# How to Plan and Schedule for Profit:
# An Integrated Model and Application for Complex Factory Operations

by

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## ABSTRACT

In the manufacturing industry, short-term production planning and scheduling requires multiple trade-offs to account for service targets, capacity utilization, setup, on-time delivery, costs and profit. If many SKUs flow in the same production line, the challenge is how to plan and schedule in such a way that an optimal trade-off between customer service, operational performance, and cost of goods sold can be achieved while maximizing gross profit.

This research project provides a novel mixed integer linear model formulation that optimizes lot sizes in a CG factory such that manufacturing capacities and efficiencies, production, inventory, holding and setup costs are considered simultaneously while maximizing the expected profit.

The model solves a multi-echelon production and inventory network and quantifies the advantages by comparing different baselines. The model application evaluated against the simulated Sponsor Company reference baseline proves to be on average 4% more profitable every week, in a quarter of a year period, in the most conservative scenarios.

The scenario analysis provides interesting managerial insights into what to expect when improvement efforts focus on minimum production lots, decoupling buffers or less-than-full deliveries and how they increase even further the overall profitability.

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# 1. Introduction

Optimization of factory operations is a fundamental aspect of any manufacturing company. Without a clear overreaching strategy between revenue maximization and cost minimization, there is a risk of being less profitable. In the context of the Sponsor Company, the production team tends to minimize the number of set-ups per working shift to guarantee continuity of operations, often at the expense of additional work in progress and holding costs between processes. On the other hand, the sales team asks for production responsiveness by means of frequent set-ups concurrently at high service level of finished goods to avoid potential production and delivery disruptions. While ever-changing consumer behaviors may render forecast driven safety stock levels obsolete, more often than not, supply chain planners find themselves squeezed in between production and sales, with the overwhelming task of delivering a feasible planning and scheduling solution that satisfies the customer and all functional constraints.

Since a feasible solution needs to be addressed in the context of profitability, a much deeper implication is how to address complex Sales and Operational Planning (S&OP) profit-driven decisions, especially when the underlying business uncertainty and operational unexpected events change the decision framework week after week. A strong S&OP process clearly helps the company in formally managing the dependences and relationships between lots, setups, capacity, demand, on time delivery and backorders.

While many cost optimization formulations, methods and tools deep dive into each subset of the S&OP process, this research proposes a Revenue Integrated Production-Inventory Planning and Scheduling (RIPIPS) model for connecting and optimizing COGS and Revenues through Mixed Integer Linear Programming.

This chapter introduces the operational context and factory landscape of the Sponsor Company addressing the problem complexity, the related challenges and how the research project scope will provide practical solutions with the proposed approach.

## 1.1 Operational context

The Sponsor Company is a Germany-based enterprise running operations in more than 100 countries worldwide, including a strong market presence in US and China. Seven production facilities around the world are responsible for the production of several hundreds of SKUs, plus many other distribution centers for trade goods.

The mix of brands and product categories sold by the Sponsor Company varies greatly between markets (EU, Asia, Americas) and targets culinary consumers with a vast assortment of knives, cookware and flatware products available at several wholesalers and retailer shops. The product categories and brands will often include numerous product variations, including shape, color, function, and packaging in order to capture additional market shares. The Sponsor Company manages production facilities and distribution centers that support global operations for thousands of SKUs and millions of items (exact numbers cannot be given due to confidentiality agreement with the Sponsor Company), either in-house produced or contract manufactured.

Marketing pressures in the consumer goods industry caused the Sponsor Company to produce and offer more and more distinct SKUs over time, under the assumption that any increases in product management costs are offset by greater sales and profitability. As a result, steel, aluminum and cast iron products have grown so much in number and variety that factory equipment, tools and laborers struggle to produce what is required when it is required.

Also, planning and operational departments have often to deal with old machinery, process variability and incorrect/incomplete information that hinder their understanding of the steps required to achieve global optimum.

## 1.2 Sponsor Company’s factory, product and processes

Among the Sponsor Company’s factories considered for testing the model, the cookware plant in France has the best mix of data quality, operational culture, and shop floor complexity for research purposes. This section highlights the relevant manufacturing, logistics and supply chain features of the French factory in order to contextualize the research project. The factory manufactures premium enameled cast iron cookware and bakeware for the culinary consumer. The enamel coating makes the cookware rustproof, and easy to clean. Pots have nubs on the interior of the lids, which enables condensation to collect and drip down to baste foods uniformly as they are cooking. The main process steps, as shown in Figure 1.2.1, are foundry, robot grinding, shot blasting, ground coating, base color or enameled color and finally pairing of lid and pot before packaging. Several buffers in between help reduce foundry process variability (10% to 20%) and protect against technical equipment downtime. Because the equipment depreciates and replacement costs are high, the sponsor company rarely invests in new process technologies.

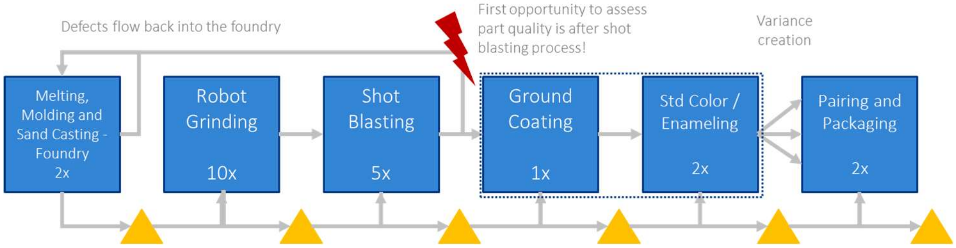


*Figure 1.2.1 Schematic Process Flow*

The material and information flows of cookware and bakeware products are shown in the Figure 1.2.2 as they travel across the factory from left to right (material and process flow) and back (information flow). For this purpose, a lean methodology called Value Stream Mapping (VSM) has been applied to map the actual state of the lines.

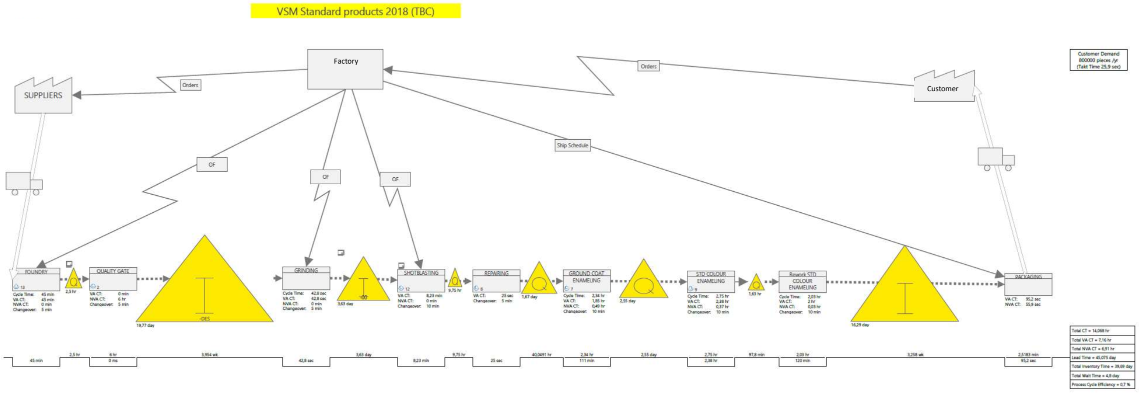


*Figure 1.2.2 Value Stream Mapping of the French cookware manufacturing plant*

Each process may contain multiple similar (but not identical) machines with different manufacturing capabilities (most of equipment age is well over its depreciation period).

Due to different size and color requirements, not every product can flow to every machine, and this has a complexity effect on the production planning and scheduling.

In terms of product shape, roughly 200 SKUs are being actively produced and more than 1000 color variances (customer end item) for the whole cookware portfolio. The SKUs Bill of Materials consists of cast iron for lids and pots, externally purchased knobs and enameled coloring components, packaging and external accessories such as wood platforms.

Packaged goods are delivered mainly to the German logistics hub and from there the hub delivers products worldwide. Sometimes, special deliveries are bundled and issued directly from the plant to the US market. The data retrieved by the current Enterprise Resource Planning / Manufacturing Execution System (ERP/MES) shows historical SKUs sales figures from 2018 and their Pareto distribution. The research project will focus on the top 30 items (Figure 1.2.3) accounting for roughly 65-70% of the total customer volume produced in the last quarter of 2018.

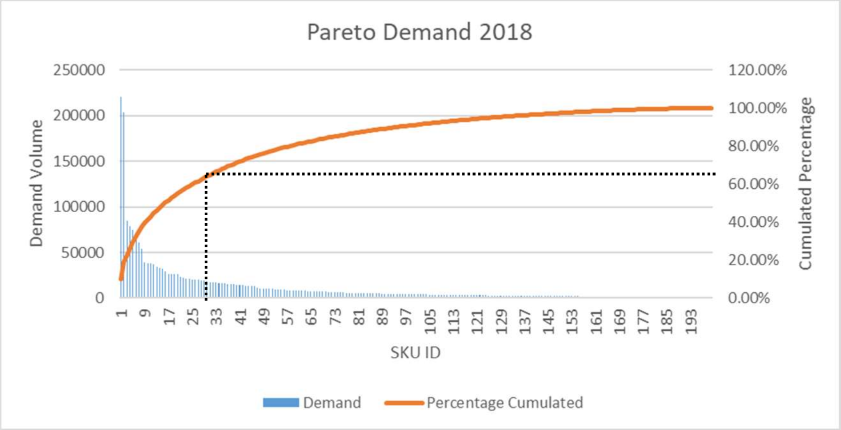


*Figure 1.2.3 Pareto and Weekly Volume by product family in 2018 for the French Subsidiary*

This will provide enough data, interactions and complexity to mimic the real behavior of the cookware plant operations.

## 1.3 Research questions

The core research question of this work is how to balance competing cost goals and maximize gross profit while planning and scheduling production and internal logistics in a complex consumer goods factory. The proposed approach answers the research question by modelling mathematically the end-to-end internal supply chain of the Sponsor Company production plant and by evaluating different scenarios, constraints and uncertainties. It encompasses raw material, pre-production, work-in-progress, final-production and finished goods area. At each stage, KPIs will be defined and fine-tuned (e.g. service levels or line performance) and their respective targets declared as constraints or relaxed/removed in the MILP model in order to develop an optimal feasible plan, which minimizes the overall cost function and maximizes the gross profit based on customer demand. However, as easy as it sounds to remove or relax a constraint in the model in order to evaluate potential benefits, it may actually take the Sponsor Company a lot of money, time and effort to do so. In this regard, the chart in Figure 1.3.1 depicts the intermediate steps required if the company were to implement change management programs (e.g. lean transformation) after an optimized baseline or a complete restructuring of the factory operations before an open baseline.

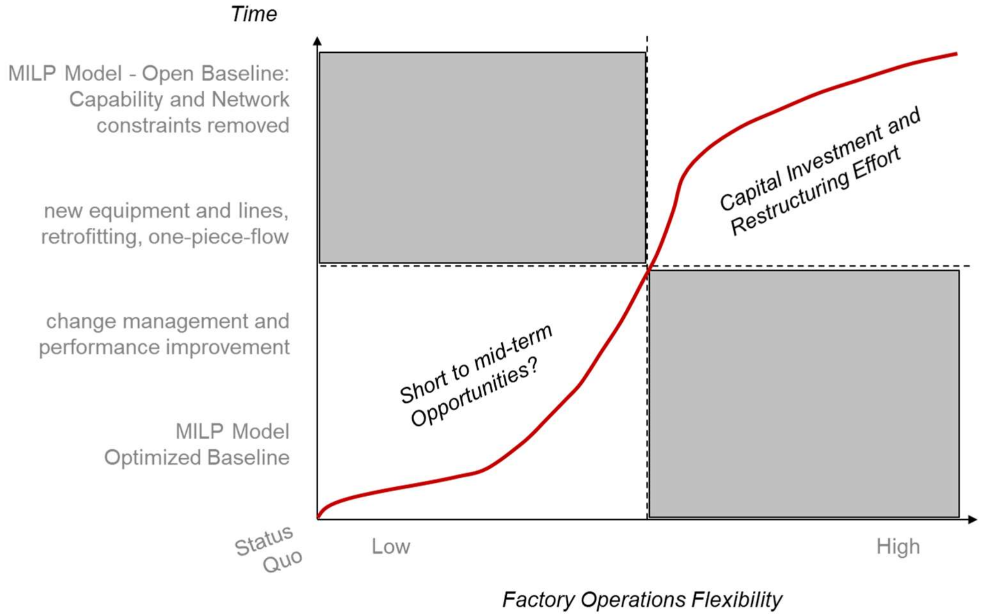


*Figure 1.3.1 operational and MILP approaches to improve Factory flexibility and seize opportunities*

Due to the inherent complexity and “stiffness” of the actual production lines and the related products being manufactured, the proposed model is believed to be a good candidate for generating short- to mid-term savings and gross profit.

## 1.4 Organization of the Capstone Document

Throughout the research project, model generalization and real life application have always developed hand in hand in the attempt to add value to the Sponsor Company and the academic world alike. The Literature Review chapter presents the strategic and operational gaps addressed in this research project and identifies a model that closely matches the Sponsor Company’s factory operations. The Methodology chapter outlines the MILP mathematical formulation, the production and S&OP data used, the required assumptions and how baselines and scenarios will be compared and analyzed. The Results chapter reviews the model performance against the status quo, using historical company data and delivering gross profit evaluations (revenues minus cost of goods sold; in this respect, transportation costs are out of scope). The scenario analysis discussion in Chapter 4 highlights managerial insights, cost saving and gross profit opportunities. Chapter 5 concludes by summarizing the key findings and offering practical implementation steps.

# 2. Literature Review

This chapter contextualizes the research project as follows:

- Addresses the relationship between integrated planning and company profitability through the perspective of a state-of-the-art Enterprise Resource Planning (ERP) approach
- Mentions a few relevant extensions of the Capacitated Lot Size Problem (CLSP) to model real life production planning and scheduling scenarios
- Underlines the importance of decoupling buffers when dealing with uncertainty and reference in this regard the Demand Driven Material Requirement Planning methodology (DDMRP)
- Summarizes and highlights the research gaps in relation to models ability to plan and schedule factory operations based on expected gross profit.

## 2.1 Integrated planning and company profitability

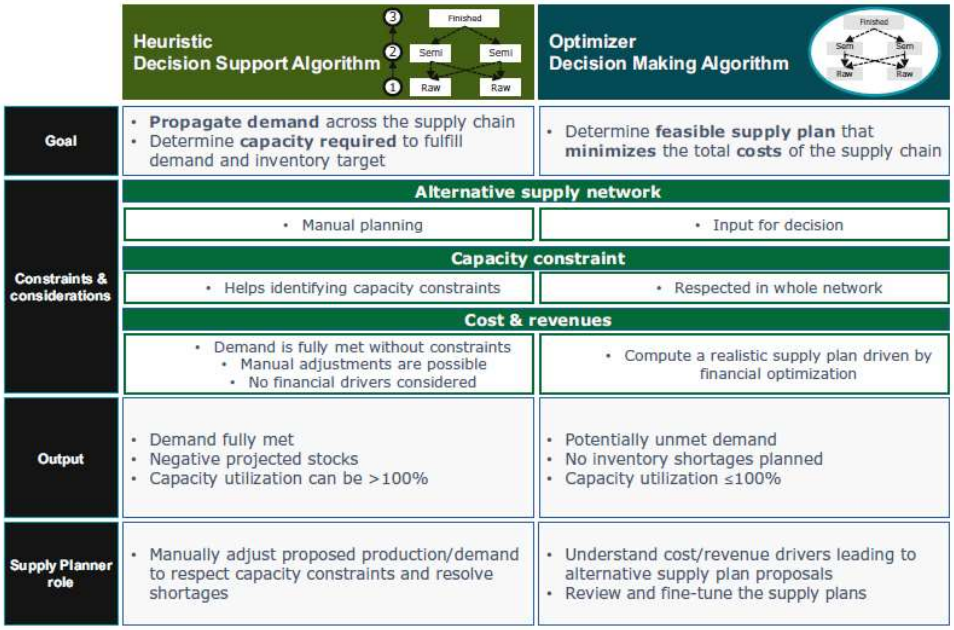
About two years ago, the company's top management decided to undertake a global ERP program transformation to standardize all local processes and systems into one global and modern platform. According to today's roadmap, the new ERP SAP S/4 HANA Production Planning and Detailed Scheduling module (in short PP/DS) will go live in Germany in Q2-2020 as part of this transformation process. For reference, the same module has been deployed as a beta pilot in the company's Italian subsidiary beginning in 2019 and will be fully integrated in 2021 in France.

By the time the ERP implementation will be completed, the Sponsor Company – like most companies - will still want to produce high quality products at the best possible cost, while maximizing their profit. It takes however many functions and qualified experts to achieve this goal through multiple meetings, system crosschecks and scenario evaluations, and even more so when the product demand mix drastically changes with customer demand (S&OP process).

The latest and most known integrated attempt to consider simultaneously all aspects of the costs and revenues involved in the planning and execution of end-to-end supply chains is provided by the German ERP vendor and global market leader "SAP" and this function is called "Integrated Business Planning" or IBP (Fig. 2.1.1).

The SAP IBP objective is to find a solution that minimizes all types of costs that are available in a supply chain, from production to distribution (Kepczynski, Jandhyala, Sankaran & Dimofte, 2018). The costs (fixed or variable) are represented by key figures:

- Stock-out costs (variable)
- Late delivery costs (Backlog, variable)
- Transportation costs (fixed and variable)
- External procurement costs (fixed and variable)
- Production costs (fixed and variable)
- Inventory holding costs (variable)
- Safety/Maximum stock violation costs (variable)



| | **Heuristic Decision Support Algorithm** | **Optimizer Decision Making Algorithm** |
|---|---|---|
| **Goal** | • **Propagate demand** across the supply chain<br>• Determine **capacity required** to fulfill demand and inventory target | • Determine **feasible supply plan** that **minimizes** the total **costs** of the supply chain |
| **Constraints & considerations** | **Alternative supply network** | |
| | • Manual planning | • Input for decision |
| | **Capacity constraint** | |
| | • Helps identifying capacity constraints | • Respected in whole network |
| | **Cost & revenues** | |
| | • Demand is fully met without constraints<br>• Manual adjustments are possible<br>• No financial drivers considered | • Compute a realistic supply plan driven by financial optimization |
| **Output** | • Demand fully met<br>• Negative projected stocks<br>• Capacity utilization can be >100% | • Potentially unmet demand<br>• No inventory shortages planned<br>• Capacity utilization ≤100% |
| **Supply Planner role** | • Manually adjust proposed production/demand to respect capacity constraints and resolve shortages | • Understand cost/revenue drivers leading to alternative supply plan proposals<br>• Review and fine-tune the supply plans |

*Figure 2.1.1 SAP IBP Decision support and Making algorithms*

*Source: Kepczynski et al. (2016)*

In 2017 SAP selected Gurobi Optimization as new OEM Partner for its IBP optimizer and MS Excel embedded tables for the S&OP planning tool within the IBP optimizer framework. The Sponsor Company has not yet defined a roadmap for implementing the IBP functionality within the ERP SAP S/4 HANA rollout plan. As of now, the upgraded Production Planning and Detailed Scheduling Module (PP/DS) will support production & distribution planning. Although PP/DS is a considerable improvement to the company's current planning and scheduling software, allowing for a smoother and leaner production, this latest module has some important limitations:

- modelling of production and supply chain costs in PP/DS to achieve the desired scheduling is challenging, complex, not user-friendly, capital intensive, and demanding in terms of training, consulting, customization and resources.
- integration with other modules does not suit discrete industry scheduling requirements when it comes to trade-off between service levels, cost of goods sold, and production KPI.
- it struggles to deal with inevitable uncertainties: machine break down, higher scrap rate, changes in customer orders, etc.
- the end-user decides in advance the weight distribution for the optimization, without knowing to what extent production and supply chain goals will be affected.

Similar limitations can be found in other major ERP vendors' solutions.
On the other hand, academic approaches mostly tend to optimize in detail a portion of the production or consider the whole at tactical/strategic level on a longer timescale, where, for example, labor or machine capacity constraints can be modified much more easily.
This capstone project focuses on a dynamic method and tool (Jzefowska & Zimniak, 2008) for evaluating and optimizing the internal supply chain, extending the scope of the mid-term (see Fig 2.1.2) Master Production Schedule (MPS) to short-term components such as lot sizing, machine scheduling, personnel planning, distribution planning, gross profit per SKU and customer, in order to balance competing production and SCM cost goals.

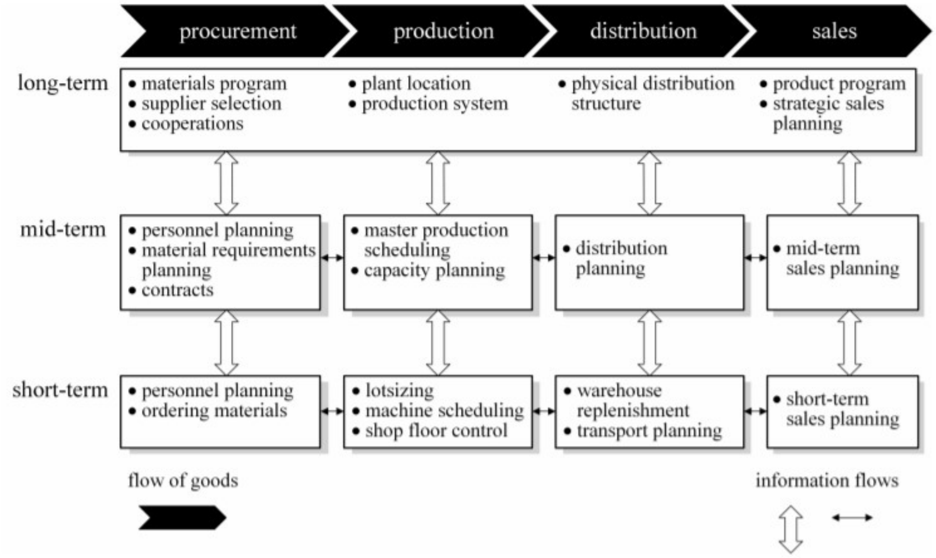


*Figure 2.1.2 Supply chain planning matrix*

*Source: Fleischmann et al. 2015, p. 77*

The research project approach can be addressed as a capacitated lot-sizing problem that needs to be simultaneously determined for multiple machines, products and stages. The next section reviews the literature on the CLSP, highlighting the standard CLSP formulation, the relevant extensions, and the additional contribution of this research.

## 2.2 Relevant dimensions and exact solutions in the Capacitated Lot Sizing Problem

Many authors have studied the Capacitated Lot Sizing Problem (CLSP). Just to cite the most relevant and recent contributions, it is worth mentioning a CLSP model consisting of up to 10.000 binary variables with computational time around 500 seconds (Bollapragada, Croce & Ghirardi, 2011) for non-identical multiple machines at different production rates and capabilities.

Other contributions have also illustrated how production of an SKU can be shared on identical machines, or exclusively assigned to one machine (Tempelmeier & Copil, 2016; Marinelli, Nenni, Sforza, 2007). Backlogging extensions have been proposed for the production as well (Toledo, de Oliveira, & Morelato Frana, 2013; Karimi, Ghomi, & Wilson, 2006) and belong to this research together with stock-out extensions in the considered planning horizon. However, machine sequence-dependent optimization is not part of this research project's scope. All these models and extensions aim at better model real life production planning scenarios at providing valuable insights for planning managers. On the other hand, the more accurate the problems become, the longer they take to be solved (NP-Hard).

Some studies have tried to solve the CLSP exactly (Eppen & Martin, 1987; Akbalik & Penz, 2009), but their methods have been limited to small capacities or a small number of items and machines. Chua and Heyward (2017) have proposed a novel mixed-integer linear programming formulation of the Capacitated Lot Sizing Problem capable of providing a solution for a wide range of items and machines in the consumer packaged industry (CGP, Niagara Bottling LCC).

Their model formulation integrates the following extensions from the basic CLSP formulation presented by Karimi (2003):

- Multi-Echelon setups, inventories and machines: the model optimizes simultaneously all these dimensions in the production network
- Multi-Period: it allows for optimization in time buckets or periods
- Multi-Item: several items can be optimized at once

However, this formulation does not take into account, stock-out or backlog items, SKUs revenues and safety stocks. For the latter, we will see in the next section how positioning and dimensioning correctly the decoupling buffers helps mitigate uncertainty in both production rates and customer demand.

## 2.3 Decoupling buffer and Demand Driven MRP method

Bottlenecks are in real life mostly dynamic, depending on machine capabilities, material flow and product demand mix. By setting decoupling buffer levels properly, lead-time and downstream utilization can be greatly improved. In this regard, Demand Driven MRP methodology (Ptak & Smith, 2016) has gained lately broad attention and it is being implemented in many industries worldwide. Ducrot and Ahmed (2019) investigated and quantified the DDMRP potential under demand uncertainty and capacity restrictions by simulating different forecast accuracy and capacity constraints scenarios. DDMRP has the strategic advantage (see Fig. 2.3.1) to force a company to look at where it makes sense to position the buffers along the production and distribution network. While the simulation in their work shows great results in terms of inventory turns, service levels and customer lead-time, the DDMRP methodology itself does not go beyond the empirical stock level rules used to define the Average Daily Usage (ADU) as a past predictor of the future demand. It is therefore safe to assume that the ADU heuristic has potential for improvement.

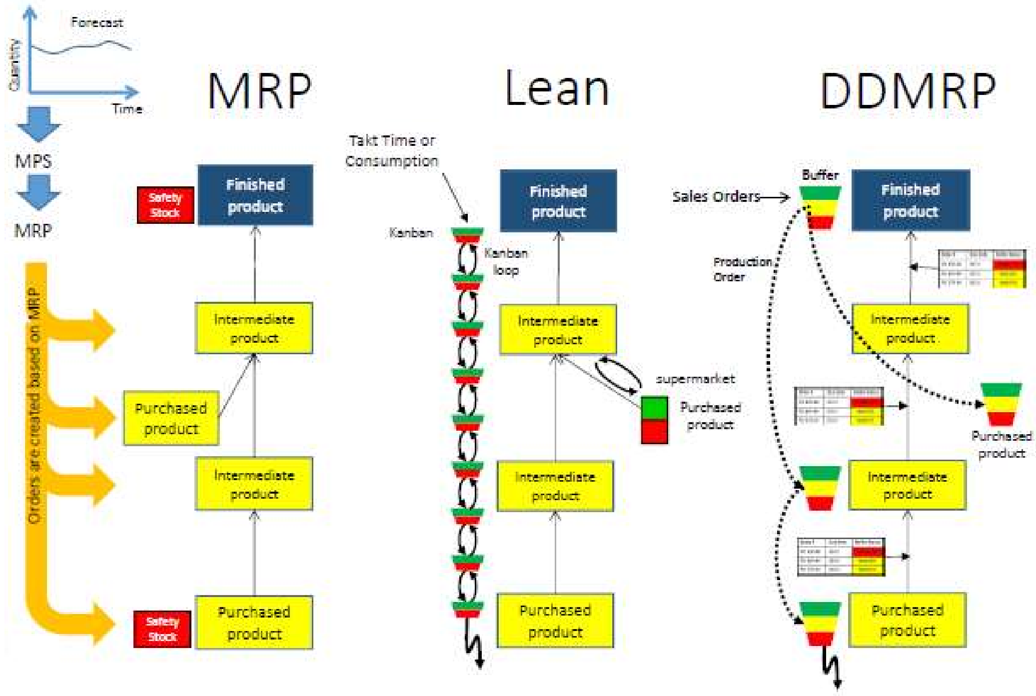


*Figure 2.3.1 MRP, Lean and DDMRP approaches for decoupling buffers*

*Source: Ptak and Smith 2016, p. 307*

In contrast to Ducrot and Ahmed (2019), this capstone approaches the decoupling buffer methodology from a fresh perspective based on a MILP optimization after defining the required safety stock in the network.

## 2.4 Summary

In the case of the sponsoring company, most of the products have a relatively simple BOM and a large number of SKUs options that could be manufactured on the line(s). Consequently, this research project's model is able to solve exactly a variety of Multi-Level CLSP with optimal decoupling buffers levels for one Sponsor Company Factory, dozens of SKUs and multiple machines, assuming that gross profit per SKUs ex-factory minus landed costs are known and independent from transportation optimization algorithms. Since the model depicts accurately the real life internal SCM / production constraints, it may very well be an effective tool to reduce organizational complexity and enhance inter-departmental decision-making process.

# 3. Methodology

The methodology and model described in the following sections are designed to address the complex nature of the relationships between business integrated planning, SKUs, production planning and scheduling, work-in-progress and end-item inventory levels, customer demand swings, and shop floor uncertainties from a cost and profit perspective. However for the purposes of this capstone, direct references to specific production, costing or profitability data have been randomized and/or renamed to prevent any back calculation of confidential information.

Also, as the number of variables involved in the model increase, the calculation time grows exponentially NP-Hard (Bitran, Haas, & Hax, 1981; Florian, Lenstra, & Rinnooy Kan, 1980; Maes, McCLain, & Van Wassenhove, 1991) to the point where an optimality gap of 1% or less cannot be achieved in reasonable time (hours in this research). Therefore, several variations of the Pareto principle have been applied at SKU level in order to find the few items that make up most of the volume. There might be few instances where low make-to-order volume (i.e. special customer color) might generate important revenues for the company that would not otherwise be captured by using a segmentation by volume approach. (i.e. Economies of Scale do not apply). These special cases are beyond the scope of this research.

## 3.1 Desirable solution region and methodology workflow

Operational cost reduction has such a large impact on gross margin for CG companies that some of them could expect to double their profits by just reducing 5% of their production and supply chain costs (OByrne, 2016). The model application goes even further by pulling both costs and revenues on opposite sides to leverage the “sweet spot” of the entire system (Fig. 3.1.1), thus providing additional room for gross profit gains.

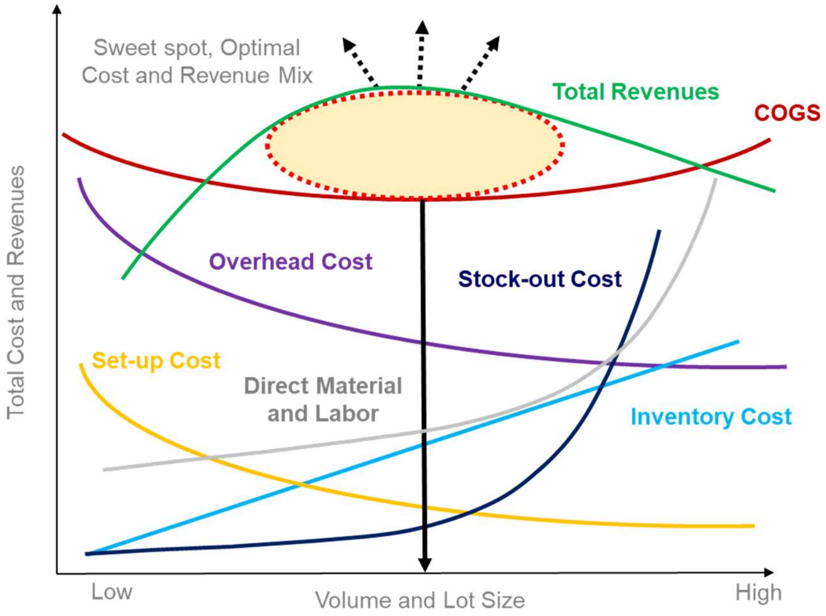


*Figure 3.1.1 Cost and Revenue curves determining the profitability "sweet spot"*

The methodology proposed in the current project allows us to achieve the desirable solution region (i.e. sweet spot) and it is composed of three blocks: data collection and analysis, baseline modeling and validation, and scenario analysis, as shown in Fig. 3.1.2 in the Methodology Workflow.

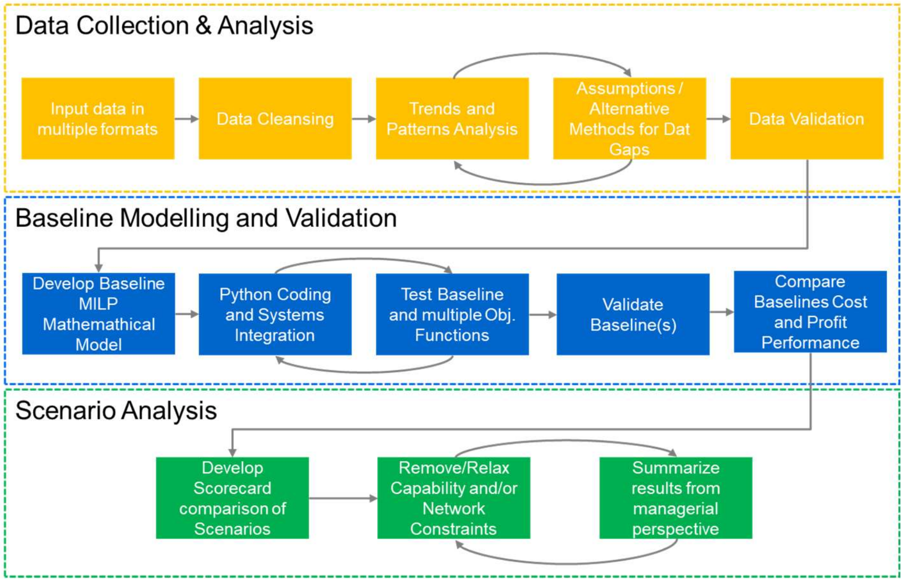


*Figure 3.1.2 Methodology Workflow*

Data Collection & Analysis starts with taking the input data in multiple formats, cleansing them of any incorrect or null values, and analyzing the underlying trends and patterns so that assumptions and alternative methods can be developed for potential data gaps. After several iterations, data are validated and can be used to develop the first MILP mathematical baseline. Python coding and integration with other systems and programs follows in an iterative process required to test the baseline and multiple objective functions and constraints. As validated baseline(s) can now be compared on many cost and profit levels, the scenario analysis removes and/or relaxes network and capability constraints in such a way that managerial perspectives can be derived and summarized.

## 3.2 Model Structure

The model focuses on the needs of the Sponsor Company factory and reflects the production network as well as the material flow on the shop floor up to the final customer (the German hub or US Market). The model captures the behavior but not the actual costs or gross margins of the Sponsor Company operations, while still providing realistic results that can improve its integrated production planning and scheduling process. This research project expands the scope of the CLSP extensions contained in Chua and Heyward's 2017 work (and their outstanding literature review) while considering simultaneously the following features:

- Multi-echelon setups and inventories: simultaneous determination of inventory levels and setups across the production network. Specific safety stock levels can be also set in the factory internal supply chain.
- Multi-machine: a production network consisting of several process steps of non-identical machines. Overall Equipment Effectiveness (OEE) is used as productivity metric estimation of process quality, performance and availability.
- Multi-item and Multi-Customer: several SKUs destined to different customers may flow through the machine network at different cycle times and efficiencies.
- Backlogging and Stock-out events are modelled and integrated at product and customer level as penalty costs.

- Costs and Revenues Multi-objective Function: the model ties together all production and process data from a costing perspective (i.e. the operational planning side as model inputs, Fig. 3.2.1) and the estimated revenues per SKU per customer in order to calculate the gross profit.

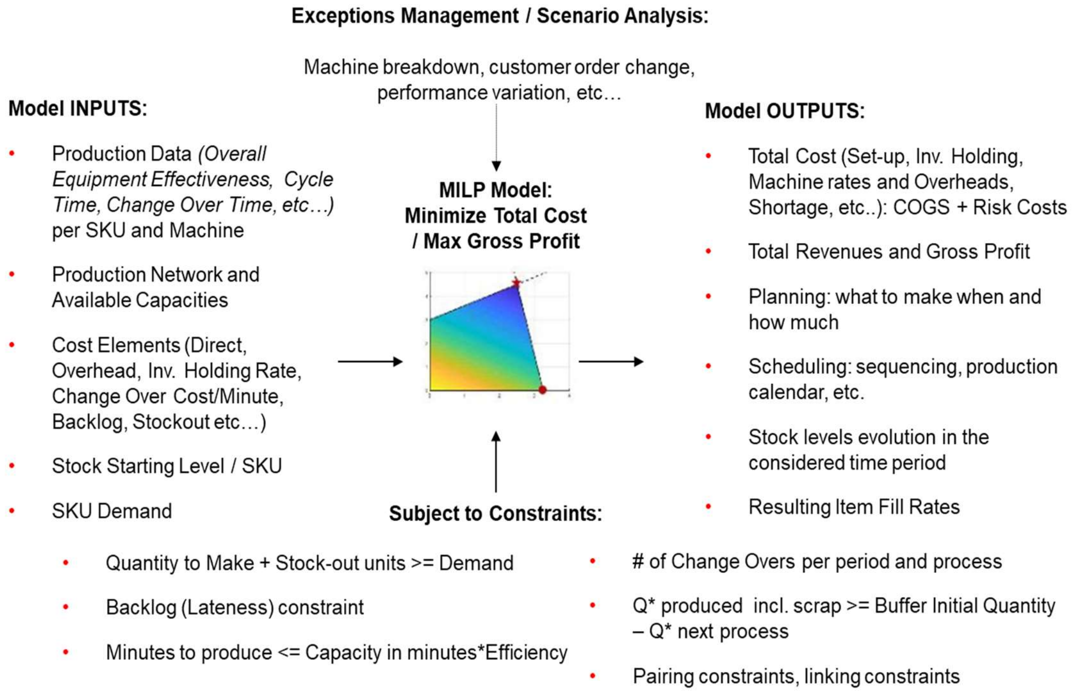


*Figure 3.2.1 Visualization of the MILP model structure used in this research*

In addition to costs and revenues for the entire factory in the short-term planning horizon, the model outputs include what to produce when on which machine and how much, production sequences and calendar, as well as the stock/buffer levels evolution in the planning horizon.

The item fill rates show, as percentages, the number of good items delivered and their respective value in euros.

The following classification scheme (Table 3.2.1) helps positioning this research against the multitude of studies related to the CLSP as well as highlighting the specifics of the model applications at the cookware plant.

*Table 3.2.1 Research Project "RIPIPS" CLSP classification scheme*

| Area | Dimension | Model Resolution Approach | Application Value |
|---|---|---|---|
| **BOM structure** | Type of Level | Single-level | Same item flows in the network |
| | Assembly | Yes | Pairing at packaging step |
| **Production stage** | Type of stage | Multi-stage | 6 stages plus customer stage |
| Sequence | Free or serial | Serial | - |
| Transfer of lots | before completion (open) | Yes | any feasible number |
| | after completion (closed) | Optional | - |
| **Machines per stage** | One machine | Yes | Stage 4 |
| | Parallel | Identical and Non-Identical | I: Stage 6, NI: Stage 1,2,3,5 |
| | Labor | unchanged per machine | Different allocation per machine |
| **Setup Time** | Sequence | Independent within process stages | |
| | Change-over | One or many per period | 1 to 10 depending on stage |
| **Time structure** | Period length | Macro periods | 8 hours |
| | Period | Discrete and Variable | Max 21 Periods, working shift dependent |
| **Lots** | Limited number | Optional | Any feasible number |
| | Products | Many | 30 items considered |
| **Buffers** | Between Processes | Yes | 6 buffers |
| | Inventories | Multi-echelon | - |
| | Safety Stock | Optional for all buffers | 95% Service Level Quantity |
| **Demand** | Backlog | Time Dependent | 5% price penalty on every late item |
| | Customer | Many | 2: German Hub and US |
| | Stock-out | Over the planning horizon | 15% price penalty on stock-out item |

Besides the practical applications and outputs of the proposed approach, the generalized benefits can be summarized as follows:

- <u>Factory Optimization Strategy:</u> as the period's duration can be increased to days or weeks, long-term effects of different production strategies (Lean, Max Throughput, Max IFR, Min Setups, etc.) could be modelled as well as their cost effectiveness.
- <u>Decisional support:</u> the model provides a decision-making framework and tool for cross-functional departments that is accurate and reasonable enough.
- <u>Model the uncertain:</u> simulate stochastic demand patterns or stochastic shop floor behaviors in order to dimension the factory buffers size and layout accordingly.
- <u>Model the unexpected:</u> adapt the original plan to unforeseen changes and determine a new course of action that minimizes the cost of unexpected events or deviations.
- <u>Cost and financial breakdown:</u> understand the COGS per SKU in detail, cost-out and compare solutions from other systems.

## 3.3 MILP Formulation: The Revenue Integrated Production-Inventory Planning and Scheduling

The Revenue Integrated Production-Inventory Planning and Scheduling model (in short RIPIPS) formulation below has been coded with PuLP, a modelling environment for building linear and integer programs within Python. The model also uses Excel and Solver Studio add-in to pass the PuLP formulation to Gurobi (MILP Solver) for resolution.

Indices, Variables and Sets:

| | |
|---|---|
| $i, p$ | *Item and period indices* |
| $j, k$ | *Sequential and parallel processes indices* |
| $c, b$ | *Customer and BOM indices* |
| $CD_{i,c,p}$ , $Q_{i,p,j,k}$ $\geq 0$ | *Variable: quantity delivered to customer, quantity to produce* |
| $BL_{i,[1..p-1],}$ $\geq 0$ | *Variable: backlog and stock-out quantity* |
| $SU_{i,p,j,k}$ $\in \{0, 1\}$ | *Variable: setup is 1 if producing in time period p an item i at the process j,k and 0 otherwise* |
| $W_{p,j,k} \in \{0, 1\}$ | *Working period constant is 1 if producing in time period p at the process j,k and 0 otherwise* |
| $c_{prod}$ | *In house production cost consisting of:* $Cycle\ Time_{i,j,k} * OEE_{i,j,k} * Machine\ Rate\ _{i,j,k}$ |
| $c_{setup}$ | *Cost to make a production run of item i at time period p in the production line j,k =* $Setup\ Time_{i,j,k} * Setup\ Rate$ |
| $c_{inv}$ | *Cost of holding inventory of item i at time period p in the production line j,k=* $Holding\ Rate_{j,j-1}$ |
| $c_{labor}$ | *Cost of labor at time period p in the production line j,k=* $Labour\ Rate_{j,k} * Period\ Cost_p$ |
| $c_{so}$ | *Cost of stocking out an item i in the planning horizon =* $Stockout\ Penalty * Retail\ Price_{i,c}$ |
| $c_{bl}$ | *Backlogging penalty that applies to an item i any time period p at the last process(es)* |
| $D_{i,p,j_{(last)}}$ | *Customer Demand at the last process j for all items i in the periods p* |
| $Lot_{j,k}$ | *Optional Minimum Production Lot at process j,k* |
| $CO\_limit_{j,k}$ | *Optional Maximum number of change-overs allowed in every period for process j,k* |
| $BUF_i$ | *Inventory levels at the start of the planning horizon per item in between sequential processes* |
| $Capacity$ | *Period duration in hours* |
| $M$ | *Larger Number Constant for linking constraints* |
| $I_{i,p,[j,j-1]}$ | *Cumulated inventory between process steps at time p for item i* |

Objective Function:

$$
\begin{aligned}
Max\ Z = {} & \sum_{i,c,p} P_{i,c,p} CD_{i,c,p} - \sum_{i,p,j,k} c_{prod} Q_{i,p,j,k} - \sum_{i,p,j,k} c_{setup} SU_{i,p,j,k} - \sum_{i,p,j} c_{inv} I_{i,p,[j,j-1]} \\
& - \sum_{p,j,k} c_{labor} W_{p,j,k} - \sum_{i,p,j,k} c_{bl}\, BL_{i,p} - \sum_{i,p,c} c_{so} [D_{i,p} - CD_{i,c,p}] P_{i,c,p}
\end{aligned}
\tag{1}
$$

Subject To:

$$\sum_{p} D_{\ i,p,j_{(last)}} \geq \sum_{c,p} [CD_{i,c,p}] \quad \forall i \tag{2}$$

$$\sum_{p,k} Q_{i,p,j_{(last)},k} - \sum_{c,p} CD_{i,c,p} + BUF_{i,j_{(last)}} \geq 0 \quad Optional:\ \geq BSS_{i,j_{(last)}}\ \forall i \tag{3}$$

$$\sum_{p,k} Q_{i,p,j_{(last)},k} + BL_{i,p} + BUF_{i,p} \geq D_{i,p} \quad \forall i \tag{4}$$

$$\sum_{i} [Q_{i,p,j_{(last)}} (LID_{i,b} - POT_{i,b})] = 0 \quad \forall p, b \tag{5}$$

$$\sum_{i,c,p} [CD_{i,c,p} (LID_{i,b} - POT_{i,b})] = 0 \quad \forall b \tag{6}$$

$$\sum_{p,k} [Q_{i,p,j,k} - Q_{i,p,j+1,k}] + BUF_i \geq 0 \quad Optional: \geq BSS_i \quad \forall i, j \tag{7}$$

$$\sum_{i} [Q_{i,p,j,k} * CT * Perf + ST * SU_{i,p,j,k}] \leq Cap * W_{p,j,k} \quad \forall p, j, k \tag{8}$$

$$\sum_{i} SU_{i,p,j,k} \leq W_{p,j,k} * M \quad \forall p, j, k \tag{9}$$

$$\sum_{i} SU_{i,p,j,k} \leq CO_{limit_{j,k}} \quad \forall p, j, k \tag{10}$$

$$M * SU_{i,p,j,k} - Q_{i,p,j,k} \geq 0 \quad \forall i, p, j, k \tag{11}$$

$$Q_{i,p,j,k} - Lot * S_{i,p,j,k} \geq 0 \quad \forall i, p, j, k \tag{12}$$

The objective function (1) sums revenues as retail price per item multiplied by customer delivered quantity against (minus) holding, setup, production, backlog, stock-out costs. The resulting sum must be then maximized to calculate the gross profit for the planning horizon in consideration. The customer-delivered items cannot exceed customer demand for any customer *c* (2), but the quantity produced at the very end of the production network plus the existing inventories can be greater than the actual items delivered to the customer (3).

The cumulated backlog at the last process offsets, period after period, any temporary negative difference between produced quantity and existing WIP versus the actual demand (4). This is extremely important in case of capacity peaks during the planning horizon.

The pairing constraint makes sure that one cookware lid goes to its respective pot according to Bill of Materials (index *b*) in the packaging step (5) as the same needs to happen for the customer(s) delivered quantities (6). The difference between the quantity to be produced in a network stage and the quantity consumed by the next stage plus the existing inventories at the beginning of the planning horizon between the two stages needs to be greater than zero (and optional, more than safety stock, equation 7) for all parallel machines in the considered stages.

The capacity equation (8) makes sure that cycle time per item (*CT*) and its performance (*Perf*) on any machine in the network plus the time consumed for any setup (*ST*) does not exceed the available capacity (Cap) at the production slots open (*W*). *W* symbolizes an array of ones and zeros for the *workable* shifts in the planning horizon. (10, 12, 15, etc.). *SU* is a binary variable (9) that is ON when setup occurs in period *p* for item *i* and it is dependent of the possibilities given by the working shift array *W* with summation over *i*. In a similar fashion, SU can be constrained (10) to be equal or less than a desired maximum amount of change-over (*CO_limit*) per shift.

Finally, the linking constraint (11) ensures that the binary flag is ON if we manufacture any quantity during the time period *p* and the minimum lot constraint (12) ensures that, at least the specified quantity has been produced in period *p*.

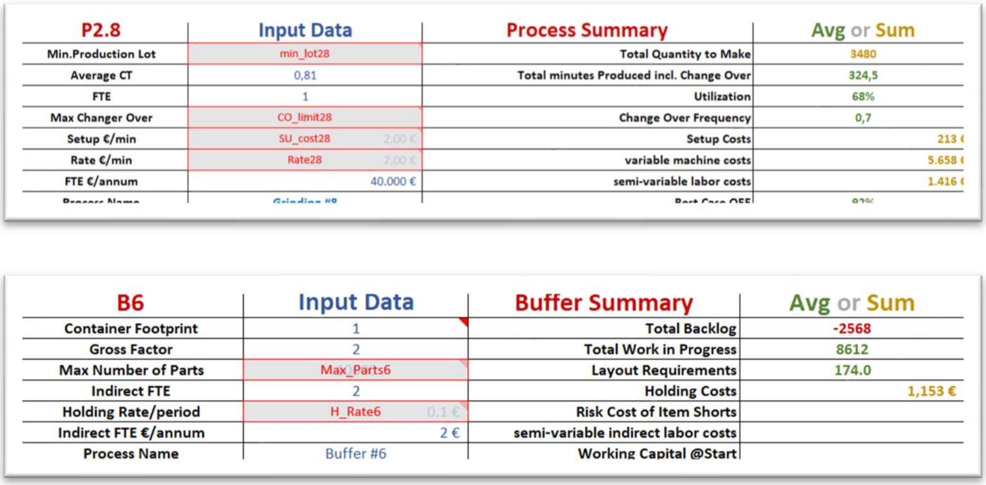
### 3.4 Production data, process data and assumptions

The production data (Fig. 3.4.1) used to describe every process in the network are:

- Ideal Cycle Time: the best possible speed at which a machine can produce a good part
- Pieces per Cycle: how many pieces are produced in every cycle
- Scrap rate: the average percentage of bad parts produced by the machine
- Change Over Time: machine setup duration between the last good part and the first good part

- Availability rate: the time when the machine is up and running
- Performance rate: the average machine speed compared to the ideal cycle time
- Overall Equipment Effectiveness (OEE): Availability * Performance * (1 – Scrap rate)

The OEE is a standard KPI in lean production and the model relies on historical data to estimate its value for each machine and SKU. In case one of its components is missing, best guess assumptions based on expert interviews with shop floor operators were used. The adjusted or real cycle time is then derived as ideal cycle time / OEE for each item.



| P2.8 | Input Data | Process Summary | Avg or Sum |
|---|---|---|---|
| Min.Production Lot | min_lot28 | Total Quantity to Make | 3480 |
| Average CT | 0,81 | Total minutes Produced incl. Change Over | 324,5 |
| FTE | 1 | Utilization | 68% |
| Max Changer Over | CO_limit28 | Change Over Frequency | 0,7 |
| Setup €/min | SU_cost28 2,00 € | Setup Costs | 213 |
| Rate €/min | Rate28 2,00 € | variable machine costs | 5.658 |
| FTE €/annum | 40.000 € | semi-variable labor costs | 1.416 |
| Process Name | Grinding #8 | Best Case OEE | 92% |

| B6 | Input Data | Buffer Summary | Avg or Sum |
|---|---|---|---|
| Container Footprint | 1 | Total Backlog | -2568 |
| Gross Factor | 2 | Total Work in Progress | 8612 |
| Max Number of Parts | Max_Parts6 | Layout Requirements | 174.0 |
| Indirect FTE | 2 | Holding Costs | 1,153 € |
| Holding Rate/period | H_Rate6 0.1 € | Risk Cost of Item Shorts | |
| Indirect FTE €/annum | 2 € | semi-variable indirect labor costs | |
| Process Name | Buffer #6 | Working Capital @Start | |

*Figure 3.4.1 Visual extract of the model: process and buffer input data*

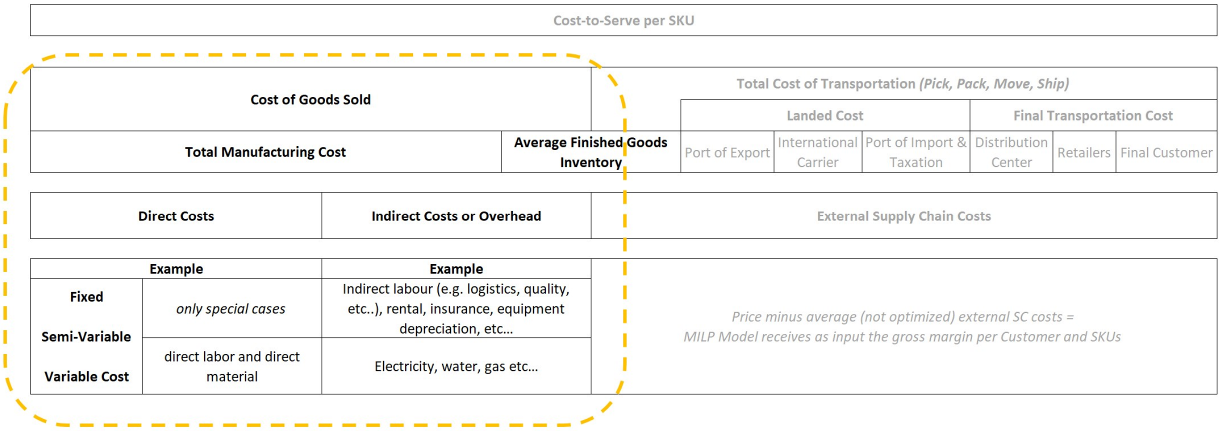
Those data will feed into an individual planning period of 8 hours, determining the real performance of each machine in the network over a maximum of 21 planning periods (one week 24/7 production).

Also, since the factory has been dimensioned to handle 100% or more of the volume, the shift plan has been reduced in most cases to account for the difference in missing volume and thus simulate enough load for the baselines to compare (volume scaling). For example, an 18-shift working week will scale down to about 12 shifts, and 15-shift working week will scale down to about 10 shifts.

## 3.5 S&OP data, costing data and assumptions

Gross profit is calculated as total revenues minus cost of goods sold (COGS, Table 3.5.1), which in this case corresponds to the sum of Total Manufacturing Costs, setup, holding, stock-out and backlog cost. This approach intentionally leaves out the inventory valuation portion of the COGS since units produced will carry over the next period in the available buffers. Components such as short-term planning and optimization of transportation activities, assets, and resources, (Gonzalez, A. 2009) are therefore out of scope.

*Table 3.5.1 Cost breakdown and area of applicability*



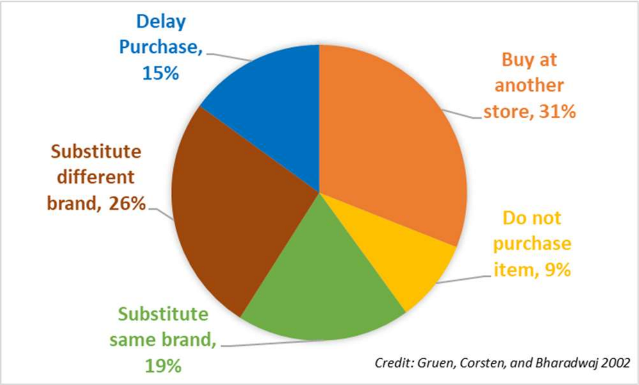
<table>
<tr><td colspan="10">Cost-to-Serve per SKU</td></tr>
<tr><td colspan="4" rowspan="2">Cost of Goods Sold</td><td colspan="6">Total Cost of Transportation <i>(Pick, Pack, Move, Ship)</i></td></tr>
<tr><td colspan="3">Landed Cost</td><td colspan="3">Final Transportation Cost</td></tr>
<tr><td colspan="3">Total Manufacturing Cost</td><td>Average Finished Goods Inventory</td><td>Port of Export</td><td>International Carrier</td><td>Port of Import & Taxation</td><td>Distribution Center</td><td>Retailers</td><td>Final Customer</td></tr>
<tr><td colspan="2">Direct Costs</td><td colspan="2">Indirect Costs or Overhead</td><td colspan="6">External Supply Chain Costs</td></tr>
<tr><td colspan="2">Example</td><td colspan="2">Example</td><td colspan="6" rowspan="3"><i>Price minus average (not optimized) external SC costs =<br>MILP Model receives as input the gross margin per Customer and SKUs</i></td></tr>
<tr><td rowspan="2">Fixed<br>Semi-Variable<br>Variable Cost</td><td><i>only special cases</i></td><td colspan="2">Indirect labour (e.g. logistics, quality, etc..), rental, insurance, equipment depreciation, etc…</td></tr>
<tr><td>direct labor and direct material</td><td colspan="2">Electricity, water, gas etc…</td></tr>
</table>

<u>Total Manufacturing Cost [TMC]:</u> expressed as the sum of all machine and labor steps required to produce the weekly output. Machine rates account for direct material (e.g. enameling color, packaging, knobs, etc.) and manufacturing overheads (e.g. electricity, water, indirect labor, rental or depreciation, etc.). Sponsor Company provides the consolidated machine rates [€/min] per machine so that the model does not have to include additional variables for purchased items required for the final product.

Since TMC within industrial costing is a complex task, especially when dealing with manufacturing overhead calculations, certain assumptions (based on the author's working experience at the Sponsor Company) are required for the model to work:

- Inventory holding rates for the manufacturing Work in Progress (WIP) increase downstream along the internal SCM but are not precisely known
- Setup costs are time dependent and not necessarily spare parts / material / tools dependent
- Back-orders and Stock-out events behave as a (lost) opportunity cost
- Indirect labor do not contribute to direct manufacturing processes
- Machine rates are time dependent
- Purchased material lead time do not affect the material costs

Stockouts: the costs associated with stock-out penalty affect more than just sales: retailer relationships, customer satisfaction, "word of mouth," and bullwhip upstream effect in the supply chain responsiveness all take a hit. Since the company's decisions on how to handle stocked-out units (Fig. 3.5.1) in the past cannot be replicated, they will not carry over into the next planning horizon and they will be accounted as lost sale opportunity for comparison purposes.



Credit: Gruen, Corsten, and Bharadwaj 2002

*Figure 3.5.1 Consumer typical responses to Stock-out events*

Backlog penalty: normally lower than Stockout penalty, it is the opportunity cost within the current planning horizon associated with a delayed delivery. (e.g. items delivered Friday instead of Wednesday of the same week). Similar to stock-outs, they do not actively influence gross profits of the current planning horizon, but they do reduce the ability of the company to increase sales and supply chain efficiencies in the mid-term.

The author's experience at the Sponsor Company has helped in implementing the required product, process and cost data. In order to reach consensus on reasonable rather than exact cost models, discussions were held with a cross-functional team (Supply Chain, Finance, Marketing, Production, etc.) to gain critical insights for building the model and validating the approach.

Because the optimization model is deterministic, the author recommends reducing operational performance variability to best benefit from it. The model could also handle stochastic inputs but, in the case of the Sponsor Company, reducing operational variability is considered to be more beneficial.

# 4. Results and Analysis

## 4.1 Assessing Baseline(s) performance and model effectiveness

The proposed model is capable of planning and scheduling production while optimizing and balancing different cost and profit goals. This chapter presents the baselines evaluation process and comparison (Fig. 4.1.1) while restating some important underlying assumptions required for the model to work properly. To assess the model's effectiveness, several scenarios will be evaluated from a managerial perspective by increasingly loosening up the technical and functional constraints. Potential real life applications and limitations to keep in mind when using the proposed approach are highlighted as well.

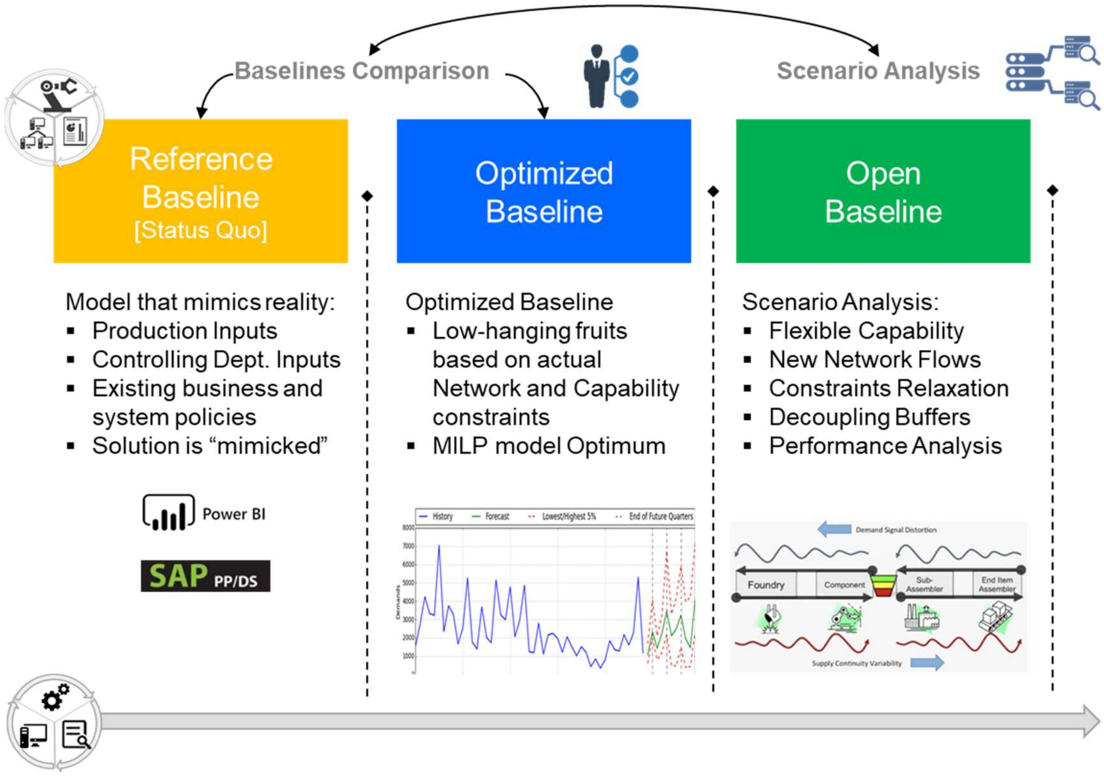


*Figure 4.1.1 Assessing Baseline Performance and Model Effectiveness*

## 4.2 Baselines comparison results

This section compares the status quo baseline versus the optimized baseline on a 12-week horizon, week after week, representing a quarter of Sponsor Company production in 2018.

Stock-out items carry over into the next planning horizon as backorders to be fulfilled in addition to the regular customer demand. The objective is not (only) to compare it with the actual or future ERP/MES capabilities present in the factory, but rather to simulate how a solely throughput and on time delivery approach would compare against the research project cost and profit based approach.

The stock-out penalty is set to 15% in addition to the money value lost in not meeting customer demand. Since the information of buffer levels per SKUs cannot be retrieved for the considered timeframe, the simulation runs at zero buffer levels first and cumulates over time, as the buffer at the end of the current planning period is the buffer level at the beginning of the next planning period.

Generally speaking, the Status Quo Baseline business and system policies aims at maximizing item fill rate and throughput while minimizing setups and risk of not having enough safety stock in the buffers placed across the production network. For the purpose of mimicking the previously described behavior, the objective function (1) seen in Chapter 3 is replaced with:

$$Max\ Z^0 = \left(\sum_{i,c,p} CD_{i,c,p}\right) * W1 + \left(\sum_{i,j} [BSS_{i,j} - BUF_{i,j}]\right) * W2 - \left(\sum_{i,j,p,k} SU_{i,p,j,k}\right) * W3$$

while keeping the rest of the constraints in place and adopting the optional formulation for Safety Stock (BSS) in equations 3 and 7. The weights *W1, W2, W3* were chosen in such a way that the end result (i.e. MILP solution) mimics Sponsor Company's 2018 expectations on IFR, capacity utilization and minimum setups. Note that the modified objective function does not know any profit or cost at any point during the optimization, which is exactly what would happen if the Sponsor Company were to use most commercial ERP/MES specialized heuristics in the planning and scheduling algorithms.

Figure 4.2.1 shows the Optimized baseline advantage in terms of COGS (Total Costs), Revenues and Gross Profit per week. In most planning horizons (i.e. weeks) the Optimized Baseline leads to better cost and profit performance while no real difference in terms of stocked out units can be noticed. The Status Quo baseline performs better only in week 5 and slightly better in week 8 and, since neither of those weeks have particularly high demand requirements, the performance gap can only be explained by a (random) difference that accumulates week after week. Actually, the reference baseline (i.e. status quo) in dashed yellow lines delivers more demanded quantity to customers, while the optimized baseline maximizes the gross profit even though there is a profit loss and a penalty associated with every stocked-out unit.

This happens because the reference baseline does not know what the sales prices are for each planned SKUs (nor the stock-out penalty for that matter) as it is not part of its objective function.

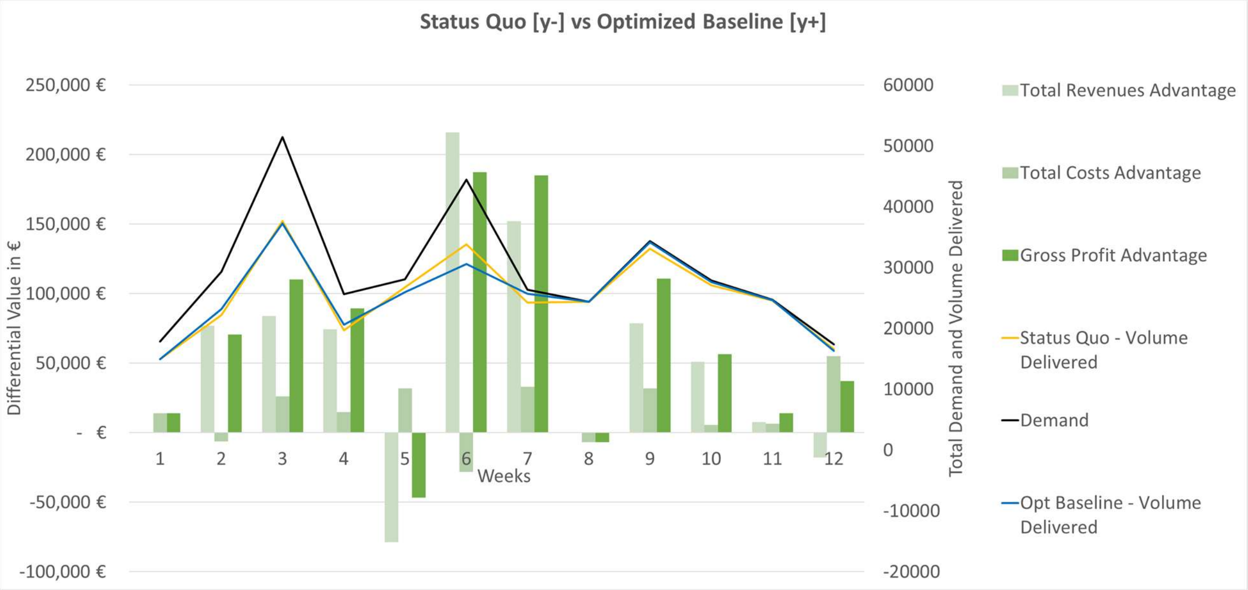


*Figure 4.2.1 Delta between Status Quo vs Optimized Baseline*

The simulation starting point for both baselines is the same at the beginning, only to evolve differently in terms of results and work in progress allocation each week. By looking at the next chart (Fig. 4.2.2), it becomes clear that the difference in performance is strongly correlated ($R^2$-adj 96%) with the IFR value for the total cumulated revenues. Each time that IFR delivered value performs better for the reference baseline, the performance variation between the two baselines finds itself in the negative y-axis region and it is shown as a drop in advantage or linear flection in weeks 5 and 8.

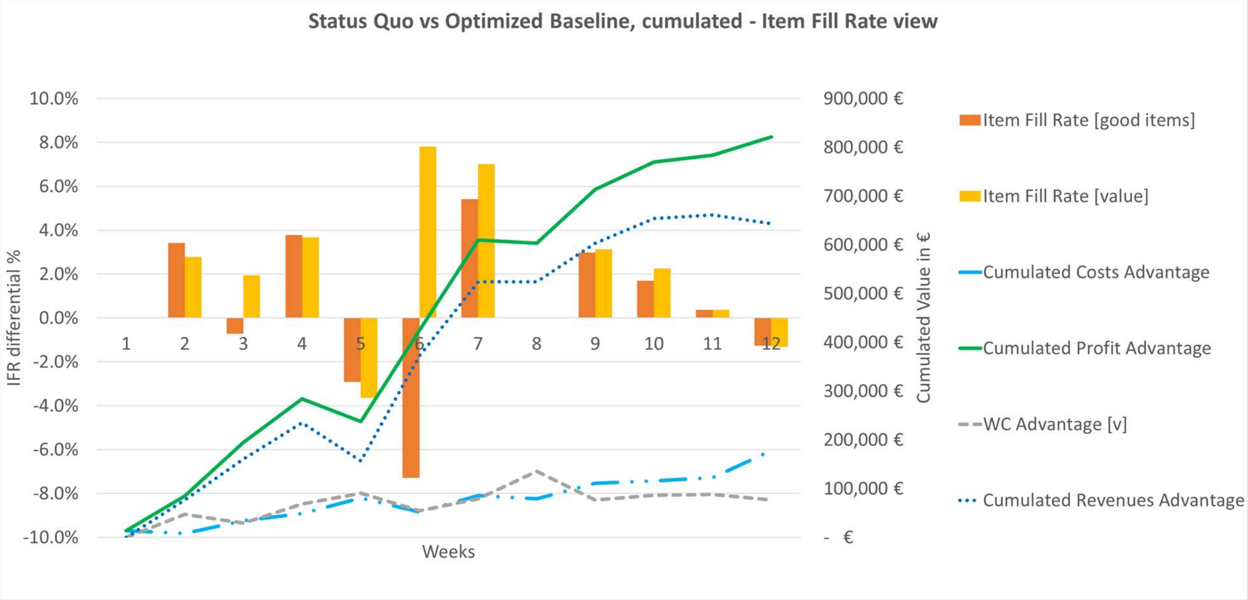


*Figure 4.2.2 Delta between baselines, cumulated performance from IFR perspective*

While the working capital is not part of the objective function for the optimized baseline, it is still remarkable that at the start of every week it is consistently lower than the reference baseline, which privileges throughput over cost (safety stock replenishing constraints are the same for both baseline). Even more so when taken into account the overall better capacity utilization of the optimized baseline, which again feels counter-intuitive to the status quo objective function.

The analysis explains well the deviations in weeks 5 and 8. Now, for week 12, even though the cumulated revenues advantage is lower, as expected by a lower delivered IFR value, the overall gross profit performs better thanks to higher savings on the cost side. It can be seen in Fig. 4.2.3 that Machine Rates, Overheads, and Stock-out Value make up almost 90% of the achieved savings, because only the items needed by the customer are produced. These items are also the ones with the greatest difference between price and producing costs.

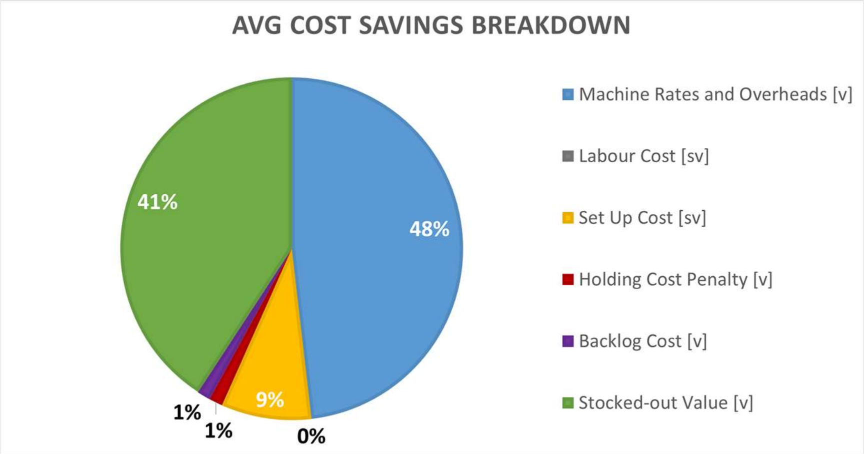


*Figure 4.2.3 Average Cost Savings Breakdown*

The MILP model traded off few percent points of IFR value for a better overall gross profit in week 12, an interesting operational consequence of such a powerful approach.

When confronted with similar scenarios, operational managers should use the proposed solutions with extreme care and only if all company stakeholders agree on the input data provided, and the implications of implementing the model suggested solutions.

There are definitely low-hanging fruits to be gathered in this research as the cumulated gross profit advantage almost topped 800K€ by the end of the quarter. However, real-world applications require both strong engineering and business judgements.

## 4.3 Model performance

The model has been developed with a fast resolution time in mind for day-to-day applications. It takes PulLP roughly 5 min to build the model and send it to Gurobi for optimization. In day to day business, a cross-functional team would run the model multiple times, trying to vary parameters such as stock-out penalty or minimum production lots. The Gurobi solver line has two conditions, either 300 seconds time limit or 1% Optimality Gap, and it stops depending on which one will be achieved before the other. Most of the 24 simulations runs (i.e. 12 for the reference baseline and 12 for the optimized baseline) have achieved 1% Optimality Gap or eventually stopped very close to it (See Appendix A for a screenshot of the solver running).

The MILP Gurobi Problem Summary is:

```
Reading time = 1.05 seconds
OBJ: 34110 rows, 28860 columns, 447936 nonzeros
Optimize a model with 34110 rows, 28860 columns and 447936 nonzero
Presolve removed 24873 rows and 21175 columns
Presolve time: 1.30s
Presolved: 9237 rows, 7685 columns, 60799 nonzeros
Variable types: 3893 continuous, 3792 integer (3789 binary)
```

Since the model is intentionally built-in with lots of flexibility across periods and items, it is normal that the pre-solve is capable of removing many rows and columns.

In other words, many time buckets horizontally (per period) and vertically (per item) are empty, due mostly to capacity and change-over constraints. In general, the Status Quo formulation solves faster as there are less terms to be calculated in the objective function. Interestingly enough, minimum production lots of 100 or greater significantly increase the solution time.

## 4.4 Scenario analysis

This section analyses how different operational scenarios affect the solution quality and the relative competitive advantage of the two baselines as well as their robustness under conservative condition. Also, initial buffer levels between processes will be set back to their respective calculated safety stock at each run. This approach is required to keep initial conditions the same for both status quo and optimized baseline so that the true advantage can be genuinely assessed.

For the purpose of having an apples-to-apples comparison, across baselines (first two rows) and in between (last two rows), a positive sign in the gross profit or a negative sign in the total cost signifies that the first term of the comparison holds an advantage against the second term. Conversely, a negative sign in the gross profit or a positive sign in the total cost signifies that the second term of the comparison holds an advantage against the first term.

1. Shop floor performance. In this scenario, the Foundry process (the first process with the highest defective rate) will see a flat positive improvement of -2% in the defected parts produced. Such an improvement is normally hard to accomplish on a regular basis and it depends on air moisture, temperature and cooling velocity among dozens of other process parameters.

| SCENARIO 1 | Improved Foundry Perf. | Δ GROSS PROFIT | Δ TOTAL COST |
|---|---|---|---|
| Opt Baseline vs Status Quo | Unchanged | -0.2% | -8.1% |
| Opt Baseline vs Status Quo | -2% defect parts | +1.6% | -5.2% |
| Status quo | -2% defects vs unchanged | +1.3% | -4.0% |
| Optimized Baseline | -2% defects vs unchanged | +3.1% | -1.2% |

The advantage of the optimized baseline over the status quo is not as important as in a situation where defected parts were to be reduced on the cost side (-8.1% to -5.2%), but it is on the profit side, where the optimized baseline recovers over the Status Quo (-0.2% to +1.6%).

In general as process variability reduces, (i.e. Status Quo -2% defects reduction vs Status Quo unchanged) gross profit (+1.3%) and total cost (-4.0%) both perform better, which was to be expected. Same goes for the optimized baseline but more on gross profit side (+3.1%) than on the total cost side (-1.2%). For illustrative purposes, the summary statistics of the scenario analysis at the Foundry are shown here below in Fig. 4.4.1.

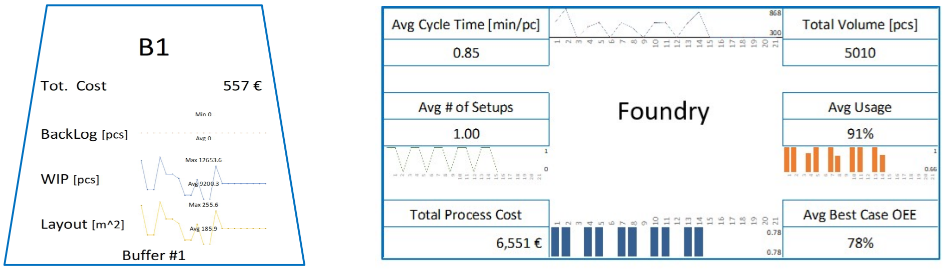


*Figure 4.4.1 Process and buffer summary output screens. Production, WIP and cost information*

2. Bottleneck relaxation. There are many ways that a production bottleneck can be relaxed and dependent on the product demand mix (i.e. demand variation in cookware physical shape), the bottleneck is either on the grinding or shot blasting process. In this case, the process performance will be arbitrarily increased by 20% to see the effects.

| **SCENARIO 2** | **Bottleneck Relaxation** | **Δ GROSS PROFIT** | **Δ TOTAL COST** |
|---|---|---|---|
| Opt Baseline vs Status Quo | Unchanged | +1.9% | +8.6% |
| Opt Baseline vs Status Quo | Relaxed | +4.9% | +9.1% |
| Status quo | Relaxed vs unchanged | +0.6% | -0.2% |
| Optimized Baseline | Relaxed vs unchanged | +3.5% | +0.2% |

Interestingly, the cost comparison across baseline shows higher costs of the optimized baseline against the status quo, to be attributed to more material flowing in the network, which results in a higher cost of producing that particular product, thus the apparent cost disadvantage. The relaxation however does prove to be profit significant (+4.9%) between the two baselines and within the optimized baseline (+3.5%). Note that having one or two parallel machines not running properly before or after the bottleneck may jeopardize the relaxation improvements and have severe repercussions on profitability (dynamic bottleneck effect). The lack of flexible capability triggers ripple effects that deteriorate the weekly profitability quickly. That is why a holistic system approach must be used when dealing with bottleneck relaxation and upstream/downstream processes stiffness.

3. Changes in minimum production lot. There are many good reasons for having relatively high minimum production lots (MPL), including extremely time-consuming setups, lack of experienced labor for more frequent setups, and ease of scheduling with upstream/downstream processes. However, the question remains, how much competitive advantage is to gain when the MPL constraint is relaxed (i.e. set to one) and how it compares to the original solutions in paragraph 4.1.

| **SCENARIO 3** | **Min. Production Lot** | **Δ GROSS PROFIT** | **Δ TOTAL COST** |
|---|---|---|---|
| Opt Baseline vs Status Quo | Lot unchanged | +4.5% | -17.0% |
| Opt Baseline vs Status Quo | Lot 1 | +2.3% | -10.7% |
| Status quo | Lot 1 vs Lot unchanged | +39.5% | -22.8% |
| Optimized Baseline | Lot 1 vs Lot unchanged | +36.5% | -16.2% |

In this scenario, baselines are compared against themselves before and after modifying the minimum production lot to one unit. Since there is no existing WIP in the buffers across the network, the scheduling has little degrees of freedom, so that one could argue that more than 35% in gross profit advantage is an inflated number. On the other hand, keeping enough inventories to actually run high production lots requires higher working capital, indirect labor and it generally slows down the material flow speed in the factory (i.e. the number of inventory turns). If we assume for a moment that a low production lot policy had already been implemented, then the relative benefit across baselines is much more contained at 2.3%, while the existing lot policy across baseline is 4.5% advantageous for the optimized baseline.

For the following scenarios, only the optimized baseline will be compared to itself under different operational assumptions or conditions.

4. Decoupling buffer. By positioning a decoupling buffer at the right place in the production network, lead time and on time delivery can be greatly improved. Normally this makes sense right after a bottleneck so that the downstream production is not affected by it, especially during high demand periods. On the other hand, to build a buffer after the bottleneck, low demand periods need to be used for this purpose, a principle called “production levelling”. In order to compare the WIP buffers after the Foundry (B1) and after the shot blasting process (B3), the initial quantity per item is calculated according to the average past demand plus two standard deviations for 95% level of service. The buffer after the bottleneck proves to be more effective at delivering value to the customer (+18% gross profit), while the buffer B1 does not improve much the ability to

retain more gross profit. Remarkably, B3 is about the half in number of total items when compared to B1, due to production lead-time differences in the safety stock formula. A profit and cost orientated result that could have not been delivered with traditional DDMRP heuristics technique on a multi-echelon network.

5. <u>Demand Product mix.</u> Weeks 11 and 8 are very similar in total demand, only 300 units apart, but different in demand product mix. After optimizing both weeks scheduling with the RIPIPS model, week 11 has a cost advantage of -6.1% and a gross profit advantage of +17.5%.

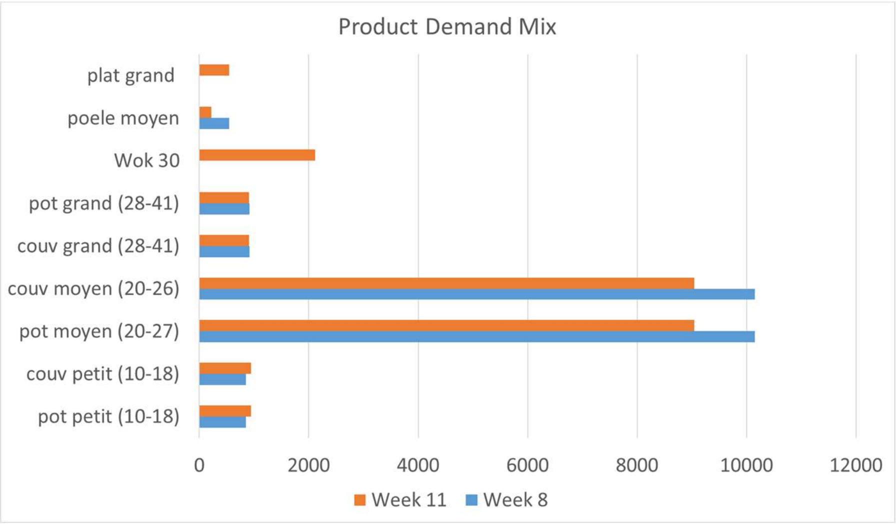
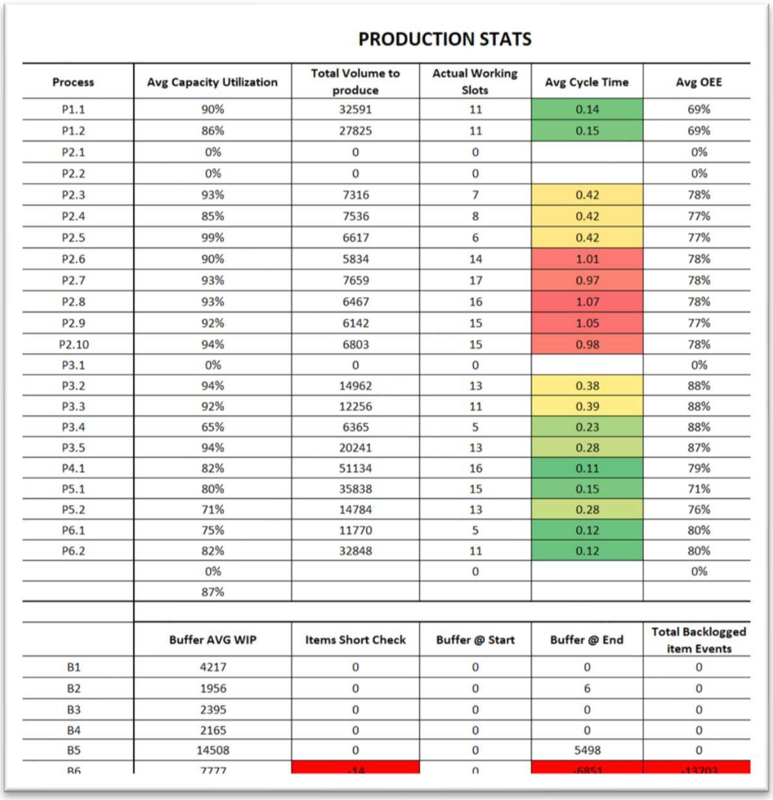


*Figure 4.4.2 Week 8 vs week 11 product demand mix*

The sales and production team could steer customer orders towards one product or another, to maximize company profitability by just adjusting the mix (Fig. 4.4.2).

Another important aspect is that in both cases, the MILP algorithm found the optimum at a fulfilment rate of 99.5%, demonstrating that it is not always profitable to deliver 100% of customer demand, assuming enough capacity is available.

6. <u>Additional option: Shift Optimizer</u>. After declaring the term $W_{p,j,k} \in \{0,1\}$ of RIPIPS equations (8) and (9) as a binary variable instead of an array of zeros and ones (i.e. shift closed or open), the MILP algorithm can find the minimum amount of production teams required (i.e. 1 team = 1 shift) to run the processes (Fig. 4.4.3). This is an interesting solution that can boost profitability even further if 100% cross-functional training of production teams were a viable option (additional outputs in Appendix B), thus for example reducing the need for temporary workers in the high season.



**PRODUCTION STATS**

| Process | Avg Capacity Utilization | Total Volume to produce | Actual Working Slots | Avg Cycle Time | Avg OEE |
|---|---|---|---|---|---|
| P1.1 | 90% | 32591 | 11 | 0.14 | 69% |
| P1.2 | 86% | 27825 | 11 | 0.15 | 69% |
| P2.1 | 0% | 0 | 0 |  | 0% |
| P2.2 | 0% | 0 | 0 |  | 0% |
| P2.3 | 93% | 7316 | 7 | 0.42 | 78% |
| P2.4 | 85% | 7536 | 8 | 0.42 | 77% |
| P2.5 | 99% | 6617 | 6 | 0.42 | 77% |
| P2.6 | 90% | 5834 | 14 | 1.01 | 78% |
| P2.7 | 93% | 7659 | 17 | 0.97 | 78% |
| P2.8 | 93% | 6467 | 16 | 1.07 | 78% |
| P2.9 | 92% | 6142 | 15 | 1.05 | 77% |
| P2.10 | 94% | 6803 | 15 | 0.98 | 78% |
| P3.1 | 0% | 0 | 0 |  | 0% |
| P3.2 | 94% | 14962 | 13 | 0.38 | 88% |
| P3.3 | 92% | 12256 | 11 | 0.39 | 88% |
| P3.4 | 65% | 6365 | 5 | 0.23 | 88% |
| P3.5 | 94% | 20241 | 13 | 0.28 | 87% |
| P4.1 | 82% | 51134 | 16 | 0.11 | 79% |
| P5.1 | 80% | 35838 | 15 | 0.15 | 71% |
| P5.2 | 71% | 14784 | 13 | 0.28 | 76% |
| P6.1 | 75% | 11770 | 5 | 0.12 | 80% |
| P6.2 | 82% | 32848 | 11 | 0.12 | 80% |
|  | 0% |  | 0 |  | 0% |
|  | 87% |  |  |  |  |

|  | Buffer AVG WIP | Items Short Check | Buffer @ Start | Buffer @ End | Total Backlogged item Events |
|---|---|---|---|---|---|
| B1 | 4217 | 0 | 0 | 0 | 0 |
| B2 | 1956 | 0 | 0 | 6 | 0 |
| B3 | 2395 | 0 | 0 | 0 | 0 |
| B4 | 2165 | 0 | 0 | 0 | 0 |
| B5 | 14508 | 0 | 0 | 5498 | 0 |
| B6 | 7777 | -14 | 0 | -6851 | -13703 |

Figure 4.4.3 Model Production Stats for the Shift Optimizer

As the scenarios analysis possibilities are endless, a cross-run between scenarios could show other directions for improvement (e.g. minimum production lot vs bottleneck relaxation as well as which implementation sequence brings most value to the company.

Ultimately, the presented analysis technique has shown what is important to compare and how to evaluate the differences from a managerial and operative standpoint.

## 4.5 Limitations

Limitations of the existing formulations with respect to an implementation at the Sponsor Company factories are:

- Not easy to use understand: probably the single most striking limitation is that the model solutions are not intuitive nor easy to understand when compared for example to lean principles and pull systems (see Appendix C for a visual scheduling example).
- Large scale comprehensive model, but large enough?: some specific processes ran with capacity utilization below 85% and including more SKUs allows for better und more uniform equipment utilization.
- Proficiency in Analytics, MILP and Scheduling: having the right set of skills to operate the model as well as the engineering and business judgment to understand what makes sense to change is a niche in the job market.
- Data accuracy: extremely important, specifically when evaluating the sales planning portion of the model (stock-out, backlog, prices). Without consensus on those critical values, the proposed model can still be used for total costs minimization.

Also, one topic worth considering in future research is the incorporation of multi-stage bill-of-materials, for example assuming that quantities produced in a period on one production stage can serve as pre-products for another production stage in the following period. Another aspect worth considering is the transportation and logistics costs, the landed costs (consisting of tax, export duties, etc.) in order to fully capture the true SKU cost-to-serve for international supply chains.

# 5. Conclusion

This research project presents a new model motivated by real-world applications that improves the Sponsor Company's factory planning and scheduling. The model lowers the operational costs and drives higher profits while addressing unique features that makes an implementation compelling:

- Simultaneous scheduling of lot sizes and sequences under volatile demand
- Multiple non-identical machines producing multiple items on multiple lines
- Productivity constraints that account for defective parts, capacity and setups at each step
- Complex WIP buffer material flow due to multi-echelon network structure
- Revenue dependent planning and scheduling
- Stock-out items penalties for value maximization

The model applied to the simulated Sponsor Company's reference baseline proves to be on average 4% more profitable every week, in a quarter of a year period, under conservative conditions. The scenario analysis section provides interesting managerial insights on what to expect under several operational settings:

- Improved Productivity (at the Foundry): increased part quality at the beginning of the line and in the process with the highest defective rate leads to additional cost savings and profit only to a certain extent before running short at the bottleneck down the line.
- Bottleneck relaxation: as the material flowing through a relaxed bottleneck increases, so do the related costs in the entire network, only to result into superior global profitability when more demand is delivered to the customer.
- Minimum Production Lot: probably the best low-hanging fruit candidate that needs to be operationally addressed. Smaller lots reduce the bullwhip effects in the production network to advantage the overall profitability and volume produced.
- Machine Breakdown: in the context of the Sponsor Company, a machine breakdown upstream or downstream to the bottleneck can have severe repercussions on profitability due to the lack of flexibility (alternative machines with similar capabilities).

- Decoupling Buffer: proven to be instrumental after the bottleneck for customer demand reduced lead-time if backed by strategic understanding of the factory network and optimization techniques (i.e. MILP).
- Demand Product mix: significant difference in mix leads to significant difference in costs and profitability at similar total demands. Volume based assumptions on cost structure and revenues may lead to wrong strategic decisions (i.e. issue with standard costing systems).
- Less-than-full Delivery: to be expected as MILP solution for a small fraction of items and dependent on marginal differences between SKUs price and SKU Total Manufacturing Costs.
- Shift Optimizer: interesting option that allows optimizing the working shift of different production teams (assuming they are cross-functionally trained) to take over different processes every week. It proves to be effective and to deliver value against fix shift model.

The research project provides a fresh perspective for factory gross profit optimization as well as an executable tool of interest for practical application. Discrete CG manufacturers with relatively low number of Bill of Materials (BOM) components and a high number of SKUs could apply the model as well by customizing a few portions of it. To avoid the typical disadvantages of in-house customized systems, this research project has been built upon standard manufacturing processes within the Sponsor Company such as automated presses or robot cells. In the future, the potential savings may justify the investment in an ad-hoc solution that integrates into ERP for planning and scheduling, thus enabling effective complexity and profit management.

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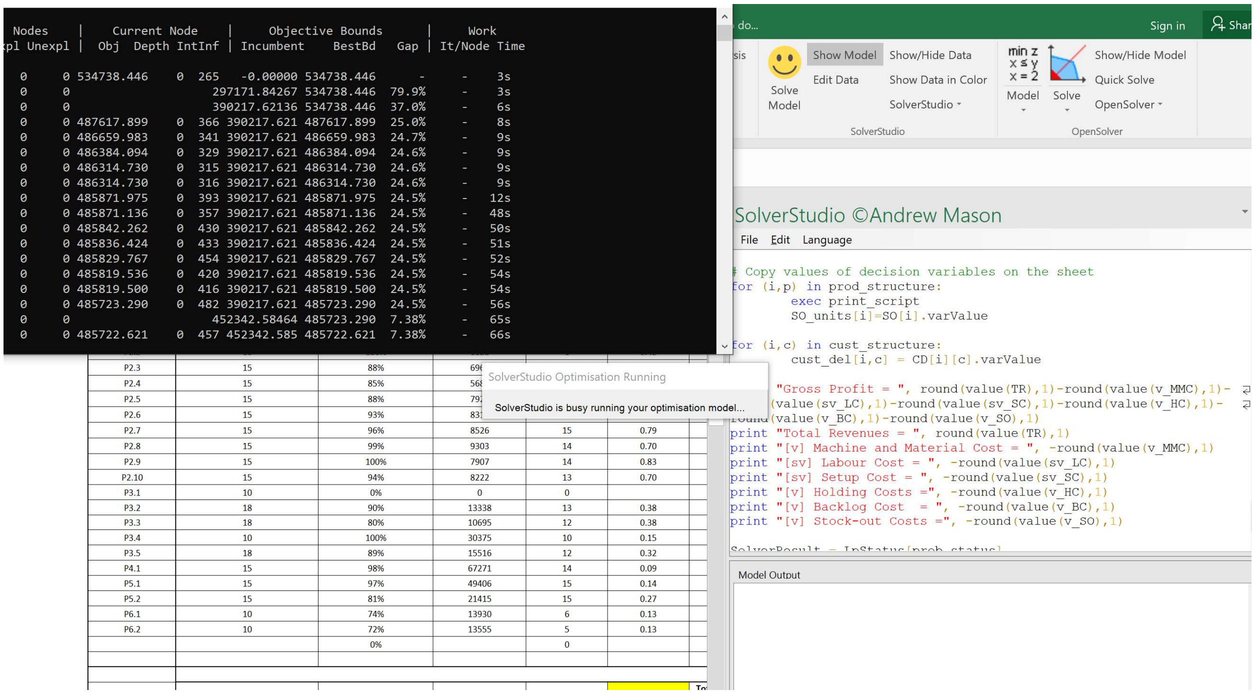
# Appendix A – Model view and solver running



```
 Nodes    |    Current Node    |     Objective Bounds      |     Work
xpl Unexpl |  Obj  Depth IntInf | Incumbent    BestBd   Gap | It/Node Time

  0     0 534738.446    0  265   -0.00000 534738.446      -      -    3s
  0     0                    297171.84267 534738.446  79.9%     -    3s
  0     0                    390217.62136 534738.446  37.0%     -    6s
  0     0 487617.899    0  366 390217.621 487617.899  25.0%     -    8s
  0     0 486659.983    0  341 390217.621 486659.983  24.7%     -    9s
  0     0 486384.094    0  329 390217.621 486384.094  24.6%     -    9s
  0     0 486314.730    0  315 390217.621 486314.730  24.6%     -    9s
  0     0 486314.730    0  316 390217.621 486314.730  24.6%     -    9s
  0     0 485871.975    0  393 390217.621 485871.975  24.5%     -   12s
  0     0 485871.136    0  357 390217.621 485871.136  24.5%     -   48s
  0     0 485842.262    0  430 390217.621 485842.262  24.5%     -   50s
  0     0 485836.424    0  433 390217.621 485836.424  24.5%     -   51s
  0     0 485829.767    0  454 390217.621 485829.767  24.5%     -   52s
  0     0 485819.536    0  420 390217.621 485819.536  24.5%     -   54s
  0     0 485819.500    0  416 390217.621 485819.500  24.5%     -   54s
  0     0 485723.290    0  482 390217.621 485723.290  24.5%     -   56s
  0     0                    452342.58464 485723.290  7.38%     -   65s
  0     0 485722.621    0  457 452342.585 485722.621  7.38%     -   66s
```

| | | | | | |
|---|---|---|---|---|---|
| P2.3 | 15 | 88% | 69 | | |
| P2.4 | 15 | 85% | 56 | | |
| P2.5 | 15 | 88% | 79 | | |
| P2.6 | 15 | 93% | 83 | | |
| P2.7 | 15 | 96% | 8526 | 15 | 0.79 |
| P2.8 | 15 | 99% | 9303 | 14 | 0.70 |
| P2.9 | 15 | 100% | 7907 | 14 | 0.83 |
| P2.10 | 15 | 94% | 8222 | 13 | 0.70 |
| P3.1 | 10 | 0% | 0 | 0 | |
| P3.2 | 18 | 90% | 13338 | 13 | 0.38 |
| P3.3 | 18 | 80% | 10695 | 12 | 0.38 |
| P3.4 | 10 | 100% | 30375 | 10 | 0.15 |
| P3.5 | 18 | 89% | 15516 | 12 | 0.32 |
| P4.1 | 15 | 98% | 67271 | 14 | 0.09 |
| P5.1 | 15 | 97% | 49406 | 15 | 0.14 |
| P5.2 | 15 | 81% | 21415 | 15 | 0.27 |
| P6.1 | 10 | 74% | 13930 | 6 | 0.13 |
| P6.2 | 10 | 72% | 13555 | 5 | 0.13 |
| | | 0% | | 0 | |

SolverStudio Optimisation Running

SolverStudio is busy running your optimisation model...

SolverStudio ©Andrew Mason

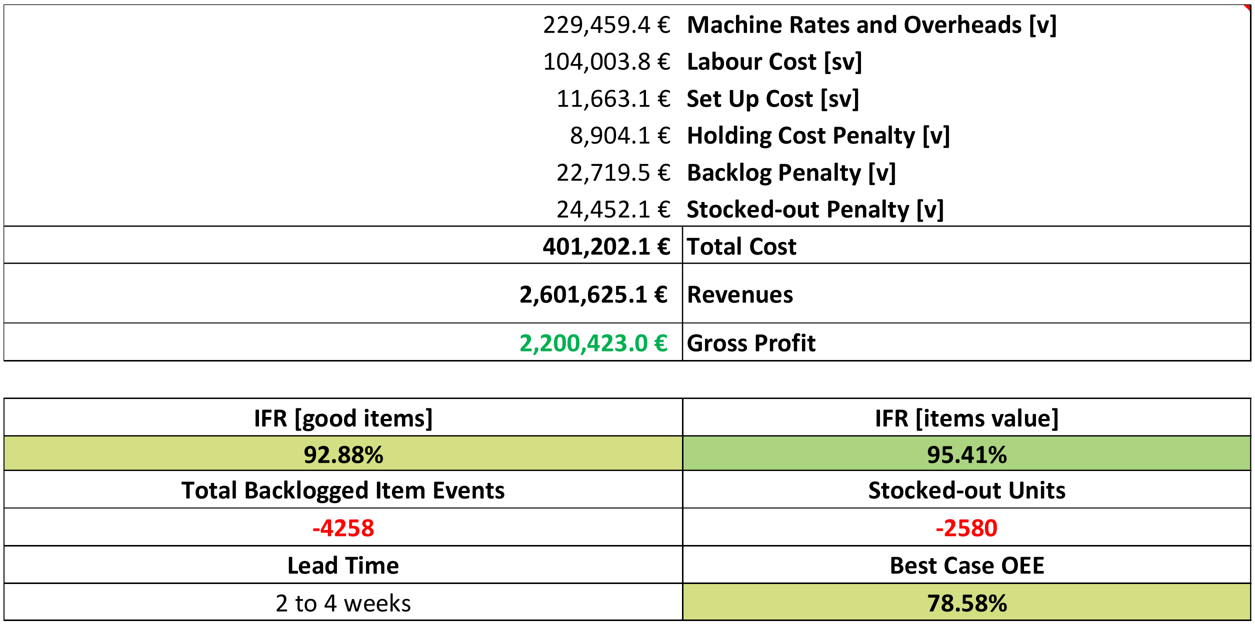
```
# Copy values of decision variables on the sheet
for (i,p) in prod_structure:
        exec print_script
        SO_units[i]=SO[i].varValue

for (i,c) in cust_structure:
        cust_del[i,c] = CD[i][c].varValue

       "Gross Profit = ", round(value(TR),1)-round(value(v_MMC),1)-
      (value(sv_LC),1)-round(value(sv_SC),1)-round(value(v_HC),1)-
round(value(v_BC),1)-round(value(v_SO),1)
print "Total Revenues = ", round(value(TR),1)
print "[v] Machine and Material Cost = ", -round(value(v_MMC),1)
print "[sv] Labour Cost = ", -round(value(sv_LC),1)
print "[sv] Setup Cost = ", -round(value(sv_SC),1)
print "[v] Holding Costs =", -round(value(v_HC),1)
print "[v] Backlog Cost  = ", -round(value(v_BC),1)
print "[v] Stock-out Costs =", -round(value(v_SO),1)

SolverResult = lnStatus[prob.status]
```

Model Output

# Appendix B – Production output summary table

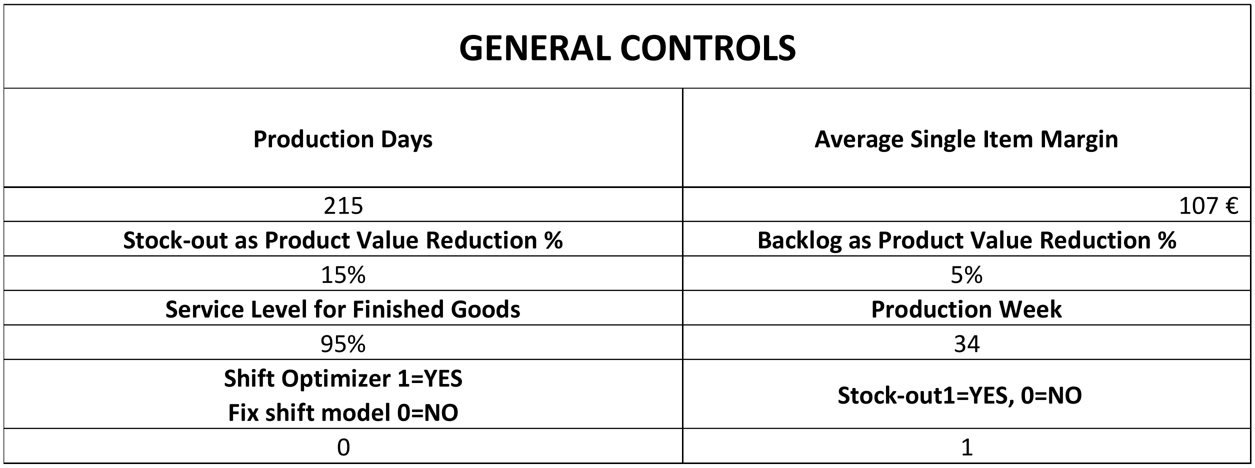
| | PRODUCTION STATS | | | | | |
|---|---|---|---|---|---|---|
| **Process** | **Planned Working Slots** | **Avg Capacity Utilization** | **Total Volume to produce** | **Actual Working Slots** | **Avg Cycle Time** | **Avg OEE** |
| P1.1 | 5 | 84% | 13199 | 4 | 0.12 | 69% |
| P1.2 | 5 | 90% | 10771 | 4 | 0.15 | 68% |
| P2.1 | 10 | 0% | 0 | 0 | | 0% |
| P2.2 | 10 | 0% | 0 | 0 | | 0% |
| P2.3 | 10 | 84% | 4724 | 5 | 0.42 | 78% |
| P2.4 | 10 | 80% | 1788 | 2 | 0.42 | 78% |
| P2.5 | 10 | 83% | 5553 | 6 | 0.42 | 77% |
| P2.6 | 10 | 81% | 2816 | 8 | 1.08 | 78% |
| P2.7 | 10 | 89% | 2753 | 7 | 1.06 | 78% |
| P2.8 | 10 | 89% | 3935 | 9 | 0.96 | 77% |
| P2.9 | 10 | 97% | 2997 | 7 | 1.07 | 78% |
| P2.10 | 10 | 88% | 3095 | 8 | 1.06 | 78% |
| P3.1 | 10 | 0% | 0 | 0 | | 0% |
| P3.2 | 12 | 95% | 9302 | 9 | 0.43 | 88% |
| P3.3 | 12 | 95% | 9102 | 9 | 0.44 | 87% |
| P3.4 | 12 | 83% | 6114 | 5 | 0.32 | 88% |
| P3.5 | 12 | 73% | 5913 | 5 | 0.28 | 88% |
| P4.1 | 12 | 88% | 30925 | 9 | 0.11 | 79% |
| P5.1 | 12 | 68% | 21445 | 10 | 0.14 | 71% |
| P5.2 | 12 | 68% | 11186 | 10 | 0.28 | 76% |
| P6.1 | 5 | 86% | 14072 | 5 | 0.15 | 80% |
| P6.2 | 5 | 92% | 17281 | 5 | 0.13 | 80% |
| | | 0% | | 0 | | 0% |
| | | 85% | | | | |
| | | | | | | |
| | **Peak Layout requirement [m^2]** | **Buffer AVG WIP** | **Items Short Check** | **Buffer @ Start** | **Buffer @ End** | **Total Backlogged item Events** |
| B1 | 341.5 m2 | 11103 | 0 | 15058 | 8970 | 0 |
| B2 | 79.6 m2 | 3572 | 0 | 4973 | 1926 | 0 |
| B3 | 96.3 m2 | 2466 | 0 | 3226 | 1211 | 0 |
| B4 | 110.6 m2 | 3557 | 0 | 3226 | 1211 | 0 |
| B5 | 212.6 m2 | 9222 | 0 | 9172 | 10124 | 0 |
| B6 | 698.6 m2 | 21832 | -8 | 3226 | -1654 | -4258 |
| | 0.0 m2 | 0 | 0 | 0 | | 0 |
| Demand | | | fullfilled: 33653 | | | |

# Appendix C – Production console and model output



| | |
|---|---|
| 229,459.4 € | **Machine Rates and Overheads [v]** |
| 104,003.8 € | **Labour Cost [sv]** |
| 11,663.1 € | **Set Up Cost [sv]** |
| 8,904.1 € | **Holding Cost Penalty [v]** |
| 22,719.5 € | **Backlog Penalty [v]** |
| 24,452.1 € | **Stocked-out Penalty [v]** |
| **401,202.1 €** | **Total Cost** |
| **2,601,625.1 €** | **Revenues** |
| **2,200,423.0 €** | **Gross Profit** |

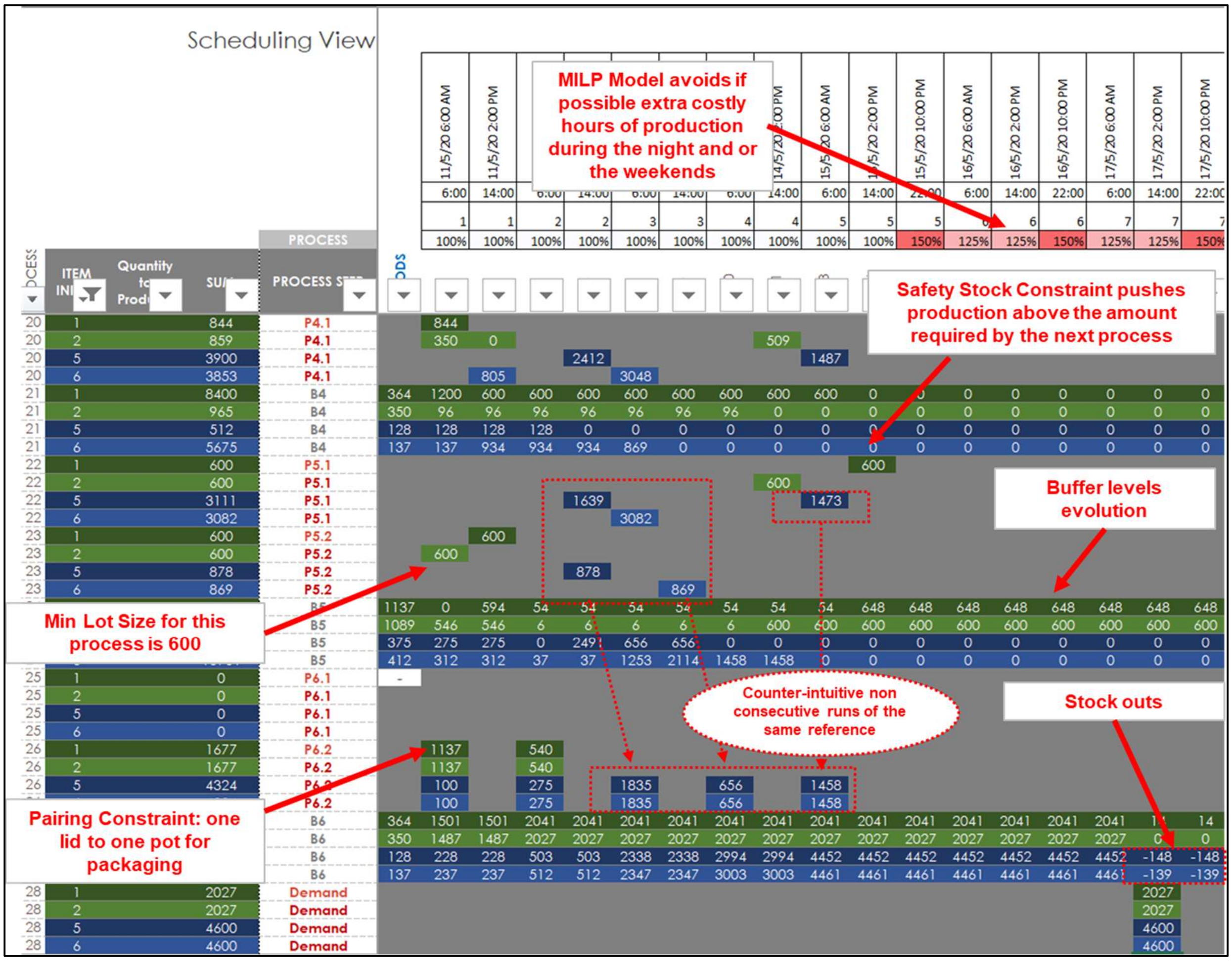
| | |
|---|---|
| **IFR [good items]** | **IFR [items value]** |
| **92.88%** | **95.41%** |
| **Total Backlogged Item Events** | **Stocked-out Units** |
| **-4258** | **-2580** |
| **Lead Time** | **Best Case OEE** |
| 2 to 4 weeks | **78.58%** |



## GENERAL CONTROLS

| | |
|---|---|
| **Production Days** | **Average Single Item Margin** |
| 215 | 107 € |
| **Stock-out as Product Value Reduction %** | **Backlog as Product Value Reduction %** |
| 15% | 5% |
| **Service Level for Finished Goods** | **Production Week** |
| 95% | 34 |
| **Shift Optimizer 1=YES**<br>**Fix shift model 0=NO** | **Stock-out1=YES, 0=NO** |
| 0 | 1 |

# Appendix D – Scheduling output sample of four items (two SKUs)



Scheduling View

| OCESS | ITEM IN | Quantity to Prod | SUM | PROCESS<br>PROCESS S | ODS | 11/5/20 6:00 AM | 11/5/20 2:00 PM | | | | | | 14/5/20 | 15/5/20 6:00 AM | 5/20 2:00 PM | 15/5/20 10:00 PM | 16/5/20 6:00 AM | 16/5/20 2:00 PM | 16/5/20 10:00 PM | 17/5/20 6:00 AM | 17/5/20 2:00 PM | 17/5/20 10:00 PM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 6:00 | 14:00 | 6:00 | 14:00 | 6:00 | 14:00 | 6:00 | 14:00 | 6:00 | 14:00 | 22:00 | 6:00 | 14:00 | 22:00 | 6:00 | 14:00 | 22:0 |
| | | | | | | 1 | 1 | 2 | 2 | 3 | 3 | 4 | 4 | 5 | 5 | 5 | 6 | 6 | 6 | 7 | 7 | 7 |
| | | | | | | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 150% | 125% | 125% | 150% | 125% | 125% | 150% |
| 20 | 1 | | 844 | P4.1 | | 844 | | | | | | | | | | | | | | | | |
| 20 | 2 | | 859 | P4.1 | | 350 | 0 | | | | | | 509 | | | | | | | | | |
| 20 | 5 | | 3900 | P4.1 | | | | | 2412 | | | | | 1487 | | | | | | | | |
| 20 | 6 | | 3853 | P4.1 | | | 805 | | | 3048 | | | | | | | | | | | | |
| 21 | 1 | | 8400 | B4 | 364 | 1200 | 600 | 600 | 600 | 600 | 600 | 600 | 600 | 600 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 21 | 2 | | 965 | B4 | 350 | 96 | 96 | 96 | 96 | 96 | 96 | 96 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 21 | 5 | | 512 | B4 | 128 | 128 | 128 | 128 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 21 | 6 | | 5675 | B4 | 137 | 137 | 934 | 934 | 934 | 869 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 1 | | 600 | P5.1 | | | | | | | | | | | 600 | | | | | | | |
| 22 | 2 | | 600 | P5.1 | | | | | | | | | 600 | | | | | | | | | |
| 22 | 5 | | 3111 | P5.1 | | | | | 1639 | | | | | 1473 | | | | | | | | |
| 22 | 6 | | 3082 | P5.1 | | | | | | 3082 | | | | | | | | | | | | |
| 23 | 1 | | 600 | P5.2 | | | 600 | | | | | | | | | | | | | | | |
| 23 | 2 | | 600 | P5.2 | | 600 | | | | | | | | | | | | | | | | |
| 23 | 5 | | 878 | P5.2 | | | | | 878 | | | | | | | | | | | | | |
| 23 | 6 | | 869 | P5.2 | | | | | | | 869 | | | | | | | | | | | |
| | | | | B5 | 1137 | 0 | 594 | 54 | 54 | 54 | 54 | 54 | 54 | 54 | 648 | 648 | 648 | 648 | 648 | 648 | 648 | 648 |
| | | | | B5 | 1089 | 546 | 546 | 6 | 6 | 6 | 6 | 6 | 600 | 600 | 600 | 600 | 600 | 600 | 600 | 600 | 600 | 600 |
| | | | | B5 | 375 | 275 | 275 | 0 | 249 | 656 | 656 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | | | B5 | 412 | 312 | 312 | 37 | 37 | 1253 | 2114 | 1458 | 1458 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 25 | 1 | | 0 | P6.1 | - | | | | | | | | | | | | | | | | | |
| 25 | 2 | | 0 | P6.1 | | | | | | | | | | | | | | | | | | |
| 25 | 5 | | 0 | P6.1 | | | | | | | | | | | | | | | | | | |
| 25 | 6 | | 0 | P6.1 | | | | | | | | | | | | | | | | | | |
| 26 | 1 | | 1677 | P6.2 | | 1137 | | 540 | | | | | | | | | | | | | | |
| 26 | 2 | | 1677 | P6.2 | | 1137 | | 540 | | | | | | | | | | | | | | |
| 26 | 5 | | 4324 | P6.2 | | 100 | | 275 | | 1835 | | 656 | | 1458 | | | | | | | | |
| | | | | P6.2 | | 100 | | 275 | | 1835 | | 656 | | 1458 | | | | | | | | |
| | | | | B6 | 364 | 1501 | 1501 | 2041 | 2041 | 2041 | 2041 | 2041 | 2041 | 2041 | 2041 | 2041 | 2041 | 2041 | 2041 | 2041 | 14 | 14 |
| | | | | B6 | 350 | 1487 | 1487 | 2027 | 2027 | 2027 | 2027 | 2027 | 2027 | 2027 | 2027 | 2027 | 2027 | 2027 | 2027 | 2027 | 0 | 0 |
| | | | | B6 | 128 | 228 | 228 | 503 | 503 | 2338 | 2338 | 2994 | 2994 | 4452 | 4452 | 4452 | 4452 | 4452 | 4452 | 4452 | -148 | -148 |
| | | | | B6 | 137 | 237 | 237 | 512 | 512 | 2347 | 2347 | 3003 | 3003 | 4461 | 4461 | 4461 | 4461 | 4461 | 4461 | 4461 | -139 | -139 |
| 28 | 1 | | 2027 | Demand | | | | | | | | | | | | | | | | | 2027 | |
| 28 | 2 | | 2027 | Demand | | | | | | | | | | | | | | | | | 2027 | |
| 28 | 5 | | 4600 | Demand | | | | | | | | | | | | | | | | | 4600 | |
| 28 | 6 | | 4600 | Demand | | | | | | | | | | | | | | | | | 4600 | |

MILP Model avoids if possible extra costly hours of production during the night and or the weekends

Safety Stock Constraint pushes production above the amount required by the next process

Buffer levels evolution

Min Lot Size for this process is 600

Counter-intuitive non consecutive runs of the same reference

Stock outs

Pairing Constraint: one lid to one pot for packaging