Case Study

A Metal Manufacturing Mill Uses Discrete-Event Simulation to Optimise Operations

Pavan Kumar Narayanan, M.S1 and Lorena D. Mathien, Ph.D2*

1State University of New York at Buffalo State, Mathematics Department, 1300 Elmwood Avenue, 332 Bishop Hall, Buffalo, NY 14222, USA
2State University of New York at Buffalo State, Business Department, 1300 Elmwood Avenue, 311 Chase Hall, Buffalo, NY 14222, USA

ABSTRACT

Simulation modeling is an important technique from mathematics and engineering for planning, implementing, and operating complex technical systems. We modeled the manufacturing operations of a local metal mill company to answer questions related to shorter product life cycle, identifying system bottlenecks, short-term budgeting, scheduling and other key decisions that may have a direct impact on revenues and costs of the company. We attempt to solve this problem using multi-method simulation modeling software, AnyLogic®, which allows room to accommodate higher levels of abstraction, thereby providing space to further extend this model for a multi-method simulation.

INTRODUCTION

The United States manufacturing mill in our study1 was founded 150 years ago and is the leading integrated metal group and the world's largest metal recycler within their domain. Their core business is the production of marketable intermediary products from metal concentrates, metal scrap, and recycling raw materials. They produce one million tonne (t) of marketable metal cathodes each year and have over 1,700 different products in their product portfolio, catering to particular metal and metal alloy needs from different industries. The market volume for the company's product has increased roughly 40% to nearly 10 million t since 1980, with China accounting for approximately 45% of total world demand. As this demand continues to grow, it is expected to reach 11.5 million t by the end of the decade. Europe is also a strong source of demand at about 3.6 million t annually, mostly satisfied by imports.

The raw material price is formed by the supply and demand dynamics on the metal exchanges, particularly the London Metal Exchange (LME). After the global financial crisis in 2008 and temporary highs of up to US$10,000/t in 2011, the price slowly moved downward. It developed sideways at an average of around US$7,000/t in 2014. At the beginning of this year, the price decreased to below US$6,000/t.

The manufacturer imports most of the metal concentrates directly from mines in different countries. The ores contain about 0.5–4% of the metal and are already processed into a concentrate in the mine. In addition to processing metal concentrates, recycling metal scrap, alloy scrap, and other recycling materials is a central production activity in the organisation. About 700,000t of recycling raw materials of varying qualities and compositions are processed annually in their facilities.

The manufacturer uses a metal that can be recycled as often as desired without a loss of quality, processing the metals into continuous cast rod, specialty wire, shapes, rolled products, strip and profiles. The manufacturing process typically follows a linear pattern, although products may be routed to different machines in the actual manufacturing process depending upon the availability of machines and the deadline constraints. The mill has various types of slitters, rollers and annealing machines that each product must use for production dependent upon the end product dimension requirements.

One of the main rollers utilised by the majority of the manufactured products is a costly piece of equipment and is routinely overworked. Maintenance and upkeep costs for this roller are high, and when it fails during production, it will create a large work-in-progress inventory queue. If these inventories are not processed within a short period of time, the metal loses its molecular integrity and is then treated as scrap. Scrap is then sent back to casting, thereby incurring many hours of direct and indirect rework costs. In addition to the added costs, orders may be delayed to customers. Moving work-in-progress inventory across the various machines is time consuming, also adding to the delays.

Despite the growing world market for their products, the manufacturer had for years addressed the complexity of inventory management and production scheduling systems by relying on...
heuristic rules and management instinct to schedule. This procedure demanded substantial time and resulted than less-than-optimal efficiencies. It was estimated that optimal utilisation of raw materials could save the company from several hundred thousand to over one million dollars per square foot. Toward this end, in 2015, the operations group brought in our author as a consultant to simulate the operations. After analysing the current scheduling process, the author presented the findings to the management team, convincing them that a scientific approach would yield tremendous benefits. The proposed simulation model, that takes the complexity of the facility into consideration and mimics the real world operations, attempts to provide information on optimal product routing, meeting order targets by planning optimal product mix, optimal resource utilization, calculating equipment ROI on various machines, and facilitate key managerial decision making.

**CHALLENGES**

Although the potential benefits of a scientific approach were clear, traditional methods do not always apply because of the complexity of operations. The manufacturing team faced several challenges in trying to apply traditional analytic methods to solve the scheduling problem. The first and most challenging problem was the business resistance to complicated mathematical and statistical formulas. In addition, the manufacturing culture was resistant to test and apply advanced planning techniques, wanting to only deploy solutions that their operations teams could easily learn, accept, and use.

The second challenge centered on the accuracy of the data used on the models. In traditional analytical models, assumptions must be made and approximations used. In addition, in the long history of the manufacturer, several disparate information systems were used to collect and store data. Therefore data had to be collected from different systems and cleaned or recoded before use. This makes it very difficult to apply traditional schedule planning algorithms. As an alternative, the author developed a simulation-optimization approach to solve the scheduling problem. Simulation approaches can provide results that are visually and easily understandable; however, simulation approaches can present computational challenges based on the complexity of the manufacturing routings and the number of products in the portfolio. Because of the significant potential savings, our objective was to develop an efficient algorithm to find near-optimal solutions to the complex scheduling problems.

**SIMULATION-OPTIMISATION APPROACH**

Simulation modeling is an important tool for planning, implementing, and operating complex technical systems. Several trends exist in the economy such as increasing product complexity and variety, increasing quality demands in connection with high cost pressure, increasing demands regarding flexibility, shorter product life cycles, shrinking lot sizes, increasing competitive pressure and shorter planning cycles. Simulation models provide pragmatic results that simpler methods may no longer provide. As a powerful tool for analysing complex stochastic systems, computer simulation has been commonly used in a wide spectrum of fields including, but not limited to, healthcare (Seleima et al. 2012), marketing (Negahban and Yilmaz 2014), supply chain (Terzi and Cavalieri 2004), and military (Naseer et al. 2009). In particular, simulation has played a significant role in evaluating the design and operational performance of manufacturing systems. Successful applications of simulation in many practical real-world problems have proven its effectiveness in approaching various problems in the manufacturing sector. Simulation has been successfully adopted in numerous studies related to manufacturing system design and operation which has led to an increased interest in this research topic (Negahban and Smith 2014).

Business metrics provide quantifiable measures to track, monitor, and assess the success or failure of various processes. The main goal of setting and measuring these metrics is to track cost management, while communicating the company’s progression toward certain long-term and short-term objectives. Each company aims at a system of targets, usually consisting of a target with the highest priority (such as profitability), that splits into a variety of sub-targets, which interact with each other. The definition of the target system is an important preparatory step to simulation modeling. Frequent targets for simulation include optimisation of processing time, utilisation, inventory levels and on-time delivery. All defined targets must be collected and analysed statistically at the end of the simulation runs, which implies a certain required level of detail for the simulation model. As a result, they govern the range of the simulation study.

First, in designing the study, a general understanding of the simulated system must be developed. Based on the objectives to be tested, decisions must be made about the accuracy of the simulation. Then, based on the accuracy of the simulation, necessary decisions determine which aspects of the system to simplify. The first modeling stage covers two activities: analysis (breakdown) and abstraction (generalisation).

In system analysis, the complexity of the system, in accordance with the defined targets, is reduced by meaningful dissection of the system into its elements. By abstraction, the number of specific system attributes will be decreased as far as is practical to form an essential limited image of the original system. Typical methods of abstraction are reduction (elimination of non-relevant details) and generalization (simplification of the essential details).

In this study, a simulation model was built and tested, and the results were included in the model documentation.
to allow for further changes of the simulation model. In practice, this step is often neglected, resulting in unusable models due to the lack of documentation of functionality. Therefore, there is a need for commenting on the models and the source code during programming so the explanation of the functionality is still available after programming is finished.

Simulation of manufacturing systems is performed using one of the three simulation methods: system dynamics (SD), discrete-event simulation (DES), and agent-based simulation (Borshehev 2013). We provide a general framework for mapping a real-world system to a model. System dynamics models are continuous models governed by differential or difference equations to simulate interactions between different components of the system. The principles of system dynamics were developed by Forrester (1965) under the name of industrial dynamics. A system dynamics model represents the system in the form of causal loops and stock and flow diagrams with positive and negative feedback relations. In the causal loops, resources flow according to specified rates causing changes to stocks. Rates and influence relations are governed by mathematical equations that can be exact, approximate, or empirical (Wöstenholme 1989). System dynamics is a computer-aided approach to policy analysis and design. It applies to dynamic problems arising in complex social, managerial, economic, or ecological systems, literally any dynamic system characterised by interdependence, mutual interaction, information feedback, and circular causality. An important limitation of system dynamics is that it describes the system in terms of deterministic mathematical equations, while in reality many operations are stochastic or do not follow mathematical or analytical models (Rabelo et al. 2003). In addition, although the model parameters can change during simulation by feedback loops, the structure of the system and the governing rules are constant.

In agent-based simulation, the system components are modeled as agents, as opposed to objects. Agents and interactions between agents are described in simple rules, while patterns, structures, behaviours and complex dynamics emerge from the interactions. Macal and North (2005) listed a set of essential characteristics for agents in agent-based systems, stating that agents must be self-contained, autonomous, have a state that varies with time, and interact dynamically with other agents. Self-contained is defined as having identifiable boundaries as well as distinctive attributes that can be distinguished and identified. Autonomous agents take decisions and act based on internal rules and information sensed from the environment. Secondary characteristics that agents may possess, such as adaptability, goal-directedness, and heterogeneity, are also identified. Adaptability is attained through learning rules that change the behaviour of agents based on experience.

Discrete-event simulation is one of the most commonly used techniques for analysing and understanding the dynamics of manufacturing systems. It is a highly flexible tool which allows for the evaluation of different alternatives of system configurations and operating strategies to support decision making in the manufacturing context. As a computationally expensive tool, the increase in computer power and memory has further increased the use of discrete-event simulation in recent years. In discrete-event simulation, system components are modeled as objects with attributes. The states of the objects change in response to specific events that do not occur at equally spaced points of time. They can occur at random and several events can occur at the same time (Schriber et al. 2013). Discrete-event simulation models are widely utilised across manufacturing, healthcare, and supply chain and distribution networks (Mielczarek 2010). In a manufacturing system, machines, workers, and material handling systems are objects. Their attributes may be availability, time required to perform a specific task, and reliability. Events may be the arrival of a work order, the breakdown of a machine, or delivery of an item from one location to another (Pollacia 1989).

**Implementation**

In this study, a discrete-event simulation model was built to analyse and optimise operations of a metal manufacturing mill. A typical discrete-event simulation process is described in Fig. 1.

The process began with definition of the model and data requirements, followed by input modeling. Input modeling defines mechanisms for generating random inputs of the simulation model. The general question

![Fig. 1 Process flow for the development of a typical discrete-event simulation model.](image)
was how to model a probabilistic element, such as the arrival process or service time, given a data set collected on the element of interest (Leemis 2001). Once the model was process-mapped and parameters from the input modeling were defined, the next step was to perform a trial run of the simulation model and observe the output.

In our model, the metal mill manufacturing operations began with examination of demand requirements for each product, which thereby determined the ideal product mix. Each product had a certain type of alloy and mix requirement that must be met. Once this was established, the product mix on the casting furnace was determined. From the casting stage, the process followed a series of rolling, slitting, and annealing stages, dependent upon the nature and type of the alloy being used. The combination of rolling, slitting and annealing processes may change from looping within two machines to following a complex flow of multiple machines, until the product meets the product requirements in terms of size, shape and metal thickness, as well as other specified parameters.

The simulation model imitates the behaviour of the entire manufacturing operations. The challenge was choosing the level of abstraction, defining how many details were actually required to be added into this model to provide a realistic output that may be used for decision-making purposes. In applying this manufacturing information to our model, we investigated a single product, to understand the product and process parameters and to understand the end-to-end product flow. This was followed by the design of a process model that would capture the actual process flow in the manufacturing operations of the mill. A system-thinking process was employed to fine tune the process flow. Once this was established, four different products were identified, based upon the nature, complexity, and variation in manufacturing processes involved, and the contribution to overall company revenues.

After the four different end-to-end process maps were developed for each of the different products, they were combined based on shared machines, resulting in a main simulation process map, as shown in Fig. 3. The models were validated and tested with the business team, built using AnyLogic®, and followed by input modeling.

The idea in input modeling is to specify the dynamics behind the random quantities, such as the distributions (e.g., inter-arrival times, service times, demand, and routing probabilities) of each machine in the system. By determining correct distribution of inter-arrival times and service completion times, the main target may be reached, thus creating simulation models that mimic the behaviour of the real-world system (Choi & Kang 2013). Data from production logs was extracted to determine the arrival process for each product, as well as the service completion times for each product for each machine in terms of distributions, providing for realistic input data. Distribution fitting is the procedure of selecting a statistical distribution that best fits to a data set generated by the given process. A data cleansing process was performed, eliminating outliers in the data and initial non-negative distributions were assigned to various processes based on graphical plots, such as frequency distribution histograms, scatter plots, normal probability plots (PP plot and QQ plot), and Cullen and Frey graphs (Fig. 2). Two or more candidate distributions were determined for each arrival process and for each service completion process for each product under each machine.

![Fig. 2 Cullen and Frey graph fitting a distribution for a key roller.](image-url)
Non-negative distributions, such as gamma, exponential, Erlang, Weibull distributions were taken into consideration as candidate distributions, although their Shapiro-Wilk test results are less significant when compared with regular distributions. Some distributions had a negative tail that would extend to negative infinity and no machine can process a product in negative time. Once a distribution was finalised, a chi-squared test was conducted to test whether the data follows a specific distribution.

Simulation models were then built for various production scenarios. The first model included all four products considered with current product routings. The other models were built to investigate different product routing scenarios based on product mix. The scenarios were modeled assuming that if the queue at one machine is overloaded based on existing product orders, products may be rerouted to a different machine that is capable of performing the same task. This assumption allowed for optimal utilization of the overall manufacturing mill, thereby meeting the delivery constraint (Fig. 3).

**BUSINESS RESULTS AND BENEFITS**

**OUTPUT ANALYSIS**

The discrete-event simulation model was built on AnyLogic® Professional Edition 7.1.2 (AnyLogic North America LLC 2015) and ran on Intel Core-i5 4200M processor with four gigabytes of physical memory. Several trial runs were performed and the following data was extracted. Output analysis was performed based on the models that were built.

**Machine Utilisation**

Each machine (roller, annealer, slitter) has a unique service completion time for every product. By running this simulation, we were able to observe the real-time machine utilization statistic at different intervals during the various times of the day for our given product mix input. During the simulation, statistics were collected for the number of hours the machine was idle and the number of hours it was busy. The ratio of the idle time to the total number of hours clocked provided for the machine productivity rate (Carrie 1988). Fig. 4, machine utilisation time, shows the machine productivity rate for the roller, slitter, and annealer machines.

**Queue Time**

When products are queued before a machine, it may overload the machine, thereby compromising the optimal utilization of the mill. The results of queue times are often used when making business decisions about the resources needed to provide a service or manufacture a product.
product. During the complex simulation process flow, if one machine enters a repair/maintenance state, then all the products downstream may be affected. After a period of time, some of the unfinished product may need to restart from casting, thus resulting in increased production cost. Thus, the number of items in queue and the amount of time each item takes to enter the system from the queue may be looked at as key performance indicators. The simulation produced a real-time distribution that captured the queue build before each machine at various time intervals. By running this simulation, we were able to see various trends and patterns in queue formation, depending on the number of products being produced. The distribution may be considered a better estimator than average queue time because the average statistic, as a measure of central tendency, is known to be a good indicator for an ideal system. Realistically, no system is perfect and will have some associated uncertainty.

Fig. 5 represents the queue time distribution for an important roller in the production process in the manufacturing mill. Even with the system randomness, diversity of product types, and complexity of product flows, queue time distribution is an accurate estimator. Moreover, the simulation may also help to determine the system bottlenecks. If a machine at a given point of time is experiencing heavy queuing, steps can be taken to re-route the products to a different machine that could perform the same task.

**Average Time in System**

The average time a product type has spent in the system from casting to shipping allows for costing of the final product. Based on multiple trial runs, it has been observed that this statistic may not be consistent due to occasional machine failure and repair status, and is dependent on the quantity (orders) of product that is required to be produced. Fig. 6 shows the distribution of time in system for all products. There is potential to model the time in system for each product or product type separately. Simulation experiments may then be conducted to minimise the time spent in system for each of the product types.

**Financial and Nonfinancial Benefits to the Manufacturer**

The quality of factory scheduling generally has a profound effect on the overall factory performance. The tangible financial benefits to the company were proven by comparing the “As Is” model (current scheduling methodology) versus the “Enhanced” (simulated) model created through the simulation optimization process. We assume two products since these reflect the majority of the sales volume for the organisation. We also assume two key pieces of equipment, one roller and one annealer, given that these comprise the two main bottlenecks in the manufacturing process.

1. **Increase in machine utilisation**: Simulation modeling helped to optimise machine routings by examining
how the machine utilization percentage changed for various input product mixes. The “enhanced” model provides a significant increase in machine utilization for both the roller and the annealer over the “As Is” model. Implementation increased overall capacity by increasing efficiencies (see Fig. 7).

2. **Reduced time in system:** By running the simulation model for various time periods, we observed that optimal product routing reduced the total time in system for each product. Increased time in system, due to queuing or inventory movement constraints, may result in the product losing its molecular integrity and recasting of the product. This result in increased scrap and production costs, as noted previously (see Fig. 8).

3. **Queue time reduction for key roller:** The manufacturer employs a key roller that processes most products, thus creating a major bottleneck in the manufacturing process. A primary challenge was to reduce the queue of this roller. By running an independent samples t-test we were able to show that the average queue time of the key roller in the “enhanced” model is significantly lower when compared with average queue time of the key roller in the “as-is” model at

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**Fig. 7** Improved machine utilisation for the main roller and annealer.

**Fig. 8** Time in system for the “As Is” model (Model 1) vs. the “Enhanced” model (Model 2).
99% confidence interval (see Table 1). This indicates a significant reduction in queue, thus improving roller efficiency and reducing scrap and rework costs.

4. Optimised product mix: By experimenting with various product mixes, we were obtained multiple statistics that identified the cost/efficiency trade-off between machine utilization (utilization and mean queue size) and total time in system for all products (see table 2). This optimised product mix allowed for improved production scheduling that will increase efficiency, and thus capacity, thereby reducing overall production and labor costs.

Table 1: Independent t-test for the “As Is” model vs. the “Enhanced” model.

<table>
<thead>
<tr>
<th>Queue time</th>
<th>Levene’s Test for Equality of Variances</th>
<th>t-test for Equality of Means</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F</td>
<td>Sig</td>
</tr>
<tr>
<td>Equal variances assumed</td>
<td>21.940</td>
<td>0.000</td>
</tr>
<tr>
<td>Equal variances not assumed</td>
<td>9.435</td>
<td>15.474</td>
</tr>
</tbody>
</table>

Table 2: Optimised product mix for the “Enhanced” model.

<table>
<thead>
<tr>
<th>Product</th>
<th>Mix scenario</th>
<th>Time in system (minutes)</th>
<th>Roller queue</th>
<th>Roller Utilisation</th>
<th>Annealer utilisation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Product 1</td>
<td>Product 2</td>
<td>R044 Q</td>
<td>R046 Q</td>
</tr>
<tr>
<td>180/180</td>
<td>1</td>
<td>2249.9</td>
<td>2284.06</td>
<td>394.59</td>
<td>1221.67</td>
</tr>
<tr>
<td>160/200</td>
<td>2</td>
<td>2142.08</td>
<td>2090.46</td>
<td>319.96</td>
<td>1107.03</td>
</tr>
<tr>
<td>140/220</td>
<td>3</td>
<td>1940.15</td>
<td>1987.19</td>
<td>273.36</td>
<td>1155.11</td>
</tr>
<tr>
<td>120/240</td>
<td>4</td>
<td>2479.04</td>
<td>2390.89</td>
<td>320.17</td>
<td>1340.05</td>
</tr>
<tr>
<td>100/260</td>
<td>5</td>
<td>2530.82</td>
<td>2393.85</td>
<td>278.26</td>
<td>1509.53</td>
</tr>
<tr>
<td>200/160</td>
<td>6</td>
<td>3275.08</td>
<td>3652.73</td>
<td>1459.43</td>
<td>1446.196</td>
</tr>
<tr>
<td>220/140</td>
<td>7</td>
<td>3497.77</td>
<td>3264.51</td>
<td>866.74</td>
<td>1889.15</td>
</tr>
<tr>
<td>240/120</td>
<td>8</td>
<td>1700.98</td>
<td>1863.82</td>
<td>489.74</td>
<td>689.79</td>
</tr>
<tr>
<td>260/100</td>
<td>9</td>
<td>3169.42</td>
<td>2706.24</td>
<td>1030.45</td>
<td>1350.83</td>
</tr>
</tbody>
</table>

5. Culture Shift: Perhaps the largest benefit to the manufacturer is the change in mindset regarding advanced scheduling systems. The easy-to-understand simulation and the outlining of potential financial benefits won the support of the management team and has prompted the adoption of an advanced planning software system. The successful simulation model has shown that operations research can highlight many process improvements for the manufacturer. While a simulation model is rarely an end in itself, modeling can help gain knowledge of the system, evaluating features, making predictions on system performance, comparing several alternatives, detecting problems, and for evaluating and improving system performance. Simulation results can help define a system’s operating limits and control systems. Models are applied as a basis for experimentation.

SCOPE AND LIMITATIONS

Our simulation models provided a good basis for analyzing existing production efficiency at a major metal manufacturing mill. From these scenario-based and routing-based models, there are several further developments that could be made to advance the models. We could incorporate the failure, repair, and maintenance status for each machine by modeling the probability of each machine entering the respective state, which could be obtained from historic data. Incorporating these variables would enable simulation trial runs for a 1-year period to determine if the system is capable of meeting demand requirements given the behaviour of the system under variety of circumstances. As we looked at various types of simulation modeling earlier, namely system dynamics and agent-based modeling, in addition to discrete-event simulation, there is opportunity to create a multi-method model where two different types of modeling practices are embedded into one model. For example, in addition to the discrete-event simulation model of the manufacturing mill, we could further extend the same model to an agent-based simulation system which
could simulate the supply chain and distribution network. We could model the shipping, geographical network, and
distribution centers as agents and observe the interactions
between the orders to further investigate on-time delivery.
In addition, we could also use stock and flow diagrams to
model the existing inventory of the products and observe
how it could change based on the magnitude of incoming orders. Based on cycle time, yield obtained, equipment price, energy consumption and resource requirements, we could calculate the return on investment on each machine. This data may be helpful in managerial decision making.

The current model also has some limitations. First, from an engineering perspective, simulation models are merely a surrogate representation of the actual physical system. There may be factors and parameters that have not been taken into consideration while building the simulation model if the level of abstraction was too high. This could result in different results than expected. Second, for many practitioners, a simulation model is a black box that can only be evaluated based on its outcomes. Unless the simulation exercise yields quick and usable results in a short period of time, it can easily be seen as an infeasible investment (Abourizk et al. 2011). These limitations also provide an avenue for expanding this research to discovering new ways of low level abstraction (e.g. yield of a product) and other opportunities. Third, although simulation models provide valuable insights for decision making purposes, the model is possible and can only be executed with data that characterises the actual manufacturing setup. If there is an error in the raw data, or if it is not thoroughly cleansed, it may impact the model output. One of the key challenges is to eliminate outliers that demonstrate huge deviation from the normal range of the data. Since we are working with service completion time for each product for each machine, chances are likely that there could be a clerical error in ‘am’ or ‘pm’, or other such attributes. Finally, simulation models consume additional processing capacity and physical memory. There were several occasions that the computer system crashed while running the simulation model because the physical memory was overworked. As we tend to increase more objects in our simulation model or incorporate agent-based system into the discrete-event simulation model, the computer would need a multi-core processor and larger physical memory. Larger simulation models may take a much longer time to run.

CONCLUSION

Simulation as a tool provides foresight into short-term planning and scheduling problems, if used appropriately. It provides an opportunity to test and experiment with various scenarios that may help to optimise the operations in a short period of time. Simulation testing is inexpensive, quick, and provides valuable output.

By examining the output data from the simulation, we observed the queuing pattern and the respective productivity rates in our manufacturing mill. Based on this information, the manufacturing mill may design rerouting of products to achieve balanced productivity and maximum efficiency. There is enough potential in this simulation approach to design multiple scenarios and analyze the productivity and efficiency of the machines. There is also a way of modeling downtime for each of the machines, during which the machines are in a repair and maintenance state. By modeling system maintenance, one could improve the level of abstraction and bring the model even closer to reality.

The implementation of a discrete-event simulation model to this metal manufacturing mill has provided valuable insights into the short-term operations of the system, and this model could probably answer more questions than expected. For example, simulation could help the management to estimate short-term operating costs.

In conclusion, the simulation model could help to optimise and prioritise costs incurred, quality of the end product, and time required for production. These are strategic priorities for organizational success and efficient manufacturing management will decrease consumption of resources, thus optimizing efficiency and cost.

APPENDIX

Appendix A

In this appendix, we provide links to visualise two of the simulation models. The models are built to investigate system bottlenecks, the ability to meet order targets under various scenarios, to determine optimal product mix, and to understand how changing the product mix affects various machines and by how much.

The first model produces four different products and each product takes a unique route: some loop and some are straightforward. The second model introduces stress shocks by looking at historical patterns of machine maintenance, breakdown, and repair data. The pattern of occurrence is modeled and incorporated into the simulation model. In addition, the second model also contains the custom routing experimentation, which investigates achievement of order targets by testing the three different product routings. For example, if one machine is heavily utilised, products can be rerouted to a different machine that performs the same task. By observing the new product routings, inventory can be seen queuing up in various downstream flows. This helps to determine which routings are worth exploring.

LINKS TO MODELS:

Model 1: http://www.runthemodel.com/models/2294/
Model 2: http://www.runthemodel.com/models/2295/
Appendix B

This Appendix contains some of the distributions that were used in input simulation modeling.

<table>
<thead>
<tr>
<th>Service completion time</th>
<th>Product 1</th>
<th>Product 2</th>
<th>Product 3</th>
<th>Product 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Casting</td>
<td>Weibull (0.72745 0.86827)</td>
<td>Weibull 0.75259 0.77171</td>
<td>Weibull 0.46739 0.55813 0.09997</td>
<td>Weibull 0.75748 0.97037</td>
</tr>
<tr>
<td>R043</td>
<td>Weibull 0.60011 0.53376 0.09977</td>
<td>Weibull 1.59701 0.63964</td>
<td>Weibull 1.59701 0.63964</td>
<td>Weibull 1.37635 0.74464</td>
</tr>
<tr>
<td>R230</td>
<td>Weibull 1.00147 0.30566</td>
<td>Weibull 1.19039 0.53333</td>
<td>Weibull 1.16717 0.24737</td>
<td>Weibull 1.59373 0.18100</td>
</tr>
<tr>
<td>R044</td>
<td>Exponential 0.62902</td>
<td>Exponential 0.62902</td>
<td>Exponential 0.386485</td>
<td>Exponential 0.348748</td>
</tr>
<tr>
<td>A143</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>Exponential 0.62734 0.20340</td>
</tr>
<tr>
<td>R046</td>
<td>--</td>
<td>--</td>
<td>Exponential 0.49569</td>
<td>--</td>
</tr>
<tr>
<td>S001</td>
<td>Gamma 1.79994 0.38468</td>
<td>Gamma 1.40351 0.64659</td>
<td>Weibull 1.17288 0.58642</td>
<td>Exponential 0.48946 0.10976</td>
</tr>
</tbody>
</table>

REFERENCES
