

A Framework for Optimizing the Supply Chain Performance of a Steel Producer

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Abstract: Supply Chain Management (SCM) is focused on developing, optimizing, and operating efficient supply chains. Efficient supply chains are characterized by cost effective decisions, lean flow and structure, high degree of integration, and well-chosen Key Performance Indicators (KPIs). Although there exists a large body of literature on optimizing individual supply chain elements (transportation, distribution, inventory, location, etc.), the literature does not provide an effective methodology that can address the complexity of the supply chain of a large scale industry such as steel producers. This paper, therefore, builds on existing research methods of supply chain modeling and optimization to propose a framework for optimizing supply chain performance of a steel producer. The framework combines deterministic modeling using Linear Programming (LP) with stochastic simulation modeling and optimization. A holistic LP deterministic optimization model is first used to characterize and optimize the supply chain variables. The model minimizes the annual operating cost of the steel company's supply chain. Simulation-based optimization with Simulated Annealing is then used to determine the operational levels of the supply chain drivers that meet a desired level of customer satisfaction. The proposed approach is applied to the supply chain of a major steel producer in the Arabian Gulf.

1 INTRODUCTION

Supply chain management (SCM) has attracted ever increasing attention over the last two decades in response to a highly competitive and globalized marketplace and the pressure to cut the cost of creating and delivering value to customers. As discussed in (Min and Zhou, 2002), a supply chain is an integrated system which synchronizes a series of inter-related business processes in order to. (1) Acquire raw materials and parts; (2) transform these raw materials and parts into finished products; (3) add value to these products; (4) distribute and promote these products to either retailers or customers; (5) facilitate information exchange among various business entities, e.g. suppliers, manufacturers, distributors, third-party logistics providers, and retailers. Figure 1 shows the main elements/stages in a supply chain network from raw materials' sources to customers.

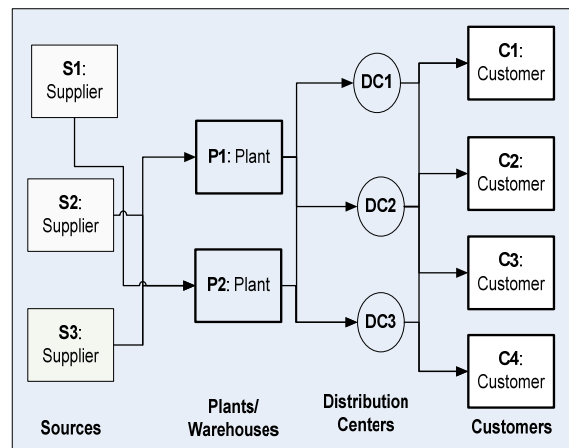


Figure 1: A generic framework for a supply chain network.

Cost effective supply chain management under various market, logistics and production uncertainties is a critical issue for companies in

general and for steel industry in particular. Such uncertainties often result in multiple planning and operational issues that challenge planners and potentially lead to bad decisions. In order to optimize the performance of a supply chain, it must be first modeled using deterministic mathematical models that maximize/minimize some or all supply chain costs or using stochastic simulation-based models. Mula et al. (Mula et al., 2010) presented a review of mathematical programming models for supply chain production and transport planning. However, the assumptions used when developing such models may not be realistic resulting in exact solutions that may be infeasible for problems of any reasonable size. Heuristic global optimization methods such as Tabu Search (TS), Simulated Annealing (SA), and Genetic Algorithms (GA) can escape some of these assumptions and can often yield good (near-optimal) solutions (Arostegui et al., 2006).

Another issue is the fact that optimizing the supply chain performance is a multi-attribute decision. Altiparmak et al. (Altiparmak et al., 2006) formulated supply chain design as a multi-objective optimization problem in which the objective is not only to minimize supply chain costs, but also to maximize customer service while at the same time maximizing the capacity utilization balance at the distribution centers. Finally, the complexity of the supply chain network largely contributes to the difficulty of optimizing supply chain performance. Jayaraman and Ross (Jayaraman and Ross, 2003) described the PLOT (Production, Logistics, Outbound, Transportation) system to address network design problems involving a central manufacturing plant, multiple distribution centers and cross-docking sites, and retail outlets stocking multiple products.

In the context of steel industry, however, little research is directed at optimizing the supply chain using deterministic or stochastic methods. Some literature is focused on optimizing individual supply chain elements (transportation, distribution, inventory, location, etc.) but it does not provide an effective methodology that can address the complexity of the supply chain of a steel producer. While optimizing the performance of each supply chain element is important, steel industry is focused on improving the overall performance of the supply chain network. This requires a comprehensive and dynamic modeling and optimization approach.

Thus, this research intends to build on the current research methods of supply chain modeling and optimization for a steel company. To this end, the

proposed research method combines deterministic modeling with LP with stochastic simulation modeling and optimization. The proposed approach develops a comprehensive deterministic LP model to minimize the annual cost of the steel company's supply chain including transportation, inventory, and distribution. The viability of decision variables resulted from the solution of the LP model is verified in a dynamic and stochastic Discrete Event Simulation (DES) model of the supply chain. The model is set to produce a specific set of Key Performance Indicators (KPIs) that are developed to characterize the supply chain performance in terms of responsiveness, efficiency, and utilization. Finally, simulated annealing is used to set values to model variables that achieve a multi-criteria tradeoff of the defined supply chain KPIs. The proposed approach will be applied to the supply chain of Qatar Steel (QS) which is a main steel producer in Qatar and the Arabian Gulf.

2 LITERATURE SURVEY

Many case studies have appeared in the literature documenting the effectiveness of SCM in reducing costs and increasing customer satisfaction. Sharma et al. (Sharma et al., 2008) analyze the results of a survey to assess the effect SCM practices have had on the Indian automobile industry, and conclude that SCM practices have had a positive impact on design quality, and on the quality of conformance, the degree to which a product's operating characteristics meet its design specifications. Walker (Walker, 2009) discusses the implementation of a SCM system at a manufacturing company, focusing on the experiences and lessons learned from a management perspective; the resulting system led to a cost savings of \$8.8 million, with an internal rate of return of 32%. Scarsi (Scarsi, 2007) reports on a case study in the steel industry, logistics challenges were dealt with successfully.

Efficient supply chains are characterized by a high degree of integration and well-chosen Key Performance Indicators (KPIs) to provide feedback and to rapidly diagnose potential problems. Stevens (Stevens, 1989) proposed a four-stage evolutionary model for supply chain integration. Potter et al. (Potter et al., 2004) discussed the benefits achieved through integration of a steel supply chain. These include a halving in cycle times for many of the more popular products, reducing the levels of safety stock required, and reducing the lead times, resulting in significant cost savings. Chae (Chae, 2009)

emphasizes the role of KPIs in closing the gap between planning and execution of supply chain operations, and offers guidelines for developing such indicators. KPIs are suggested for four of the processes in the Supply Chains Operations-Reference (SCOR) framework; Plan, Source, Make, and Deliver.

Simulated Annealing, in particular, plays a critical role in keeping the time required to optimize the model manageable for practical problems. Ulungu et al. (Ulungu et al., 1995) conceived a Multi-Objective Simulated Annealing (MO-SA) algorithm for solving combinatorial optimization problems. Alrefaei and Diabat (Alrefaei et al., 2009) also proposed a simulated annealing for solving a multi-objective optimization problem and implemented it on an inventory problem. Another example of using SA for SCM optimization can be found in (Yanling et al., 2009). There has been also an increasing interest in the use of simulation to model the performance of supply chains. Jahangirian et al. (Jahangirian et al., 2010) provide a comprehensive review of the simulation literature as it relates to manufacturing and business. Terzi and Cavalieri (Terzi and Cavalieri, 2004) survey the literature on the use of simulation in a supply chain context. Other examples of simulation-based supply chain management applications can be found in (Longo and Mirabelli, 2008; Jung et al., 2004; Yoo et al., 2010). A complete list of advantages and disadvantages in using simulation approach for supply chain modeling can be found in (Ingalls, 1998).

Existing analytical methods, however, are not able to handle all the dynamically changing supply chain variables. A dynamic simulation approach is a better tool for managing the stochastic behavior of supply chains. Effective supply chain management, therefore, requires the integration of deterministic and stochastic optimization the supply chain based on a dynamic simulation platform. To this end, we propose the integration of LP, DES, and SA. A holistic LP deterministic optimization model is first used to characterize and optimize the supply chain variables. The problem of determining the operational levels of supply chain drivers to meet a desired level of customer satisfaction is then approached using a simulation-based optimization method based on simulated annealing. An industrial-scale case study (i.e., Qatar Steel) is presented to demonstrate the utility of the proposed approach. This includes modeling and analyzing the supply chain of the steel company, verifying the results of deterministic LP using DES, developing a specific

set of KPIs to measure the performance of QS supply chain, and optimizing such performance with simulated annealing.

LP model is solved with GAMS software tool. Supply chain simulation is carried out in general purpose simulation software. The SA module is developed to function with simulation in an integral mode. Anticipated results include developing a total cost model using key elements of QS supply chain, recommending optimal settings to critical decision variables in the cost model, and recommending a set of operational KPIs to maintain a high level of QS supply chain performance.

In addition to industry contributions, research contributions to existing literature include developing a comprehensive LP model of key supply chain components (supply, warehouse, production, inventory, and distribution), combining LP optimization (a classical supply chain deterministic optimization method) and simulation-based optimization (a stochastic optimization method), and optimizing the supply chain performance using multiple KPIs. The approach can be adapted to other steel industries and will be generalized to a flexible company structure.

3 RESEARCH DESIGN AND METHOD

This research proposal consists of three major phases; Phase I is data collection and network development for Qatar Steel supply chain. Phase II is formulating and solving a LP that minimizes the total cost of QS supply chain subject to supply, demand, and operational constraints. Phase III is the developing of DES model of QS supply chain including a set of KPIs. Finally, Phase IV is optimizing the supply chain using Simulated Annealing. Figure 2 summarizes the four stages of the research method.

As this is an ongoing research project, further details of the research methods will be specified later. The functionality of the proposed research method is depicted in Figure 3. Once QS supply chain (QS-SC) is analyzed and pertinent data is collected, a LP model is developed so the total cost (C) of the supply chain is minimized subject to given constraints at the company. A DES model of QS-SC is also developed to include other stochastic variables that impact the supply chain performance. The resulting set of decision variables (X) is used in the DES model and the model is set to generate the

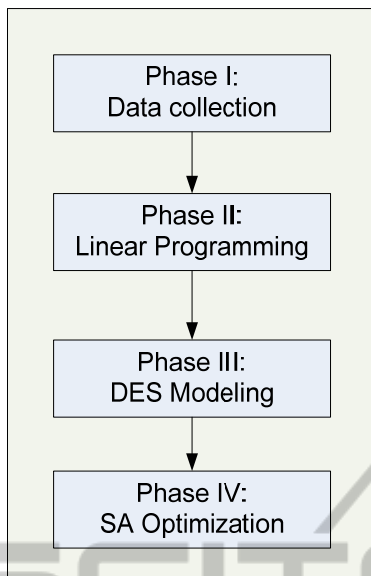


Figure 2: Research method plan.

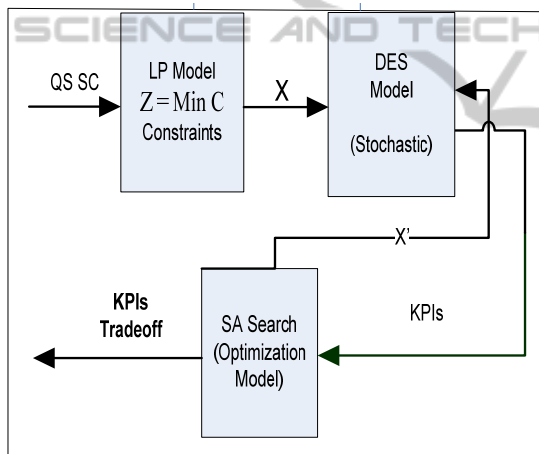


Figure 3: Prototype of the proposed SC optimization framework.

defined set of KPIs. The Simulated Annealing (SA) module is used to optimize similar or enhanced set of decision variables (X') using the DES model as a multi-criteria objective function. Iteration of SA search and simulation evaluation of KPIs will eventually lead to an efficient tradeoff of the defined KPIs of QS-SC. The QS-SC performance will be monitored using the SA-set levels of KPIs.

3.1 The LP Module

A LP model is developed and will be later customized to the SC of the application case study. The theoretical background of LP method is assumed to be well known to readers. In this

research, the LP model formulation includes the following:

- Objective function: Minimize total yearly cost of inbound transportation, inventory, and distribution
- Decision Variables: Pricing, inventory policies, quantity shipped from each supplier, and quantity shipped to traders (distributors)
- Constraints: Capacity, demand, and budget

Based on the preliminary analysis of the supply chain optimization problem, a generic LP optimization model is developed for the supply chain. The data, variables, objective function, and constraints of the proposed LP model are not presented here for the sake of efficiency.

3.2 The DES Module

In the proposed method, simulation is used as an overall representation of the supply chain. The DES model incorporates variability in terms of demand, lead time, process reliability, etc., into the supply chain model and it is used to assess supply chain performance based on multiple KPIs. The preliminary plan for the DES model of the supply chain can be described as follows:

Model Structure

A simulation module is developed to represent each component in the underlying supply chain including supply, warehouse, production, Inventory, and Shipping. The details of each module (in terms of structure, logic, and data) will be developed during Phase III of the project.

Model Variables

The variables defined in the LP model will be included in the DES model. This includes material supplies, inventory, and processing in addition to facility activities and capacity. However, time-based variables and probabilistic variables will be dynamically changed during run time to mimic the actual behavior of the supply chain.

Model Data

The data elements defined in the LP model will be included in the DES model. Pertinent data will be collected from the five modules; supply, warehouse, production, inventory, and shipping. Collected data will also include supply chain constraints (facility,

capacity, etc.) as well as supply and demand requirements.

Model Logic

The flow logic of materials, information, and money throughout the supply chain will be developed using the flexibility of DES software tool. This includes material flow from suppliers (local and international) to the company's warehouse, through production, finished items inventory, and shipping to customers.

Model Outcomes

The DES model will be set to produce relevant statistics that are essential to optimize the performance of the supply chain. For the case study application, the developed KPIs of QS-SC can be categorized as follows:

- Responsiveness:
 - Average yield time: order-to-delivery time.
 - Fill rate: Fraction of orders/demand met on time from inventory.
- Efficiency:
 - Average inventory measured in units, days of demand, and financial value.
 - Average inbound transportation cost as % of sales or cost of each ton of steel.
- Utilization: Four KPIs are developed; one for each of the four main operations in steel production including Direct Reduction, Electrical Furnace, Continuous Casting, and Rolling Mill.

3.3 The SA Module

SA is an optimization method that is based on the structural properties of materials (mainly metals) undergoing the annealing process, where materials are melted down and then cooled slowly in a controlled manner (Metropolis et al., 1953). Such process resembles the SA search in seeking global optima while avoiding being trapped at local optima. As a global search engine, SA has become a popular tool for solving problems where mathematical programming formulations become intractable. This includes solving various combinatorial optimization problems in circuit design, scheduling, path generation, and many others. Further descriptions of

SA and its applications can be found in (Eglese, 1990; Laarhoven and Aarts, 1987).

SA algorithm starts by setting SA control parameters; initial temperature (T), cooling parameter (α), number of T decrement steps (S), and the maximum number of iterations (n) at each T step. The temperature T , which is modulated by a predetermined cooling schedule, controls the degree of randomness presents within the search. Determining the initial T value is a problem-specific that depends on the scaling of the objective function. Generally speaking, T must be high enough to allow the search to move to almost any neighbourhood state in order to avoid being trapped in local optima. The search will seek convergence to the local optima toward the end of the computation, when the *temperature T* is nearly zero.

The cooling parameter $\alpha \in [0,1]$ controls the rate at which the temperature is reduced, where large values (typically between 0.70 and 0.99) will produce better results through slow cooling schedules. Longer temperature steps (large number of iterations n) will also produce slower cooling rate at a fixed α by allowing the system to stabilize at that temperature step. The combination of cooling rate (α) and the length of temperature step (or cooling time) in terms of n establishes the SA cooling schedule. Such schedule is highly problem-dependent and has a considerable impact on the quality of the solution found. Slow SA cooling results in longer computation time and higher chance of finding the optimum solution.

After setting SA parameters, an initial solution is generated randomly and used as the first current solution. The initial solution, as well as future solutions, is evaluated using some objective function (the MCS-based estimation of NP in this case). When employed with SA search, a modification to the simple Monte Carlo method is made so that a new point in search space is sampled by making a slight change to the current point and unrealistic samples are not placed into the ensemble. This modified procedure, which is known as a Metropolis MCS or Metropolis annealing, was proposed by Kirkpatrick in 1983 to find the lowest energy (most stable) orientation of a system.

The SA module will interact with the DES model during search iterations. The DES model will serve as an evaluation mechanism of the supply chain objective function under stochastic and dynamic conditions. Model KPIs will be assessed using multiple simulation runs and fed into the SA "evaluate solution" step. A mechanism will be developed to combine KPIs into a multi-criteria

utility function. The plan is to translate supply chain KPIs into an overall cost/revenue model that can be used in the SA search method. An excel sheet interface will be used to implement the communication between SA module and the DES model. An alternative is to use a built-in SA module that comes with some of the new simulation packages such as WITNESS™ (Lanner Group Inc., 2011).

4 APPLICATION CASE STUDY

The proposed framework will be applied to optimize the performance of supply chain at Qatar Steel (QS). Qatar Steel (QS) is one of the leading companies in the region that has impact on the growth of Qatar economy. With the price of steel declining over the past year, due to recession in the shrinkage in construction sector, steel companies face tight margins and fierce competition. Therefore, steel companies are increasingly looking for methods to cut costs in their production and business operations and provide extra value to their customers throughout the supply chain. To stay competitive, QS is increasing its focus on cutting cost and adding more value to customers rather than increasing prices. A major cost element is contributed by the company’s supply chain.

Steel manufacturing at Qatar Steel (QS) comprised of four integrated primary units: Direct Reduction (DR), Electric Arc Furnace (EAF) for molten steel production, continuous casting, and rolling mill. DR plant produces solid iron using Iron ore pellets. The reformer converts natural gas into hydrogen and carbon monoxide. These gases remove oxygen from the heated ore in the furnace, converting the ore into metallic iron. Cool gas/water circulates through the lower part of the furnace and cools the iron. The process produces what is called Directly Reduced Iron (DRI), and is fed into the Electric Arc Furnace (EAF). The EAF is used to produce molten steel from DRI. The furnace, with its roof swung aside, is charged with scrap using powerful electric current arcs (jumps) between the electrodes and the charge. This action produces intense heat, which melts the charge and promotes chemical reactions that produce steel.

Workers turn off the power to the electrodes at the end of the refining process. Then they tilt the furnace, which is mounted on rockers, to pour out the slag. After the slag has been poured off, the electric arc furnace is tilted in the opposite direction. The liquid steel rushes out through the tap hole and

is collected in a ladle. The molten steel produced in the electric furnace is poured into the continuous casting unit, which shapes molten steel into billets. The steel flows through a specially shaped mold. Cold water quickly cools the steel, causing it to harden as it moves through the rolls of the caster. These billets are one type of QS products. This is another unit which shapes molten steel. Rolling Steel bars takes place in a bar mill, which resembles a hot-rolling mill. A bar mill has rolls that are grooved to roll hot billets into square, round, oval or hexagonal. Figure 4 depicts the steel manufacturing process at QS.

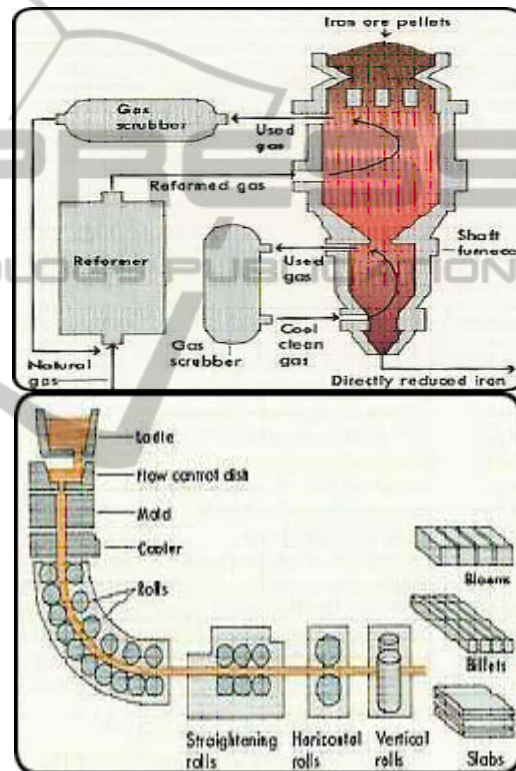


Figure 4: QS manufacturing process.

The main functions of Qatar Steel’s supply chain include procurement, logistics, warehousing, and distribution. Procurement focuses raw materials, equipment, spares and consumables, and supply contracts. Logistics is focused on customs and transportation. Warehousing is focused on inventory control, warehouse operations (receiving and shipping), and item management. Bulk materials do not enter the warehouse. They are stored in the outside yard. Finished items are not also entered to the warehouse and stored in the plant’s internal storage bays prior to shipping. Bays can host items up to 14 days of production. Distribution is a

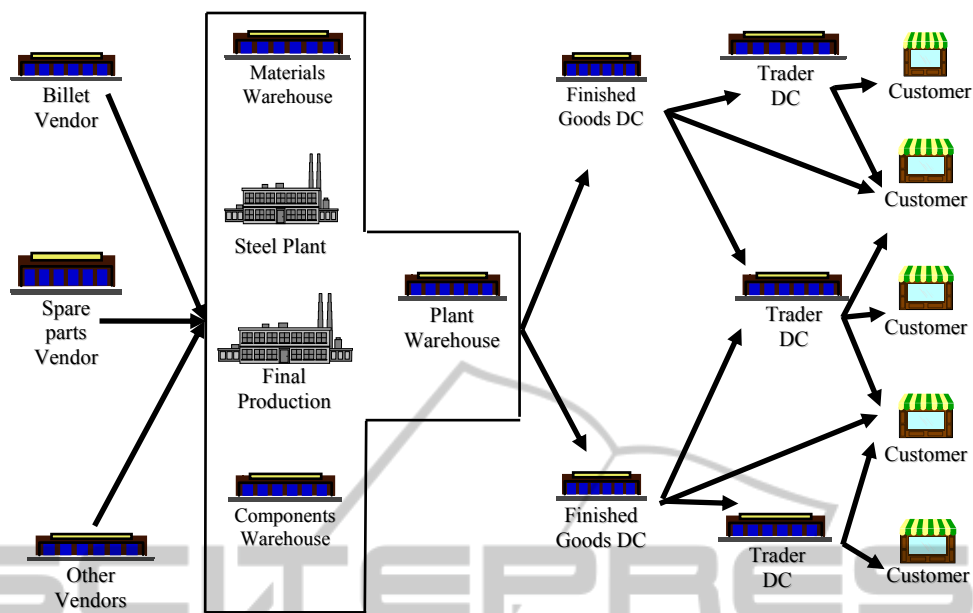


Figure 5: QS supply chain.

function controlled by the domestic and regional traders (dealers) who order steel products and pick up their orders from the plant. Figure 5 depicts the generic structure of QS supply chain network.

5 ANTICIPATED RESULTS

This is still an ongoing research project so results are not ready yet. However, preliminary data collected from QS company indicates some operational and coordination problems with the supply chain. This resulted in increased cost at various elements of the supply chain including inbound transportation, inventory, and distribution. Anticipated results include the QS-SC KPIs, decision variables, total cost, and pull framework. Several other useful findings and results are expected from analyzing the supply chain of steel industry. Few researchers have approached this before including (Potter et al., 2004; Heidrich, 2002). In particular key results will be specified when developing an Integrated Supply Chain Network (ISCN) for QS Company and developing DES to model a dynamic and stochastic network.

Developing a set of informative KPIs for QS-SC. Measuring the supply chain performance using a specific set of KPIs is imperative to quantify improvement, monitor progress, identify potential problems, and reveal gaps between planning and execution. As discussed in (Chae, 2009), KPIs can

be developed to cover each stage of the Supply Chain Operations Reference (SCOR) model which includes Planning, Sourcing, Making, and Delivery. Alternatively, and as discussed in (Chopra and Meindl, 2007), KPIs can be developed for each supply chain driver including facilities, inventory, transportation, sourcing, pricing, and Information Technology (IT). In this research, KPIs will be developed based on what is essential for the success of QS supply chain in terms of responsiveness, efficiency, and utilization. The final form of the proposed KPIs will be set after collecting further information on QS supply chain stages and drivers. As a starting point, however, the following set of KPIs will be developed for QS supply chain:

- Average yield time: order-to-delivery time
- Fill rate: Fraction of orders/demand met on time from inventory
- Average inventory measured in units, days of demand, and financial value
- Average inbound transportation cost as % of sales or cost of each ton of steel
- The utilization of the four main operations in QS steel production: Direct Reduction, Electrical Furnace, Continuous Casting, and Rolling Mill

Measuring and validating the values of these KPIs will be used to evaluate the research results as well as for monitoring the QS-SC performance. To validate project results, these KPIs will be first

measured for previous year of supply chain operation and then used for planning the coming year. The flexibility of DES model will facilitate the validation of current performance and the prediction of the future performance. The total cost results from the LP model will be more meaningful to company's management and can be used to validate the project results. The total cost of supply chain using last year data will be first computed from the LP model. The result will be compared to the actual values as reported in the company's book.

The values of defined decision variables in the QS-SC will be also produced as project outcomes. These variables will be identified during the project, approved by management, and used to formulate the LP total cost model. The DES model will be used to test the QS-SC performance under other stochastic variables and the SA algorithm will be used to develop robust settings for these variables under similar-to-real-world conditions. The proposed solution is expected to result in a reduced total cost of the supply chain. Finally, a pull framework for the QS-SC case study is also expected from this research to reduce the waste and costs and develop a lean supply chain. This result can be evaluated by implementing the proposed framework and reassessing the developed KPIs. Other issues that would make this research significant to QS include:

- The accuracy of demand forecasting including market traders orders, sales, and marketing. This forces the company to keep 14 days' worth of finished products in inventory.
- Currently, the company adopts a push system for the supply chain. As a result, staged inventory is increasing across the facilities due to production fluctuation.
- Difficulties in monthly plan translation into RM requirements and weekly production plan. Estimated variability of mismatch is 5-10%.
- Long order lead time of 1-2 months for inbound shipments. This results in keeping 1-3 months safety stock of raw material: Overseas suppliers use ships to deliver RM through company operated port and additives from Doha port.
- Material management: bar-coding project is still in progress for items excluding bulk materials. Along with that, better material handling equipment and methods are in need.

- MRP module is not effective when linked to company's Enterprise Resources Planning (ERP) system

6 CONCLUSIONS

This paper presented a framework for optimizing the supply chain of a major steel producer. This framework integrates mathematical programming with simulation and simulated annealing. This includes modeling and analyzing the supply chain of the steel company, verifying the results of deterministic models using simulation, developing a specific set of KPIs to measure the performance of the supply chain, and optimizing such performance with simulated annealing. The framework defines specific set of Key Performance Indicators (KPIs) that are developed to characterize the supply chain performance in terms of responsiveness, efficiency, and utilization. The framework is part of an ongoing research project. Further details and results will be presented at the conference.

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