Optimal Supply Chain Networks Under Failure Risks Using Meta-Heuristic Algorithms

Abdulhadi Altherwi
Department of Industrial Engineering
Jazan University
Jazan, Saudi Arabia
aaaltherwi@jazanu.edu.sa, a.aaltherwi@hotmail.com

Daw Alwerfalli
A Leon Linton Department of Mechanical Engineering
Lawrence Technological University
Southfield, MI 48075, USA
dalwerfal@ltu.edu

William Edwards
Department of Industrial and Systems Engineering
Oakland University
Rochester, MI 48309, USA
wedwards@oakland.edu

Abstract

Many industrial companies continue to face global uncertainties in demand and failures in supply. The main purpose of this research is to design and optimize a supply chain network (SCN) that performs under completely uncertain environment. In this paper, three advanced meta-heuristic algorithms based on Broyden-Fletcher-Goldfarb-Shanno (BFGS), POWELL, and Non-dominated Sorting Genetic Algorithm (NSGA-II) are used to solve the optimization problem. A real-life case study for a steel manufacturing integrated supply chain is used to demonstrate the efficiency of the model and the solutions obtained by meta-heuristic algorithms. The objective was to maximize the total profit of supply chain network under disruption conditions. The presented mathematical modeling provides an understandable overview of the system for managers to make appropriate decisions to achieve the maximum profit. Findings revealed that advanced meta-heuristic algorithms were the most efficient technique to solve the proposed model when compared with the traditional method.

Keywords
Meta-Heuristic Algorithms, Supply Chain Networks, Global Optimization, Stochastic Demand, Advanced Optimozation.

1. Background

Supply chain networks (SCNs) face many global difficulties in product delivery operations, including demand and delay uncertainties. Shen (2003) used a nonlinear optimization model to solve integrated supply chain problems. The objective was to minimize the total expected costs of the system associated with inventory, locations, and distributions operations during shipping. The design of supply chain network decisions can be affected by supply chain disruptions (SCD) (Qi et al. 2010). The authors discussed an integrated supply chain network design to determine retailers' locations.

The objective considered also was to minimize the total expected costs associated with inventory, transportations, and locations. In addition, Liu et al. (2014) proposed a knowledge management framework to improve the competitiveness of organizations. The researchers identified critical knowledge for global supply chains to support different decisions simultaneously. The framework was categorized into three kinds of global knowledge including knowledge of global capacity, knowledge of global market, and knowledge of global supply networks. Gu et al. (2012) used system dynamic methodology models for integrated supply chains. The researchers proposed the dynamic methodology model to test the long-term decisions for integrated supply chains associated with remanufacturing. Hsieh et al. (2014) conducted a study of effect of ordering decisions on a multi-stages supply chain. The multi-stages supply chain considered consisting of multiple manufacturers and retailers under demand uncertainty (Hsieh et al. 2014). The results revealed that the decentralized system will gain the optimal profit of centralized integrated system once specific profit allocations are met. Li et al. (1999) analyzed two levels of the supply chain performance including operations and chains. The authors also discussed the effect of profit, delivery, elimination of waste to improve the efficiency and effectiveness of supply chains.

In this paper, we propose different integrated decisions to help the managers improving the chains of goods operations and minimizing the total expected costs. These decisions include shipping scheduling, time of selling or buying products, and production scheduling while the demand is unknown per seasons. Vernimmen et al. (2007) discussed the impact of scheduling online-shipping. They found that the performance of shipping can be affected by the decreasing schedule integrity. The authors presented a case study to show how the safety stock level can be affected by schedule unreliability. The results showed that the company can save money by the improvement of schedule reliability.

Meta-heuristic algorithms, such as Firefly Algorithm (FA), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Ant Colony Optimization (ACO) are computational algorithms used to solve the optimization problems in many different applications. They have been used to solve the global optimization of supply chain networks associated with large-scale problems. For example, Olivares-Benitez et al. (2015) used a meta-heuristic algorithm combination of Greedy Function (GF) and Scatter Search (SS) to solve a multi-objective optimization problem associated with a two-echelon supply chain. Bottani et al. (2019) also formulated the problem as a bi-objective mixed-integer programming. The authors addressed the Resilient Food Supply Chain Design (RFSCD). They used a meta-heuristic algorithm based on ant colony optimization to solve the problem. The multi-objective considered to be optimized are total profit maximization and total lead time of supply chain minimization. Castillo-Villar et al. (2014) applied a meta-heuristic algorithm based on genetic algorithms to solve bioenergy supply chain problems. The authors found that meta-heuristic algorithms are considered an effective approach to solving large-scale problems associated with bioenergy supply chains. The objective was to design the best route of goods transportation. Another objective under consideration was to optimize the task and trucks scheduling for the distribution operations of biomass.

This research is engaged in designing a multi-objective supply chain network that performs under disruption conditions during the delivery of goods. We implemented advanced met-heuristic optimization algorithms and compared the results with traditional algorithms to test the performance of meta-heuristic algorithms. A real-life case study for a steel manufacturing company was conducted to test the effectiveness of our model using four advanced optimization algorithms, including BFGS, POWELL, and NSGA-II.

2. Related Work

The optimization techniques for product delivery have been used in many applications in many industries. For instance, Mukherjee and Ray (2006) reviewed the optimization techniques in the metal cutting process. The scholars classified the optimization techniques into two categories, including conventional and non-conventional techniques. The conventional techniques, such as Dynamic Programming (DP), Non-Linear Programming (NLP), and Linear Programming (LP) can get the optimal solutions, whereas the non-conventional techniques, such as Genetic Algorithm (GA), Simulated Annealing (SA), Tabu Search, and Firefly Algorithm (FA) can get only the near-optimal solutions. Medic and Radovanović (2014) introduced a deterministic direct search optimization named a Pattern Search algorithm (PS). The results showed that the meta-heuristic algorithms are considered the most powerful optimization tools to solve complex problems. The researchers applied the Pattern Search algorithm to get the optimal solutions for machining processes. The researchers discussed the optimization problems in statistics, focusing on quality control (Carlyle et al. 2000). They described several optimization techniques including simulated annealing and genetic algorithms. Yang and Chou (2005) proposed finding the solution of a multi-response optimization problem using a decision-making approach.

Researchers found that the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a powerful tool to solve a multi-response optimization problem. Venter (2010) presented the standard form of the general non-linear and constrained problems. The researcher suggested how to select the appropriate optimization technique to solve the optimization problems. Jayal et al. (2010) presented optimization techniques for sustainable manufacturing processes. They found that using optimization techniques can determine the issues related to sustainable manufacturing.

Kobetski and Fabian (2009) presented a Mixed-Integer Linear Programming (MILP) model to optimize the time coordination of flexible manufacturing systems. They integrated the strength of Mixed-Integer Linear Programming for the scheduling of manufacturing systems. The results showed that the formulation of MILP is able to use the power of MILP to create schedules of time optimization. The researchers also used a nonlinear mixed-integer programming model to solve the production planning problems (Stecke 1983). Saxena and Jain (2011) presented the dynamic cell formation problem. They proposed a mixed-integer nonlinear programming model to solve the dynamic cellular manufacturing systems under stochastic demand. Zimmermann et al. (2001) solved large manufacturing system problems by using a two-phase optimization method including robust and efficient optimization techniques. The researchers proposed a metaheuristic based on simulated annealing to present the tool for automated optimization of Discrete Event Dynamic Systems (DEDS). Nouira et al. (2014) presented optimization models for manufacturing systems with a consideration for environmental impacts. The authors classified the optimization models into two models. For the first model, they assumed that the company offers the final product to ordinary and green customers. They formulated the problem as a MILP model. For the second model, they proposed that the company offers two separate kinds of products: one of them is offered to the ordinary customers, and the other one is offered to the green customers. The objective function of the model is to maximize the company's profit. Table 1 summarizes the existing literature using meta-heuristic algorithms in supply chain applications.

Table 1. The summary of some literature using meta-heuristic algorithms in supply chain applications

References	Application	Objective	Method
Olivares-Benitez et al. 2013	A multi-Stage SC for single product. This system includes plants, distribution centers, and customers.	The objective was to minimize the transportation costs and transportation time from plants to customers.	Meta-heuristic based on Greedy Function (GF) and Scatter Search (SS).
Bottani et al. 2019	They addressed a Resilient Food Supply Chain Design (RFSCD).	The objective was to maximize the total profit and total lead time of supply chain network.	They used a meta-heuristic algorithm based on ant colony optimization to solve the problem.
Castillo-Villar et al. 2014	Bioenergy supply chain problems.	The objective was to design the best route of goods transportation.	They applied a meta-heuristic algorithm based on genetic algorithm to solve bioenergy supply chain problems.
Moncayo-Martínez and Zhang 2011	Supply chain design problem was to select the options that can minimize the total costs of supply chain This system includes suppliers, plants, and products.	The objective function was to minimize the total costs of supply chain and lead time of deliveries simultaneously.	The authors used a meta-heuristic algorithm based on pareto ant colony optimization (PACO) to solve the problem.
Atabaki et al. 2019	They addressed a closed-loop supply chain with price sensitive demand with forward and reverse flows.	The objective was to maximize the profits associated with capacity and the constraints number of facilities opened.	They used a meta-heuristic algorithm based on firefly algorithm to solve large-sized problems.

Reviewing the existing literature shows supply chain networks that perform under uncertainty can result in incurring high expected penalty cost and minimal profit. To overcome these difficulties, this study proposes a mathematical modeling to help mangers improve chains of goods' operations and maximize the total profit.

3. Problem Description

In this paper we introduce mathematical models using advanced meta-heuristic algorithms based on BFGS, POWELL, and NSGA-II. The objective of the model is to maximize the total profit of supply chain network when facing uncertainties in failures in supply and demand. This paper proposes a model considering demand uncertainty and failures in supply to meet customers demand and prevent any costs related to penalties due to failures in supply. In this study, we consider that supply chain networks consist of multi-suppliers, multi-manufacturers, and multi-markets, as shown in Figure 1. This model was developed to help managers determine which decisions can minimize the total expected cost of the system and improve the shipment of materials without disruptions and delays, preventing any related penalty costs. The raw materials are supplied by suppliers to manufacturers. The manager must determine the limited number of finished products that should be shipped from manufacturers to markets or final customers. Moreover, manufacturers have three programs of selling, buying, and stocking the finished products at a warehouse at a later time. The manager must achieve the optimized program of selling, stocking, and buying units. The manager also faces disruptions and delays in the production operations, which result in high penalty costs due to disruptions and delays. The finished-products will be stored at a warehouse, and the managers must decide when to sell or buy the finished-products. The manager also faces disruptions and delays in the shipment of finished products to the final customers or markets, which result in increasing penalty costs.

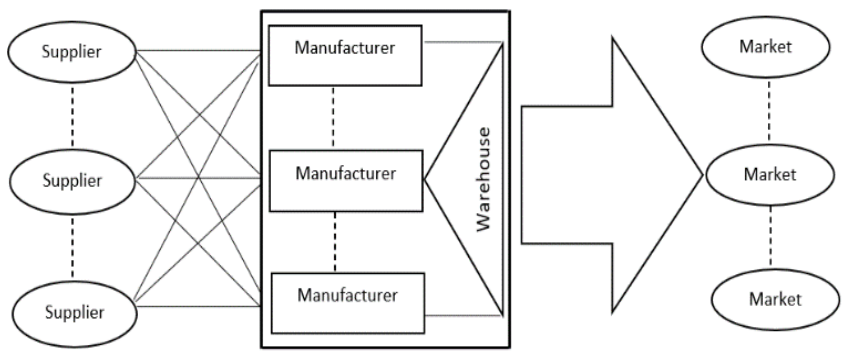

Figure 1. The stages of supply chain network considered in this research

4. Methodology

The main goal of this model is to develop a mathematical method to optimize a supply chain network that faces failure risks during the delivery of products using advanced optimization algorithms. The risks include shortage of raw materials and shortage of finished products. The proposed methodology is presented in Figure 2. We consider that supply chains work under uncertainty. The main purpose of the model is to maximize the profit and minimize the total expected costs associated with extra inventory and penalties for shortages. The model is implemented at a real-life case study for a steel manufacturing integrated supply chain for validation. The case study manages 13 supply chains work under uncertainty. All of them support the same product. Equation (1) calculates the total profit and costs associated with inventory and penalties for shortages, as follows:

$$P_{c,i} * Q_{i,t} - C_{p,i} * PU_{i,t} - CI_i * I_{i,t} - UR_i * SF_{,i,t} \tag{1}$$

Where $P_{c,i}$ and $Q_{i,t}$ present the cost of product of supply chain i and quantity of products in supply chain i at time t. Additionally, $C_{p,i}$ and $PU_{i,t}$ indicate the cost of production at supply chain i and production of units at supply chain i at time t. CI_i and $I_{i,t}$ present the carrying cost at supply chain i and inventory of units at supply chain i at time t. The last term calculates supplier failure penalty cost at supply chain i. Equation (2) determines that raw materials supplied by suppliers is considered the total production, as follows:

$$PU_{i,t} = \sum_{all\ suppliers} \left[SF_{,i,t} * Q_{r,i} - Q_{r,i}\right] \tag{2}$$

Where $SF_{,i,t}$ and $Q_{r,i}$ indicate the supplier failure penalty cost at supply chain i and quantity of raw materials in supply chain i respectively. Equation (3) indicates the demand of raw materials ($D_{r,i}$) and their inventories at the current time must equal raw materials' inventory and production from last time.

$$D_{r,i} + I_{i,t} = PU_{i,t} + SF_{,i,t} + I_{i,t-1} \tag{3}$$

In this research, we used advanced optimization algorithms based on BFGS, POWELL, and NSGA-II for optimizing a multi-objective supply chain network under failure risks. Literature indicate that the traditional mathematical models cannot achieve the optimal solution of large-scale models (Castillo-Villar 2014). So, we used advanced optimization algorithms based on meta-heuristic to get the near optimal solution of the model and compare the results with the traditional algorithm (SIMPLEX).

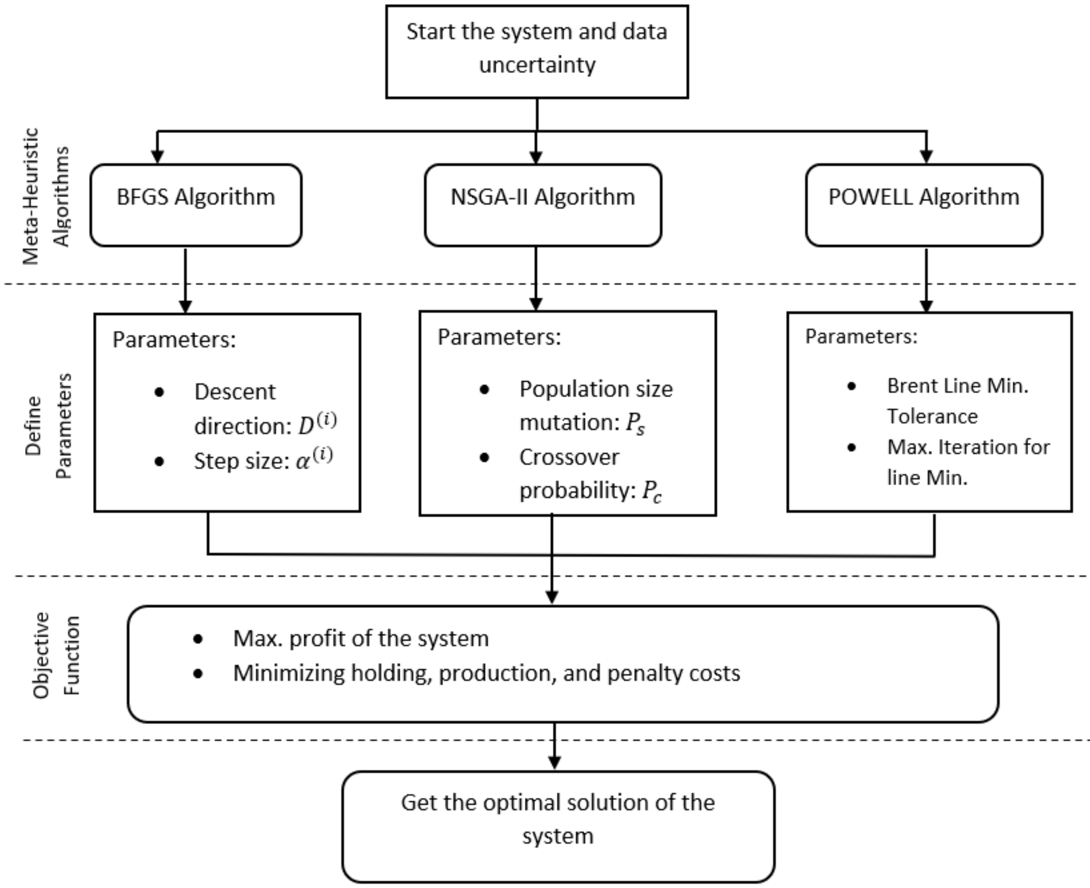

Figure 2. The proposed methodology used in this research

The Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm, which is Quasi-Newton optimization algorithm, is used to find the total expected costs of holding and penalties for shortages, as follows:

$$C_{p,i} * PU_{i,t} - CI_i * I_{i,t} - UR_i * SF_{,i,t} \quad (4)$$

The optimality of the step size of BFGS algorithm ($\alpha^{(i)}$) is calculated in Equation (5), as follows:

$$\alpha^{(i)} = arg\ min\, f(x^{(i)} + \alpha * D^{(i)}) \quad (5)$$

Where $X^{(i)}$ represents the vector of solution of BFGS algorithm at stage i. The descent direction ($D^{(i)}$) is determined in Equation (6), as follows:

$$D^{(i)} = -W^{(i)}\left[\nabla_x f(X^{(i)})\right] \quad (6)$$

Where $W^{(i)}$ represents the Hessian matrix. For validation, we used POWELL algorithm to find the local minimum function of the proposed supply chain network. Moreover, non-dominated sorting genetic algorithm (NSGA-II) is used to solve a multi-objective problem, which is maximization and minimization problems. We also used response surface methodology (RSM) algorithm based on statistical model (Kriging) to compare the test and validation of each optimization algorithms using three performance indexes including Mean Absolute Error (MAE), R-squared and Akaike Information Criterion (AIC). The mean absolute error is used to get the best performance of model using meta-heuristic algorithms, which can be determined in Equation (7), as follows:

$$MAE = \frac{\sum_{i=1}^{n} |(x_i - x)|}{n} \tag{7}$$

Where n represents the number of error while the absolute value is the difference between predicted and observed values. Akaike Information Criterion can calculate the relative information that can be lost by a model and can be calculated in Equation (8), as follow:

$$AIC = 2 * I - 2\,ln(L) \tag{8}$$

Where I and L represent the number of independent variables and likelihood estimate respectively.

5. Results and Discussion

The main objective of this paper is to optimize a muti-objective supply chain network that perform under failure risks of shortages. The traditional optimization algorithm such as SIMPLEX cannot achieve the optimal solution of large-scaled models. So, to find the better findings, we used advanced optimization algorithms based on meta-heuristic to get the near optimal solution of the model and compare the results with the traditional algorithm (SIMPLEX). The model is implemented at a real-life case study for a steel manufacturing integrated supply chain for validation. The case study manages 13 supply chains, which work under uncertainty and face failure risks of shortage. The multi-objective is to maximize the profit and minimize the total expected costs of supply chains. We also trained RSM, which is trained upon a design of experiment (DOE) based on statistical models (Kriging), as shown in Table 2. This table illustrates that the best value of the selected validation criterion is represented by BFGS algorithm. Then, we compare the result of this algorithm with other powerful optimization algorithms to determine which algorithm has the best optimized solution and satisfactory results. The best algorithm is one with lowest MAE and AIC values and highest R-squared value. The result revealed that the best algorithm is BFGS, as shown in Table 2.

Table 2. Model training using RSM algorithms

Algorithm	**MAE**	**R-SQUARED**	**AIC**
BFGS	$2.13E^{-07}$	1	-1831.92
NSGA-II	0.002029	0.999997	-151.658
POWELL	2.69335	0.0283381	927.573
SIMPLEX	0.017218	0.99997	12.2258

For BFGS algorithm, we ran the model for 400 iterations to get the optimal solution. Table 3 shows the best design iteration for the optimal solution using BFGS. The best optimal objective function was 44.7150 based on 98 iterations, as shown in Table 3.

Table 3. The optimal solution of model Using BFGS algorithm

Iterations	**Algorithm**	**Phase**	**Objective Function**
88	BFGS	Evolution	43.8064
90	BFGS	Evolution	43.8064
93	BFGS	Evolution	43.8064

95	BFGS	Evolution	43.8064
96	BFGS	Evolution	43.8064
98	BFGS	Evolution	44.7150

We also ran the model for 400 iterations to get the optimal solution using NSGA-II algorithm. Table 4 shows the best design iteration for the optimal solution. The best optimal objective function was 41.7237 based on 383 iterations, as shown in Table 4. We also ran the model for 400 iterations to get the optimal solution using POWELL algorithm. Table 5 shows the best design iteration for the optimal solution. The best optimal objective function was 44.7150 based on 126 iterations, as shown in Table 5.

Table 4. The optimal solution of model using NSGA-II algorithm

Iterations	**Algorithm**	**Phase**	**Objective Function**
373	NSGA-II	Evolution	41.0207
375	NSGA-II	Evolution	40.9793
377	NSGA-II	Evolution	41.2199
379	NSGA-II	Evolution	41.2796
380	NSGA-II	Evolution	41.2351
381	NSGA-II	Evolution	41.3677
383	NSGA-II	Evolution	41.7237

The feasible solution of SIMPLEX, BFGS, and NSGA-II algorithms is shown in Figure 3, Figure 4, and Figure 5 respectively. The training and validation of model using NSGA-II algorithm are shown in Figure 6.

Table 5. The optimal solution of model using POWELL algorithm

Design ID	**Algorithm**	**Phase**	**Objective Function**
111	POWELL	Evolution	44.7140
113	POWELL	Evolution	44.7146
119	POWELL	Evolution	44.7138
122	POWELL	Evolution	44.7149
125	POWELL	Evolution	44.7146
126	POWELL	Evolution	44.7150

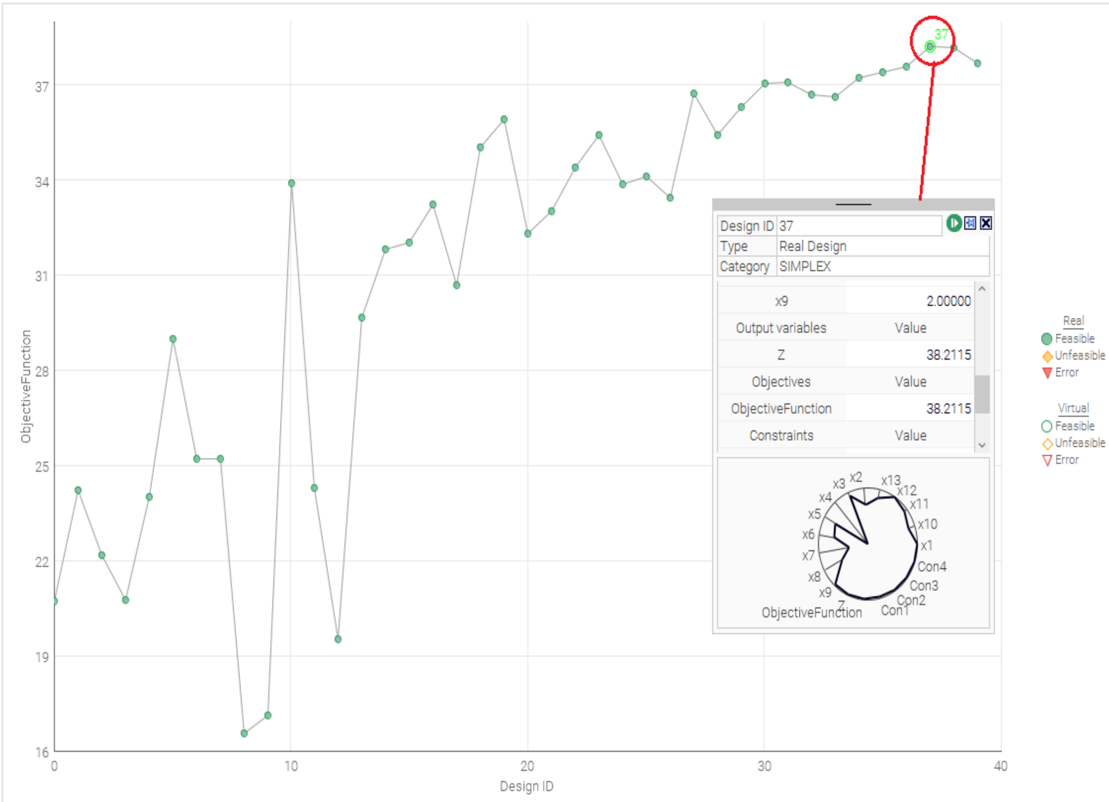

Figure 3. The feasible solutions of using SIMPLEX

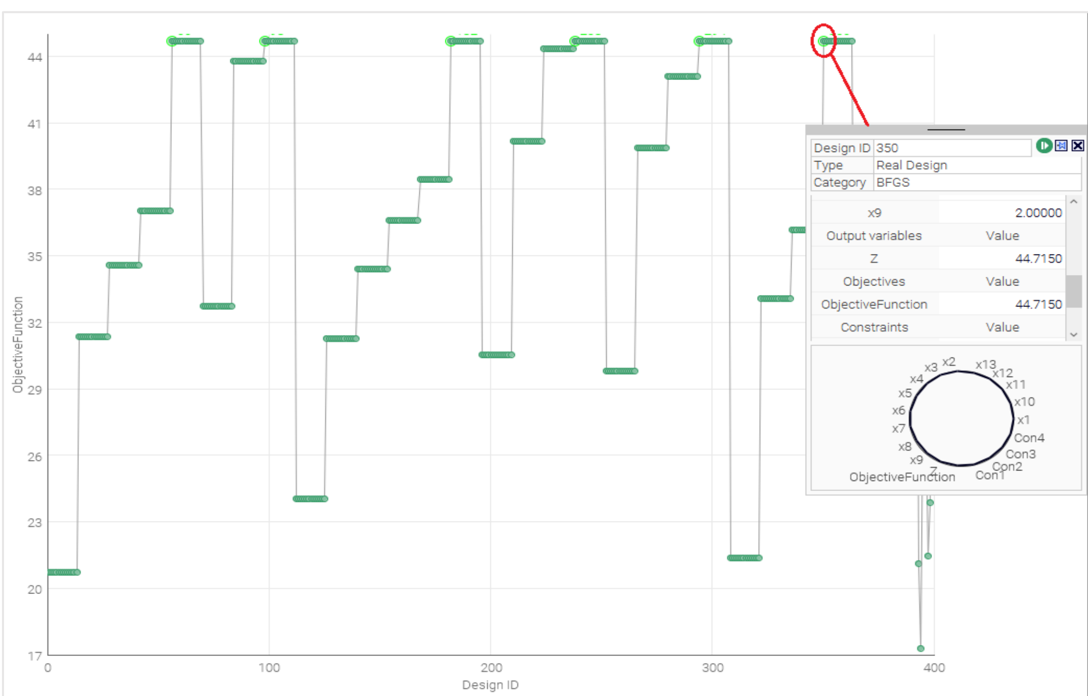

Figure 4. The feasible solutions of using BFGS

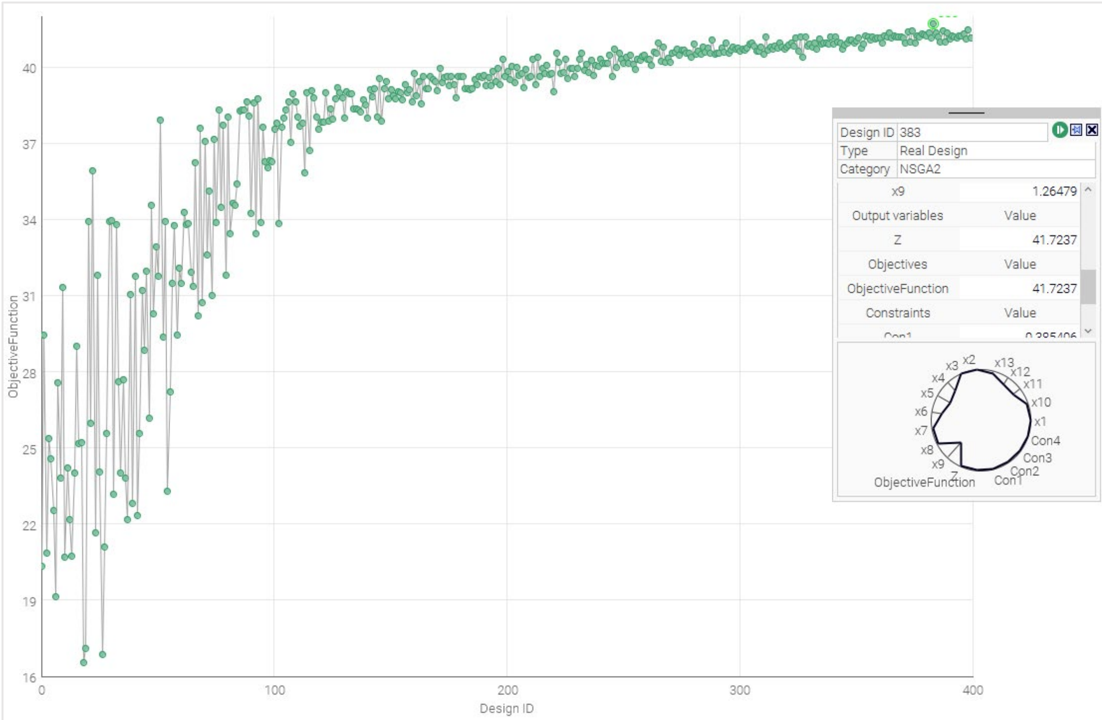

Figure 5. The feasible solutions of NSGA-II algorithm

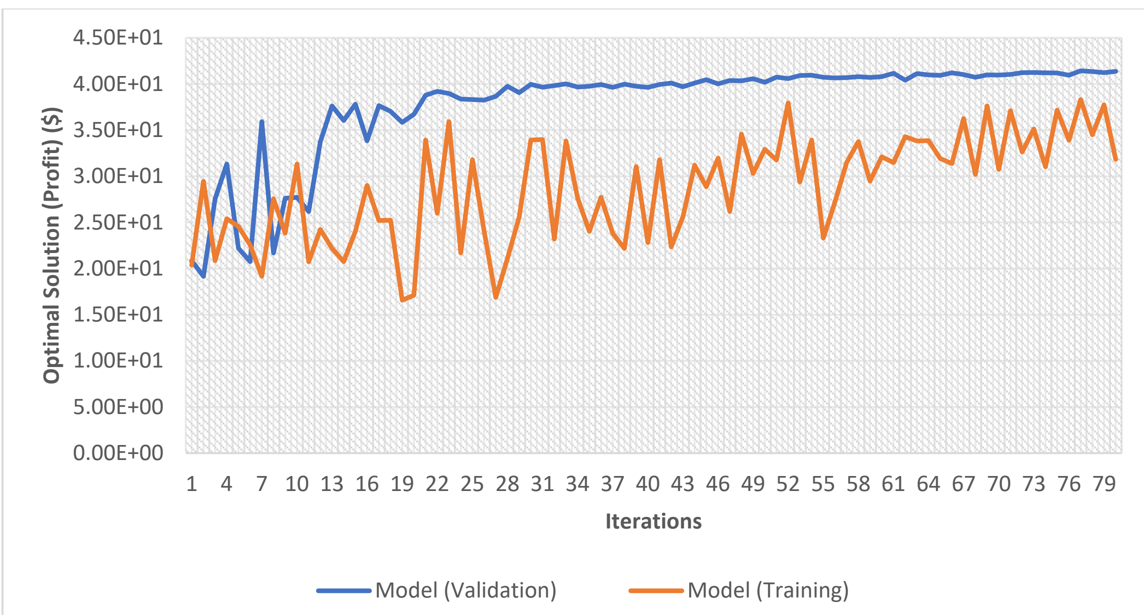

Figure 6. Training and validation of the model using NSGA-II algorithm

6. Conclusion

Global Supply Chain Networks (GSCNs) experiencing failures in supply require investigation to discover the cause of supply delays. In this study, a mathematical model was developed to predict the delays and failures in supply. The problem was developed as a multi-objective function to optimize multi-stage supply chain networks under risks of failure in order to achieve the least cost and greatest profit. The model considered in this paper presented integrated supply chain decisions to optimize the delivery of products under demand uncertainty and failure risks (disruptions, delays, etc.). The results of the proposed model can help managers achieve optimal solutions for inventory operations and determine when they can apply make-to-order policies. This research can be extended by considering different objectives and methodologies. This research can also be extended by using different meta-heuristic algorithms to achieve near optimal solutions and compare the results of each algorithm based on their accuracies.

References

Shen, Z. J. M., Coullard, C., and Daskin, M. S. A joint location-inventory model, *Transportation Science*, vol. 37, no. 1, 2003.

Qi, L., Shen, Z. J. M., and Snyder, L. V. The effect of supply disruptions on supply chain design decisions. *Transportation Science*, vol. 44, no. 2, pp. 274-289, 2010.

Liu, S., Moizer, J., Megicks, P., Kasturiratne, D., and Jayawickrama, U. A knowledge chain management framework to support integrated decisions in global supply chains. *Production Planning and Control*, vol. 25, no. 8, pp. 639-649, 2014.

Gu, Q. L., and Gao, T. G. Joint decisions for R/M integrated supply chain using system dynamics methodology, *International Journal of Production Research*, vol. 50, no. 16, pp. 4444-4461, 2012.

Hsieh, C. C., Chang, Y. L., and Wu, C. H., Competitive pricing and ordering decisions in a multiple-channel supply chain, *International Journal of Production Economics*, vol. 154, pp. 156-165, 2014.

Li, D., and O'Brien, C. Integrated decision modelling of supply chain efficiency, *International Journal of Production Economics*, vol. 59, no. 1, pp. 147-157, 1999.

Vernimmen, B., Dullaert, W., and Engelen, S. Schedule unreliability in liner shipping: origins and consequences for the hinterland supply chain, *Maritime Economics and Logistics*, vol. 9, no. 3, pp. 193-213, 2007.

Olivares-Benitez, E., Ríos-Mercado, R. Z., and González-Velarde, J. L. A metaheuristic algorithm to solve the selection of transportation channels in supply chain design, *International Journal of Production Economics*, vol. 145, no. 1, pp. 161-172, 2013.

Bottani, E., Murino, T., Schiavo, M., and Akkerman, R. Resilient food supply chain design: Modelling framework and metaheuristic solution approach, *Computers and Industrial Engineering*, vol. 135, pp. 177-198, 2019.

Castillo-Villar, K., Metaheuristic algorithms applied to bioenergy supply chain problems: theory, review, challenges, and future. *Energies*, vol. 7, no. 11, pp. 7640-7672, 2014.

Mukherjee, I., and Ray, P. K. A review of optimization techniques in metal cutting processes, *Computers and Industrial Engineering*, vol. 50, pp. 15-34,2006.

Madić, M., and Radovanović, M. Optimization of machining processes using pattern search algorithm, *International Journal of Industrial Engineering Computations*, vol. 5, no. 2, pp. 223-234, 2014.

Carlyle, W. M., Montgomery, D. C., and Runger, G. C. Optimization problems and methods in quality control and improvement, *Journal of Quality Technology*, vol. 32, no. 1, pp. 1-17, 2000.

Yang, T., and Chou, P. Solving a multi-response simulation-optimization problem with discrete variables using a multiple-attribute decision-making method, *Mathematics and Computers in simulation*, vol. 68, no. 1, pp. 9-21, 2005.

Venter, G. Review of optimization techniques, *Encyclopedia of aerospace engineering*, 2010.

Jayal, A. D., Badurdeen, F., Dillon Jr, O. W., and Jawahir, I. S. Sustainable manufacturing: Modeling and optimization challenges at the product, process, and system levels, *CIRP Journal of Manufacturing Science and Technology*, vol. 2, no. 3, pp. 144-152, 2010.

Kobetski, A., and Fabian, M. Time-optimal coordination of flexible manufacturing systems using deterministic finite automata and mixed integer linear programming, *Discrete Event Dynamic Systems*, 19(3), 287-315, 2009.

Stecke, K. E. Formulation and solution of nonlinear integer production planning problems for flexible manufacturing systems. *Management science*, vol. 29, no. 3, pp. 273-288, 1983.

Saxena, L. K., and Jain, P. K. Dynamic cellular manufacturing systems design—a comprehensive model, *The International Journal of Advanced Manufacturing Technology*, vol. 53, no. (1-4), pp. 11-34, 2011.

Zimmermann, A., Rodriguez, D., and Silva, M. A two-phase optimization method for Petri net models of manufacturing systems, *Journal of Intelligent Manufacturing*, vol. 12, no. 5-6, pp. 409-420, 2001.

Nouira, I., Frein, Y., and Hadj-Alouane, A. B. Optimization of manufacturing systems under environmental considerations for a greenness-dependent demand, *International Journal of Production Economics*, vol. 150, pp. 188-198, 2014.

Moncayo-Martínez, L. A., and Zhang, D. Z. Multi-objective ant colony optimization: A meta-heuristic approach to supply chain design, *International Journal of Production Economics*, vol. 131, no. 1, pp. 407-420, 2011.

Atabaki, M. S., Khamseh, A. A., and Mohammadi, M. A priority-based firefly algorithm for network design of a closed-loop supply chain with price-sensitive demand, *Computers and Industrial Engineering*, vol. 135, pp. 814-

837, 2019.

Biographies

Abdulhadi Altherwi is a lecturer in the Department of Industrial Engineering at Jazan University, Jazan, Saudi Arabia. He earned a B.S in Industrial Engineering from Jazan University, Jazan, Saudi Arabia and a Master's in Industrial Engineering program from Lawrence Technological University, Michigan, USA. Mr. Altherwi is a Ph.D. candidate in Systems Engineering program at Oakland University, Michigan, USA. His research interests include Operations Research, Supply Chain Networks, Advanced Optimization Techniques, and Simulation and Modeling. He is a member of IISE and ICCC.

Daw Alwerfalli is a Professor and Director of Engineering Management Program, A. Leon Linton Department of Mechanical, Robotics and Industrial Engineering at Lawrence Technological University. Prominent professor, senior technical industry consultant and manufacturing engineering educator with tremendous expertise in program and curriculum development in higher technical education. Dr. Alwerfalli is a Highly experienced and dedicated community leader with great ability to work with an array of constituencies and coalitions in developing shared organizational vision to create and implement strategies aimed at advancing common causes to accomplish goals in fulfilment of the organization's mission. He possesses good analytical and decision-making skills and the ability to conceptualize new initiatives and solutions to problems while possessing an outcomes orientation. He has presented many well recognized technical papers in local, national and international conferences.

William Edwards is a Professor in the Department of Industrial and Systems Engineering at Oakland University, Rochester, MI, USA. He earned a Ph.D. in Systems Engineering from Oakland University, Rochester, MI, USA. He has published journal and conference papers and has completed research projects with many local and global industries. His research interests Move It Forward Theory (MIFT) Production Management, Rare Event Downtime Analysis, and Rare Event Prediction. He has presented many well recognized technical papers in local, national and international conferences. He was awarded Ford Customer Driven Quality Award and Ford Complexity Reduction Award. He is a member of SAE, TBP, IEEE, ASME, ESD, M-SUG, and NAERG organizations.