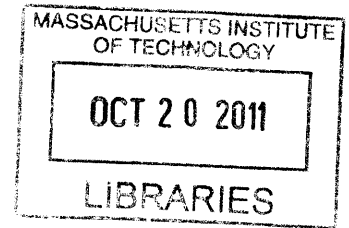# Marine Dock Optimization
for a Bulk Chemicals Manufacturing Facility

by

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and

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Messiah College, 2007

Submitted to the Engineering Systems Division in Partial Fulfillment of the
Requirements for the Degree of

Master of Engineering in Logistics

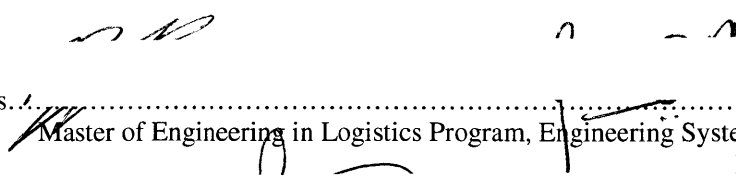at the
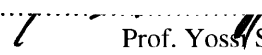
Massachusetts Institute of Technology

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ABSTRACT

U.S. petrochemical manufacturers operate in a very challenging environment on account of the recent economic crisis, volatility in crude oil prices, rising capacity in the Middle East, etc. Recently, there has been a focus on logistics costs and, in particular, capacity utilization as a means to retain a competitive edge. This thesis focuses on marine dock optimization for a major bulk chemicals manufacturer. The authors have surveyed the research literature to find commonalities in various approaches to the problem of dock optimization– in the petrochemical shipping industry as well as in allied operational environments such as container shipping. They discuss the inputs that would be needed to build a decision-support-system designed for the express purpose of measuring dock utilization.

Following a review of the industry context and relevant literature, the authors develop a demonstrative framework that captures the key variables and constraints affecting loading and unloading operations. The authors speculate that multiple simulation and optimization techniques could sufficiently address the quantification of operational uncertainties at the marine dock. However, emphasis is placed upon the need for thorough data gathering and correct prioritization of variables and constraints affecting efficiency of dock operations.

Thesis Supervisor: James B. Rice, Jr.
Title: Deputy Director, Center for Transportation and Logistics

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1   Introduction

1.1 Context

The influence of the petrochemicals industry in daily life is well known – petrochemical products go into the manufacture of soaps, pharmaceuticals, plastics, tires and other objects vital to the onward march of civilization. However, before consumers can reap the benefits of petrochemicals in the form of household goods, a great deal of logistical planning goes into the manufacture, transport and processing of petrochemicals. The raw materials used in petrochemical manufacturing are typically supplied from refineries to manufacturing plants via pipelines. The chemical plant then processes these raw materials and stores inventories of finished product in various tank farms. The product is then transported via truck, rail, pipelines and marine movements. Of these four modes of transport, maritime transport is often the most feasible because demand points are often located far away from manufacturing clusters, and manufacturing operations commonly require large batches of these raw materials. Also, maritime modes of transport offer the lowest cost per ton-mile (Li, Karimi & Srinivasan, 2010). Refer to Figure 1 for an example of marine-dock operations for a bulk-chemicals manufacturer. Pictured are loading arms for bulk liquids connected to a vessel or barge.

Figure 1: Loading Arms at Dock
(Kanon Loading Equipment, 2011)

Our research focuses on the marine dock-side operations of a major US petrochemical manufacturer referred to herein as Al-Chem Inc. As with any large petrochemical manufacturer with a global footprint, raw materials as well as finished products are shipped

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to world-wide clients via ocean-going tankers. Domestic clients who are accessible via inland water ways are served via barges. Typically, a marine dock for a bulk chemicals manufacturer provides berths for one or more vessels to pull alongside so that product can be loaded onto vessels via direct hose-hookups or marine loading arms (as seen in Figure 1). A team of logistics planners and marine operations experts work together to ensure that any vessel which arrives at the port is "turned around," i.e., loaded or unloaded, as fast as possible within the bounds of safety and process requirements. Figure 2 illustrates the layout of a typical bulk chemicals marine dock. When a vessel pulls alongside its allotted berth, a loading arm or transfer hose is connected from the dock to the vessel so that product can be transferred from the manufacturing plant to the vessel's holding compartments. Some of the main determinants of capacity at the dock are the number of berths, loading arms and availability of labor.
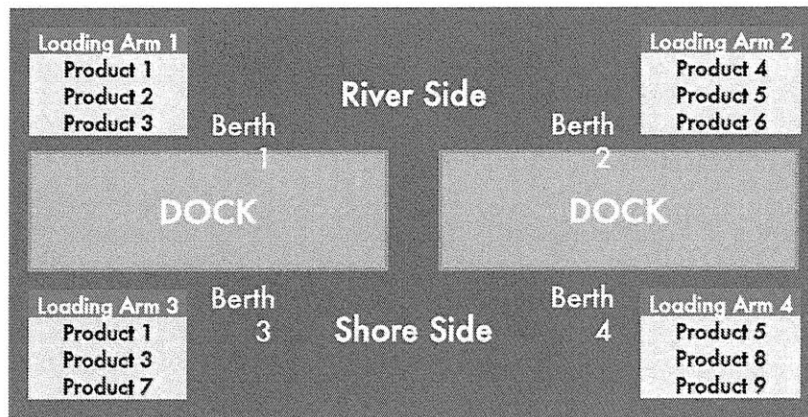
Figure 2: Al-Chem Inc. Visual of Berth Schematics

The logistics cost of planning and executing loading and unloading operations constitutes a significant proportion of the operating budget for an Al-Chem Inc. manufacturing facility. In our research, we seek to study the problem of marine dock optimization. We survey the literature on petrochemical marine logistics and propose a high level design for modeling marine loading and unloading activities for Al-Chem Inc. Our proposed design is based on

sales and loading data from one of Al-Chem Inc.'s facilities but is generalized enough that the principles may be applied to their other facilities and companies as well.

1.2 Relevance

In the US economy, petrochemical manufacturing is a $77.9 billion industry, and the nation's dependence on this sector is expected to propel revenue growth over the next five years. By one estimate, from 2011 to 2016, revenue is projected to grow by 3.8% per annum to $93.7 billion (Gotaas, 2011).

However, the recent recession has been challenging for this sector for various reasons including falling demand and volatility in the prices of crude oil and natural gas. Demand and supply imbalances in this sector further contribute to volatility. Figure 3 demonstrates how average returns to share-holders in the chemicals industry have fallen by 55% (McKinsey & Co., 2009).
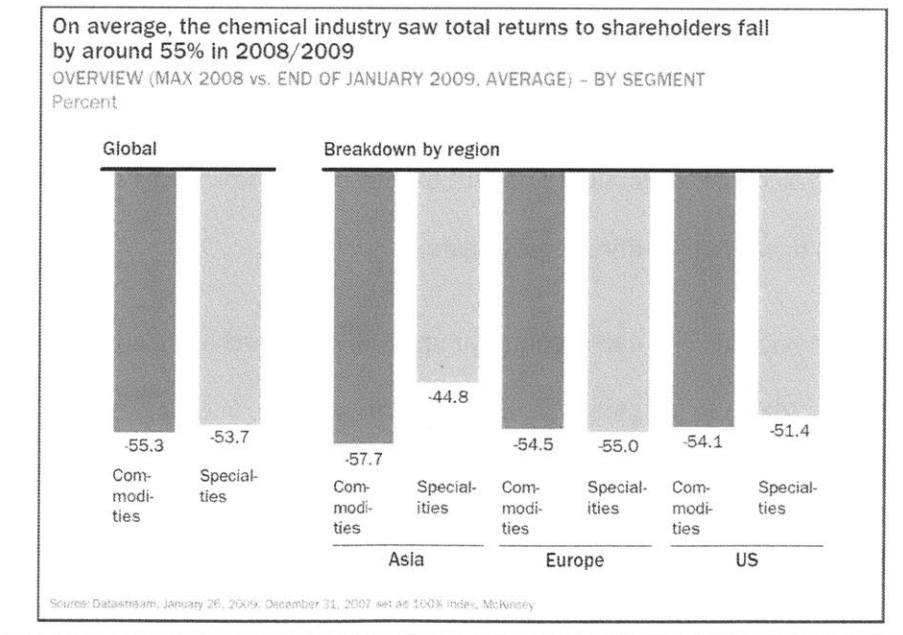
Figure 3: Returns to share-holders

In a 2011 report on *Top Ten Trends in the Petrochemical Industry*, leading market research experts make the case that one of the key factors for the recent slowdown in the US petrochemicals industry has been caused by the emergence of increased "competition from price-competitive producers in the Middle-East and Asia" (Research and Markets, 2011).

The report goes on to state that "rising feedstock prices are forcing many North American petrochemical producers to reassess their profit margins in comparison to that of global players. The capacity additions in the global petrochemical industry are increasingly favoring Asia-Pacific and Middle Eastern locations. The major reason for this shift is the economies of production in these regions. The Middle East has an unparalleled feedstock advantage and Asia-Pacific countries like China and India offer very low labor costs compared to North American and European countries" (Research and Markets, 2011). Feedstock prices refer to the cost of raw materials used as inputs to manufacturing processes used by Al-Chem or other North American petrochemical manufacturers.

In the face of such profound forces now buffeting the US petrochemicals industry, optimization of capacity utilization is now a key success factor (Gotaas, 2011). To stay competitive, it has become especially important to seek out improvements in working capital and to drive costs down in the entire supply chain.

By one estimate, logistics costs can account for up to 20% of purchasing costs (Karimi, Srinivasan & Han, 2002) in the global chemicals industry. Thus, maritime bulk transport is an integral part of logistics because bulk shipping offers the lowest cost per ton-mile (Li et al., 2010). The major chemical manufacturers are located in centralized hubs around the world, whereas demand points are scattered around the globe. Therefore, the use of maritime-transport of bulk chemicals is both necessary and crucial to the operation of chemical supply chains. As ports and ships are both expensive to invest in and operate, it is easy to see how

any improvements in operational efficiency can translate to lower costs for the end customer, increasing competitiveness.

1.3 Research Direction

Following a survey of the relevant research literature, we propose a high level design for a decision-support-system (DSS) to maximize utilization/reliability at the level of the marine-dock. We do not go deeply into the specific parameters for Al-Chem Inc. docks but use available sales data and existing research literature to indicate how a DSS might quantify utilization at the level of the berth.

Several variables and constraints impact day to day dock operations and introduce unpredictability to operations. By first modeling the key elements (number of tanks, loading arms, labor availability, etc.) of a typical bulk-chemicals dock in database terms, we present an analytical approach to measuring the impacts of variability and operational constraints on capacity utilization. Different manufacturing facilities may choose to emphasize different metrics for measuring berth utilization – for example, by choosing to maximize the number of orders that can be shipped from a given berth, over the course of a year. We utilize an implicit assumption that berth utilization is maximized when we minimize the time required for a vessel to complete operations and depart from the berth.

We show how it may be possible to model, simulate and benchmark dock operations to identify areas of weakness and opportunity by using probabilistic tools in a decision-support-system. At present, logistics planners at the port are able to consider forecasted supply (the plant is primarily a supplier of chemicals, i.e., onshore to offshore) and give a "by-the-gut" estimate of what sales orders (referred to in the bulk chemicals trade as 'parcels') the dock will be able to handle. Our research aims to translate this semi-structured operational decision

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making process into a more quantitative approach based on the key constraints and variables at play. Figure 4 indicates the high-level elements that would interact together to serve as a DSS. We cover the individual modules in greater depth in Appendix A.
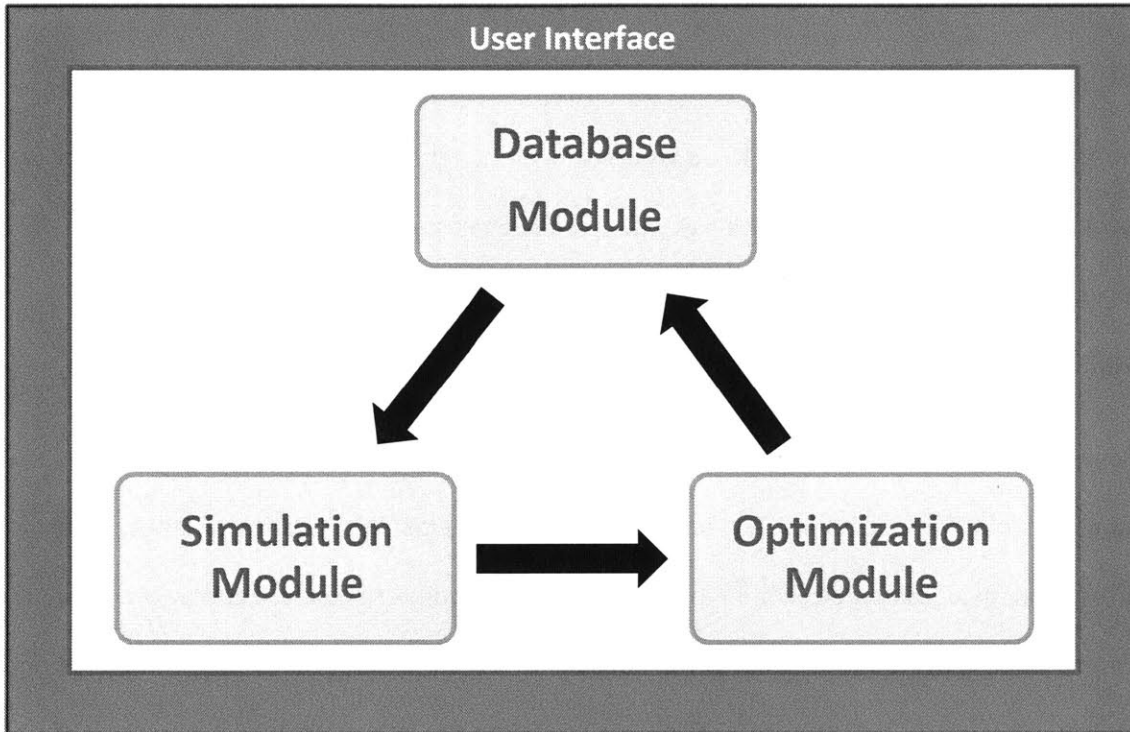
Figure 4: Decision Support System

2 Literature Review

Whereas the scope of our research is limited to analysis of a single marine-dock for one of Al-Chem Inc.'s manufacturing facilities, in our research we have considered literature pertaining to supply chain optimization in the broader petrochemical industry as well as efforts relating to dock optimization in other types of shipping, e.g., container shipping. We note the complexity inherent to globally distributed petrochemical supply chains and consider the role of uncertainty in optimizing for efficiency at the marine-dock. We also discuss a research gap in the marine dock optimization space for the petrochemicals industry.

2.1 Supply Chain Optimization in the Petrochemicals Industry

For Al-Chem Inc., a global player in the petrochemicals sector, the overall supply chain spans production, storage and distribution sites over several countries. Al-Chem Inc. also serves customers in several markets. Thus, the overall supply chain experiences uncertainty in several dimensions. According to one 2005 paper "Uncertainty propagates through the supply chain network from the market at supply side, quantity and quality of raw material, to production quality and yield, and from the other side to the market economics and customer demands" (Lababidi et al., 2004).

This uncertainty is further compounded at the marine dock owing to various operational variables and constraints – in effect, an ever-changing combination of strategic, commercial and operational considerations are always in play during loading and unloading operations. To define the level of utilization or efficiency in such an environment requires a clear prioritization of certain key factors, which, we assume, will be generated by company management. The mathematical modeling approach proposed by Lababidi et al. in 2004 is a good example of such prioritization: they generate an objective function which takes into

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account such things as the *planning horizon* ("the time period representing the duration over which a company tries to forecast production and allocate demands"), *products* ("final outputs produced by the process industry"), *demand sources* ("market places and distribution centers"), *lost demand* ("sales orders that will not be satisfied"), etc. The objective function is designed to minimize "the total production costs and raw material procurement, as well as lost demand, backlog, transportation, and storage penalization" (Lababidi et al., 2004).

The above approach is one example of optimizing the supply chain for a petrochemicals manufacturer. Different organizations may have different approaches to building their individual optimization functions. For example, petrochemical companies that are competitors in the marketplace may collaborate on certain tasks or projects to improve overall profitability for each participant. Supply chains become more efficient when competing companies find ways to share or swap assets or information to better serve the end customer while reducing total costs for each participant. Al-Husain et al. describe the concept as follows:

> In a commodity-type industry such as oil and petrochemicals, the source of the commodity is often of no interest to the final customer as long as the commodity adheres to its required specifications and the delivery of that commodity is made by the promised due date. Therefore, competing oil and petrochemical companies form supply chain alliances when delivering commodities to customers in order to reduce transportation and inventory costs and improve customer service. In return, cost savings for transportation in the overall supply chain are shared among participating companies. This form of collaboration is referred to as shipment swapping" (Al-Husain et al., 2008).

Collaboration in the form of such "swaps," where entities can swap shipments, assets or entire business units, is a creative way to achieve improved supply chain efficiency in the industry. This approach to supply chain optimization constitutes what may be termed "paradigmatic change," which can supersede certain operational considerations at the level of the marine-dock in favor of larger, systemic gains.

However, according to Al-Husain et al., this is still an emerging science: "...despite the significant advantages this practice has generated for companies, a defined model for making such decisions does not exist. The subject has barely received any attention in the operations management literature. Currently, no specific method has been adopted to determine when companies should attempt to make swap decisions" (Al-Husain et al., 2008).

The above overview is intended to illustrate, at a macro level, some of the complexities involved in trying to optimize supply chains in the petrochemical industry – multiple transport options, fluctuating prices of raw materials, capacity constraints, legacy systems, long lead times are only some of the factors in play at any given time. In the next section, we show how uncertainty at the macro-level manifests itself even at the level of the marine dock.

2.2 Efficiency at the dock level – a research gap in the petrochemicals industry

Logistics planning for bulk chemicals is an under-represented area of research (De et al., 2004). This may be because bulk chemical operations are affected by a number of different factors which make the measurement of utilization level difficult. Some of the constraints are vessel/barge capacities, product pump speeds, line switches, parallel loading, procedure-time-cycles, safety requirements and storage capacities. Several variables also impact day-to-day operations: asset conflicts, vessel and barge availability/timing, weather, river water level, product demand, product availability and equipment failure. Furthermore, the order quantity

is not always fixed but can be within a range specified by contractual agreements. Also, chemical cargo is subject to various rules and regulations, which influence the loading process of chemical tankers/barges (Stadtler, 1983).

However, logistics planning and analysis of dock-side operations are well defined for certain other types of shipping, such as container shipping or crude-oil shipping. It is well known that operating tankers and container vessels can be quite expensive on a daily or even hourly basis (Zeng & Yang, 2009) – hence, there have been numerous studies dedicated to minimizing these costs while maintaining a high level of operational efficiency. In container shipping, berth utilization is defined in terms of time spent at the berth by a container vessel – this includes "several components such as paperwork, ballasting/de-ballasting, opening and closing the hatches, actual loading/unloading as well as repair times in case equipment fails during operation" (Jagerman & Altiok, 2003). Jagerman and Altiok define berth utilization as "the asymptotic proportion of time that the berth is occupied by a vessel." Thus, in container shipping, port time per vessel and berth utilization are critical measures of performance for berth operations. Optimizing the dock for efficiency and cost is further aided by the fact that "docks can be viewed as more highly divisible-- multiple cranes serve single vessels or multiple vessels served by single crane i.e. discrete units to load/unload" (Wadhwa, 1992).

Figure 5: Container Tanks with a Quay Crane, Truck & Chassis at Port (Alibaba.com, 2011)

For bulk chemicals, on the other hand, several factors have contributed to a lack of research in this space. Chemical cargo is shipped in (tank) containers, as seen in Figure 5, but also in various other modes such as trucks, trains, barges, pipelines and multi-parcel chemical tankers. At the typical chemical berth, operations can be locally optimized in several ways. Planners could choose to optimize the amount of inventory stored on site to minimize holding costs, minimize vessel loading/unloading time, truck waiting time, pipeline service costs etc. To arrive at a single metric that can encompass all of the above factors is not feasible, especially when different sets of constraints and variables apply to each of the above operational metrics.

We further speculate that a high level of IP protection in a fragmented industry, coupled with traditionally high margins for chemical products, has led to a lack of interest in analyzing dock-side operations.

Next, we survey some of the work done in the area of dock optimization in the container shipping industry, where, as mentioned earlier in this section, the issue has received significant research attention.

2.3 Dock Optimization in Container Shipping

The fast-paced growth in containerized shipping has created a highly competitive climate amongst world ports (Park & Kim, 2002). Though there are levers available to port planners to differentiate their services, a primary criterion for port success is operational excellence. Key measures used to evaluate ports, and hence to make impactful industrial site and sourcing location decisions, are based on a port's ability to efficiently load and unload cargo (Steenken, Voβ & Stahlbock, 2004). For these reasons, quantitative modeling of port operations for the container shipping industry has been recorded in the academic literature as

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early as 1987 (Li & Vairaktarakis, 2004). Though the objectives may differ, by industry and even amongst the various container-shipping related models, elements of this knowledge stream prove useful for application to the chemical logistics issue at hand.

The objectives of different container port operations models have varied significantly: studies consider different aspects of ship-berth link planning such as the degree of berth occupancy, the percentage of congestion in port, the optimum cost combination, the minimal ship time in port, the total cost of port system, the optimal determination number of berths and cranes in port, the mutual QCs interference exponent, the optimal combination of berths/terminal and quay cranes/berth etc. (Dragović, Park & Radmilović, 2006).

However, in spite of these divergent purposes, much of the literature has held that some time-based performance measurement should be used. Mak and Sun hold that one such measure, vessel turnaround time, is the most important port service level evaluation measure available (Mak & Sun, 2009).

Further complicating the issue, some of the models attempt to balance optimization of vessel loading and unloading and optimization of yard storage simultaneously (Boros, et al., 2008). These dual objective approaches make abstraction of dock optimization techniques more difficult. Despite the differing opinion on which criteria to optimize for, there is considerably greater agreement on technique and methodology.

In the next section, we survey some of the literature around routing and scheduling vessels arriving at the berth. In so far as a marine-dock is a link between sea and land operations, we believe it is important to understand the notion of "optimized operations" from the perspective of the ship-owner or charterer.

2.4 Bulk Liquid Chemicals – loading and unloading from the ship's perspective

As mentioned earlier, the objective at the level of the marine dock is to "turn around" vessels as soon as possible – this process refers to completing operations in the least amount of time possible while the vessel is in berth.

Therefore, unpredictability in vessel arrivals can impact on dock utilization – berths which have been reserved for a particular vessel are un-utilized if the vessel is delayed.

Our survey of the research literature indicates a wide availability of material focusing on the logistics of chemical tankers – their routing as well as scheduling. For this reason, in our thesis, we assume this to be a separate problem to optimizing operations at the dock itself.

We direct the reader to the work of Jetlund and Karimi (2004) (multi-integer linear programing) and Jagerman and Altiok (2003) (a study of queuing behavior), as illustrative examples of approaches to routing and scheduling optimization. The approach taken by Jetlund and Karimi seeks to maximize profit (Jetlund & Karimi, 2004) for the vessel operator whereas the approach taken by Jagerman and Altiok seeks to measure the impact of uncertainty in vessel arrival times on two critical factors: port time per vessel and berth utilization (Jagerman & Altiok, 2003).

2.5 Simulation and Optimization Techniques

In the preceding sections, we have mentioned some of the many factors that impact upon efficiency at the dock. Experienced logistics planners and marine operations personnel develop certain heuristics, over time, for determining what the dock is able to handle for a given level of product demand. However, it is impossible for humans to calculate a quantifiable level of certainty about berth utilization without help from computerized

simulations. Computer simulation models would be able to solve complicated objective

functions – such as the one suggested by Lababidi et al. (2004) in Section 2.1 – by taking into

account several uncertain variables which can each be represented by a probability

distribution.

Thus, simulation as a tool to understand and improve dock operations has been in use for at

least two decades; due to the complexity of berth scheduling, simulation models are

increasingly being utilized to understand this aspect of port operations (Kozan & Casey

2006).

Dragović et al. provide a detailed survey of the different approaches, including modeling

languages that researchers have taken to deal with issues of berth assignment and equipment

scheduling (Dragović, et al., 2006). A type of simulation technique often used in modeling of

port operations is known as discrete-event simulation. This type of simulation takes a

procedural approach to scenario generation. The advantage of this technique is in the

possible precision—each event in a work cycle can be individually quantified for a more

accurate representation of system as a whole.

Hartmann addresses the interplay of theoretical scenarios, simulation and optimization and

asserts that "simulation models are developed to evaluate the dynamic processes on container

terminals" (Hartmann, 2004).

Once a scenario is generated, it is typically subject to either a simulation model or an

analytical model for optimization. As described in Dragović et al. (2006), this scenario could

take form in an off-the-shelf software application, a custom computer program, or a purely

mathematical analysis.

3 Research Methods

As mentioned previously, dock operations are complicated by variables and constraints. Variables include asset conflicts, vessel and barge availability/timing, weather, river water level, product demand, product availability and equipment failure. Constraints can include vessel/barge capacities, product pump speeds, line switches, parallel loading, procedure-time-cycles, safety requirements and storage capacities.

To model for efficiency at the dock, we must express the impact of each variable or constraint in terms of cost. Cost can be expressed as a combination of monetary terms – dollars – or in units of time – hours. In our investigation of a design for modeling for dock efficiency, we have chosen to express delay in hours.

Our design is based on two sets of inputs: commercial and operational. The commercial inputs refer to forecasts of demand data for a given period into the future, weeks, months or years. Operational data refers to foreseeable variables and constraints, which might impact on loading operations.

Through the use of a database, user-interface, simulation and optimization engine, the model is designed for use by a marine operations expert. The model is a high-level proof-of-concept for analysis of dock utilization/reliability, and, as such, the generation of actual utilization figures for a particular dock is outside the scope of this paper. To accurately model the variables and constraints in terms of actual cost will require detailed inputs from operational and commercial staff, which are not available in this instance. The demonstration in Appendix A goes deeper into the design of such a system, but lacks fundamental elements of a real-world implementation such as consideration of conflicting parcel priorities, special prioritization of certain parcels or customers, expedited orders and unscheduled demand, etc.

3.1 Simulation

Computer simulation as an analytical tool in engineering design for ship-berth link has been in use since at least the early 1970s (Dragović et al., 2006). The type of computer simulation we propose for use in this DSS is based on applied probability. Any complex physical system will possess some degree of variability. In most cases, the primary sources of variability can be analyzed and approximately characterized using the framework of probability. The simulation approach attempts to represent the possible output of a system (or systems) by subjecting a set of input data to a model of the system containing quantified characterizations of the system's key variables. As computer processing power has increased, it has become feasible to run a large number of complex simulations iteratively for combinatorial analysis of multiple result sets. To put it simply, we are able simulate effects of multiple factors within a system simultaneously and analyze the end result. Further, we can perform this exercise multiple times to understand the range of possible occurrences within the system.

3.2 Variability

Because the simulation approach we propose is grounded in applied probabilities, the investigation and definition of the key variables within the target system is of utmost importance to the accuracy of the simulation model. For some variables, data will already exist from which approximate probability distributions can be derived. One such example from our data collection is vessel/barge actual arrival date. Combined with volumetric information at the parcel-level, this database of vessel arrival dates and order sizes allows us to understand seasonality by chemical type in terms of demand on the dock assets.

In some cases, new reporting practices should be put in place in order to begin collecting data on a key variable. However, there will be many variables which should not be modeled through abstraction from quantitative data. The value of precision gained through formal

quantitative data collection should always be weighed against the time and effort required. An example where this trade-off favors qualitative data collection is vessel-to-dock equipment conflicts. A data collection regimen could record each occurrence of an asset conflict over time, but this would be unlikely to produce a sufficiently more valuable approximation than interview-based data gathering with on-site operations personnel.

3.3 Benchmarking

Simulated demand scenarios alone provide valuable information in that they project a potential future based on the input data and the variability quantified in the simulation model. However, even greater insight can be gained through the iterative application of computer simulation (e.g., Monte Carlo simulation) combined with an additional engineering systems problem solving approach—optimization. A thorough treatment of optimization and the ship-berth link problem can be found in Dragović et al., 2007. The fundamental question that optimization attempts to answer is as follows: Given a certain set of constraints and a certain objective, how fully can the objective be met?

As with computer simulation, the domain of optimization comprises many different approaches and techniques and as mentioned previously in our literature review, for the optimization module in our demonstration, we have chosen to use Palisade Corporation's Risk Optimizer with its Genetic Algorithm approach.

An optimization program has two primary components: the objective function and the constraints. The objective function is typically stated in terms of maximization or minimization and is subject to the satisfaction of all constraints. In designing a program focused on optimization of marine dock operations, the objective function could be considered in many different ways. For instance, the program might seek to minimize the

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amount of free work time at the facility or the amount of money spent on demurrage charges. Alternatively, the program could attempt to maximize the throughput of the dock in terms of liquid weight, vessels served, or parcels dispensed. In our implementation of the proposed DSS design (see Appendix A), we developed an objective function which seeks to minimize the total idle time of the marine dock.

With the objective function defined, we are able to implement the constraints that the solver will be subject to during the solution search. In our case, the constraints will primarily consist of the simulated demand scenario derived from a single iteration of the Monte Carlo simulation module. This scenario will define what chemicals will be demanded at what time and in what quantity. Based on that information, and additional constraints imposed by the model of actual dock operations (e.g., product pump speeds, parallel loading requirements, dock-side safety requirements, etc.), the solver will seek to satisfy the objective function to its fullest ability.

Once the solver has arrived at an acceptable solution, this process can be repeated for the remaining iterative outputs of the simulation module. After all potential future scenarios have been optimized based on the objective function it is possible to express the level of asset utilization for the marine dock in terms of confidence intervals. For instance, we could say: according to the model, this dock can satisfy 99.5% of this demand plan at 73.4% confidence. Confidence in this context refers to the amount of certainty with we can predict the occurrence the fulfillment of product demand *based on the model*. So, in this case, if we ran the model through 1,000 iterations, we could expect demand satisfaction to be at or above 99.5% for approximately 734 iterations.

3.4 Gathering Data to Support the Models

Though the purpose of this research is to present a framework for the decision support system, it is important to include a note on minimum and recommended data requirements. As described previously, there are several different methods for gathering data and, depending on the intended use and anticipated benefit of the data, a more or less rigorous methodology will be appropriate. For the purposes of this investigation and proposal, we will discuss our own data gathering and the recommended additional data gathering to support a fully-operational (in terms of benefit to operational efficiency projects) implementation of the DSS.

The data can be divided into three different categories—expected demand data, unplanned variable data, and known constraint data. For our implementation of the DSS, the expected demand data was provided by the sponsor company in the form of Enterprise Resource Planning (ERP) order history. Though we received several years of data, not all data was required to apply simple forecasting algorithms to the historical demand patterns. Ideally, in a full implementation of the DSS, the forecast data used will be the best available forecast that is used for other operational and business decision making processes.

3.5 Proposed Process Flow
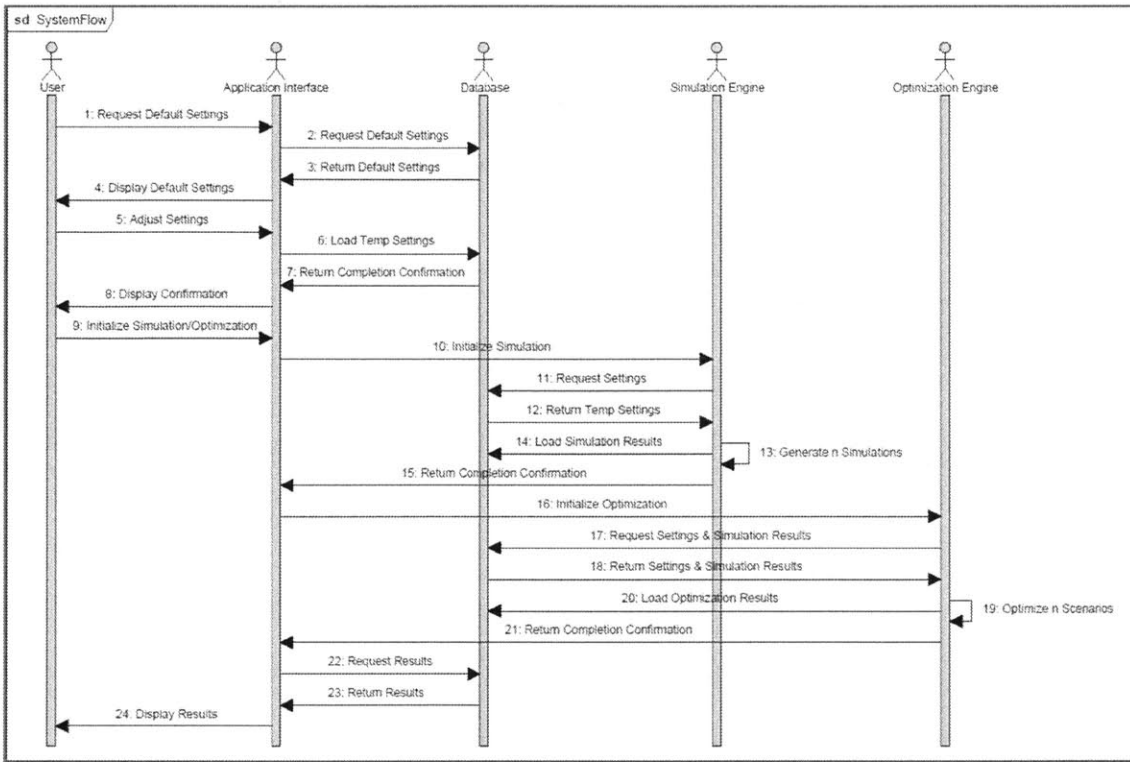
Figure 6: Model System Flow

Figure 6 describes our proposed flow of information through the system over time. An expert user (such as an experienced logistics planner) interacts with the user interface (refer Appendix A) to run simulations and optimization scenarios based on forecasted demand. Dock-side operations are modeled in a database such as in Appendix A, Figure 8. The database in turn is accessed by the simulation and optimization modules after the user has defined the particular variables and constraints he or she wishes to consider for the exercise.

In its essence, the simulation module would allow a user to see the effects of different variables for a given order-mix of chemical parcels that are to be loaded in the near future. It would express various possibilities of delays that might ensue based on expected variance in such factors as water level or weather related delays. The user would be presented with multiple scenarios from the simulation module from which he or she could extract a subset of

scenarios which could then be further optimized based on operational constraints. The activities carried out in the simulation and optimization modules are described in greater detail in Appendix A.

3.6 User Interface

We've reviewed the gathering, modeling, simulating and optimizing of data from marine dock operations. However, for routine operational use, the processes undergone to generate the final output are overly complex. In order to simplify the process for the operational user, all the components and modules of the system should be implemented behind a single, seamless user interface. This interface should allow the user to input the base data for the simulation module, select variables (and variable settings for advanced users, e.g. distribution types, gamma values, p-values, etc.), select constraints (and constraint settings for advanced users), and then start the system. For an example of what such a user interface might look like, see Figure 7.

Figure 7: Hypothetical User Interface

4   Conclusions

4.1 Review of Demonstration Decision Support System

The above illustrative model of a DSS for dock optimization works on the following premises related to data gathering and decision making:

- Availability of sales/demand data from operations, sales.

- Availability of quantitative and qualitative data on variables and constraints affecting dock operation

- Prioritization of key variables and constraints by operations staff – this list of key impacting factors will differ from dock to dock or manufacturing facility to manufacturing facility.

- Design of an objective function for a given marine dock by management and operations staff – a marine dock can be optimized for vessel time spent at berth, cost per hour of operation, throughput of chemical product per year, etc.

The choice of simulation model or data gathering techniques will vary from dock to dock; however, the principles of optimizing for efficiency or utilization will remain the same. It is indeed possible for operations personnel to derive quantifiable metrics on utilization and efficiency provided there are clear assumptions or guidelines on what constitutes efficiency (cost, time, throughput or a weighted combination of these and other factors) and which variables and constraints have the most impact on day-to-day operations.

4.2 Implications and Recommendations

We discussed in Section 1.2 that the US petrochemicals industry can expect revenues to grow over the coming years. However, the competitive landscape for players in the petrochemical industry is currently a challenging one, on account of volatility in prices of oil and raw

materials, rise of additional refining capacity in the Middle-East and Asia and after-shocks of the 2009 economic recession still being felt. In this environment, a focus on reducing logistics costs and optimizing capacity utilization is a key success factor. Whereas maritime transport of bulk chemicals is a primary mode of transport for bulk chemical manufacturers like Al-Chem Inc., not enough research has been carried out on optimizing operations at the dock. In our thesis, we have surveyed the literature on optimizing marine-dock operations from the perspective of the ship-owner as well as container port operators, and we have used the relevant findings to suggest a model of a decision-support-system. We speculate that the complexity of factors affecting loading and unloading operations has delayed the emergence of an industry-wide standard, or even in many cases a company-wide standard, for measuring marine dock utilization levels. However, without a unified framework for such evaluation, comparison between docks, and thus prioritization of capital- and process-improvement initiatives is not possible. We have shown that it is possible to quantify marine dock utilization using processes and tools proven in other related operational environments. We recommend the adoption of a unified, robust and repeatable decision support system framework for implementation across multiple petrochemical manufacturing facilities. This approach will enable the benchmarking capabilities necessary to remain operationally competitive in the 21st century.

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Appendix A – Demonstration Decision Support System

Notes

The unplanned variable data, such as water level problems, inclement weather delays, other vessel/barge arrival delays, equipment failure, etc., were gathered qualitatively for this study. The categories of variables were derived through interviews and conversations with the sponsor company.

Finally, the known constraint data were reported both quantitatively and qualitatively. Details of many constraints, such as chemical-to-dockside compatibility, were provided by the sponsor company. While other constraints, such as co-loading restrictions, were described only in terms of functionality. Where full detail of constraints has not been provided, placeholder values have been used. In a fully-functional implementation of the DSS these values will be replaced by actual values based on equipment, environmental and regulatory restrictions.

Modeling the Data

As seen in Figure 8, the data model reflecting the operational structure of the dock and loading/unloading activity should remain largely the same between implementations of the DSS. The DELIVERY table is the only table required for the hosting of information on expected demand. However, most implementations will also include subsidiary reference data tables with additional information on customers, products, etc. The other tables seen in the figure provide the constraint data required to formulate the final optimization problem.

In Figure 9 we see a simple representation of unplanned variable data as probability distributions. The last field in the table provides the formulation of the probability

distribution to whichever off-the-shelf or custom simulation software package is being used

for the DSS. We will discuss the use and functionality of these fields and tables in greater

detail within the following section.
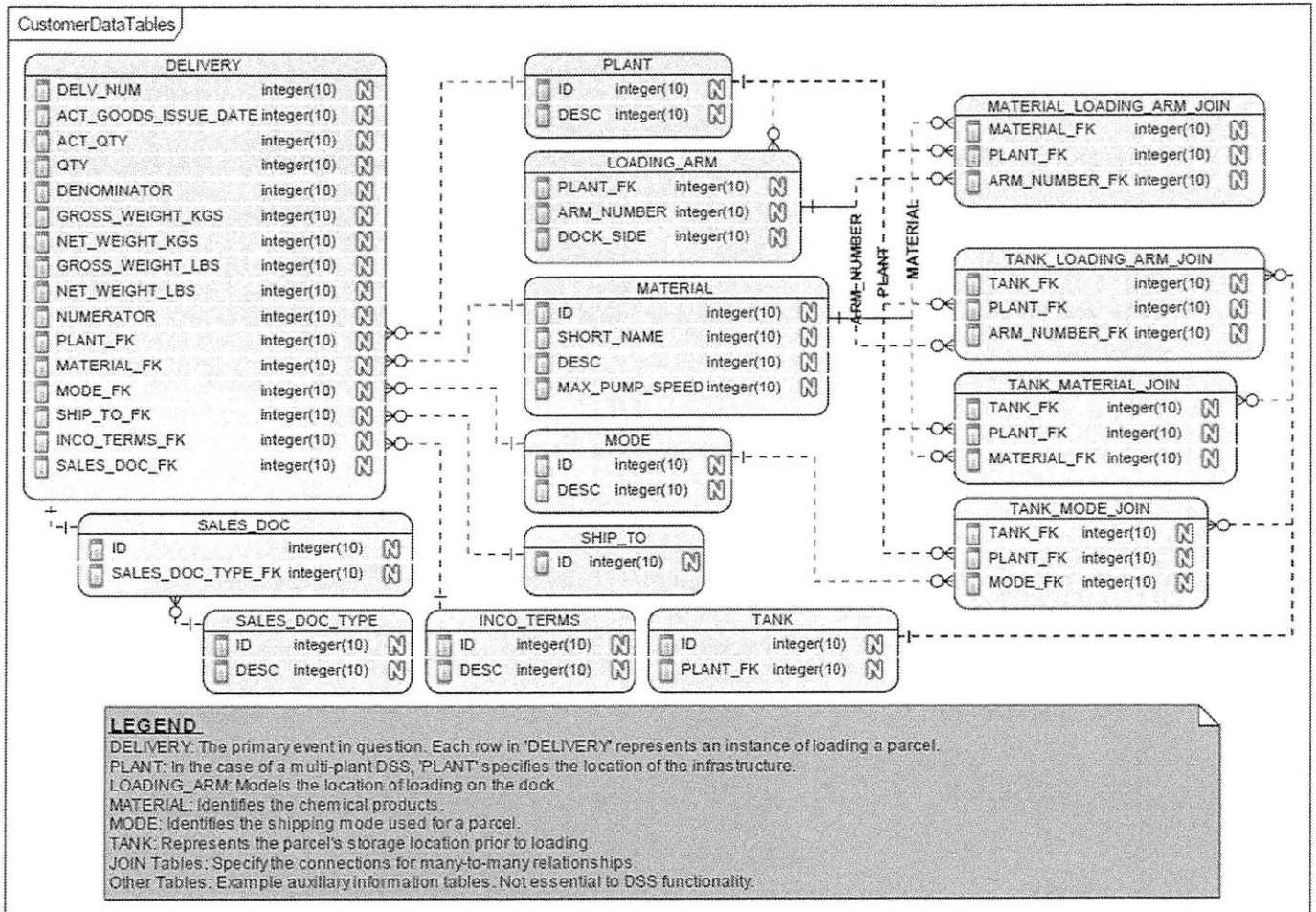
Figure 8: Illustrative database to model marine dock operations
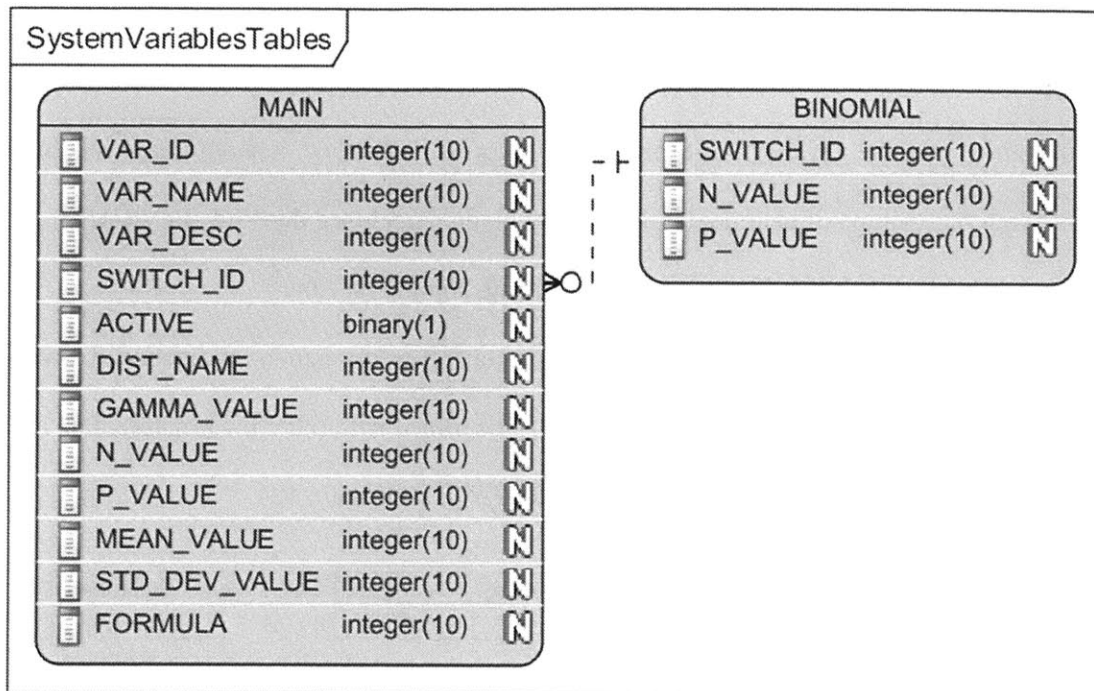
Figure 9: Illustration of how variables may be represented in a database

Simulating the Effects of Unplanned Events on Unloading/Loading Times

Though many simulation techniques exist (such as discrete-event-simulation which we mentioned in Section 2.5) and could be utilized within our proposed framework, we use Monte Carlo simulation due to two key benefits. First, through its iterative approach, Monte Carlo simulation helps to uncover unexpected interactions between the multiple variables having unique probability distributions typically present within complex systems. Second, because it is a widely-used analytical technique, many commercial software vendors provide easy-to-use Monte Carlo simulation engines that interface with common enterprise and home office software suites. For the simulation module in our implementation of the proposed DSS, we use Palisade Corporation's @RISK and the DecisionTools® Suite.

To begin the simulation of the unplanned events affecting unloading and loading times at the marine dock, we begin by extracting a set of data from our operational database, referred to in

Figure 7 as *CustomerDataTables*. This data extract need only contain a minimal amount of information—only 4 columns. First, it should have a column identifying the chemical type for the parcel (see the *CHEM_DESC* column in Figure 10). Second, it should have a column quantifying the volume of chemical ordered for a given parcel (see the *NET_VOLUME* column). Third, it should have an expected ship date column (see the *ACT_GOODS_ISSUE_DATE* column). Last, as a general recommendation, it should have a unique identifier that allows for the information to be joined with other informative data after the simulation and optimization routines (see *ORDER_ID* in Figure 10).

CHEM_DESC	NET_VOLUME	ACT_GOODS_ISSUE_DATE	SHIP_TO_FK	ORDER_ID
NDNE 8 9000 KG	2498338.839	12/31/2010	605231	12/31/2010-605231
N25P1-2.5 9000 KG	2955994.81	12/31/2010	B003	12/31/2010-B003
NDNE 10/1112IO/12	2652538.83	12/30/2010	613433	12/30/2010-613433
MEG-F GL 9000 KG	4722761.697	12/29/2010	617643	12/29/2010-617643
NDNE 12 9000 KG	2495690.838	12/28/2010	605067	12/28/2010-605067
NDNE 8 9000 KG	2497073.84	12/27/2010	605231	12/27/2010-605231

Figure 10: Sales History - Example

Once the source data has been extracted from our database, we must choose and/or adjust the probabilistic variables affecting time spent loading and unloading. To model these variables, the DSS contains two separate probability distributions for each event. The first is a binomial distribution with *n* equal to 1 and p equal to the approximate probability that the event should occur. We refer to this as the binary switch as it controls the active state of variable in an "ON/OFF" manner. In an iteration of the simulation where the outcome is a "1," the variable is active. In an iteration of the simulation where the outcome is a "0," the variable is inactive. As an example, in Figure 11, for the variable named *Inclement Weather,* we see that p has been set to '0.05'. This indicates that the *Inclement Weather* variable should be activated in approximately 5% of the simulation runs. Because we are using Monte Carlo simulation, i.e. with a limited number of iterations, it is unlikely that we will often see an exact 1 in 20 ratio.

34
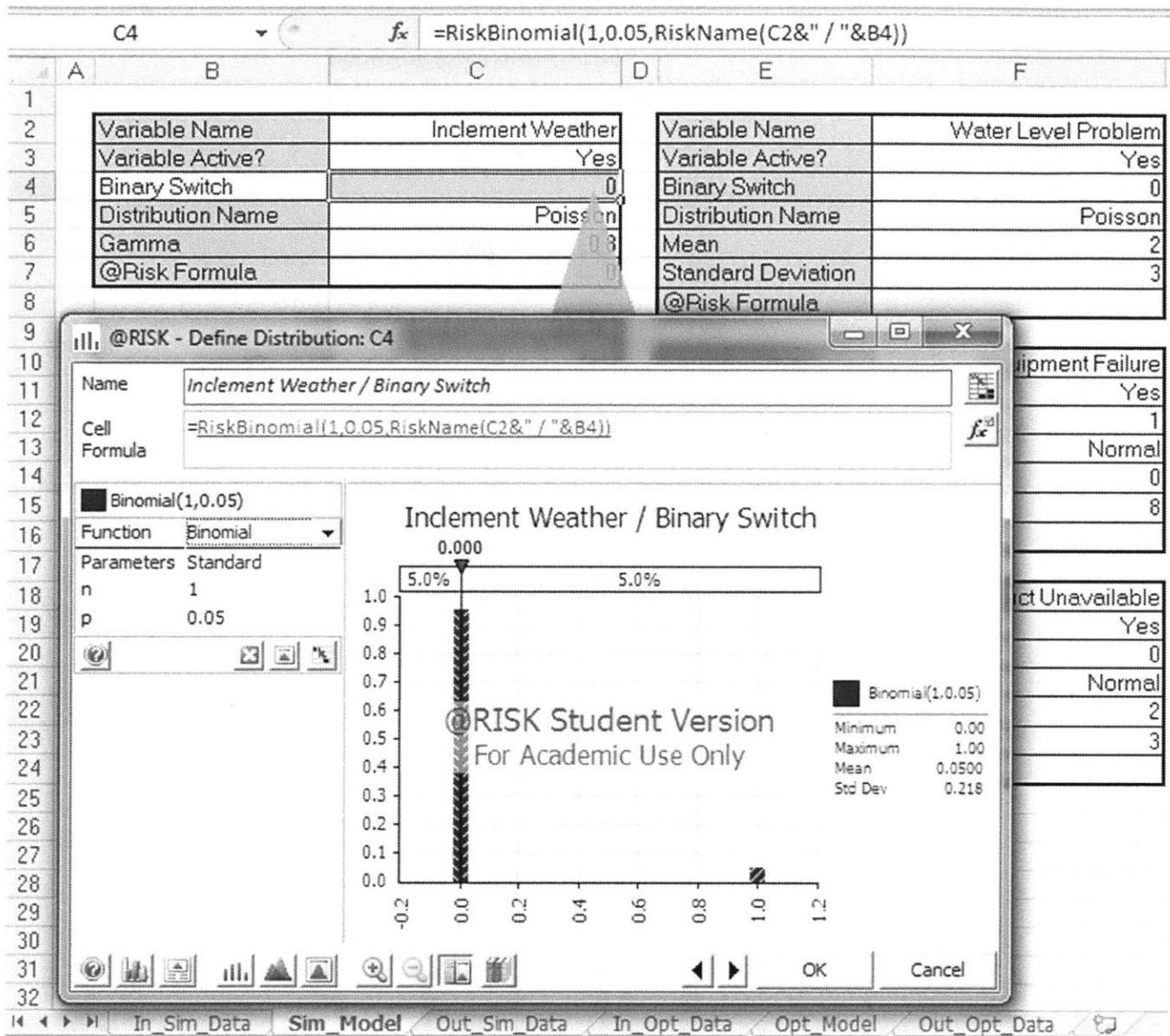
Figure 11: Variable - Inclement Weather

Figure 12 shows the formulation for the main distribution itself. As can be seen in the screen

capture, the distribution is of the *Poisson* type with a Gamma value of '1.2'. This

formulation is the multiplied by the binary switch result value (to control activation, then so

time multiplier (in this case '4'). The end result of this formulation is that the value in the

selected cell ('C14') will be calculated subject to the previously mentioned binary switch and

a *Poisson* distribution with a defined gamma value and a multiplier of 4. This end value will

represent the number of hours delay experienced for the parcel in question.
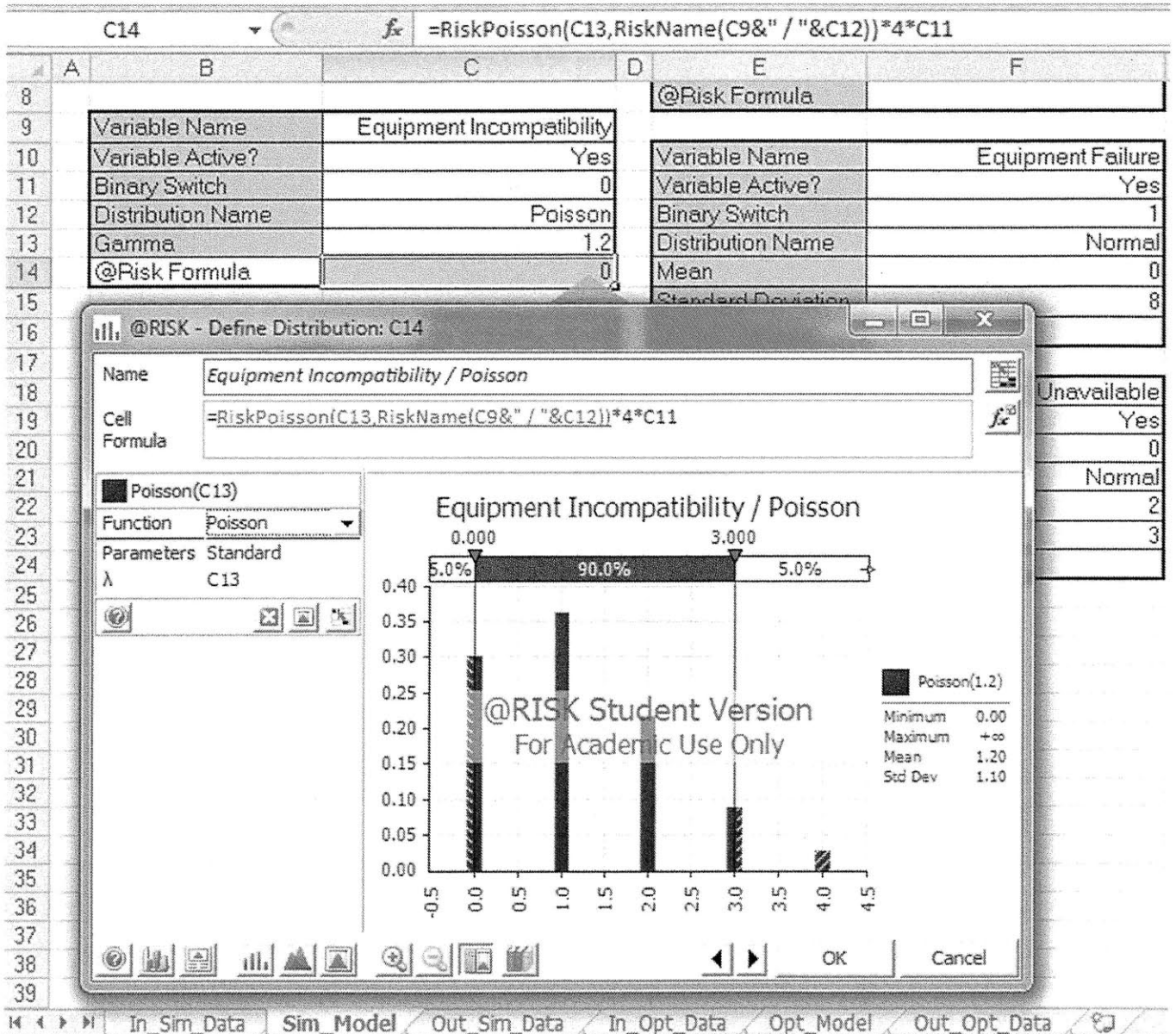
Figure 12: Equipment Incompatibility

Below, in Figure 13, the same is shown for a variable with a *Normal* distribution having a
mean of '0' and a standard deviation of '8'.
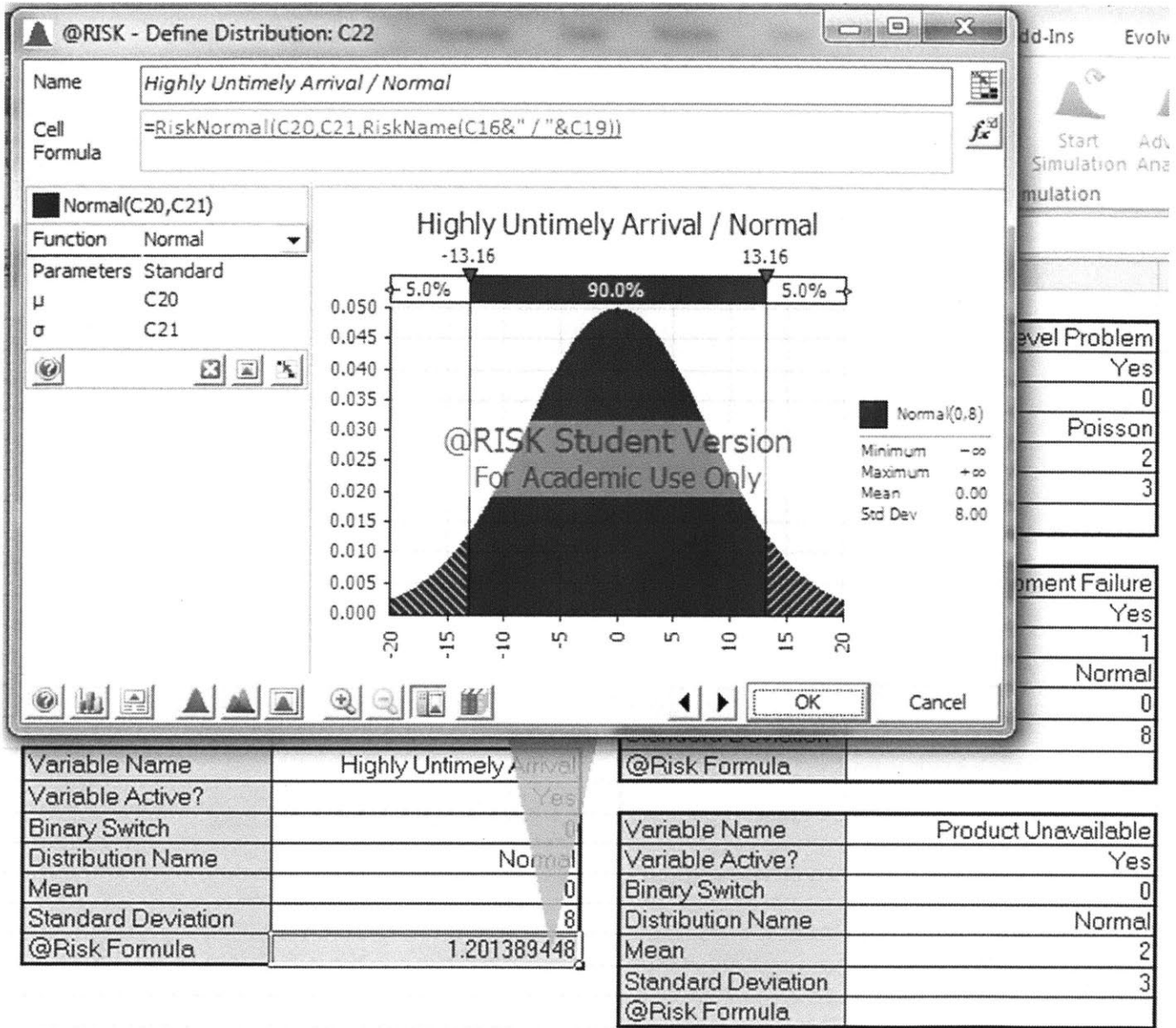
Figure 13: Normal Distribution Example

Following the definition of all variables and their two respective probability distributions, we

are able to calculate the potential time adjustment for each parcel en masse. As shown in

Figures 14 and 15, @Risk will calculate multiple iterations of the model at a single

command. In this case, 100 iterations of the model were run, the results of which can be seen

below, as distributions, for the two parcels selected.

The first parcel, identified by the order number *12/26/2010-613539*, shows a distribution of values such that '0' occurred more than 95% of the time and the rest of the iterations resulted in either 4 or 8 hours of delay. We find a mean value of 0.12 hours of delay with a standard deviation of 0.891 hours.
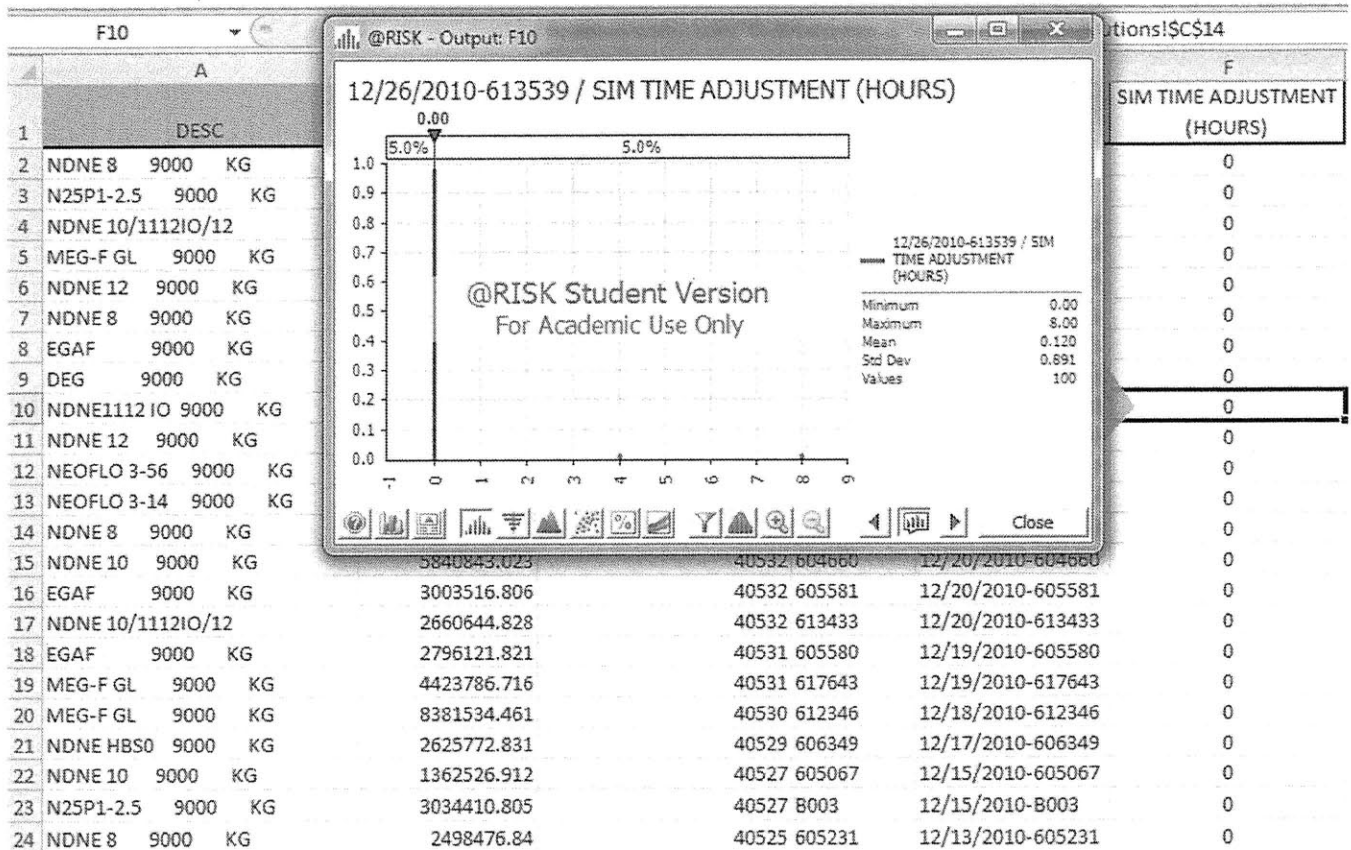
Figure 14: Parcel 1, Simulation Process

The second parcel, identified by the order number *12/20/2010-604660*, shows a more widely distributed results set with values ranging from 0 to 16 hours and just less than 95% of the results with a zero value. The descriptive statistics show a mean of 0.440 and a standard deviation of 2.19 for this result set (also 100 iterations, from the same simulation run).

	A				F
					IM TIME ADJUSTMENT
1	DESC				(HOURS)
2	NDNE 8	9000	KG		0
3	N25P1-2.5	9000	KG		0
4	NDNE 10/11121O/12				0
5	MEG-F GL	9000	KG		0
6	NDNE 12	9000	KG		0
7	NDNE 8	9000	KG		0
8	EGAF	9000	KG		0
9	DEG	9000	KG		0
10	NDNE1112 IO 9000		KG		0
11	NDNE 12	9000	KG		0
12	NEOFLO 3-56	9000	KG		0
13	NEOFLO 3-14	9000	KG		0
14	NDNE 8	9000	KG		0
15	NDNE 10	9000	KG	5840843.023 40532 604660 12/20/2010-604660	0
16	EGAF	9000	KG	3003516.806 40532 605581 12/20/2010-605581	0
17	NDNE 10/11121O/12			2660644.828 40532 613433 12/20/2010-613433	0
18	EGAF	9000	KG	2796121.821 40531 605580 12/19/2010-605580	0
19	MEG-F GL	9000	KG	4423786.716 40531 617643 12/19/2010-617643	0
20	MEG-F GL	9000	KG	8381534.461 40530 612346 12/18/2010-612346	0
21	NDNE HBS0	9000	KG	2625772.831 40529 606349 12/17/2010-606349	0
22	NDNE 10	9000	KG	1362526.912 40527 605067 12/15/2010-605067	0
23	N25P1-2.5	9000	KG	3034410.805 40527 B003 12/15/2010-B003	0
24	NDNE 8	9000	KG	2498476.84 40525 605231 12/13/2010-605231	0

@RISK - Output: F15

12/20/2010-604660 / SIM TIME ADJUSTMENT (HOURS)

0.00

| 5.0% | 5.0% |

@RISK Student Version
For Academic Use Only

12/20/2010-604660 / SIM
TIME ADJUSTMENT
(HOURS)

Minimum	0.00
Maximum	16.00
Mean	0.440
Std Dev	2.19
Values	100

Close

Figure 15: Parcel 2. Simulation Process

We have demonstrated in the previous figures that Monte Carlo simulation can be used to convert real-life unplanned operational interruptions into multiple potential planning scenarios. We achieve this by using two-stage variables with a binomial probability distribution as a binary switch and an additional probability distribution to represent incident severities.

Optimizing Simulated Scenarios to Determine Dock Utilization Confidence Intervals

The simulated scenarios created by the previous process represent the potential actual demand at the dock. Since the expected demand and the eventual actual demand are expected to differ based on numerous factors, we constructed a simplified model in which the key variables were cast in probabilistic terms. These probabilities, implemented through the

@Risk simulation software package, generate the input for the next module in our proposed decision support system.

The problem of berth scheduling is very similar to the more frequently discussed operations research problem known as *crew scheduling*. Similarly, this problem has been approached by many different analytical tools - Lagrangian Relaxation, Sub-Gradient method, Mixed-Integer-Linear-Programming, Simulated Annealing, Tree Search Procedure, etc. (Dragović et al., 2006). To maintain approach and interface continuity, we use Palisade Corporation's RISKOptimizer for the optimization module of our illustrative approach to building a DSS. RISKOptimizer combines the simulation and Genetic algorithm approaches making it useful for large combinatorial problems where individual near-optimal solutions are acceptable for the sake of iteration volume.

The first step in optimizing the simulated scenarios is identifying and quantifying the constraints for the optimization model. Examples of these constraints for are shown in Figure 16. These constraints include the rate at which each individual chemical is pumped from dock to vessel/barge, certain berths that a parcel cannot be loaded from, certain chemicals that a parcel cannot be loaded adjacent to, cleaning penalties incurred if a berth is switched to load a different chemical and latency penalties incurred due to special handling required by certain chemicals (e.g., pre-heating/cooling). Each constraint restricts the way in which the parcels can be loaded and thus reduces the expected utilization of the dock.

PUMP_RATE	EXCLUDED_BERTH_1	EXCLUDED_BERTH_2	EXCLUDED_PARALLEL_PRODUCT_1	EXCLUDED_PARALLEL_PRODUCT_2	CLEANING_PENALTY	LATENCY_PENALTY
250	0	0	0	0	3	0
380	0	0	0	0	2	0
250	1	2	0	0	2	1
350	1	2	DEG 9000 KG	EGAF 9000 KG	4	0
275	3	4	0	0	1	0
250	0	0	0	0	3	0
200	0	0	NEOFLO 3-56 9000	NEOFLO 3-14 9000	1	0
500	3	4	0	0	1	1
400	3	4	0	0	1	0
275	3	4	0	0	1	0
340	0	0	0	0	3	0
340	0	0	0	0	1	1
250	0	0	0	0	3	0
375	0	0	0	0	3	0
200	0	0	NEOFLO 3-56 9000	NEOFLO 3-14 9000	1	0

Figure 16: Example Constraints

The next step is the optimization itself. Though the optimization needn't be observed or overseen, we will use a model to explain the functionality it achieves. The model seen in Figures 17-20 is based on a demonstration problem and spreadsheet included with Palisade Corporation's RISKOptimizer software. In the first figure we find a graphical representation of job queues (the five rows of colored bars) with a randomly determined job schedule in place (the order and placement of the colored bars). The queues represent the berths and the colored bars represent parcels. The random job schedule is far from optimal, but obeys all of the constraints within the problem. As we see based on the progression of time and the subsequent minimization of the idle time required, the RISKOptimizer engine continues to test various solution attempts based on genetic logic and chooses improved solutions to the problem. Finally, when the optimization has reached a certain time limit or goal value, it will be stopped and the new schedule can be displayed in the chart. Again, this is not necessary for most uses of the DSS, but could prove useful for an operational user at the dock.

RISKOptimizer Progress

Iteration:	200
Simulation:	12
Runtime:	00:00:19
Original:	704.5801
Best:	584.2487

OPTIMIZE -->

Randomize Order

The "Total Idle Time" is highest at the onset of the optimization reflecting the random generation of a schedule.
There will be high "Late Start" penalties for the parcels in this random schedule.

Total Idle Time 1094.116

INITIAL VALUES

Mean (Best Simulation) = 584.2487

...ASSIGNED/OPTIMIZED VALUES

parcel list	parcel / berth ID	berth ID	product required	Time	parcel list	parcel / berth ID	berth ID	product required	Proc Time	Available for Next Task .			
										P1	P2	P3	
1	11	1	1	52.8974	16	41	4	1	71.694	n/a	n/a	n/a	71
2	12	1	2	64.6875	5	15	1	5	43.392	43.392	n/a	n/a	
3	13	1	3	25.2589	24	54	5	4	14.785	n/a	n/a	n/a	
4	14	1	4	91.6797	1	11	1	1	52.897	124.59	n/a	n/a	
5	15	1	5	43.3915	9	24	2	4	14.874	n/a	29.66	n/a	
6	21	2	1	6.48482	12	32	3	2	71.483	n/a	n/a	71.483	

Figure 17: Optimizer Model Running, 1 of 4

Draw Schedule

OPTIMIZE -->

Randomize Order

Re-drawing the schedule visually shows the optimization improvements to the schedule in the chart above.

INITIAL VALUES

Mean (Best Simulation) = 584.2487

...ASSIGNED/OPTIMIZED VALUES

parcel list	parcel / berth ID	berth ID	product required	Time	parcel list	parcel / berth ID	berth ID	product required	Proc Time	Available for Next Task .			
										P1	P2	P3	
1	11	1	1	74.3417	16	41	4	1	63.838	n/a	n/a	n/a	63
2	12	1	2	71.1093	5	15	1	5	36.5	36.5	n/a	n/a	
3	13	1	3	32.4371	24	54	5	4	14.287	n/a	n/a	n/a	
4	14	1	4	82.4418	1	11	1	1	74.342	138.18	n/a	n/a	
5	15	1	5	36.4995	9	24	2	4	14.107	n/a	28.394	n/a	
6	21	2	1	6.78378	12	32	3	2	67.084	n/a	n/a	67.084	

Figure 18: Optimizer Model Running, 2 of 4
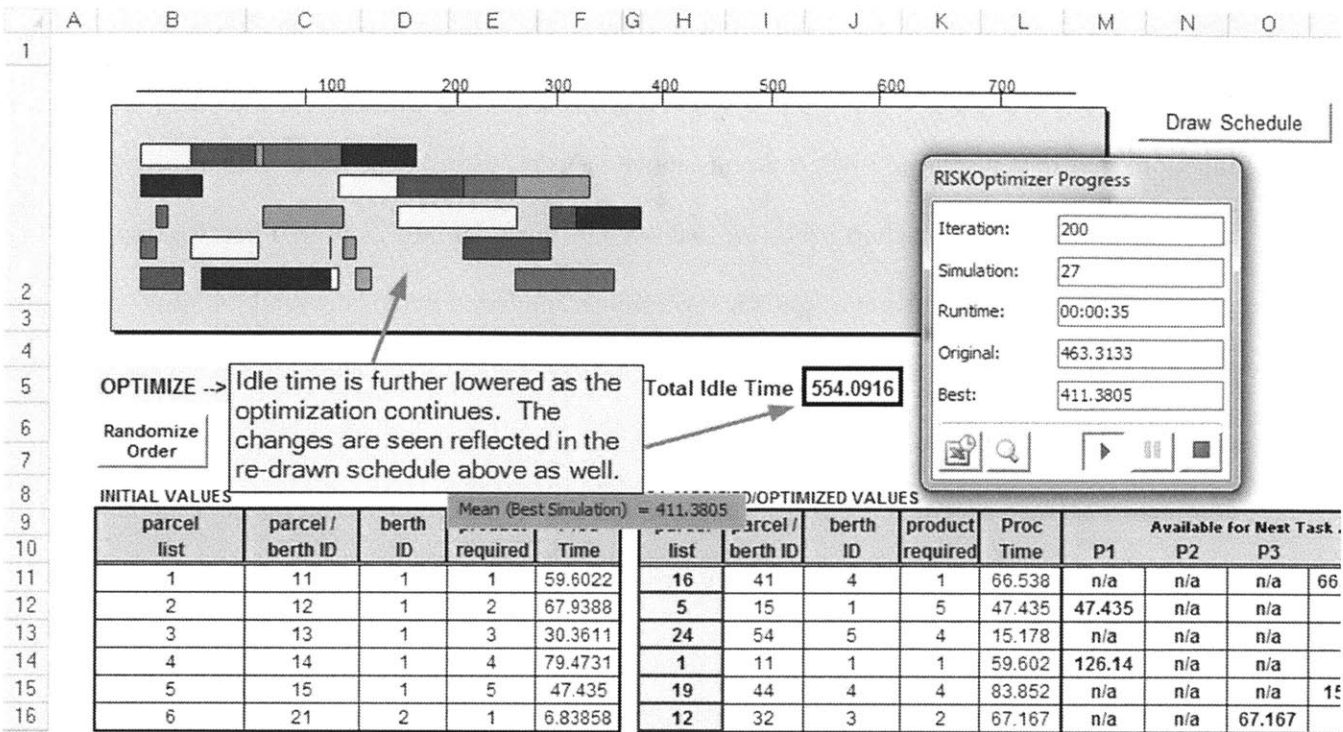
Figure 19: Optimizer Model Running, 3 of 4

RISKOptimizer Progress

Iteration:	200
Simulation:	27
Runtime:	00:00:35
Original:	463.3133
Best:	411.3805

OPTIMIZE --> Idle time is further lowered as the optimization continues. The changes are seen reflected in the re-drawn schedule above as well.

Randomize Order

Total Idle Time   554.0916

INITIAL VALUES

Mean (Best Simulation) = 411.3805

MODIFIED/OPTIMIZED VALUES

parcel list	parcel / berth ID	berth ID	product required	Proc Time	parcel list	parcel / berth ID	berth ID	product required	Proc Time	P1	P2	P3	
1	11	1	1	59.6022	16	41	4	1	66.538	n/a	n/a	n/a	66
2	12	1	2	67.9388	5	15	1	5	47.435	47.435	n/a	n/a	
3	13	1	3	30.3611	24	54	5	4	15.178	n/a	n/a	n/a	
4	14	1	4	79.4731	1	11	1	1	59.602	126.14	n/a	n/a	
5	15	1	5	47.435	19	44	4	4	83.852	n/a	n/a	n/a	15
6	21	2	1	6.83858	12	32	3	2	67.167	n/a	n/a	67.167	

Figure 20: Optimizer Model Running, 4 of 4

OPTIMIZE --> When the optimization is stopped, due to a goal or time limit being reached, the final result may be displayed, both in numerical and graphical terms.

Randomize Order

Total Idle Time   485.2506

INITIAL VALUES

Mean (Best Simulation) = 411.3805

MODIFIED/OPTIMIZED VALUES

parcel list	parcel / berth ID	berth ID	product required	Proc Time	parcel list	parcel / berth ID	berth ID	product required	Proc Time	P1	P2	P3	
1	11	1	1	70.3184	16	41	4	1	57.145	n/a	n/a	n/a	57
2	12	1	2	77.9946	5	15	1	5	41.743	41.743	n/a	n/a	
3	13	1	3	29.0292	24	54	5	4	18.198	n/a	n/a	n/a	
4	14	1	4	83.1641	1	11	1	1	70.318	127.46	n/a	n/a	
5	15	1	5	41.7434	19	44	4	4	70.018	n/a	n/a	n/a	12
6	21	2	1	7.3118	12	32	3	2	72.808	n/a	n/a	72.808	

The last feature of the decision support system is the results display, post-optimization. As seen in Figure 21 and 22, the results will typically be displayed as a probability density function. The data displayed in the columns above the chart describe the mean outcome of the simulation. Within the chart itself, we find two key pieces of information. First, we find the distribution of dock utilization statistics within the simulation (that is the total job time over the total available time). Then, we find the confidence interval at which a given level of dock utilization can be predicted. For instance, in the example below we see that with 99.5% confidence we may state that *according to our simulation-optimization model the dock should not reach greater than 94.5% utilization*. Again, in the last example we see that with 99.9% confidence we may state that *according to our simulation-optimization model the dock should not reach greater than 100% utilization* (that is the point at which assigned parcels cannot be handled). This is the key statistic and evidence produced by the decision support system.

	G2		f_x	=RiskOutput()+C2/B2		
	A	B	C	D	E	F	G
	SIMULATION_ID	AVAILABLE_TIME	MAX_JOB_TIME	WORK_TIME	WORK_TIME_RANK	TOTAL_IDLE_TIME	DOCK_UTILIZATION
	1-091	1600	894.245099	894.245099	0.3	705.754901	56%
	1-093	1600	1101.126185	1101.126185	0.8	498.8738149	69%

@RISK - Output: G2

1-091 / DOCK_UTILIZATION

@RISK Student Version
For Academic Use Only

1-091 / DOCK_UTILIZATION	
Minimum	14.3%
Maximum	107.8%
Mean	62.5%
Std Dev	12.5%
Values	5000

Figure 21: Compiled Optimization Results, 1 of 2

	G2		▼		f_x	=RiskOutput()+C2/B2	

	A	B	C	D	E	F	G
	SIMULATION_ID	AVAILABLE_TIME	MAX_JOB_TIME	WORK_TIME	WORK_TIME_RANK	TOTAL_IDLE_TIME	DOCK_UTILIZATION
	1-091	1600	894.245099	894.245099	0.3	705.754901	56%
	1-093	1600	1101.126185	1101.126185	0.8	498.8738149	69%

@RISK - Output: G2

1-091 / DOCK_UTILIZATION

−∞   100.0%

99.9%   0.1%

@RISK Student Version
For Academic Use Only

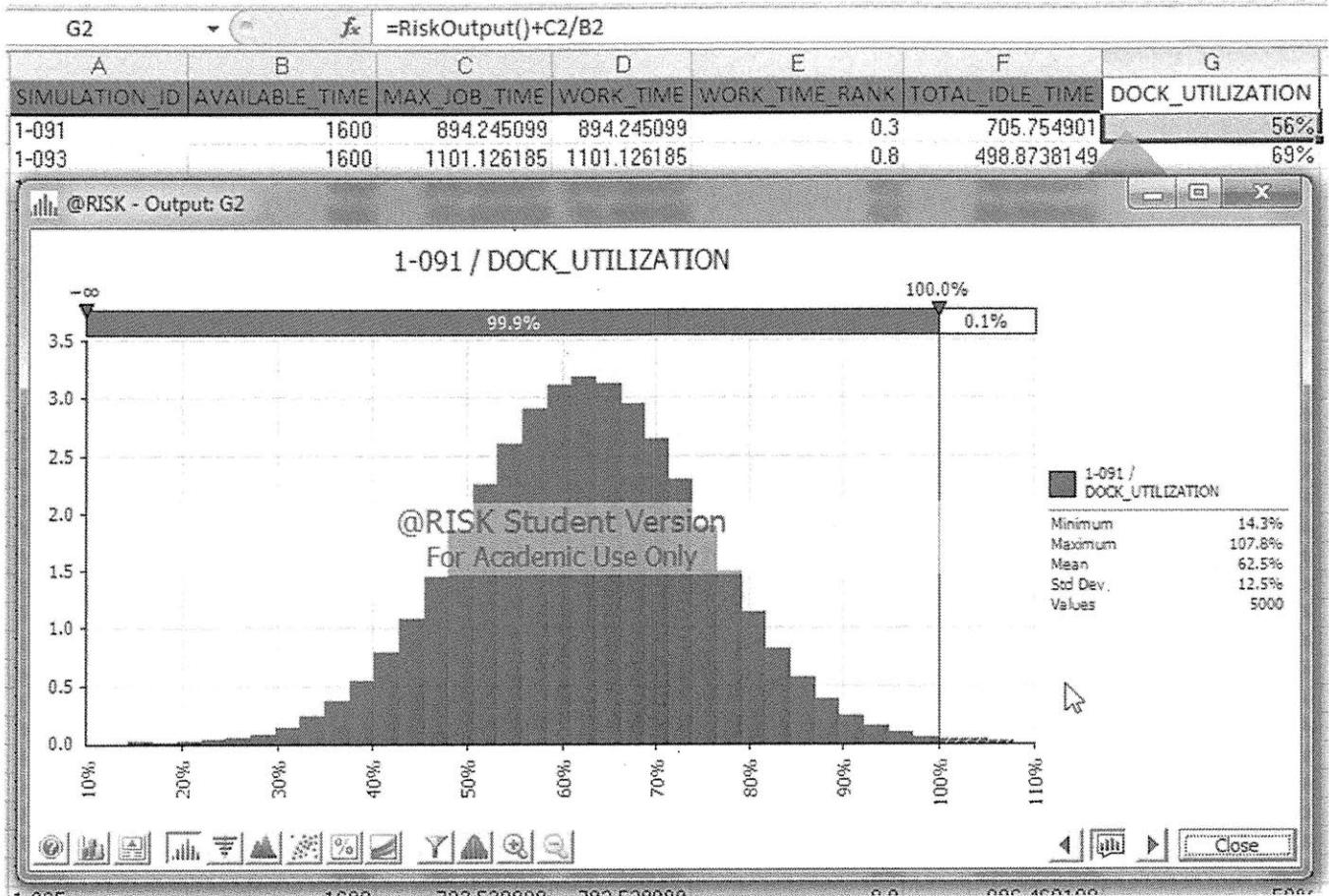| ▨ 1-091 / DOCK_UTILIZATION	
Minimum	14.3%
Maximum	107.8%
Mean	62.5%
Std Dev.	12.5%
Values	5000

Figure 22: Compiled Optimization Results, 2 of 2