** we used **a** precomputed list of small 3-input 1-output **NOR/NOT** circuits. These circuits were found **by** computationally enumerating all NOR/NOT circuits with ≤ 6 layers, evaluating each circuit's truth table, and then selecting the circuit with the fewest number of gates for each truth table. We computationally enumerated all circuits **by** constructing them in levels. Level **1** comprises the circuit input wires: **A,** B, **C,** and **0,** where **0** is a Boolean 'false'. Note that when **0** is one of the inputs to a NOR gate, this results in a **NOT** gate for the other input. To enumerate all circuits in Level 2, all pairwise combinations of Level **1** output wires **(A,** B, **C,** and **0)** are input into a NOR gate. For example, **(A** NOR B) is a Level 2 circuit. To enumerate all circuits in Level **3,** all pairwise combinations of wires containing an output from Level 2 and an output from any level are input into a NOR gate. For example, **((A** NOR B) NOR **A)** is an example of a Level **3** circuit. **If** the two circuits being joined have a duplicate logic motif (in the previous example, input **A** was specified twice), a fan-out wire is used and the redundant gates are removed. This process was continued until all Level **6** circuits were enumerated. After each individual circuit construction, the circuit's truth table output was evaluated. **If** the circuit used fewer gates than all previous circuits implementing that truth table, the circuit was stored until a smaller one was found. This algorithm resulted in small motifs for each 3-input 1-output circuit. We used these motifs for subcircuit replacement in the final step of logic synthesis.

5.3.17 RPU plasmid characterization using smRNA-FISH.

To determine the steady state number of *yfp* mRNA copies per cell at midexponential growth with the RPU standard plasmid **(pAN1717),** we used smRNA-**FISH** to label the *yfp* mRNA molecules. We designed a set of **25** oligonucleotide probes, fluorescently labeled with TAMRA, each 20 bases in length, against the yfp transcript (Table **S10)** using Stellaris Probe Designer version 4.1. Three independent replicates were performed on three separate days for each measurement, and the average number *of yfp* mRNA/cell was calculated.

Sample preparation. The RPU plasmid **(pAN1717),** the non-YFP plasmid **(pAN1201)** and the measurement plasmid **(pAN1818)** were transformed to create an RPU standard, a background control, and a standard curve for mRNA/cell estimates, respectively. The plasmids were transformed in separate reactions into *E. coli* NEB **10** beta (New England Biolabs, MA, **C3019),** grown on LB **+ 50** pg/mL kanamycin agar plates, and then a colony was inoculated into 200 µL of M9 minimal media with 50 pig/mL kanamycin in a V-bottom 96-well plate (Nunc, Roskilde, Denmark, 249952). The cultures were grown for **16** hours at **37** C shaking at **1000** rpm in an ELMI Digital Thermos Microplates shaker incubator (Elmi Ltd, Riga, Latvia). The next day, the liquid culture was diluted 178-fold into M9 minimal media with kanamycin and grown for three hours in the same shaking-incubator conditions. Subsequently, the culture was diluted 658-fold into M9 minimal media with kanamycin and IPTG to induce the YFP production from the **pAN1818** plasmid. The IPTG concentrations used were: **0,** 5, **10, 20, 30,** 40, **50, 70, 100, 150,** 200, and **1000** pmol/L. Cells were grown for five hours in the same shaking-incubator conditions, and then **6** mL of culture per sample was pooled together in **15** mL Corning centrifuge tube and the cells were pelleted **by** centrifugation (10 minutes, $4000 \times g$, 4 °C). The supernatant was removed and the cells were resuspended in **1** mL 1x PBS (diluted from 10x PBS, Ambion, **#AM9625)** to wash the cells.

The cells were transferred to RNase free microfuge tubes and pelleted **by** centrifugation (5 minutes, $4500 \times g$, $4 °C$). The supernatant was removed and the cells were resuspended in **1** mL freshly prepared **3.7%** formaldehyde (Fisher, #BP531) in $1 \times$ PBS (diluted from $10 \times$ PBS). The cells were then mixed on a nutator at room temperature for **30** minutes. The cells were pelleted **by** centrifugation **(8** minutes, $400 \times g$. The supernatant was removed and the cells were washed in 1 mL $1 \times$ PBS twice (i.e. resuspended in 1 mL $1 \times$ PBS, centrifuged at $600 \times$ g for 3.5 minutes, and supernatant removed). The cells were resuspended in **300** pL water and then **700** pL of **100%** ethanol was added and mixed twice to get to a final concentration of **70%** ethanol. The cells were left at room temperature with mixing on a nutator for **1** hour to permeabilize the cell membrane.

Hybridization procedure. After permeabilization, cells were centrifuged **(7** minutes, $600\times g$ and the supernatant was removed. The cells were resuspended in 1 mL of 50% formamide wash buffer **A** (Biosearch Technologies Cat no SMF-WA1-60). Reagents containing formamide were prepared fresh, right before use. The stock formamide was stored at -20 **"C** in **1.5** mL aliquots and thawed right before use. Next, **50%** formamide hybridization buffer (Biosearch Technologies Cat no SMF-HB1-10) was prepared **by** adding **12.5** pmol/L mixed probe stock to make a final **62.5** pmol/L probes concentration. The cells were then centrifuged (7 minutes, $600 \times g$) and the supernatant was removed. The cells were resuspended in 50 μ L of the 50% formamide hybridization buffer with probes and left to incubate in the dark at **30 *C** overnight. Next, 400 pL of **50%** formamide Wash Buffer **A** was added to the tube and mixed well. Cells were pelleted by centrifugation (7 minutes, $600 \times g$) and the supernation was removed. The cells were washed **3** more times (i.e. resuspended in 200 **pL** of **50%** formamide Wash Buffer A, incubated at 30° C for 30 minutes, centrifuged at $600 \times g$ for 3.5 minutes, and supernatant removed). 4',6-diamidino-2-phenylindole **(DAPI,** Fisher Scientific, #PI-46190) was added to the wash solution to a final concentration of **10** pg/mL in the last wash. The cells were resuspended in 500 μ L of Wash Buffer B (Biosearch Technologies Cat no SMF-WB1-20), centrifuged at $600 \times g$ for 3.5 minutes, and supernatant removed. The cells were resuspended in 40 μ L to 50 μ L of 2×SSC and imaged under the microscope.

Microscopy. 2 µL of sample was pipetted onto a 45 mm \times 50 mm $\#1$ coverslip (Fisher Scientific, $\#12-544F$). A 1 mm thick \times 10 mm \times 7 mm 1.5% agarose gel pad π (in 1 x PBS) was laid on the sample. A 22 mm \times 22 mm $\#1$ coversity (Fisher Scientific, $\#12-545B$) was placed on top of the agarose gel pad. The sample was imaged using an inverted epifluorescence microscope (Zeiss Axio Observer.Z1), a 100x, **N.A.** 1.46 oil immersion objective (Zeiss, alpha-Plan APO), and a cooled digital **CMOS** camera (Hamamatsu Orca Flash 4.0). The microscope and camera were controlled using the Zen Pro Software (Zeiss). The mRNA labeled **by** smFISH probes were imaged using a TAMRA filter set (Zeiss, 43 **HE),** a HXP-200 excitation light source set on **50%** intensity, and an integration time of **1** s. **DNA** stained **by DAPI** was also imaged using a multi-band filter set (Zeiss, **81 HE), 353** nm excitation with an **LED** source (Zeiss,

Colibri) set to **100%,** and an integration time of **50** ms. Zstacks with **9** slices and 200 nm spacing were acquired for bright field and TAMRA images. Each sample was imaged at multiple locations to get a total of at least **300** cells per sample.

Image and data analysis. Image processing and data analysis were performed using MATLAB and Mathematica. Cell recognition and segmentation was performed on brightfield images of cells using the *Schnitzcells* MATLAB module (Young *et al*, 2012). The program applies edge detection and other morphological operations, using the MATLAB Image Processing Toolbox. The output was checked and corrected using the manual interface offered **by** *Schnitzcells.*

Spot recognition was performed on the segmented TAMRA fluorescence images using the *Spatzcells* MATLAB module (Skinner *et a],* **2013).** The *Spatzcells* software detects each fluorescent spot within the segmented cell image stacks, finds its location **(x, y,** z-slice), and fits it to a 2D-Gaussian function to obtain the height and intensity of the spot.

Estimating mRNA copy numbers. For cells with low mRNA copy number, the smFISH spots are typically well separated within the cells, and so they can be visualized and counted as individual spots (see example images in Figure S33a). For cells with higher copy number, the spots overlap significantly. Quantitative estimation of the copy number for a full range of expression levels therefore requires a method for extrapolating from the low expression regime to the high expression regime. The mRNA target described in (Skinner *et al.* 2013) was relatively long $($ $\tilde{ }$ 3000 base pairs). so that **72** different probes (each ~20 nucleotides long) could be designed to span the length of the target sequence. The mRNA target for the measurement described here *(yfp)* is considerably shorter **(720** base pairs) so that only 20 different 20 nucleotide probes could be designed to span the target sequence (see Table **S10).** Consequently, the spot intensities (the heights of the fitted 2D-Gaussians) for the bright spots corresponding to intact *yfp* mRNAs were only partially resolved from the background, lower-intensity spots. Because of the partial overlap in the typical spot heights for the labeled mRNA and background spots, the thresholding method described in (Skinner *et a],* **2013)** for distinguishing the two types of spots did not work reliably. Therefore, a new method for extrapolation to high expression levels was used, based on the assumption that the total **FISH** fluorescence signal measured for each cell is a linear function of the number of mRNAs in the cell.

Briefly, for each sample, a histogram was constructed of the spot heights for all detected spots (see Figure **S33b),** and the histogram was fitted to a sum of two lognormal distributions to obtain estimates of the total number of dim spots and bright spots for that sample. For low-expression samples, the two spot populations were partially resolved and the fit was unconstrained (see, for example, Figure **S33b,** panel 2, "PTac-YFP **(10** 11M IPTG)"). The fits to the low expression sample histograms were used to define a constraint value equal to the mid-way point between the locations of the two fitted log-normals.

For higher expression, the location parameters for the $1st$ log-normal distribution was constrained to be less than the constraint value and the location parameter for the **² nd** log-normal was constrained to be greater than the constraint value. The total number of bright spots for each sample was estimated from the integrated area of the **² nd** log-normal (the one corresponding to the brighter spots) from each fit. The number of bright spots divided **by** the total cell area was then plotted vs. the average **FISH** signal per cell area, and the result was fit to a form assuming a Poisson filling process of the available image area with spots:

 $n_{spots} = n_{max} \left(1 - \exp \left(- \frac{x - \beta}{\alpha \cdot n_{max}} \right) \right)$, where n_{spots} is the number of bright spots per

cell area, x is the FISH signal per cell area, and the fitting parameters: n_{max} is the maximum number of resolvable spots per cell area, α is the typical FISH signal for a single mRNA, and β is and the background FISH signal per cell area (see Figure S33c). The linear portion of the fit curve was then used to extrapolate to higher expression levels, giving an estimate for the mRNA copy number for each cell: $N_{est.} = \frac{s - \beta \cdot A}{\alpha}$, where *S* is the total **FISH** signal for the cell and *A* is the image area of the cell (pixels). Example histograms of the estimated mRNA copy number are shown in Figure **S33d.** The mean mRNA copy number per cell was calculated for each sample.

The estimation procedure (including fitting to the spot height histograms, estimation of number of bright spots, fitting with the Poisson filling process model, and estimation of the mean mRNA copy number per cell) was done independently for each replicate experiment. The values obtained from the replicate measurements were then averaged to produce the final mRNA copy number per cell estimates as shown in Figure S33e.

6 Appendix: User Constraint File (UCF) for genetic circuit design automation

6.1 File overview

Verilog code is compiled to a circuit architecture that is defined **by** the user constraint file (Figure 4-45). This is a **highly** specified system that defines a particular library of gates as well as rules to be enforced for preferred logic motifs and genetic structure. In addition, it contains the definition of the particular strain and "landing pad" $(e.g., a defined set of plasmids or genomic locations)$ as well as the environmental conditions where the circuit models are valid. New UCFs can be developed for new gate libraries and/or strains and environments. While in practice a particular **UCF** may be valid for differing genotypes or changes in media/growth rate, out recommendation is that a new **UCF** file should be built for each end application.

This section describes the format of the **UCF,** as well as the specific Eco1C1G1T1 file used in this manuscript. Within the genetic gates library category, genetic parts and experimental data for the each gate are specified. The experimental measurements and associated standards for data in the **UCF** are described in Chapter 4. This section focuses on the data structure of the **UCF,** with the intention of guiding the composition of files for new gate libraries, organisms, and operating conditions.

6.2 File format

The **UCF** is specified using JavaScript Object Notation **(JSON). JSON** is a widely used and language-independent format based on attribute:value pairs, which is human readable, machine parseable, and can be converted to common data structures in other languages. In a **JSON** attribute:value pair, the values are restricted to these types: string, number, boolean, null, array (square brackets), and object (curly brackets).

SBOL XML was also considered as a file format for the **UCF.** SBOL Version **1.1** (Galdzicki et al, 2014) is tailored for specifying parts and composite parts in a genetic design hierarchy, where URIs (uniform resource identifiers) are used to uniquely and globally identify parts via the World Wide Web. While this format would be directly applicable for our *gate parts and parts* **UCF** collections, the other collections required a more flexible representation. However, the proposed versions of SBOL will have more versatile data model (Roehner *et al.*, 2015), have the ability to specify custom objects, and will be able to read/write data in **JSON** format.

Required collections:

header, measurement std, logic constraints, gates, response functions, gateparts, parts

These collections specify the experimental system, the available gate types for logic synthesis, response function data for assignment, and gate parts to build the final **DNA** sequence.

Optional collections:

motif library if omitted, subgraph substitution will not occur as an optimization step in logic synthesis.

gate_ cytonetry if omitted, the output predictions will be median values, as opposed to cytometry distributions.

gate toxicity if omitted, the prediction of growth impact will not be calculated. *eugene_ rules-* if omitted, unconstrained circuit layout design will occur. This will result in variations in tandem promoter order, variations in gate order, and variations in gate orientation.

geneticlocations- if omitted, the output **DNA** sequence will contain the circuit components only, and the user will be responsible for deciding and implementing the genetic context of the circuit design.

In the sections below, each describes a different collection with a brief description and a box containing an example object. For all collections, attribute names are parsed in Cello.

6.2.1 Header

The header collection specifies the operating conditions, strain, and genetic location where the gate measurements were made and the circuit predictions would be valid. These data do not impact circuit design in Cello. However, it is required to describe the operating conditions for which the circuit designs are valid. Thus, it is required **by** Cello to accept the file as a valid **UCF.**

version: This demarcates the iteration of the **UCF.** Version updates could include larger gate libraries, changes in experimental conditions, more accurate data, etc. Our current numbering system is shown below, but this particular format is not required. example:

"version": "Eco1C1G1T1"

<string> Organism identifier (Eco for *E. coli)*

Eco<number> Strain identifier (counting up from **1;** Ecol **= NEB** 10-beta)

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C<number> Experimental conditions identifier

G<number> Genetic gates and insertion location identifier

T<number> Technology mapping and motifs identifier

required: yes

author: Intended to help document versions and modifications of UCF files.

required: no

"collection": "header",

"version": "EcolClGlTl",

"date": "2015-04-08",

"author": ["Bryan Der", "Alec Nielsen', "Prashant Vaidyanathan"],

"organism": "Escherichia coli **NEB** 10-beta",

"genome": **"NEB** 10-beta A(ara-leu) **7697** araD139 fhuA AlacX74 galK16 galE15 e14- ϕ 80dlacZAM15 recA1 relA1 endA1 nupG rpsL (Str^a) rph spoT1 Δ (mrr-hsdRMS-mcrBC) (New England Biolabs)",

''media'': ''M9 minimal media composed of M9 media salts (6.78 g/L Na₂HPO,, 3 g/L KH₂PO,, 1 **g/L NHCl, 0.5** g/L NaCl, *0.34* **g/L** thiamine hydrochloride, 0.4% D-glucose, 0.2% Casamino acids, 2 mM **MgSO,** and **0.1** mM CaClb; kanamycin **(50** ug/ml), spectinomycin **(50** ug/ml)",

"temperature": **"37",**

"growth": "Inoculation: Individual colonies into M9 media, **16** hours overnight in plate shaker. Dilution: Next day, cells dilute -200-fold into M9 media with antibiotics, growth for **³**hours. Induction: Cells diluted -650-fold into M9 media with antibiotics. Growth: shaking incubator for **5** hours. Arrest protein production: PBS and 2mg/ml kanamycin. Measurement: flow cytometry, data processing for **REU** normalization.

organism: Defines the organism, species, and strain for which the circuits are compiled.

example:

 $\overline{}$

"organism": "Escherichia coli **NEB** 10-beta"

required: yes

allowed values: should be the full organism name

genome: Specifies the genotype of the organism.

example:

"genome": **"NEB 10** A(ara-leu) **7697** araD139 fhuA AlacX74 galK16 galE15 e14- φ 80dlacZ \triangle M15 recA1 relA1 endA1 nupG rpsL (StrR) rph spoT1 \triangle (mrrhsdRMS-mcrBC)"

example:

"genome": "K-12 **MG1655*** [F-lambda-ilvG-rfb-50 rph-1 A(araCBAD) A(LacI)] required: yes

allowed values: any string, including the entire genome sequence

temperature: Specifies the temperature at which the circuits are expected to perform (and gates measured).

required: yes

allowed values: units of Celsius

growth: Specifies the growth conditions at which the circuits are expected to perform (and gates measures).

required: yes

6.2.2 Measurement standard

This collection specifies the unit of measurement that is used for all signals (sensor **ON/OFF** levels, gate response functions, output levels). The standard unit in **UCF** Eco1C1G1T1 is RPU (relative expression unit). It also includes a description of the standard plasmid, which contains a constitutively expressed YFP cassette from a standard promoter with ribozyme insulation, the complete plasmid **DNA** sequence for the plasmid is specified, and instructions for normalization.

required: yes

"collection": *"measurement_* std",

''signal carrier units" **: "REU'',**

"plasmid description": "p15A plasmid backbone with kanamycin resistance and a YFP expression cassette. Upstream isulation **by** terminator **L3S3P21** and a 5'-promoter spacer. Promoter BBaJ23101, ribozyme RiboJ, RBS BBa B0064 drives constitutive YFP expression, with transcriptional termination **by L3S3P21.',**

"plasmid sequence'': [all lines of the Genbank file (not shown) for the measurement standard plasmid],

"normalization instructions": "The following equation converts the median YFP fluorescence
to REU. REU = (YFP - YFPO)/(YFPREU - YFPO), where YFP is the median fluorescence of the cells
of interest, YFPO is the median autof

signal carrier units: Different circuit design frameworks might use different units for quantifying high **/** low signals. **If** a different unit is used, the unit should be used for all signal-related fields in a **UCF** *(response_ function, gate_ cvtometl:v, gate toxicity*). The following data should all have the same signal carrier unit: sensor **ON/OFF** levels and gate response function input/output levels. For example, in *EcolCIGiTi, response_ finction* collection is generically written, but the input/output response has units of RPU as specified **by** this attribute.

required: yes

example: RPU

plasmid description: Instructions and experimental conditions for normalizing experimental measurements for the standardized units (RPU in Eco1C1G1T). Instructions should include the full plasmid name, growth, measurement, and other conditions necessary to normalize the data.

required: yes

allowed values: plain text

plasmid sequence: Plasmid **DNA** sequence containing the expression cassette that serves as the measurement standard for normalization of all signal levels in the **UCF** (RPU).

required: yes

allowed values: Genbank file format, with or without annotations before the sequence.

normalization instructions: **A** brief set of instructions describing how data is normalized using the measurement standard.

required: yes

6.2.3 Logic constraints

In this collection, the allowed Boolean gate types are specified, and the maximum number of instances is specified for each gate type. These Boolean constraints cannot exceed the genetic gates available in the library, but they can be more restrictive. For example, if 12 NOR gates are in the library, the user could constrain logic synthesis to use a maximum of **9** NOR gates. Furthermore, if there are 20 **NOT** gates in a library but only 12 unique repressors due to RBS variants, the Boolean constraint would be 12 **NOT/NOR** gates.

```
"collection": "logic constraints",
"available_gates": [
     ''type'" : "NOR",
     ''max instances" : 12
     "type" : "OUTPUT OR",
     ''max instances" : null\overline{1}
```
available gates: Specifies a gate type and maximum number of instances of each gate type for a circuit topology from logic synthesis.

required: yes

 \mathbf{f}

Note: **A** 1-input NOR gate is equivalent to a **NOT** gate, so a value of 12 for *max_ instances* indicates a maximum of 12 NOR **+ NOT** gates in the circuit.

Note: An **OUTPUT OR** gate does not require a transcription factor, so a value of null indicates that there are no restrictions on the number of OUTPUT OR gates in the circuit.

Note: Specifying fan-in constraints, such as allowing a 3-input NOR gate motif, is not done here. This NOR motif would be specified in the *motif library* collection.

6.2.4 Motif library

In this collection, the user can define logic motifs that can be swapped for logically equivalent subcircuits in the last stage of logic synthesis. Subcircuits are specified using a "netlist" format (Sleight *et al*, 2010), which is standard for specifying the connectivity of a list of gates. Specifying subcircuits in this way is similar to specifying structural

Verilog, and the input names and output names must be defined before listing the gate connectivity.

```
"collection": "motif library",
  ''inputs'' : [ ''a'' , ''b'' , '' c'']
  ''outputs" ["y"
  "netlist":
    "NOT(WireO, b)",
    "NOR(Wirel, Wire0, c)",
    "NOR(Wire2, Wirel, a)",
    "NOR(Wire3, Wire2, a)",
    "NOR(Wire4, Wire2, Wirel)",
    "NOR(y, Wire3, Wire4)"\mathbf{I}\overline{)}
```
inputs, the names of input wires

example:

"inputs" $:$ $[$ "a","b","c" $]$

example:

```
"inputs" : ["in1","in2","in3"]
```
required: yes

allowed values: input names must match the input wire names in the netlist.

outputs, the names of output wires. Allows single- or multiple-output subcircuits to be defined.

example:

"outputs" **: I"y"]**

example:

"outputs" : ["out1","out2"]

allowed values: output names must match the output wire names in the netlist.

netllst **A** gate type is listed, followed **by** the output wire name, followed **by** the list of input names. The examples show a multi-level (layered) **NOR/NOT** motif, an **OUTPUT** OR motif, a 3-input NOR motif, and a primitive AND motif:

example of a precomputed **NOR/NOT** motif:

```
"netlist": [
```
"NOT(WireO, **b)",**

"NOR(Wire1, Wire0, c)",

"NOR(Wire2, Wirel, a)",

"NOR(Wire3, Wire2, a)",

"NOR(Wire4, Wire2, Wirel)",

```
"NOR(y, Wire3, Wire4)
```

```
\mathbf{I}
```
example of an **OUTPUT OR** gate motif:

" $netlist"$: \lceil

```
"OUTPUT OR(y, a, b)"
```
I

example of a 3-input NOR. gate motif:

"netlist" **:** [

```
"NOR(y, a, b, c)"
```
I

example of an **AND** gate motif:

"netlist" **:** [

```
"AND(y, a, b)"
```
I

required: yes

 \sim

allowed values: gate names are restricted to **NOT,** NOR, **AND,** OR, OUTPUT OR, NAND, XOR, XNOR.

6.2.5 Gates

Gates in the library are specified in this collection. This is **a** concise collection that does not include other gate-related data collections (gate parts, response functions, gate cytometry, gate toxicity). For modularity, these data are stored in other collections, which are linked to the gate through the gatename attribute. The attribute system allows other genetic logic systems to be specified in future versions, including zinc fingers, TALEs, CRISPRi, activator-chaperone pairs, etc.

 $\overline{1}$ "collection": "gates", ''group name'' **:** "BM3Rl", "gate name": ''B3_BM3R1'', "gate_type<mark>": "</mark>NOR", "system": "TetR",

group name: this attribute is used to group variants of gates that cannot be used together in a circuit design. For example, all RBS variants of a certain repressor (B1_BM3R1, B2_BM3R1, B3_BM3R1) would belong to the same group (BM3R1), since a repressor is can only be used once per circuit assignment. Furthermore, if known cross-talking interactions between different repressors are known, these could also be put into the same group. Similarly, if homologous recombination is a concern and two gates have the same large part, then they can be placed in the same group.

required: yes

allowed values: Using the repressor name would be typical for RBS variants, but any name can be used.

gate name: this attribute is used to link gate data in other collections to the gate *object (response_ function, gate parts, etc).*

required: yes

allowed values: Only alphanumeric and underscore characters are allowed, which complies with allowed names in the Eugene language. The gate name must be identical to the string used in the *gate name* attribute in other collections

gate type: used during the assignment algorithm; for example, a genetic NOR gate cannot be assigned to an **AND** gate in the circuit topology.

required: yes

allowed values: NOR, **NOT,** OR, **AND, NAND,** XOR, XNOR. Note: To allow for multiple inputs, **NOT** gates must be specified here as a NOR gate. **If** a repressing gate can only have a single input, the gate type can be **NOT.**

system: used to specify the type of biochemistry from which the gates are built. **A** single **UCF** could have gates based on different biochemistries.

required: yes

allowed values: any string, such as "TetR", "CRISPRi", or "Activator-chaperone"

6.2.6 Gate parts

This collection specifies the transcription units and output promoters for a genetic gate, which is mapped to a gate through the *gate name* attribute. **A** NOR or **NOT** gate may have a different number of parts compared to, say, an **AND** gate. Thus, the

transcription units attribute is an array instead of a single object for flexibility for different genetic gate types. As with Boolean primitive gates, all genetic primitive gates are restricted to have a single output promoter. The restriction of a single output promoter name is not to be confused with fan-out, where multiple instances of the named promoter are used in the circuit.

```
\sqrt{ }"collection": "gate_parts",
   "gate_name": "A2_AmtR",
   'transcription units": [
        "BydvJ", "A2", "AmtR", "L3S2P55"
  \mathbf{1}.
  "promoter": "pAmtR"
\overline{\mathbf{3}}
```
gate name: The name of the gate.

required: yes

allowed values: the name must be identical to the *gate_ name* value in the gate collection.

transcription units: The part composition of the gate. The regulable promoter is listed separately from the transcription unit, because the promoter driving the transcription unit depends on the circuit diagram.

example:

Some gate types might require two transcription units, such as an activatorchaperone **AND** gate (Moon *et al,* 2012). For this reason, the value of this attribute is an array of arrays. The first element of the array is the transcription unit for InvF, and the second element of the array is the transcription unit for SicA:

"collection": "gate parts",

"gate name": "SicA-InvF",

"transcription units": \int //note that this begins the outer array

I //element 1 of the inner array

"RiboJ11", "RBS-InvFO", "InvF", "M13"

I //element 2 of the inner array

"RiboJ10", "RBS-SicA0", "SicA", "BBa B1006U10"

 \vert ,

 \mathbf{I}

1,

"promoter": "pSicA"

required: yes

allowed value: array of arrays. The outer array contains the list of transcription units, excluding promoters, and the inner array contains the list of part names that make up each transcription unit. The part names can be any string, but the string must match a part name in the *part* collection.

promoter: The output promoter of a gate.

required: yes

allowed value: single promoter name (alphanumeric and underscore characters only).

6.2.7 Parts

This collection specifies basic genetic parts: promoters, ribozymes, ribosome binding sites, coding sequences, terminators, scars, spacers, etc. This collection specifies the part name, part type, and part **DNA** sequence. The part names listed in the *gate parts* collection must match a part name from this collection. For example, all parts used in the A2 AmtR gate from the previous section are specified:

```
\sqrt{ }"collection": "parts",
      "type": "ribozyme",
      "name": "BydvJ",
      "dnasequence":
"CTGAAGGGTGTCTCAAGGTGCGTACCTTGACTGATGAGTCCGAAAGGACGAAACACCCCTCTACAAATAATT TTGTTTAA"
    \overline{\phantom{a}}
```

```
\overline{1}"collection": "parts",
  "type": "rbs",
  "name": "A2",
  "dnasequence": "AATGTTCCCTAATAATCAGCAAAGAGGTTACTAG"
\mathbf{r}
```
 $\overline{1}$ "collection": "parts", "type": "cds", "name": "AmtR", "dnasequence":

"ATGGCAGGCGCAGTTGGTCGTCCGCGTCGTAGTGCACCGCGTCGTGCAGGTAAAAATCCGCGTGAAGAAATTCTGGATGCAAGCGCAGAACTG TTTACCCGTCAGGGTTTTGCAACCACCAGTACCCATCAGATTGCAGATGCAGTTGGTATTCGTCAGGCAAGCCTGTATTATCATTTTCCGAGCA AAACCGAAATCTTTCTGACCCTGCTGAAAAGCACCGTTGAACCGAGCACCGTTCTGGCAGAAGATCTGAGCACCCTGGATGCAGGTCCGGAAAT GCGTCTGTGGGCAATTGTTGCAAGCGAAGTTCGTCTGCTGCTGAGCACCAAATGGAATGTTGGTCGTCTGTATCAGCTGCCGATTGTTGGTAGC GAAGAATTTGCAGAATATCATAGCCAGCGTGAAGCACTGACCAATGTTTTTCGTGATCTGGCAACCGAAATTGTTGGTGATGATCCGCGTGCAG AACTGCCGTTTCATATTACCATGAGCGTTATTGAAATGCGTCGCAATGATGGTAAAATTCCGAGTCCGCTGAGCGCAGATAGCCTGCCGGAAAC CGCAATTATGCTGGCAGATGCAAGCCTGGCAGTTCTGGGTGCACCGCTGCCTGCAGATCGTGTTGAAAAAACCCTGGAACTGATTAAACAGGCA GATGCAAAATAATAA"

 $\bar{1}$

```
"collection": "parts",
"type": "terminator",
"name": "L3S2P55",
"dnasequence": "CTCGGTACCAAAGACGAACAATAAGACGCTGAAAAGCGTCTTTTTTCGTTTTGGTCC"
```
type: The part class.

required: yes

allowed values: any string, but the string might be used during enumeration of part-based Eugene rules, and will be used for annotation of the output **DNA** sequence.

name: The name of the part.

required: yes

allowed values: the part name must match the part name specified in the *gate parts* collection.

dnasequence: The sequence of the part.

required: yes

allowed values: only ATCGatcg characters and the **DNA** sequence is in the forward orientation.

6.2.8 Response functions

This collection specifies the response function for a gate identified **by** the gate_name attribute. The response function includes a mathematical equation as well as a set of parameters that map to the variables in that equation. Different gate types may be captured **by** different mathematical forms and this can be specified in this

collection. For **NOT/NOR** gates, a Hill equation describes the cooperative and monotonic decrease in output with respect to input, and the parameters y_{max} , y_{min} , K, and n are fitted from experimental data for each gate. Note that **ymax, ymin,** and K are specified generically without units; units are described in the header collection, and these units should be used consistently throughout all data related to signal levels.

Cello uses a math evaluator that solves equations expressed as strings. User-defined equations with user-defined parameters can be accommodated, as long as parameter names match the variable names in the equation string. This is an example of a Hill equation for the A2_AmtR gate:

```
\mathbf{I}"collection": "response_functions",
  "gate-name": "A2 AmtR",
   "variables": ["x"
   "parameters'':
     \left\{ \right."name": "ymax",
        ''value": 13.18696
     \mathcal{E}\mathfrak{t}''name'': 'ymin'',
        ''value": 0.316394
     \mathcal{E}\mathbf{f}''name" : "K",
        ''value": 0.169953
     \},
     \mathfrak{f}''name" : ''n'
        ''value": 1.319126
     \},
  \mathbf{1}"equation": "ymin+ (ymax-ymin) / (1.0+(x/K)^n)"
\rightarrow
```
gate name: The name of the gate.

required: yes

allowed values: name must match the intended gate name from the *gate* collection.

variables: The input to each gate; for example, the activity of the input promoter. example: if there are multiple inputs (x and **y)** to the response function:

"variables": $[$ "x", "y"],

required: yes

allowed values: array of strings, where each string must match a variable name in the equation.

parameters: Definition and numerical value of each parameter in the response function.

required: yes

allowed values: array of objects, where each object is a parameter with a name attribute and value attribute. The name must match the equation string.

equation: The mathematical form of the response function.

example: a two input response function, this equation can be used for an **AND** gate:

"equation": $-\log(D) + ((A-D)/(1+((x/C)^B)) + D + ((A-D)/(1+((y/C)^B)))$), required: yes

allowed values: right-hand side of an equation of interest; the calculated lefthand side value is returned **by** the evaluate function. It can take any form and is not restricted to a Hill equation. The math evaluator class supports common operators, constants, and functions such as:

power

```
* multiply
       implicit multiply
\overline{1}/ divide
       + add
       subtract
LN2 natural log
loglo log base 10
       min minimum of
       max maximum of
       sqrt square root
```
6.2.9 Gate cytometry

This collection specifies histograms that describe the response function of each gate. Note that cytometry data is not required for Cello to run, but including it allows Cello to predict distributions for the simulated circuit output. In its absence, the output of Cello will be predicted values, as opposed to predicted cytometry distributions.

When the response function is characterized, a set of distributions is measured for different activities of the input promoter. Thus, *cytometry data* for a gate must be in the form of an array, where each element of the array represents a promoter activity. The data could represent one representative experiment or could be obtained **by** averaging the distributions from experimental replicates. In the *cytornetry_ data* data structure, an input signal level (input) is paired with a histogram representing the measured output level *(output bins, output counts).* Importantly, cytometry data must be consistently binned for all gates; the number of bins **(NBINS),** minimal value **(MIN),** and maximum value (MAX) must be used when generating the histogram for a cytometry sample. This consistency is required to propagate distributions through each layer in the circuit. Typical values would be:

NBINS **= 250.** MAX **= 100.** (RPUs, linear space, not log space) MIN **= 0.001.** (RPUs, linear space, not log space)

To generate the cytometry data for Cello, fluorescence values from flow cytometry must first be converted from arbitrary units to RPUs. This process is described in

Chapter 4. Thus, for a single response function, each titration point with a defined input level has a corresponding histogram. These discrete titration points are used to generate a continuous distribution response function **by** overlaying histograms on the median determined **by** the Hill equation. As a result, any input RPU value can produce a predicted output histogram. In Cello, a single histogram can still be used to generate histograms for the entire distribution response function (if the parameters for the average response function are provided), though histograms from **8** or more titration points are the expected use case.

input: This attribute specifies the input promoter activity of the distribution.

required: yes

allowed values: a single RPU value for the current titration.

output bins: For the given input level of the current titration, the bins of output levels are listed.

required: yes

allowed values: an array of values (RPU) specifying the histogram bins. The array length (number of bins) must be the same for all histograms specified in this collection. When generating the histogram, binning must be done in log space **(loglO** RPU), but the bin values must be specified in linear space (RPU). For consistency in the **UCF,** all RPU values are specified in linear space.

output counts: counts for each output bin.

required: yes

allowed values: an array of counts for the histogram. Counts can be integers, or fractional counts: Cello will normalize each histogram so the sum of all counts equals **10,000.** The array length must be the same as the *output bins* array, and must be the same for all histograms specified in this collection. Scientific notation **(E)** is allowed for very low fractional count values.

Thus, the **JSON** object for each cytometry titration point consists of the attributes *input, output bins, and output counts.* Each titration point is listed in an array representing the full response function titration, and this array of objects is the value of an attribute called *cytometry data:*

cytometry data: list of titrations for characterizing a response function using flow cytometry

required: yes

allowed values: a list of **JSON** objects for each titration point, described above *(input, output bins, and output counts).* Note that the number of titration points can range from **1** to **N,** where **N** is any number of titration points used in response function characterization. Unlike the histogram binning, which must be consistent across all gates, the number of titration points can differ across gates.

An example of a JSON object in the gate cytometry collection is shown below. For readability, only two titrations with a small number of values are shown. Notice that the output_c bins are consistent, but the output counts vary between titrations. See the provided **UCF** for an example of this organization.

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```
\overline{1}"collection": "gate cytometry",
  "gate name": "B3 BM3R1",
   "cytometry data":
     \left("input'' : 0.018,
                          ''output bins": [ ... 0.129, 0.136, 0.144, 0.152, 0.161, ... 1,
       ''output counts": [ ... 0.005, 0.002, 0.003, 0.001, 0.0005,...]
     \} ,
       ''input": 0.028,
       ''output bins": [ ... 0.129, 0.136, 0.144, 0.152, 0.161, ...
       ''output counts": [ ... 0.002, 0.003, 0.004, 0.004, 0.003, ...
    \overline{\mathcal{X}}(only two titration points shown)
\rightarrow
```
6.2.10 Gate toxicity

This collection specifies the growth curve for each gate. The object has two data attributes: "input" is the input level (promoter activity in standard units) driving expression of the gate, and "growth" contains growth values normalized **by** a control cell population. **A** value of **1.0** indicates full growth, and a value of **0.0** indicates no growth. Growth measurements could take the form of OD_{600} endpoint measurements, cytometry events, growth rates, colony counts, etc. In this manuscript, growth values are OD_{600} endpoints when P_{Tac} is driving the NOT gate, divided by the OD_{600} of cells with P_{Tac} driving YFP. Because titrations are discrete and input levels during circuit simulation are continuous, an input promoter activity requires interpolation of the data to generate a growth value for that specific input level. Interpolation is used to compute a growth value that is a weighted average of the two nearest *growth* values, where the weight is determined **by** proximity of the input level to the two nearest *input* values. **If** an input level is less than the lowest input in the growth curve, the

first growth value is used. **If** an input level is greater than the highest input in the growth curve, the last growth value is used.

gate name: The name of the gate.

required: yes

allowed values: gate name must correspond to the correct name in the *gate* collection.

input: promoter activity driving expression of the regulator.

required: yes

allowed values: input RPU values used in the growth curve titration. Values must be ordered from low to high.

growth: normalized cell growth measurement.

required: yes

allowed values: growth values normalized **by** a control cell population. The length of the array must be equal to the length of the *input* array. After Cello reads the data, values ≤ 0.0 will be set to 0.0, values > 1.0 will be set to 1.0.

6.2.11 Eugene rules

This collection specifies constraints on the physical layout of the circuit, written using Eugene (Oberortner *et al*, 2014). These rules are used in tandem with combinatorial design algorithms to build the **DNA** sequence of the circuit that is the output of Cello. In addition, these rules will be enforced if more than one construct is designed. Our use of the Eugene rules is organized into two attributes in this **UCF** collection: *eugene part_ rules and eugene gate rules.* Due to the hierarchical Eugene specification, rules are applied to the parts within a gate device separately from the rules applied to the gates within a circuit device (Section V.E). Note that "device" is a Eugene term for a collection of parts, or a collection of other devices. Rule is also a Eugene term, where a rule is applied to a device to constrain its design.

Part rules. The part rules in the Eco1C1G1T1 **UCF** enforce the following. Roadblocking requires that a promoter *(e.g., P_{SrpR})* be in the upstream position of a NOR gate. In other words, when PSrpR is in the forward orientation, PSrpR must be the first part in the gate device (and this is inverted if the gate is in the reverse orientation). Roadblocking is not the only reason to enforce particular promoter orders and this is a generalized approach to constraining a particular part order.

example:

STARTSWITH pSrpR

In EcolC1G1T1, we also use rules to constrain a preferred promoter order (Figure 4-13).

example:

pAmtR BEFORE pBetl

For a given gate device in the Eugene file (Section V.E), all part rules are parsed from the **UCF,** but a part rule will not be applied to the gate device if the gate does not contain a part with that name.

Gate rules. Gate rules can be used to specify the order in which regulators appear in the circuit construct. Because the **UCF** must accommodate any possible circuit assignment, a combinatorial list of rules is needed to constrain the gate order for any assignment. Given a circuit assignment, Cello scans all of the *eugene gate rules,* and if any gate name in a rule is absent from the current assignment, that rule is omitted. For example, the rule below would be omitted if PhIF is not assigned to the current circuit.

example:

gate PhlF BEFORE gate BM3R1
Note that some gate rules do not list a gate name, such as ALL FORWARD. For the ALLFORWARD rule, no gate names are parsed, so it is not possible for the ALL_FORWARD rule to be omitted based on the gates assigned to the circuit.

examples:

ALL FORWARD

(all gates will be in the **5'** to **3'** forward orientation)

ALTERNATE ORIENTATION

(example: gate **1** forward, gate 2 reverse, gate **3** forward, gate 4 reverse)

(example: gate **1** reverse, gate 2 forward, gate **3** reverse, gate 4 forward)

SOME REVERSE

(one or more gates will be in the **3'** to **5'** reverse orientation)

eugene part rules. rules that constrain parts within a gate device

required: no

allowed values: Any Eugene rule can be used(Oberortner *et al,* 2014). Part names in the Eugene rules must be identical to the part names specified in the *parts* collection of the **UCF.**

eugene gate rules: rules that constrain gate order/orientation within a circuit device

required: no

allowed values: Any Eugene rule can be used(Oberortner *et al,* 2014). Gate names must follow a naming convention for correct automatic generation of the Eugene file. This convention uses the "gate_" prefix followed **by** the repressor name, for example gate PhlF.

6.2.12 Genetic location

This collection defines the physical location of the sensor module, circuit module, and output module in the context of the plasmid and/or genomic landing pads. The sensor module encodes the transcription factors that are required **by** the sensors. This could be a transcription factor and its necessary transcription/translation parts *(e.g.,* promoter, RBS, AraC, terminator). **If** all of the machinery is endogenous to the host organism, then there may not be a sensor module. The circuit module encompasses the circuit designed **by** Cello. The output module contains the circuit regulable promoter(s) assigned to the output gates in the circuit, followed **by** the actuator gene(s) of interest. Note that the locations for each of the modules may differ from the context in which the gates were characterized. Attributes are provided for correction factors to be included *(e.g.,* to correct for copy number or the fluorescent protein used).

locations: This attribute lists genetic locations that will be referred to **by** name in the sensor, circuit, and output location attributes.

name: the name of the plasmid or genomic landing pad.

required: yes

allowed values: Any string, but the name needs to be internally consistent when referred to in the *sensor* module *location, circuit module location*, and *output module_ location* objects.

file: The **NCBI** sequence file for the plasmid.

required: yes

allowed values: all lines of the GenBank file. The GenBank file can have annotations prior to the first base pair of the **DNA** sequence, but the sequence should have the following format.

The **JSON** collection for *genetic locations* is given below, but **DNA** sequence files are not shown. Note that each of the locations is structured as an array of objects, where each object is a location. The example only includes one location per array, but there might be designs that require multiple sensor modules. It is also possible to insert sensor modules in series, rather than concatenating individual sensor modules ahead of time. Thus, the **UCF** is written to accommodate a list of locations for each type of module (sensor, circuit, output).

```
\{: ''geneticlocations',
''collection''
      "locations" : [
                  ''name'' :
''file' :
                                             ''pAN1717",
FULL GENBANK FILE NOT SHOWN, SEE BELOW
          \overline{1}''name'' : ''pAN1201'',<br><mark>''file'' : FULL GENBANK FILE NOT SHOWN, SEE BELOW</mark>
           \},
           \mathfrak{c}''name'' : ''pAN4020'',<br>''file'' : FULL GENBANK FILE NOT SHOWN, SEE BELOW
          \overline{ }\begin{array}{c} \end{array}"sensor\_module\_location" :
              \mathbf{f}"location-name": "pAN1201",
"bp range" : [58, 556]
             \overline{1}\begin{array}{lll} \texttt{''circuit\_module\_location''} & \texttt{:} \\ \texttt{[} & \text{"location name": "pAN1201',
"bprange" : [58, 556]
                   \,\mathbf{1}"output_module_location":<br>[
                       "location name": "pAN4020'',
                       "bp range"' : [953, 953],
'unit conversion" : 0.40
                   \overline{1}\mathbf{I}}
```
sensor module location: genetic location where the sensor module (if any) will be inserted. The sensor module encodes transcription factors that regulate the circuit input promoters, and contain all of the necessary parts for expression (constitutive promoter, RBS, **CDS,** terminator).

required: yes

circuit module location: genetic location where the circuit module will be inserted. The circuit module is designed **by** Cello, and it contains the user-defined input promoters, and parts from the Cello gates library.

required: yes

output module location: genetic location where the output module will be inserted. Expression of the output module/modules is/are driven **by** the promoters assigned **by** Cello.

required: no

location name: the name of the GenBank file listed in the *locations* attribute where the module(s) will be incorporated.

bp range: the starting and ending base pair numbers in the GenBank file where the module will be inserted.

allowed values: to insert without removing any bases, the start, end base pair numbers will be the same. **If** region of **DNA** is removed during cloning, for example, a region between two restriction sites, the start, and base pair numbers should span that range.

unit con version: **If** the output plasmid differs from the plasmid used to characterize the circuit, a conversion factor may be necessary. One example would be if it has a different copy number. In the case of the EcolC1G1T1 **UCF,** we measured a conversion factor of 0.40 to convert promoter activities on **p15A** (RPU) to promoter activities on **pSC101** (RPU) (Methods). **All** output levels (RPU) are multiplied **by** this conversion factor.

The sensor, circuit, and/or output modules could be inserted into the genome, rather than plasmids. Here we provide an example of a possible specification for choosing a genomic site for the circuit output module. This example specifies genomic landing pad that is **highly** expressed and is amenable to large sequence insertions in any orientation.

```
"output module genomic locations' : [
     "organism": "Escherichia coli str. K-12 substr. DH10B",
     "taxid": 316385,
     "location name" : "atpl-gidB intergenic region",
     "bp_range": [4018174, 4018497],
     "flanking upstream sequence'': "ATACGGTGCGCCCCCGTGATTTCAAACAATAA",
     "flanking downstream sequence": "TTGTGATATTTTCACTAATGACTTATTTTCTGCT'
.1]
```
 \mathcal{F}_α

7 Appendix: References

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