A META-HEURISTIC ALGORITHM BASED ON MODIFIED GLOBAL FIREFLY OPTIMIZATION: IN SUPPLY CHAIN NETWORKS WITH DEMAND UNCERTAINTY

by

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To my beloved parents

To my wife: Thekra Altherwi

To my kids: Jwad & Eyad

To my brothers: Fahad, Yehya, Ahmed, Moosa, and Saud

To my sisters: Hawyah, Maha, Salha, Roqya, and Reem

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ABSTRACT

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Nowadays, many challenges affect global supply chain networks including disruptions, delays, and failures during shipment of products. These challenges also incur penalty costs due to customers' unmet demands and failures in supply. In this dissertation, the model was developed as a multi-objective supply chain network under two risk factors including failure in supply and unmet demand based on three different scenarios.

The objective of scenario I was to minimize the total expected transportation costs between stages for each supply chain and penalty costs associated with shortage of products. Supply chain with no failure in supply will communicate with supply chain with failure to deliver its product to the final customer. For scenario II, the objective was to maximize the profits of the supply chain that face extra inventory. This supply chain with surplus products will collaborate with supply chains with shortage of products to prevent any undesirable costs associated with extra inventory.

The objective of scenario III was to develop a multi-objective function, which maximizes the profit and minimizes the total costs associated with production, holding, and penalties due to supplier failure of raw materials. Once a supply chain faces failure in supply of raw materials, other supply chains with no supply failure will collaborate to prevent any associated costs.

This research investigates the applicability of the Modified Firefly Algorithm for a multi-stage supply chain network consisting of suppliers, manufacturers, storages, and markets under risks of failure. Commercial software cannot obtain the optimal results for these problems considered in this research. To achieve better findings, we applied a Modified Firefly Algorithm to solve the problem. Two case studies for a pipe and a steel manufacturing integrated supply chain demonstrated the efficiency of the model and the solutions obtained by the Firefly Algorithm. We used four optimization algorithms in ModeFRONTIER and MATLAB software to test the efficiency of the proposed algorithm. The results revealed that when compared with other four optimization algorithms, Firefly Algorithm can help achieve maximum profits and minimizing the total expected costs of supply chain networks.

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LIST OF ABBREVIATIONS

SCNs	Supply Chain Networks
MFA	Modified Firefly Algorithm
SFA	Standard Firefly Algorithm
SOSCP	Single-Objective Supply Chain Problems
MOSCP	Multi-Objective Supply Chain Problems
DDP	Direct Delivery Policy
MINLP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
RSM	Response Surface Methodology
DOE	Design of Experiments
BFGS	Broyden-Fletcher-Goldfarb-Shanno Algorithm
NSGA	Non-dominated Sorting Genetic Algorithm
NLP	Non-Linear Programming
FRS	Failure Risk of Supply
GSCNs	Global Supply Chain Networks

CHAPTER ONE

INTRODUCTION

1.1 Introduction

1.1.1 Firefly Algorithm for Global Optimization

The firefly algorithm stands out amongst the best new bio-inspired optimization techniques, which introduced by Yang [1]. Firefly algorithm is considered one of family members of swarm intelligence algorithm, which have displayed significant performances in solving optimization issues. The main concept of firefly algorithm is that the bioluminescence of insects could be used to communicate. The fireflies' flashing lights can warn fireflies of potential predators and attract mating other fireflies. Some characteristics of flashing lights of fireflies can design a firefly-inspired algorithm effectively by three idealized rules: 1) All fireflies are unisex, so one firefly can attract others regardless of the sex. 2) The quality of solution is based on the brightness of fireflies, which is proportional to the objective function. 3) A firefly with less brightness will be moved toward the brighter one. Otherwise, it will move randomly if it is the brighter one. For example, if firefly J is brighter than firefly I, then, the position after the movement of fireflies will be considered as follows:

$$x_i^{t+1} = x_i^t + \beta_0\left(x_j^t - x_i^t\right) + \alpha_i \varepsilon_i^t \tag{1.1}$$

Where $\beta = \beta_0 \exp(-\Upsilon r^2)$ is considered as the attractiveness, with β_0 indicating the attractiveness at distance r = 0, while the light absorption coefficient is Υ.

Parameter $\boldsymbol{\varepsilon_i^t}$ is a vector of arbitrary numbers drawn from a Gaussian or uniform distribution at time t, and $\boldsymbol{\alpha_i}$ is a parameter controlling the progression measure (step size) which means the randomization parameter. Note that if β_0 is equal to zero, the movement of fireflies walk randomly. Equation (1.1) is summarized three parameters mentioned above, which are the parameter of randomization, the attractiveness, and the third parameter is the coefficient of absorption. Firefly algorithm identifies two behaviors of asymptotic:

- If Υ goes to zero, the attractiveness will be constant, which results $\beta = \beta_0$ during the search space.
- If Υ is very large, then, the fireflies will be moved randomly according to Equation (1.1).

Optimization is a common practice in daily decision-making process hence creating a universal aspect of applicability of optimization as shall be seen in this study. The recent past decades have witnessed rise in the interest of use of biologically based and evolutionary based optimization algorithms [2]. In this chapter, we examine how the global optimization problems can be solved using new variations of the biologically optimized algorithms.

Different optimization methods have been formulated to solve different and specific problems and no one optimization approach can solve all the problems. Accordingly, the non-traditional optimization methods have also been introduced to solve complex engineering problems.

Most complex engineering problems can be solved by popular and powerful optimization techniques such as Colony Optimization Algorithm (COA), fuzzy optimization, Genetic Algorithm (GA), and firefly algorithm [3]. Figure 1.1 shows Pseudo code of standard firefly algorithm.

Algorithm 1: Pseudo code of the basic firefly algorithm for

Input: objective function $f(x_i)$, generate population of fireflies $x = (x_1, x_2, \ldots, x_N)$;
Output: find the best solution;
While (t < Max Generation)
$\boldsymbol{For\ i = 1{:}N}$
$\boldsymbol{For\ j = 1{:}N}$
$\boldsymbol{If\ I_j > I_i}$
by using uniform distribution, move firefly i towards j;
evaluate new solution and update light intensity $f(x_i^{(t)})$;
rank fireflies and find the best;
$t = t + 1$;
End if
End for
End for i
End while
End

Figure 1.1. Pseudo Code of Standard Firefly Algorithm [1]

1.1.2 Challenges in Global Supply Chain Networks

Supply chain networks (SCNs) face many global difficulties in product delivery operations, including demand and delay uncertainties. Shen [4] used a nonlinear optimization model to solve integrated supply chain problems. The objective in [4] 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) [5]. The researchers in [5] discussed an integrated supply chain network design to determine retailers' locations.

The objective considered in [5] also was to minimize the total expected costs associated with inventory, transportations, and locations. In addition, Liu et al. [6] proposed a knowledge management framework to improve the competitiveness of organizations. The researchers in [6] 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. [7] used system dynamic methodology models for integrated supply chains. The researchers in [7] proposed the dynamic methodology model to test the long-term decisions for integrated supply chains associated with remanufacturing. Hsieh et al. [8] conducted a study of effect of ordering decisions on a multi-stages supply chain. The multi-stages supply chain considered in [8] consisting of multiple manufacturers and retailers under demand uncertainty. 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. [9] 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. [10] discussed the impact of scheduling online-shipping.

They found that the performance of shipping can be affected by the decreasing schedule integrity. The authors in [10] 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. Wang et al. [11] formulated container routing and schedule design problems to minimize the total expected transportation of shipments and penalty costs associated with long transit-time.

They applied the model in a liner shipping company to design the schedule of shipping to minimize the transit-time. Notteboom [12] proved that time factor plays an essential role in schedule reliability in a liner service company. The author in [12] determined the tradeoffs associated with the time factor for shipping line. The author addressed the causes of schedule unreliability to maximize the schedule reliability.

Production schedule optimization has been caried out by many researchers to minimize the time associated with production operations. Dietrich et al. [13] proposed methods of allocation to generate a schedule of production. These methods included the quantity of products, a required quantity of components allocations, and fulfillment of the remaining products at time later. The authors in [13] preferred to use these methods in material requirements planning systems (MRP) for generating a schedule of production. Tang et al. [14] proposed a model for a master production schedule (MPS) under demand uncertainty. This model was considered to cover the scheduling change cost. The results showed that the safety stock is optimized once the effective planning and replanning of MPS is met. Nehring et al. [15] proposed a new mathematical modeling to optimize production schedule for underground mining.

The authors in [15] formulated the model as a mixed integer programming (MIP) model to solve the production schedule problem. Göthe-Lundgren et al. [16] also proposed a model to optimize the refinery production scheduling. The model considered in [16] described the planning and scheduling of production associated with an oil company. The main objective of production scheduling was to determine which operation mode used to minimize the production cost. The researchers in [16] formulated a mixed integer linear programming model to solve the scheduling problem. Riepshoff et al. [17]

applied hybrid meta-heuristic algorithm based on genetic algorithm to optimize the inventory operations based on production scheduling. Peng et al. [18] conducted an experimental study to optimize the production scheduling for a multi-layer superposed of coalbed methane (CBM). The authors in [18] proposed physical simulation of production of coalbed methane based on large-sized problem. They also presented a production scheduling for gas backfilling prevention. Tambe et al. [19] presented that the performance of a production system can be improved by considering production scheduling constraints. The researchers developed a model to solve the optimization problem of quality plan and maintenance with constraints of production scheduling, repair, and detection times. They used meta-heuristic algorithms based on simulated annealing (SA) and genetic algorithm (GA) to achieve the near optimal solution of the model. Chang et al. [20] proposed a model for integrated production and distribution scheduling to minimize the expected costs of distribution and delivery time. The problem considered in [20] was to determine which job can be processed first by single machine. The researchers applied a meta-heuristic algorithm based on ant colony optimization (ACO) to achieve the near optimal solution.

1.1.3 Overview of Optimization Approaches of Global Supply Chain Networks

Several kinds of production optimization problems have been solved using exact techniques, such as Linear Programming (LP) [21], Integer Linear Programming [22], and Mixed Integer Linear Programming [23]. However, these exact optimization techniques cannot achieve an appropriate solution in a reasonable run time. In this context, a metaheuristic algorithm is applied to an optimization problem to reach an appropriate solution with a high search space.

Stochastic methods are a powerful tool in determining a global optimum solution. In this context, there are metaheuristic algorithms, which are classified as one of various population-based algorithms, such as particle swarm optimization [24], the League Championship Algorithm [25], the Cuckoo Search Algorithm (CSA) [26], the Symbiotic Organisms Search Algorithm (SOSA) [27], the Artificial Bee Colony Algorithm [28], and the Firefly Algorithm (FA) [1].

Several researchers have applied metaheuristic algorithms to solve optimization problems, including Ant Colony Optimization [29], Particle Swarm Optimization (PSO) [30], and Artificial Bee Colony (ABC) [31]. The main goal of this paper is to present a method for optimizing production line using a metaheuristic algorithm based on the firefly algorithm (FA). One of the benefits of metaheuristic algorithms over exact optimization techniques is the capacity to discard bad optimal solutions when the model is running and use the best solutions.

According to Yang [1], the FA can solve constrained and non-constrained optimization problems and achieve the best optimal solution in a reasonable run time. A review of the existing literature reveals that this algorithm has been improved by some researchers to solve different optimization problems. As an example, Khalifehzadeh and Fakhrzad [32] modified the FA to optimize a multi-stage network with stochastic production capacity. Xiao et al. [33] proposed a modified FA to improve the forecasting capacity in reaching an appropriate optimal solution. Memari et al. [34] proposed a new modified FA to optimize a supply chain problem. In this present work, the standard FA, as developed in 2008 by Yang (2009), is implemented to solve a production optimization problem.

1.2 Motivation

The meta-heuristic algorithms such as Firefly Algorithm (FA), Genetic Algorithm (GA), Ant Colony Algorithm (ACA), and many others, are considered one member of the swarm intelligence algorithm, which has displayed significant performance in solving optimization issues. The main concept of the firefly algorithm is that the bioluminescence of insects could be used to communicate [35]. The firefly algorithm can develop communication as part of social behavior just as in swarm intelligence algorithms. Moreover, the algorithm is considered a metaheuristic algorithm that has the capability to find the optimal solution simply based on its exploitation abilities. It also can find the best global value.

Yang [35] has demonstrated that the Firefly algorithm efficiently deals with multimodal problems as well as performs better than other bio-inspired optimization algorithms. Hence, researchers have been attracted to it in solving optimization problems [36].

Although the firefly algorithm has been used as a Robust Optimization Problem (ROP) solution, since its first introduction in 2009, it needs improvements. The firefly algorithm and the swarm optimization algorithm, as cited above, have the ability to solve complex problems in engineering as well as in science. The performance results of the original firefly algorithm and its variant algorithms are presented in Chapter Three. Therefore, further study and exploration of the firefly algorithm is suggested to produce a more novel algorithm with a higher efficiency and performance rating.

The main objective in this research is to apply meta-heuristic algorithms to solve large-sized problems related to supply chain networks under failure risks in supply. In this study, we demonstrate the efficiency of our model using a meta-heuristic algorithm based on a modified firefly algorithm by implementing our model at a pipe manufacturing company, which manages the supply of three main different pipes: Reinforced Concrete Pipes (RCP), Glass Reinforced Epoxy Pipes (GREP), and Glass Reinforced Plastic Pipes (GRPP). In this case study, we applied a collaborative strategy for the supply of goods under failure risks of supply including shortage of products and demand uncertainty in order to help mangers meet customers satisfaction. The role of the manager is to be focused on the inventory level to overcome the expected shortage that may occur during shipping.

Once shortages occur, the industrial plants collaborate with industrial plants that face shortage of products to overcome penalty costs associated with shortage of products and unmet demand.

Moreover, we present a comparison of the results using commercial software and meta-heuristic algorithms to test the effectiveness of the proposed algorithm.

1.3 Problem Statement

In this research, the objective function is to reduce the total expected costs associated with transportations and penalty costs associated with delivery delays, product shortages, and unmet demand. In this research, we consider the supplier implements only one policy for the supply of goods, which is a direct-delivery policy under demand uncertainty. The role of the supplier is to focus on the inventory level to overcome the expected shortage that may occur at the industrial plants. The direct-delivery system is applied in industrial plants as a non-collaborative strategy.

Many significant challenges, including high supply chain costs, quantity and cost balancing, delivery delays, and the availability of product from suppliers affect the delivery of products. This research mainly considers the use of meta-heuristic algorithms, such as a Modified Firefly Algorithm (MFA), for global optimization of supply chain networks to minimize its costs and maximize its own profit when facing uncertainties in demand and failures in supply. In this study, we consider that supply chain networks consist of multi-suppliers, multi-manufacturers, and multi-markets. Figure 1.2 presents the proposed supply chain networks under failure risks of supply.

The main objective of this model was to minimize the total expected cost of proposed supply chain networks based on three different decision scenarios. We modeled all three decision scenarios mathematically.

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. 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 results 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.

To overcome these issues, the proposed model was based on a collaborative strategy and developed to help managers minimize the total expected costs based on three different problems, as follows:

- Problem I: A supply chain may face shortage of products due to high demand from its customers. This supply chain may face high penalty costs due to the shortage of products, which leads to customers unsatisfactory.
- Problem II: A supply chain may face extra inventory, which leads to high holding costs of surplus products.
- Problem III: A supply chain may face failure in supply of raw materials from supplier to manufacturer. This supply chain may face high penalty costs due to supplier failure, and high production cost.

1.4 Research Objectives

The main objective of this research was to apply the meta-heuristic algorithms for global optimization of supply chain networks under failure risks of supply including shortage of products and unmet demand. Achievement of this objective yields solutions to single objective and multiple-objective optimization problems through system improvements. The modified version of the firefly algorithm can be utilized for exploration and exploitation mechanisms to speed up the convergence and to enhance the performance of the firefly algorithm, thus resulting in faster and optimal solutions.

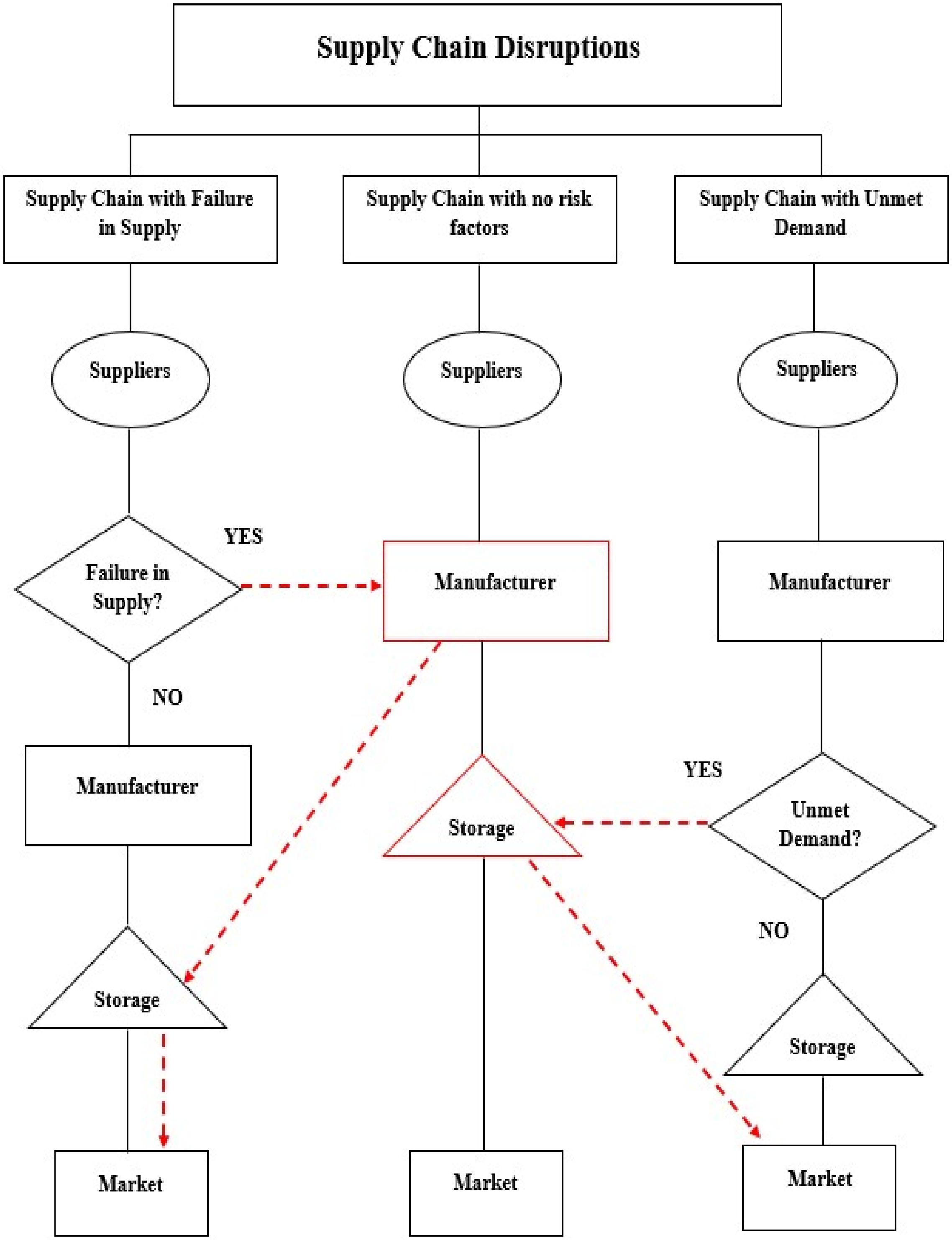

Figure 1.2. Proposed Supply Chain Networks Under Failure Risks in Supply

The objective is to design a multi-objective supply chain networks under two risks of factors including failure in supply and unmet demand based on three different scenarios, as discussed in Chapter 1: Section 1.3:

- ✓ The objective of scenario I was to minimize the total expected transportation costs between stages for each supply chain and penalty costs associated with shortage of products. Supply chain with no failure in supply will communicate with supply chain with failure in supply due to shortage of products to deliver its product to the final customer, as shown in Figure 1.3.
- ✓ The objective of scenario II was to maximize the profit of supply chains that face extra inventory. This supply chain with surplus products will collaborate with supply chains with shortage of products to prevent any undesirable costs associated with extra inventory, as shown in Figure 1.4.
- ✓ The objective of scenario III was to develop a multi-objective function, which maximizes the profit and minimizes the total costs associated with production, holding, and penalty due to supplier failure of raw materials. Once a supply chain faces failure in supply of raw materials, other supply chains with no failure in supply will collaborate to prevent any costs associated with supplier failure, as shown in Figure 1.5.

1.4.1 Case Study: Pipe Manufacturing Integrated Supply Chain

In this study, we demonstrated the efficiency of our model using a meta-heuristic algorithm based on a modified firefly algorithm by implementing our model at a pipe manufacturing company.

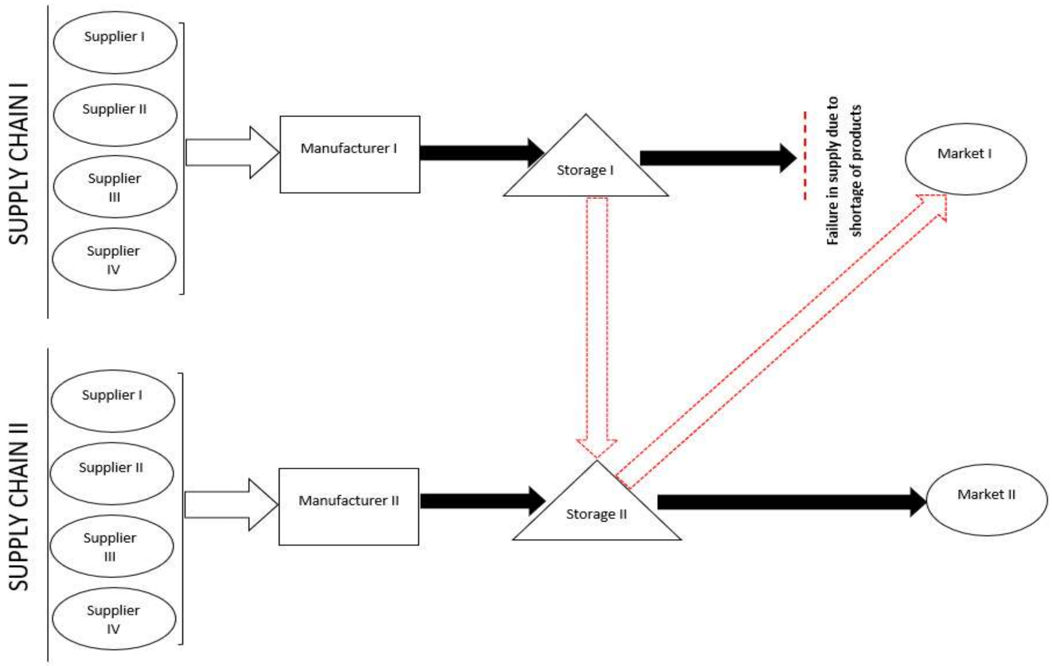

Figure 1.3. The Proposed Collaborative Supply Chain of Scenario I

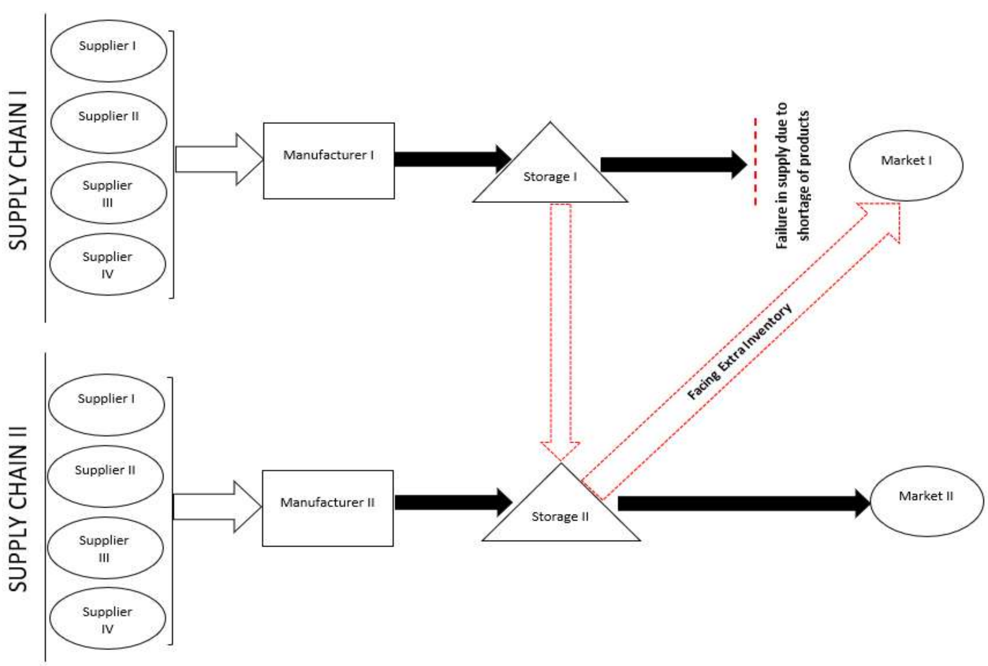

Figure 1.4. The Proposed Collaborative Supply Chain of Scenario II

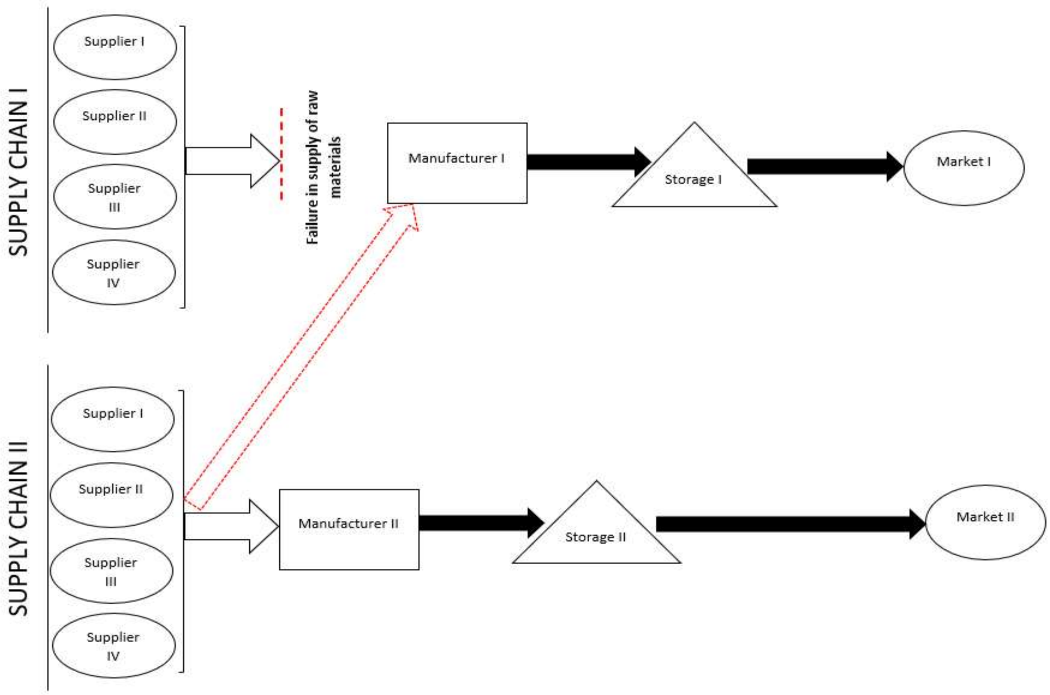

Figure 1.5. The Proposed Collaborative Supply Chain of Scenario III

This company manages the supply of three main different pipes: Reinforced Concrete Pipes (RCP), Glass Reinforced Epoxy Pipes (GREP), and Glass Reinforced Plastic Pipes (GRPP). In this case study, the manager applied a collaborative strategy to optimize global supply chain networks under failure risks including shortage of products and demand uncertainty. The role of the supplier was to be focused on the inventory level to overcome the expected shortage that may occur in industrial plants. Once shortages occur, the industrial plants with extra inventory collaborate with industrial plants with shortage of products. We presented a comparison of the results using commercial software and meta-heuristic algorithms.

1.5 Research Methods

This section explains the research methods as follows:

1. Formulation of the research problem. The research questions include gaps, which are to be resolved and addressed, as well as how to optimize supply chain networks under failure risks using meta-heuristic algorithms with deterministic and stochastic demand. A modified firefly and standard firefly algorithms for global optimization of supply chain networks also is addressed.
2. Literature review. An extensive review of literature was conducted to discover current trends in techniques and methods, as well as to note areas of improvement and to categorize findings based on their applicability to the meta-heuristic algorithms for large-sized problems related to supply chain networks.
3. Research gap. The gap can be drawn from the literature review, which includes improvements to the algorithm for recent applications that can be helpful in identifying shortcomings.
4. Solving the optimization problem related to supply chain networks under failure risks using the proposed algorithm.
5. Showing results for comparison, evaluation, and interpretation.

1.6 Contributions

This research significantly adds value to the existing literature as it incorporates most sought after and applicable concepts with an aim to create improvements. For instance, the proposed firefly algorithm introduces a modified exploration and exploitation mechanism characterized with adaptive randomness and absorption coefficients. Therefore, the modified firefly algorithm has been applied for global optimization of the supply chain network under risks of failure, as it employs the adaptation of randomness and absorption coefficients to be a function of time or iterations.

The meta-heuristic algorithms used in this research consider effective algorithms to solve large-sized problems related to supply chain networks under risks of failure to achieve near optimal solutions. Additionally, relational analysis indicates that advanced firefly algorithms can be used to allocate different information more effectively from the appealing ones.

Moreover, we optimized supply chain networks with deterministic and stochastic demand, formulated the model mathematically, and solved it using meta-heuristic algorithms.

Furthermore, many production companies continue to face financial difficulties. Another contribution of this study is to present an effective method for these companies to maximize profits and minimize costs associated with production, transportation, holding, and penalty costs. The problem presented here was initially developed as a multi-objective supply chain model. To achieve the best results, the firefly algorithm (FA) was applied to solve the model and obtain an optimum solution. To test the efficiency of the algorithm, a standard firefly algorithm was used, and the results of both algorithms were compared. The results revealed that when compared with a standard FA, a modified FA can help achieve maximum profits and minimizing costs associated with production, transportation, holding, and penalty costs.

1.7 Organization of Dissertation

In this section, we briefly introduce the organization of this dissertation. In Chapter one, we presented the background of meta-heuristic algorithms for global optimization of supply chain networks, motivation and objectives of this research, and problem statement. In Chapter two, we described the related works associated with the meta-heuristic algorithms for global optimization of supply chain networks. In Chapter three, we discussed the methodology of using meta-heuristic algorithm based on the modified firefly algorithm and standard firefly algorithm for integrated decisions in supply chain applications. In Chapter four, we discussed the solution of MFA for multi-objective supply networks under failure risks. In Chapter five, we showed the results of models for case study I and II. Additionally, we concluded the ideas of this research, future works, and limitations.

CHAPTER TWO

LITERATURE REVIEW

2.1 Literature Review

2.1.1 Overview of Optimization Techniques for Supply Chain Applications

The optimization techniques for product delivery have been used in many applications in many industries. For instance, Mukherjee et al. [37] reviewed the optimization techniques in the metal cutting process. The scholars in [37] 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 et al. [38] 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 in [38] applied the Pattern Search algorithm to get the optimal solutions for machining processes. The researchers in [39] discussed the optimization problems in statistics, focusing on quality control. They described several optimization techniques including simulated annealing and genetic algorithms. Yang et al. [40] proposed finding the solution of a multi-response optimization problem using a decision-making approach.

They 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 [41] presented the standard form of the general non-linear and constrained problems. The researcher in [41] suggested how to select the appropriate optimization technique to solve the optimization problems. Jayal et al. [42] presented optimization techniques for sustainable manufacturing processes. They found that using optimization techniques can determine the issues related to sustainable manufacturing.

In [43], researchers 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 in [43] showed that the formulation of MILP is able to use the power of MILP to create schedules of time optimization. The researchers in [44] used a nonlinear mixed-integer programming model to solve the production planning problems. Saxena et al. [45] 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. [46] solved large manufacturing system problems by using a two-phase optimization method including robust and efficient optimization techniques. The researchers in [46] proposed a meta-heuristic based on simulated annealing to present the tool for automated optimization of Discrete Event Dynamic Systems (DEDS). Nouira et al. [47] 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. Wilcox et al. [48] presented robotic scheduling for co-workers and mentors.

The authors used the Adaptive Preferences Algorithm (APA) to model the preferences of tasks for different workers. Gong et al. [49] addressed a synthesis framework to integrate the optimization of product distributions in the chemical manufacturing process. The authors in [49] formulated the model as a mixed-integer nonlinear program to optimize the design of processes. They developed a multi-objective mixed-integer non-linear programming model to determine incorporated shale gas processing.

2.1.2 Meta-Heuristic Algorithms for Global Optimization of Supply Chain Networks

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. [50] 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.

The problem in [50] was formulated as a bi-objective mixed-integer programming. The multi-objectives considered to be optimized are transportation costs and times. The authors in [50] found that a meta-heuristic algorithm is a preferable method to solve large instances associated with supply chain problems. Moreover, Bottani et al. [51] 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. [52] applied a meta-heuristic algorithm based on genetic algorithms to solve bioenergy supply chain problems. The authors in [52] found that meta-heuristic algorithms are considered an effective approach to solving large-scale problems associated with bioenergy supply chains. The objective considered in [52] 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. Moncayo-Martínez et al. [53] proposed a supply chain design consisting of multiple components. The supply chain design problem considered in [53] was to select the options that can minimize the total costs of the supply chain while maintaining the lead times during required due dates of deliveries. The authors used a meta-heuristic algorithm based on pareto ant colony optimization (PACO) to solve multi-objective optimization problems. The objective function was to minimize the total costs of the supply chain and lead times of deliveries simultaneously.

Cardona-Valdés et al. [54] proposed a two-stage production distribution network containing warehouses, plants of manufacturing, and distribution centers. The authors in [54] used a two-echelon distribution networks to combine the demand uncertainty of distribution centers within locations of warehouses and transportation allocation decisions. The multi-objective approach was to minimize the total costs and service times simultaneously. The authors used a meta-heuristic algorithm based on tabu-search to develop the procedure of solution for the distribution networks problems. Sahebjamnia et al. [55] developed a sustainable tire closed loop supply chain network problem as a multi-objective mixed-integer linear program. The authors in [55] proposed a model to optimize the total cost and transportation of tires after processing. A multi-stage tire closed loop supply chain considered in [55] containing supplier, customer, recyclers, distributer, and manufacturer. The authors used four different developed hybrid meta-heuristic algorithms based on H-RS, H-WT, H-RW, and H-WG. The authors developed these new hybrid meta-heuristic algorithms and found them a powerful and effective algorithm to solve large-scale network issues associated with a tire closed loop supply chain problem. H-RS stands for hybrid of red deer algorithm & simulated annealing. This algorithm is developed to reduce the computational time. H-WG stands for hybrid of water wave optimization & genetic algorithm. This algorithm is developed to improve the characteristics of exploration mechanisms. H-WT stands for water wave optimization & tabu-search. This algorithm is developed to change the operators of search to get the possible zones. H-RW stands for red deer algorithm & water wave optimization. This algorithm is developed to minimize the computational time of red deer algorithm.

Memari et al. [56] proposed a new and modified firefly algorithm for optimal supply chain networks. The supply chain network problem considered in [56] consisted of distribution centers, retailers, and products delivered from distribution centers. The results revealed that the modified firefly algorithm reduced the computational time as compared with other meta-heuristic algorithms. The objective function formulated in [56] was to minimize the total cost of a two-echelon supply chain networks associated with the cost of shipping, holding costs, and penalty charges for backorders. Atabaki et al. [57] also used a meta-heuristic algorithm based on the firefly algorithm to solve large-sized problems associated with a closed-loop supply chain with price-sensitive demands and forward and reverse flows. A multi-stage closed-loop supply chain consisting of the supplier, redistributor, center of disassembly, center of disposal, distribution center, and hybrid distributor and redistributor, was developed. The problem was formulated as a mixed-integer linear program to create decisions of allocation, location, and price. The objective function considered in [57] was to maximize the profits associated with capacity and the constraints on the number of facilities opened. Shu et al. [58] analyzed the total cost of disruption with three different scenarios, including disruption in distribution and manufacturing centers, disruption from manufacturing to distribution center, and disruption from distribution center to customer zones. The authors in [58] used a meta-heuristic algorithm based on the firefly algorithm to solve the model of supply chain disruption. The mathematical model proposed in [58] was formulated as a mixed-integer linear planning. The objective of this model was to address the complexity of robustness and efficiency simultaneously.

Robustness is represented by the cost of disruption whereas the efficiency is indicated by the cost of operation. The results revealed that the increase of the cost of operation would be lower than the decrease of the cost of disruption by reducing efficiency for operating cost and improving robustness in supply chain. Khalifehzadeh et al. [59] proposed a multi-stage supply chain network under a stochastic environment, particularly for production distribution network (PDN). This proposed model contained multiple suppliers, a potential depot, retailer, producer, outland customers, and inland customers. The demand of customers and lead time for delivery considered in [59] are known with a normal distribution under stochastic. The problem was formulated as mixed-integer linear programming. Since some models cannot be solved using exact optimization techniques, the authors in [59] used two meta-heuristic algorithms based on the firefly algorithm and genetic algorithm to solve the model and get the near optimal solution. Table 2.1 summarizes some existing literature of using meta-heuristic algorithms to solve complex supply chain network problems.

2.2 Conclusion

The applications of meta-heuristic algorithms based on firefly algorithms for global optimization of supply chain networks which considered large-sized problems were reviewed, especially for solving complex optimization problems. We also reviewed the exact optimization techniques used in different supply chain applications based on small-sized problems. of failure. Moreover, the convergence accuracy and speed in the firefly algorithm are required to be improved in solving constrained and multi-objective functions.

These exact optimization techniques are not able to solve the large-sized problems related to supply chain networks. Thus, meta-heuristic algorithms have the capability to solve large-sized problems related to supply chain networks under risks.

Table 2.1. Overview of Existing Literature Using Meta-Heuristic Algorithm in Supply Chain Applications

References	Application	Objective	Method
Olivares-Benitez et al. [50]	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. [51]	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. [52]	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 et al. [53]	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.
Cardona-Valdés et al. [54]	They proposed a two-stage production distribution network containing warehouses, plants of manufacturing, and distribution centers.	The multi-objective approach was to minimize the total costs and service time simultaneously.	The authors used a meta-heuristic algorithm based on tabu-search to develop the procedure of solution for the distribution networks problem.
Sahebjamnia et al. [55]	They developed a sustainable tire closed loop supply chain network problem as a multi-objective mixed-integer linear program. A multi-stage tire closed loop supply chain include supplier, customer, recyclers, distributer, and manufacturer.	The authors proposed a model to optimize the total cost and transportation of tires after processing.	The authors used four different developed hybrid meta-heuristic algorithms based on hybrid of red deer algorithm & simulated annealing.
Memari et al. [56]	Two-echelon supply chain networks. This system includes distribution centers, retailers, and products delivered from distribution centers.	The objective function is to minimize the total cost of a two-echelon supply chain networks associated with cost of shipping, holding costs, and penalty charges for backorders.	They proposed a new modified firefly algorithm for optimal supply chain networks.

Table 2.1 Overview of Existing Literature Using Meta-Heuristic Algorithm in Supply Chain Applications - CONTINUED

References	Application	Objective	Method
Atabaki et al. [57]	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.
Shu et al. [58]	Supply chain System with disruption in distribution and manufacturing centers, disruption from manufacturing to distribution center, and from distribution center to customer zones.	The objective of this model was to address the complexity of robustness and efficiency simultaneously.	They used a meta-heuristic algorithm based on firefly algorithm to solve the model of supply chain disruption.
Khalifehzadeh et al. [59]	They proposed a multi-stage supply chain networks under stochastic environment, particularly for production distribution network (PDN). This proposed model containing multi-supplier, potential depot, retailer, producer, outland customers, and inland customers.	The objective was to maximize the total profit and minimize the lead time of supply chain network.	They used two meta-heuristic algorithms based on firefly algorithm and genetic algorithm to solve the model and get the near optimal solution.
Our Model	We proposed two strategies named collaborative and non-collaborative SC for a multi-objective supply chain networks for delivering multi-products under stochastic and deterministic demands.	The objective was to minimize the total costs of supply chain networks and compared the results using different algorithms for collaborative and non-collaborative strategies for supply chain networks.	We used five different meta-heuristic algorithms based on firefly algorithm, SIMPLEX, POWELL, BFGS, NSGA-II algorithms.

CHAPTER THREE

METHODOLOGY: A MODIFIED FIREFLY ALGORITHM AS AN OPTIMIZATION TOOL FOR GLOBAL SUPPLY CHAIN NETWORKS UNDER RISKS OF FAILURE

3.1 Abstract

In this section, we discuss the methodology of this research including mathematical models of each scenario proposed. The model was developed as multi-stage supply chain networks (MSSCNs) to determine the decisions that help the managers to minimize the total expected costs and prevent any related penalty costs associated with disruptions and delays in the production operations or during shipping. We ran the model using MATLAB software to achieve the optimal solutions of the model, using meta-heuristic algorithms based on firefly algorithm and particle swarm optimization to determine the optimal solution of inventory control.

The objective function of the model was to minimize the total expected transportation cost and maximize the profit of the supply chain that face two risk factors including failure in supply and unmet demand based on three different scenarios. A collaboration strategy between supply chains can help the managers to overcome any penalty costs associated with delivery delay and unmet demand. Each supplier provides raw materials for production and transports all raw materials to the manufacturer. Then, the final product is sent to storage and will be delivered to the final customer. However, during the delivery of products, the risk factors based on failure in supply are determined.

Thus, other supply chains will collaborate to continue delivering the same products to the customer to prevent any penalty costs associated with delivery delay and transportation costs to meet customers' satisfaction.

3.2 A Modified Firefly Algorithm (MFA) for Global Optimization Problems

The modified firefly algorithm is introduced to solve supply network optimization problems. The need for modifying the algorithm is that the standard firefly algorithm has limitations. We implemented the standard firefly algorithm to compare it with the new modified version. The modified firefly algorithm is employed and used for validation and verification. The firefly algorithm is upgraded and can be sketched out in the pseudo-code, as shown in Figure 1.1. The mathematical articulation used to improve the movement of the firefly is done in [60], see Equation (3.1):

$$x_{i+1} = x_j + \beta(t)(x_i - x_j) + \alpha(t)\varepsilon_i \tag{3.1}$$

Where $\alpha(t)$ is the randomness coefficient at time t, ε_i is the random number, and $\beta(t)$ is the attractiveness coefficient at time t. X_i and X_j are the initial random population with less brightness (i) and more brightness (j). Sababha et al. [60] considered that an exploitation technique is represented by the first two terms to demonstrate a superior answer for the remainder of the operators while exploration procedures are depicted by the last term for inquiry space exploration in equation (3.2). To enhance the precision of the algorithm of the extraordinary worth, at that point, their movements should be focused on.

Sababha et al. [60] showed and expressed the randomness coefficient (α) in equation (3.2) as follows:

$$\alpha(Itr_i) = \exp\left(1 - \left(\frac{Itr_{max}}{Itr_{max} - Itr_i}\right)^c\right) \tag{3.2}$$

C is considered as the whole or integer number to decide the speed of rotting of the irregularity, while $\boldsymbol{Itr_{max}}$ is considered as the maximum iteration number, and $\boldsymbol{Itr_i}$ is considered as the current number of iterations. In addition, parameter ϒ is a crucial viewpoint in describing the distinctions of the speed of the assembly and the attractiveness. The result is that, when a steady (c) is connected in taking care of the issues of optimization, the firefly algorithm execution will be detectably obliged, as done in a customary firefly algorithm. Sababha et al. [60] showed and expressed ϒ equation as follows:

$$\Upsilon(Itr_i) = 1 - \exp\left(1 - \left(\frac{Itr_{max}}{Itr_{max} - Itr_i}\right)^c\right) \tag{3.3}$$

Because of the modification, the proposed and modified firefly algorithm will not get caught in the neighborhood extraordinary, and it will heighten the combination speed improving the arrangement at ideal a superior since there will be a balance among nearby and worldwide hunt.

In the inquiry procedure, two refreshing formulas are clarified, picked arbitrarily, and are introduced in equation (3.4) as done in [60]:

$$x_{i+1} = \begin{cases} \beta(i)x_i + x_j\big(1 - \beta(i)\big) + \alpha(i)\varepsilon_i & rand > 0.5 \\ \dfrac{NG - i}{NG}(1 - \delta)x_i + \delta x_{best} & Elsewhere \end{cases} \tag{3.4}$$

Parameter δ is considered as the gray coefficient and, NG is considered as the generation number. The fireflies can secure increasingly valuable data from others and change the bearings of light adaptively. At the last point, the progression estimation is intended to cause the algorithm to have a balance between exploitation and exploration procedures, and to improve the algorithm on the off chance that the pursuit conditions are in modern and plentiful space and high terms. Figure 3.1 shows the flow chart of the modified firefly algorithm.

3.3 Deterministic Approach

The deterministic solution is one of approaches employed in Chapter Three of this research. We formulated the problem mathematically with deterministic demand; hence, all parameters in decision variables and objective functions are known and precise. Additionally, we ran the model as a minimization problem, so the objective function of the total cost is minimized. Outcomes and findings of the deterministic approach were defined, which considered not having fixed known inputs with random variations and uncertainty.

3.4 Stochastic Approach

Another method of the optimization techniques is a stochastic algorithm. The stochastic approach is a powerful optimization technique that has been used in different supply chain network applications based on demand. In this research, we applied meta-heuristic algorithms to solve the optimization problem based on large-sized problems related to the supply chain network under stochastic demand. We also ran the model as a minimization problem, so the objective function is to minimize the expected total costs of the supply chain network, as discussed further in next chapters.

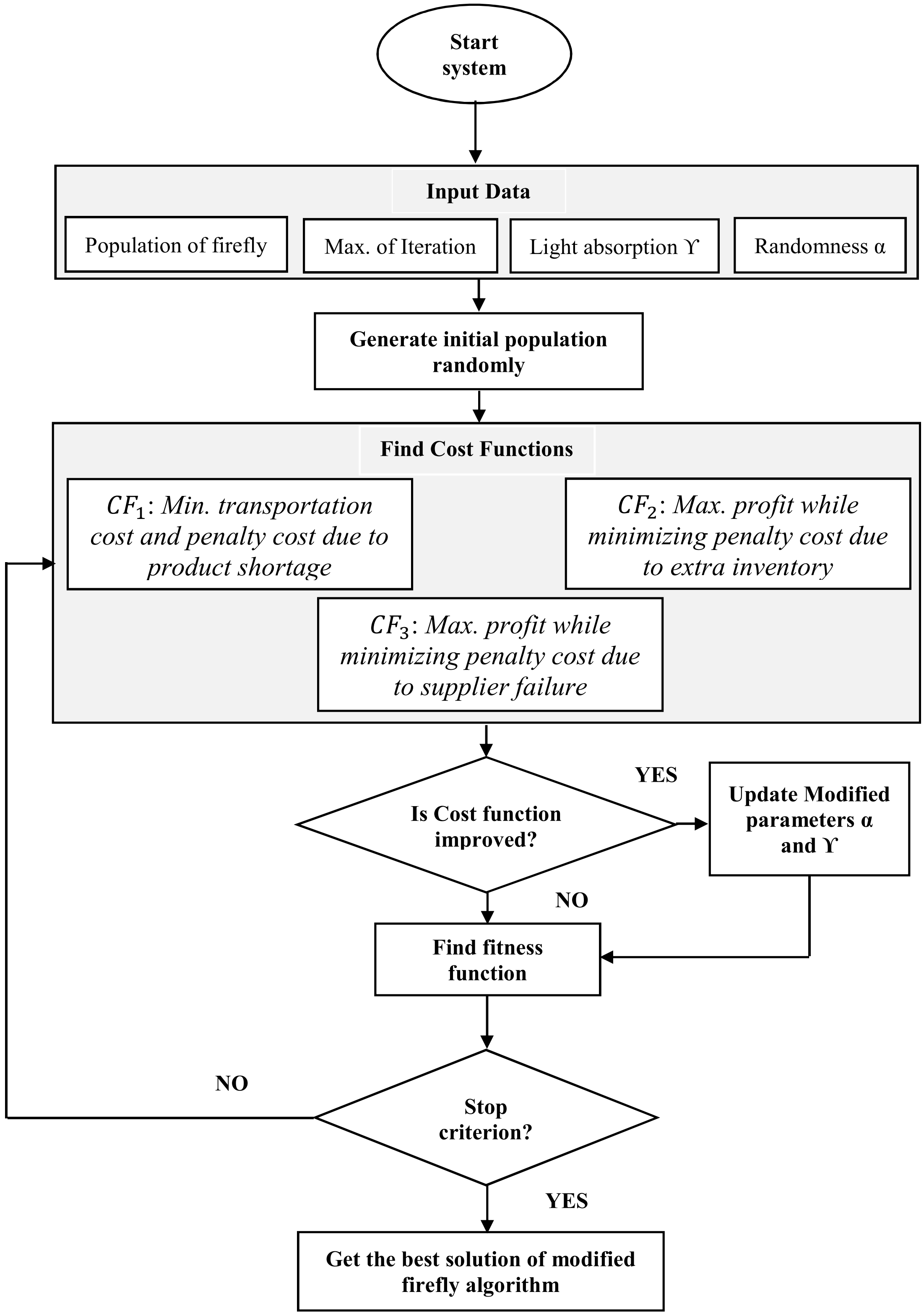

Figure 3.1. The Flow Chart of the Modified Firefly Algorithm

3.5 Notations

$T_{s,m}$ Total transportation cost of raw materials from suppliers s to manufacturer m of supply chain with failure in supply.

$T_{m,i}$ Total transportation cost of products from manufacturer m to storage i of supply chain with failure in supply.

$T_{i,i'}$ Total transportation cost of products from storage i of supply chain with failure in supply to storage i' of supply chain with no failure in supply.

$T_{i',c}$ Total transportation cost of products from storage i' of supply chain with no failure in supply to the final customer of supply chain with failure in supply.

U_r Total units of raw materials.

$D_{s,m}$ The distance from suppliers s to manufacturer m.

$DC_{s,m}$ Cost of delivery from suppliers s to manufacturer m.

U_p Total units of product.

$D_{m,i}$ The distance from manufacturer m to storage i of supply chain with failure in supply.

$DC_{m,i}$ Cost of delivery from manufacturer m to storage i of supply chain with failure in supply.

$D_{i,i'}$ The distance from storage of supply chain with failure in supply to storage of supply chain with no supply failure.

$DC_{i,i'}$ Cost of delivery from storage of supply chain with failure in supply to supply chain with no failure in supply.

$D_{i',c}$ The distance from storage i' of supply chain with no failure in supply to the customer c of supply chain with failure in supply.

$DC_{i',c}$ Cost of delivery from storage i' of supply chain with no failure in supply to the customer c of supply chain with failure in supply.

$P_{s,i}$ The selling price of supply chain i.

$P_{c,i}$ The cost of product of supply chain i.

X_{sc_i} The total units of product for supply chain i.

$Q_{i,t}$ Quantity of products in supply chain i at time t.

$C_{p,i}$ Cost of production at supply chain i.

$PU_{i,t}$ Production of units at supply chain i at time t.

CI_i Carrying cost at supply chain i.

$I_{i,t}$ Inventory of units at supply chain i at time t.

SP_i Shortage of products Penalty cost at supply chain i.

$PU_{i,t}$ Units of products shortage at supply chain i at time t.

HE_i Holding cost for extra inventory at supply chain i.

SF_i Supplier failure penalty cost at supply chain i.

UR_i Units of raw material failure to supply at supply chain i.

3.6 Mathematical Modeling

3.6.1 Mathematical Modeling of Scenario I

We calculated the total expected cost of transportations between stages for each supply chain. Supply chain with no failure in supply will communicate with supply chain with failure in supply due to shortage of products to deliver its product to the final customer. This scenario can prevent any penalty costs associated with delivery delay. The total transportation cost from suppliers to the final customer of scenario I is determined in Equation (3.5). The main objective is to minimize the total expected transportation costs and penalty costs associated with shortage of products.

$$Min \quad T_C = T_{s,m} + T_{m,i} + T_{i,i'} + T_{i',c} + SP_i * PU_{i,t} \tag{3.5}$$

The transportation cost of raw materials $T_{s,m}$ is determined by multiplying the total units of raw materials from suppliers to manufacturer U_r with the summation of cost of delivery and total distance from suppliers to manufacturer of supply chain with failure in supply. Equation (3.6) is defined as the total transportation cost from suppliers to manufacturer of supply chain with failure in supply as follows:

$$T_{s,m} = U_r \sum_{s}^{m} D_{s,m} \, DC_{s,m} \tag{3.6}$$

The transportation cost of products $T_{m,i}$ is determined by multiplying the total units of products from manufacturer to storage U_p with the summation of cost of delivery and total distance from manufacturer to storage of supply chain with failure in supply. Equation (3.7) is defined as the total transportation cost from manufacturer to storage of supply chain with failure in supply as follows:

$$T_{m,i} = U_p \sum_{m}^{i} D_{m,i} \, DC_{m,i} \tag{3.7}$$

The transportation cost of products $T_{i,i'}$ is determined by multiplying the total units of products from storage of supply chain that face failure in supply to storage of supply chain with no failure in supply multiplying with the summation of cost of delivery and total distance from storage of supply chain with failure in supply to storage of supply chain with no failure in supply. Equation (3.8) is defined as the total transportation cost from storage of supply chain with failure in supply to storage of supply chain with no failure in supply as follows:

$$T_{i,i'} = U_p \sum_{i}^{i'} D_{i,i'} \, DC_{i,i'} \tag{3.8}$$

The transportation cost of products $T_{i',c}$ is determined by multiplying the total units of products from storage of supply chain with no failure in supply to the final customer of supply chain with failure in supply multiplying with the summation of cost of delivery and total distance from storage of supply chain with no failure in supply to the customer of supply chain with failure in supply.

Equation (3.9) is defined as the total transportation cost from storage of supply chain with no failure in supply to the customer of supply chain with failure in supply as follows:

$$T_{i',c} = U_p \sum_{i'}^{c} D_{i',c} \, DC_{i',c} \tag{3.9}$$

3.6.2 Mathematical Modeling of Scenario II

The main objective of this scenario is to maximize the profit of the supply chain that faces extra inventory. This supply chain with surplus products will collaborate with supply chains with shortage of products to prevent any undesirable costs associated with extra inventory. There are 13 supply chains delivering their products. Once some supply chains face unmet demand, the other supply chains with no unmet demand will collaborate to deliver products. Equation (3.10) is the objective function which maximizes the profit of supply chain with extra inventory as follows:

$$Max \sum_{Supply\ Chains} \left(P_{s,i} - P_{c,i}\right) X_{sc_i} - HE_i \tag{3.10}$$

3.6.3 Mathematical Modeling of Scenario III

This model of this scenario is developed as a multi-objective function, which maximizes the profit and minimizes the total costs associated with production, holding, and penalty due to supplier failure of raw materials.

Once a supply chain faces failure in supply of raw materials, other supply chains with no failure in supply will collaborate to prevent any costs associated with supplier failure. Equation (3.11) is defined the objective function of scenario III as follows:

$$P_{c,i} * Q_{i,t} - C_{p,i} * PU_{i,t} - CI_i * I_{i,t} - UR_i * SF_{,i,t} \tag{3.11}$$

Equation (3.12) determines that raw materials supplied by suppliers is considered the total production, as follows:

$$PU_{i,t} = \sum_{all\ suppliers} \left[SF_{,i,t} * Q_{r,i} - Q_{r,i}\right] \tag{3.12}$$

Where $Q_{r,i}$ indicates the quantity of raw materials in supply chain i.

Equation (3.13) 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.

$$D_{r,i} + I_{i,t} = PU_{i,t} + SF_{,i,t} + I_{i,t-1} \tag{3.13}$$

3.7 Objectives

The main research objective is to design a new collaborative strategy to optimize Multi-Stage Supply Chain Networks (MSSCNs) once facing risks of failure during delivery operations using a meta-heuristic algorithm based on modified firefly algorithms.

The methodology is to design a multi-objective supply chain networks under two risks of factors, including failure in supply and unmet demand, based on three different scenarios as follows:

- ✓ The objective of scenario I was to minimize the total expected transportation costs between stages for each supply chain and penalty costs associated with shortage of products. Supply chain with no failure in supply will communicate with supply chain with failure in supply due to shortage of products to deliver its product to the final customer.
- ✓ The objective of scenario II was to maximize the profit of the supply chain that faces extra inventory while minimizing the holding cost. This supply chain with surplus products will collaborate with supply chains with shortage of products to prevent any undesirable costs associated with extra inventory.
- ✓ The objective of scenario III was to develop a multi-objective function, which maximizes the profit and minimizes the total costs associated with production, holding, and penalty due to supplier failure of raw materials.

CHAPTER FOUR

RESULTS

4.1 Results and Discussion

This research presents an effective method for these companies to maximize profits and minimize penalty costs. To achieve the best results, the Firefly Algorithm (FA) was applied to solve the model and obtain an optimum solution. In order to test the efficiency of the algorithm, four optimization algorithms were used, and the results of algorithms were compared. The results revealed that the Modified Firefly Algorithm (MFA), when compared with other four optimization algorithms, can help achieve maximum profits and minimizing penalty costs. Response surface methodology was applied to tune the parameters' algorithms and trained to test the validity of the model.

A case study for a pipe manufacturing company was conducted to implement the model. The main objective of the company was to achieve maximum profits and minimum penalty costs by using appropriate limited resources.

Sensitivity analysis is a powerful technique for testing the efficiency of an optimization algorithm. This technique helped us to find more interesting results by altering the parameters of optimization algorithms in order to improve the optimal solution and determine the effect of the solution. This study describes how this technique was applied to reach more interesting optimal solutions for the presented model. In this section, we demonstrate the results of models based on case studies I and II.

The optimization problems include Simplex Algorithm (SA), Broyden-Fletcher-Goldfarb-Shanno Algorithm (BFGS), POWELL Algorithm, and Non-dominated Sorting Genetic Algorithm (NSGA).

4.1.1 The Results of the Model for Case Study I

The integrated decision scenarios are modeled mathematically using the proposed supply chain network considered in this research, as shown in Figure 1.2.

We ran the proposed model using MATLAB software to get the optimal solutions for each scenario. The results revealed that the manager should focus on the available number of finished products from other supply chains that have surplus products stored at a warehouse and apply a corporation strategy with them when facing shortage of products at storage. The results showed that a collaborative strategy was able to minimize the total expected costs of the proposed supply chain networks under risk of failure and prevent any related penalty costs due to disruptions and delays. The optimal solution of objective function for each decision scenario I, II, and III is shown in Figures 4.1, 4.3, and 4.5 respectively.

The optimal solution obtained by Firefly Algorithms for scenario I is presented in Figure 4.1. The objective of scenario I is to minimize the total expected cost of transportation using a meta-heuristic algorithm based on firefly algorithm. This scenario is applied to a collaborative strategy that helps the manager to minimize total transportation and penalty costs when there is a possibility of shortage of products. Figure 4.1 shows that the total expected cost of scenario I was minimized.

The results reveal that optimal solution of scenario I was obtained by using a modified firefly algorithm is the best as compared with the standard algorithm.

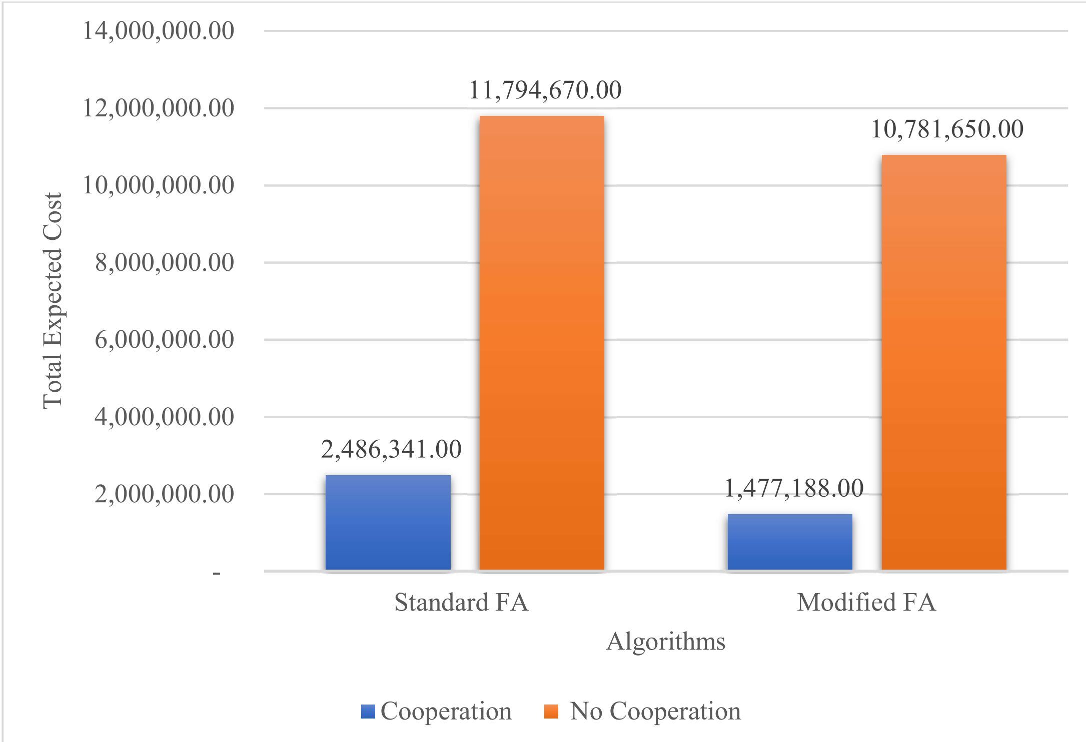

Figure 4.1. The Optimal Solution of Scenario I

Furthermore, results show that the optimal number of units of product needed from other supply chains with surplus products is shown in Figure 4.2.

The optimal number of units that should be provided by other supply chains with surplus products is determined in Figure 4.2. This figure also shows that supply chains with a shortage of products can borrow products from only three supply chains with surplus products. A collaborative strategy is able to help managers to minimize the penalty costs associated with shortage of products by borrowing 10,960 units of product from supply chains with surplus products.

The main objective of scenario II is to maximize profit of supply chains with surplus products while minimizing the holding cost for extra inventory.

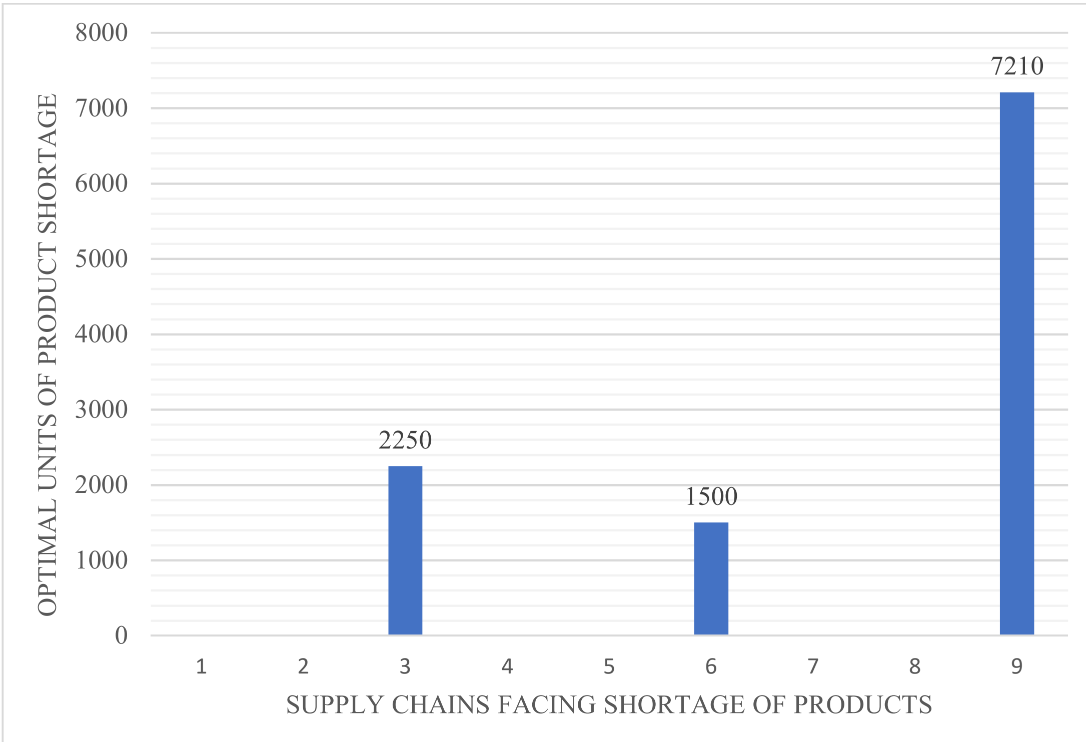

Figure 4.2. The Optimal Units of Product Shortage

This scenario applies a collaborative approach to overcome holding costs and to minimize the penalty cost of other supply chains due to shortage of product. The optimal solution of scenario II is determined in Figure 4.3.

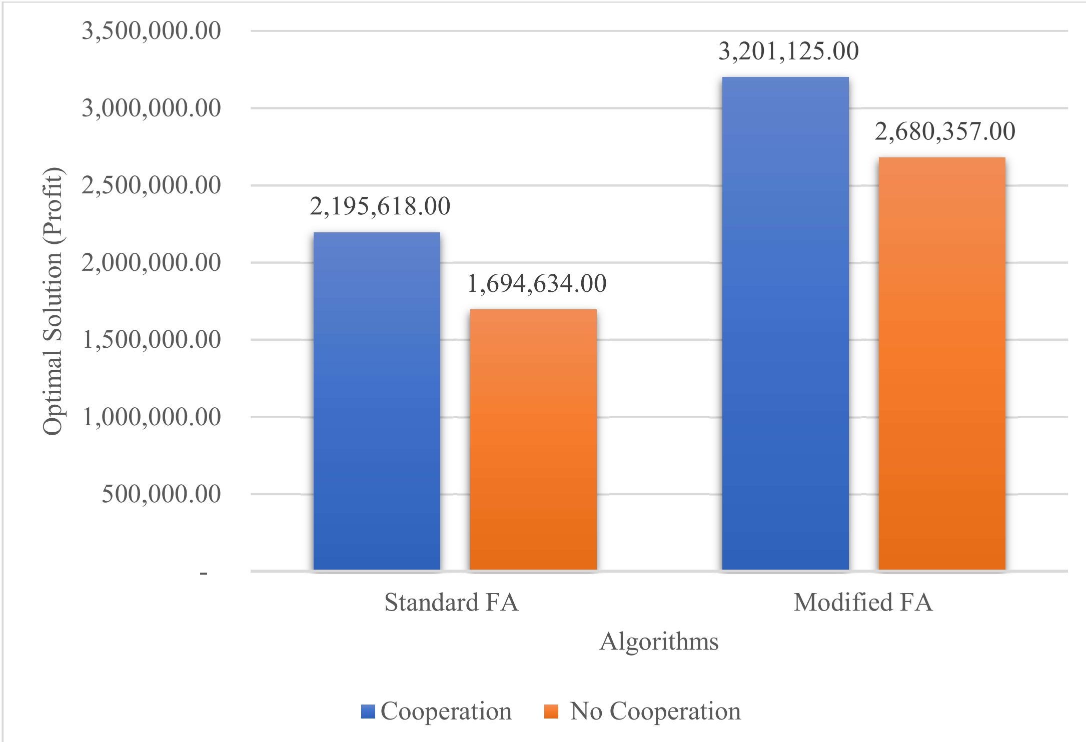

Figure 4.3. The Optimal Solution of Scenario II

Figure 4.3 shows that the optimal solution obtained by a modified firefly algorithm was better than the standard one. It represents that the profit obtained by MFA is higher than the profit obtained by the standard algorithm.

The optimal number of units that should be delivered to the supply chain with shortage of products is determined in Figure 4.4. A collaborative strategy is able to help managers to minimize the holding cost for extra inventory by sending 11,690 units of product to supply chains with a shortage of 10,960 products, as shown in Figure 4.4.

The results show that the optimal number of units that can be delivered to the supply chain with shortage of products is shown in Figure 4.4.

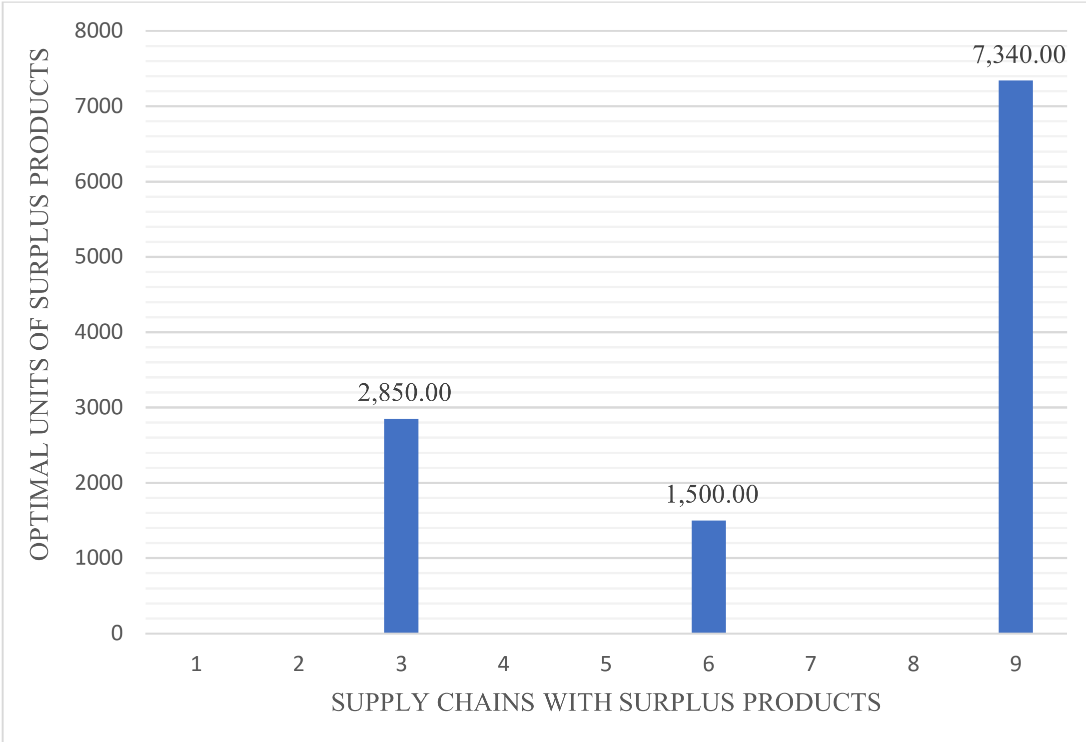

Figure 4.4. The Optimal Units of Surplus Products

The main goal of scenario III is to maximize the profit while minimizing the total penalty cost associated with failure delivery of raw materials from supplier to manufacturer. A collaborative approach was applied to minimize the total penalty cost due to supplier failure of raw materials with other supply chains with surplus raw materials. Figure 4.5 shows the optimal solution obtained by meta-heuristic algorithms based on firefly algorithms.

The optimal solution of scenario III using a modified firefly algorithm is the best as compared with the standard algorithm. It indicates that the profit obtained by MFA is higher than the profit obtained by a standard algorithm.

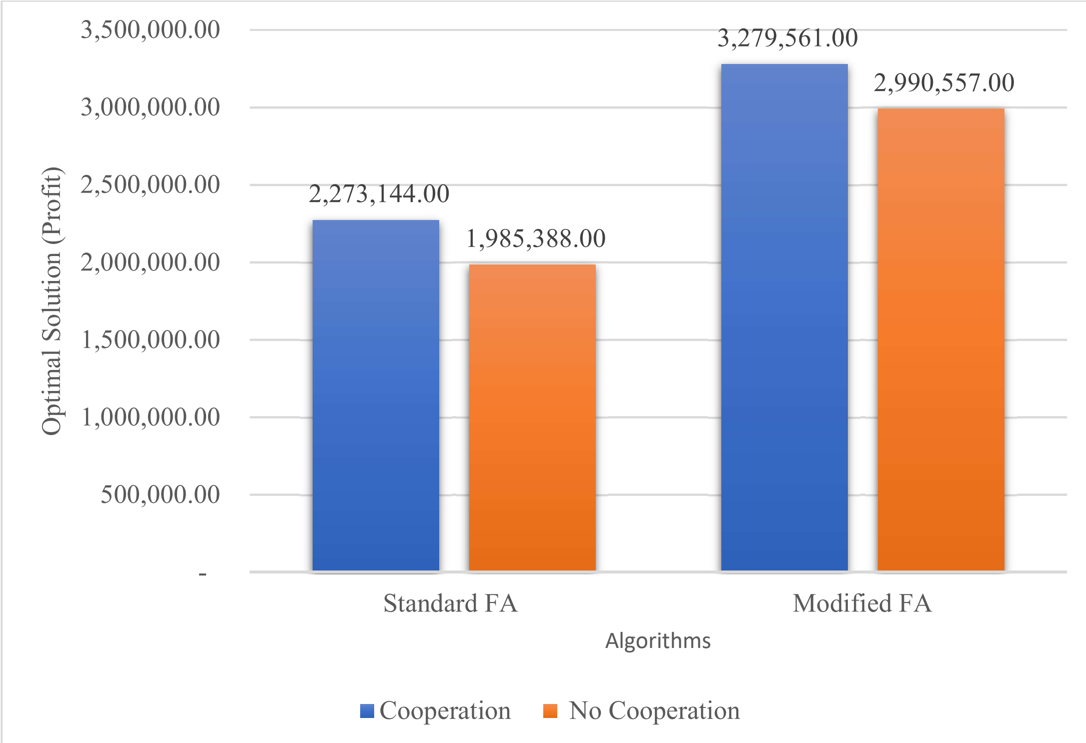

Figure 4.5. The Optimal Solution of Scenario III

Moreover, results show that the optimal number of units of raw materials needed from other suppliers with surplus raw materials is shown in Figure 4.6.

The optimal number of units of raw materials that should be provided by other supply chains with surplus raw materials is determined in Figure 4.6. This figure also shows that supply chains with shortage of raw materials can borrow some from only four suppliers with surplus raw materials. A collaborative strategy is able to help managers to minimize the penalty costs associated with supplier failure by borrowing 11,900 units of product from suppliers with surplus raw materials.

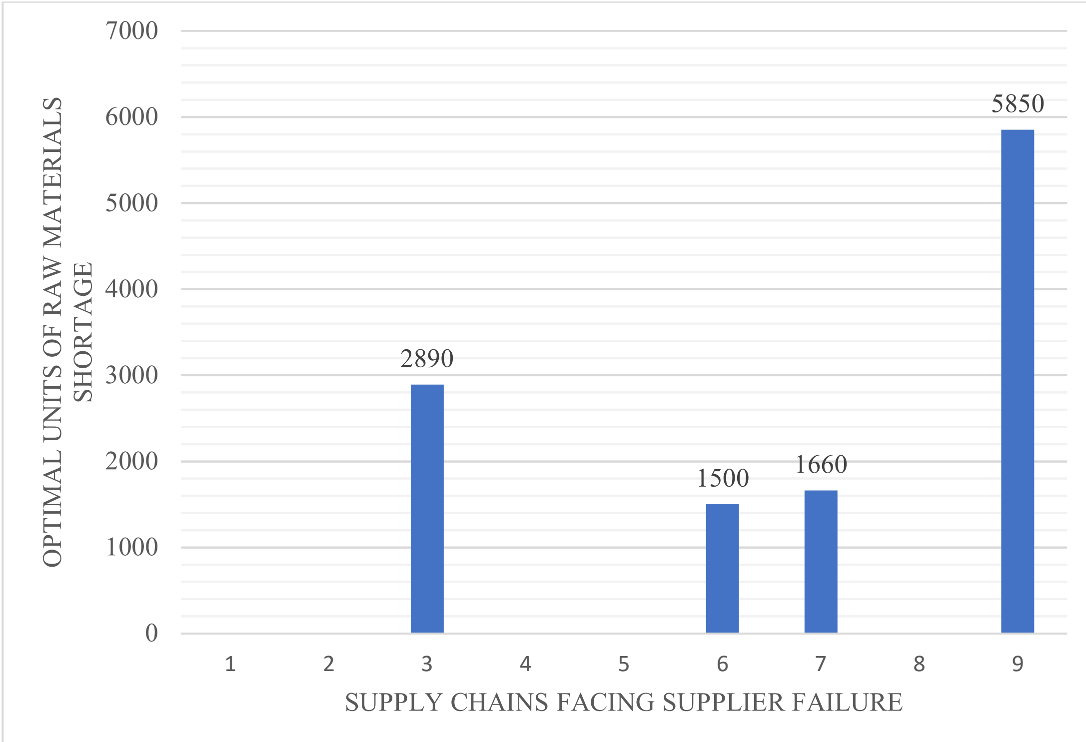

Figure 4.6. The Optimal Units of Raw Materials

Furthermore, the optimal number of units of raw materials that should be delivered to suppliers with shortage of raw materials is determined in Figure 4.7.

A collaborative strategy is able to help managers to minimize the penalty cost associated with supplier failure, sending 13,220 units of raw materials to suppliers with a shortage of 11,900 units of raw materials, as shown in Figure 4.7. The results show that the optimal number of units that can be delivered to suppliers with failure delivery of raw materials is shown in Figure 4.7.

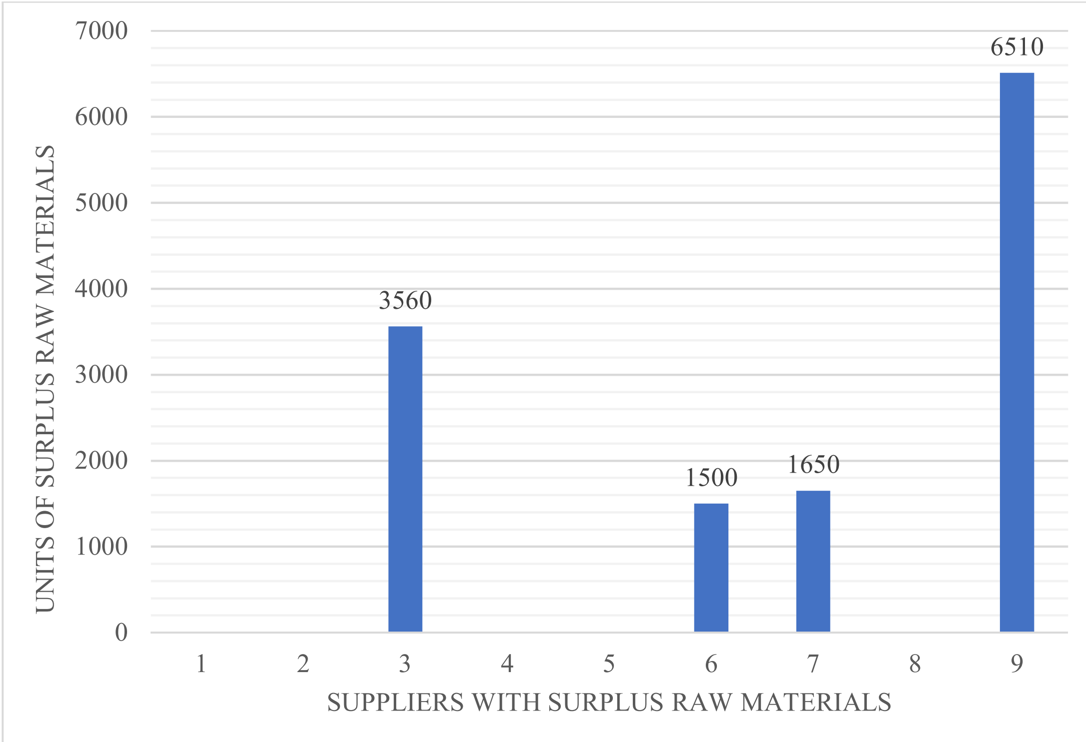

Figure 4.7. The Optimal Number of Units of Surplus Raw Materials

To track the optimal solutions of inventory operations, a meta-heuristic algorithm based on the Firefly Algorithm is used. We ran the model using MATLAB to get the optimal solutions based on 500 iterations. Results obtained by the firefly algorithm will help the managers track the limited number of orders and the limited stock for products and raw materials, as shown in Figure 4.8 and Figure 4.9.

The effect of randomness coefficient (α) on the optimal solution of each scenario is presented in Figures 4.10, 4.11, and 4.12. The objective of scenario I was to minimize the total transportation cost of the supply chain under the risk of shortage of product and minimize the penalty cost associated with product shortage.

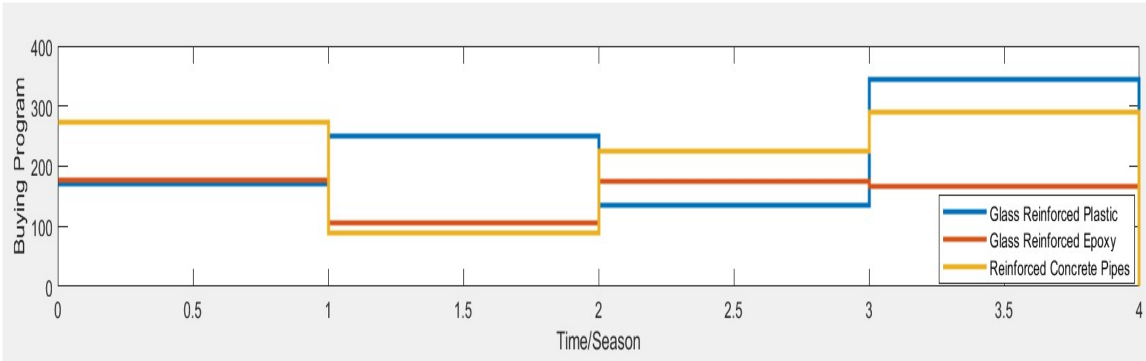

Figure 4.8. Buying Program per Four Seasons (Winter, Spring, Summer, and Fall)

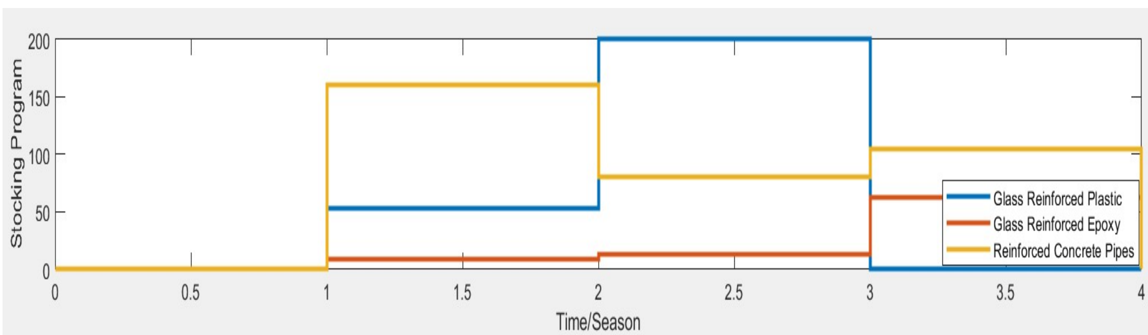

Figure 4.9. Stocking Program per Four Seasons (Winter, Spring, Summer, and Fall)

The results showed that the randomness coefficient for c=3 achieved the best solution of scenario I, which indicates the lowest cost as compared with other levels, as shown in Figure 4.10. The objective of scenario II is to maximize the profit while minimizing the holding cost for extra inventory of the supply chain with surplus products. The result showed that the randomness coefficient for c=5 achieved the best solution of scenario II, which indicates the highest profit as compared with other levels, as shown in Figure 4.11.

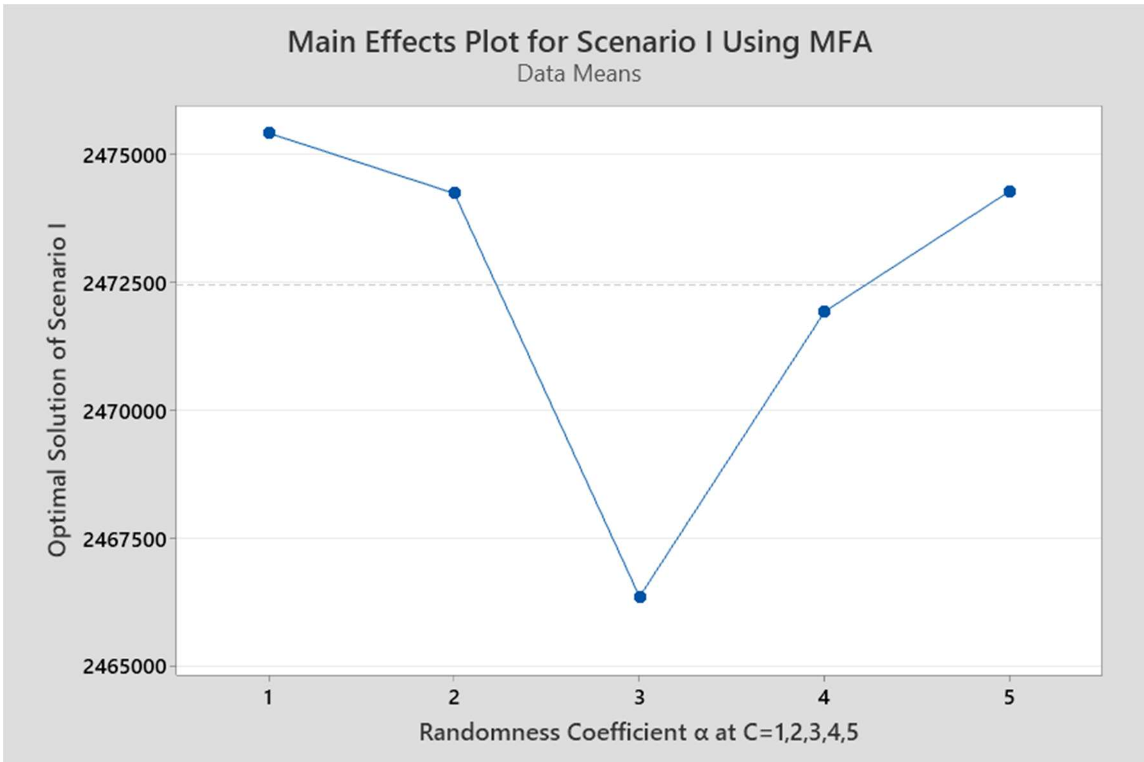

Figure 4.10. The Effect of Randomness Coefficient α on Scenario I Using MFA

The objective of scenario III was to maximize the profit while minimizing the penalty cost associated with shortage of raw materials of supply chain with supplier failure. The result showed that the randomness coefficient for c=4 achieved the best solution of scenario II, which indicated the highest profit as compared with other levels, as shown in Figure 4.12.

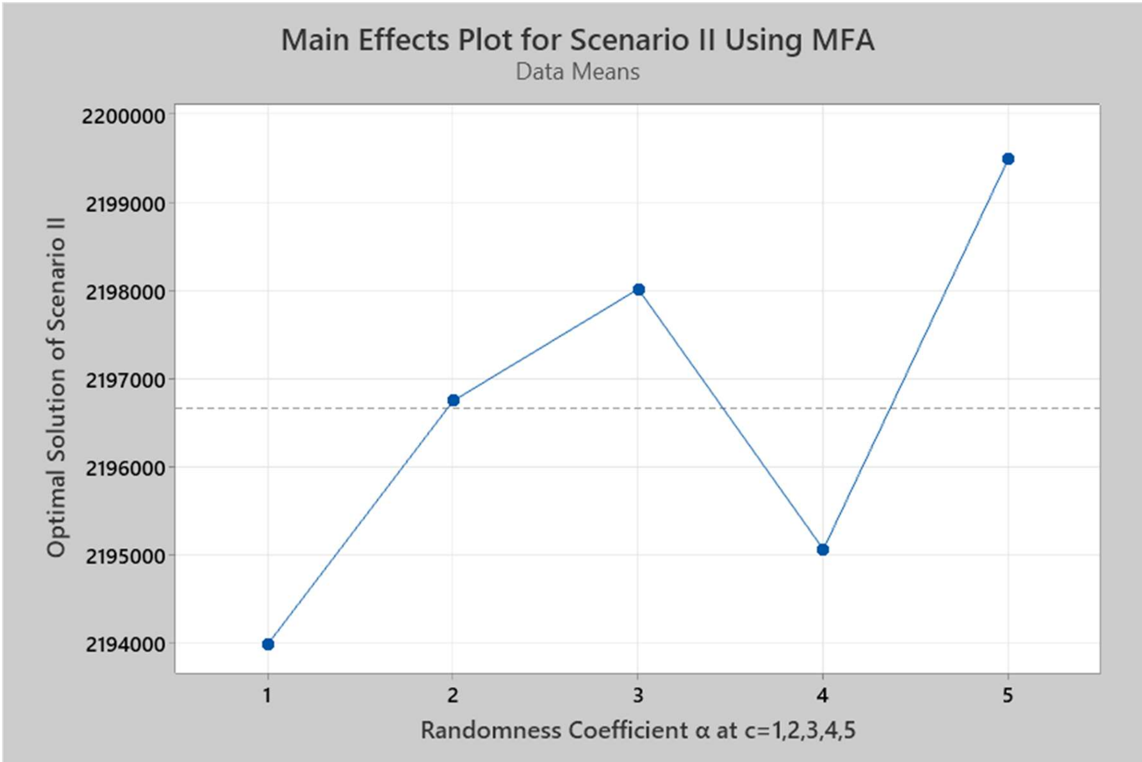

Figure 4.11. The Effect of Randomness Coefficient α on Scenario II Using MFA

4.1.2 <u>The Results of the Model for Case Study II</u>

This case study manages 13 multi-stages supply chain networks. Each supply chain would like to maximize its profit. The supply chain network includes four different stages including, supplier, manufacturer, storage, and market. Each supplier delivers units of raw materials to manufacturer. The raw materials are used for production at a manufacturer. Then, the finished products are sent to storage. Once orders received, the products will be delivered to the market.

4.1.2.1 The Optimal Solution Using SIMPLEX Algorithm

Simplex Algorithm (SA) is one of the optimization algorithms used to solve the optimization problems related to supply chain applications.

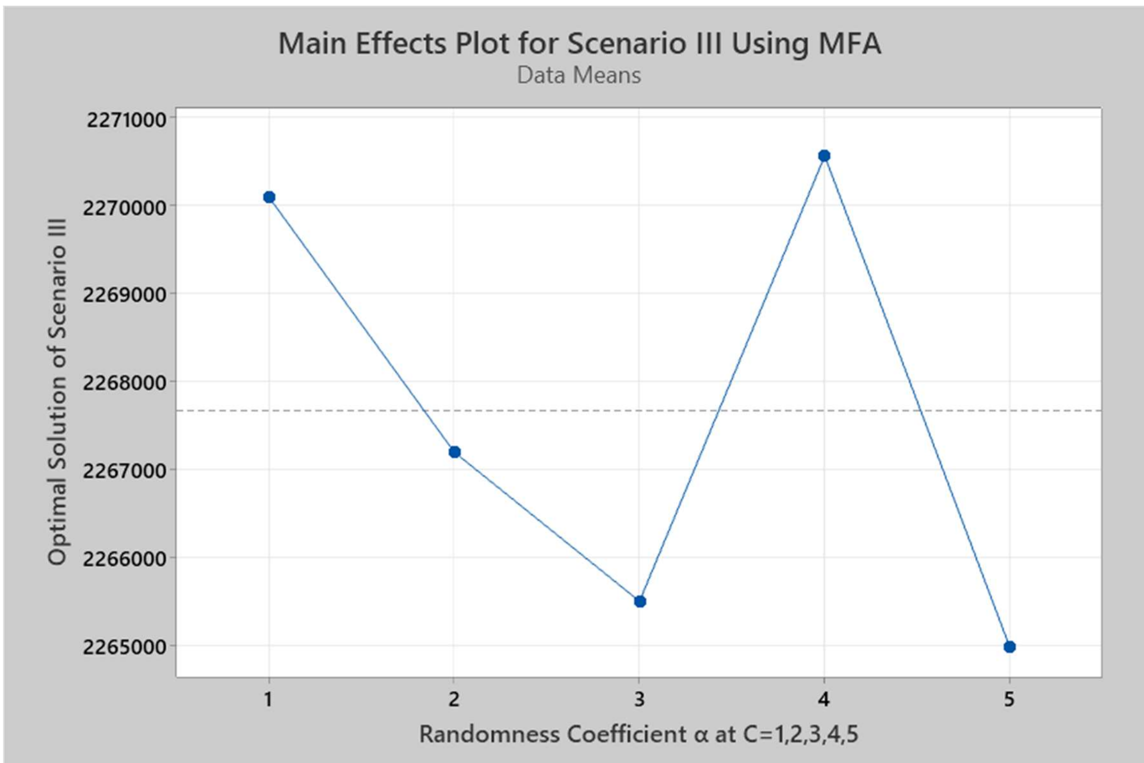

Figure 4.12. The Effect of Randomness Coefficient α on Scenario III Using MFA

It has been used to solve many optimization problems, especially for linear programming. In this study, we use this algorithm to solve the optimization problem. Then, we compare the result of this algorithm with some other powerful optimization algorithms to determine which algorithm has the best optimized solution and satisfactory results. We use the optimization software based on ModeFRONTIER to run the model. Figure 4.13 shows the workflow of a model created using a simplex algorithm.

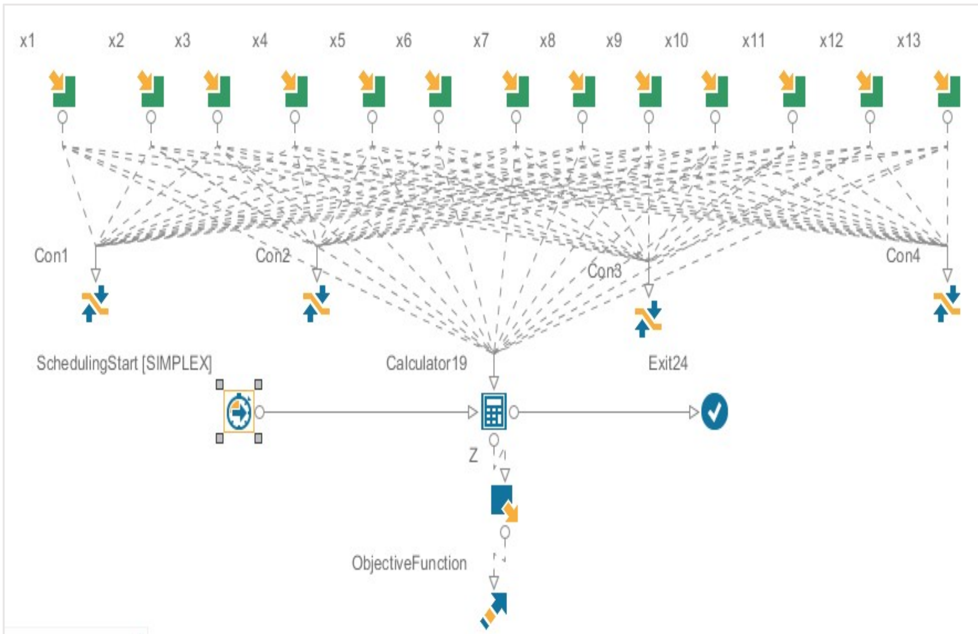

Figure 4.13. The Workflow of Model Using Simplex Algorithm

We ran the model for 40 iterations to achieve the optimal solution. Figure 4.14 shows the best design iteration for the optimal solution. It indicates that the best optimal solution is indicated by the shaded area shown in Table 4.1. The best optimal objective function is 38.2115.

In addition, the optimal solution for all decision variables is indicated as shown in Table 4.1. Figure 4.14 further indicates that all design iterations are feasible.

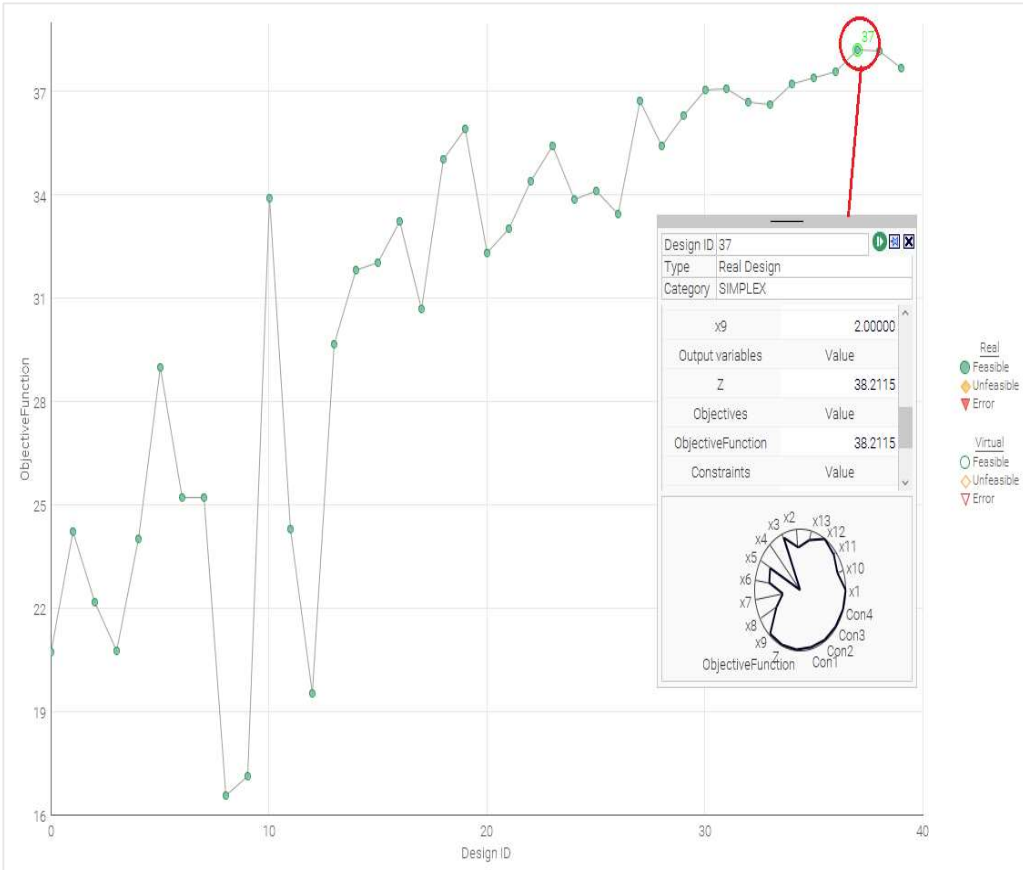

Figure 4.14. The Optimal Objective Function Using Simplex Algorithm

We also trained RSM, which is trained upon a design of experiment (DOE), based on three algorithms: statistical models (Kriging), and classical models (stepwise regression and Polynomial singular value decomposition), as shown in Table 4.2. This table illustrates that the best value of the selected validation criterion is represented by the Stepwise regression model based on five performance indexes, including mean absolute error, mean relative error, mean normalized error, R-Squared, and Akaike information criterion.

Table 4.1. The Optimal Solution of Model Using Simplex Algorithm

Design ID	Algorithm	Phase	Objective Function
12	SIMPLEX	DOE	19.5504
13	SIMPLEX	DOE	29.6587
16	SIMPLEX	Evolution	33.2405
19	SIMPLEX	Evolution	35.9434
22	SIMPLEX	Evolution	34.4056
24	SIMPLEX	Evolution	33.8753
27	SIMPLEX	Evolution	36.7471
29	SIMPLEX	Evolution	36.3172
31	SIMPLEX	Evolution	37.1028
32	SIMPLEX	Evolution	36.6939
35	SIMPLEX	Evolution	37.3964
37	SIMPLEX	Evolution	38.2115
38	SIMPLEX	Evolution	38.1730
39	SIMPLEX	Evolution	37.6836

Table 4.2. Model Training Using RSM Algorithm for Simplex Algorithm

RSM	Mean Absolute Error	Mean Relative Error	Mean Normalized Error	R-squared	AIC
Statistical Model (Kriging)	0.0172177	0.000702212	0.000973388	0.999970	12.2258
Stepwise Regression	$4.44089e^{-15}$	$1.36501e^{-16}$	$2.51063e^{-16}$	1.00000	-488.908
Polynomial singular value decomposition	$1.37668e^{-14}$	$3.92589e^{-16}$	$7.78294e^{-16}$	1.00000	-478.871

4.1.2.2 The Optimal Solution Using BFGS Algorithm

Broyden-Fletcher-Goldfarb-Shanno Algorithm (BFGS) is another powerful algorithm that can be used to solve the model. This algorithm is based on the popular quasi-Newton method. In this research, we also use this algorithm to solve the optimization problem. Then, we compare the result of this algorithm with some other powerful optimization algorithms to determine which algorithm has the best optimized solution and satisfactory results. Figure 4.15 shows the workflow of a model created using the BFGS algorithm.

We ran the model for 400 iterations to get the optimal solution. Figure 4.16 shows the best design iteration for the optimal solution. It shows that the best optimal solution is indicated by shaded area, as shown in Table 4.3. The best optimal objective function is 44.7150. In addition, the optimal solution for all decision variables is also indicated in Table 4.3. According to Figure 4.16, all design iterations are feasible.

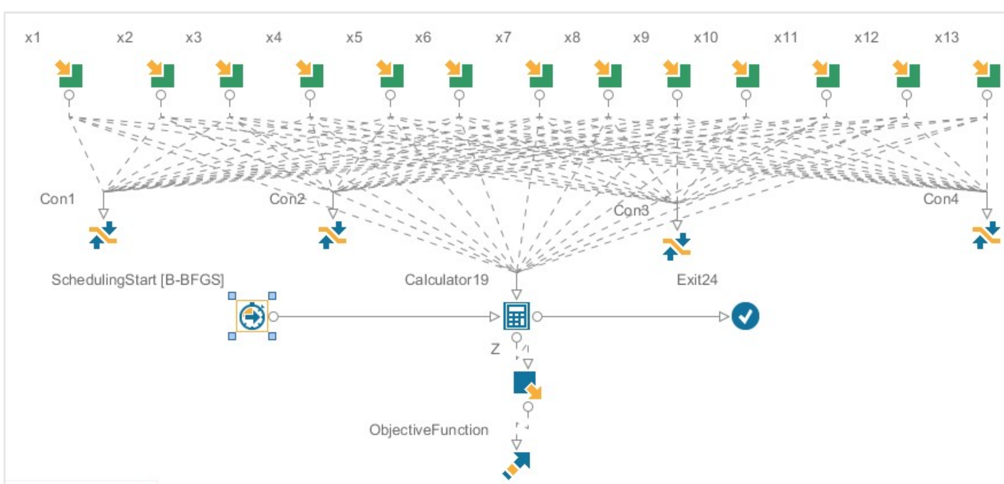

Figure 4.15. The Workflow of Model Using BFGS Algorithm

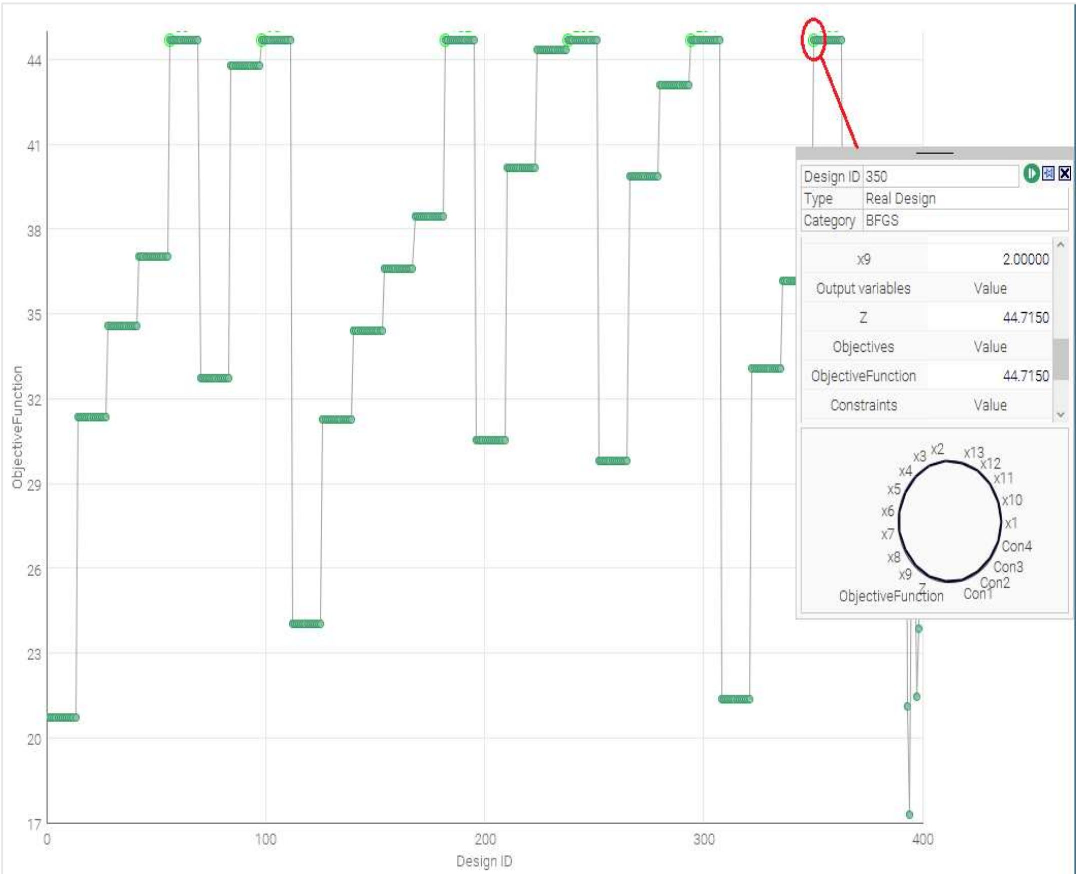

Figure 4.16. The Optimal Objective Function Using BFGS Algorithm

We also trained RSM, which is trained upon a design of experiment (DOE), based on three algorithms: statistical models (Kriging), and classical models (stepwise regression and Polynomial singular value decomposition), as shown in Table 4.4. This table shows that the best value of the selected validation criterion is represented by the stepwise regression model based on five performance indexes including mean absolute error, mean relative error, mean normalized error, R-Squared, and Akaike information criterion.

Table 4.3. The Optimal Solution of Model Using BFGS Algorithm

Design ID	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
99	BFGS	Evolution	44.7150
102	BFGS	Evolution	44.7150
105	BFGS	Evolution	44.7150
109	BFGS	Evolution	44.7150
110	BFGS	Evolution	44.7150
111	BFGS	Evolution	44.7150
112	BFGS	Evolution	24.0586
113	BFGS	Evolution	24.0586

Table 4.4. Model Training Using RSM Algorithm for BFGS Algorithm

RSM	Mean Absolute Error	Mean Relative Error	Mean Normalized Error	R-squared	AIC
Statistical Model (Kriging)	$2.13033e^{-07}$	$5.88418e^{-09}$	$8.88103e^{-09}$	1.00000	-1831.92
Stepwise Regression	$6.56364e^{-14}$	$2.22785e^{-15}$	$2.73629e^{-15}$	1.00000	-4795.92
Polynomial singular value decomposition	$1.24123e^{-13}$	$3.91492e^{-15}$	$5.17451e^{-15}$	1.00000	-44717.25

4.1.2.3 The Optimal Solution Using POWELL Algorithm

The POWELL algorithm is based on POWELL's method, proposed by Michael Powell to find the local minimum function. In this research, we also use this algorithm to solve the optimization problem. Then, we compare the result of this algorithm with some other powerful optimization algorithms to determine which algorithm has the best optimized solution and satisfactory results. Figure 4.17 shows the workflow of a model created using the POWELL algorithm.

We ran the model for 400 iterations to get the optimal solution. Figure 4.18 shows the best design iteration for the optimal solution. It indicates that the best optimal solution is indicated by shaded area as shown in Table 4.5. The best optimal objective function is 44.7150. In addition, the optimal solution for all decision variables is indicated in Table 4.4 and Figure 4.18, all design iterations are feasible.

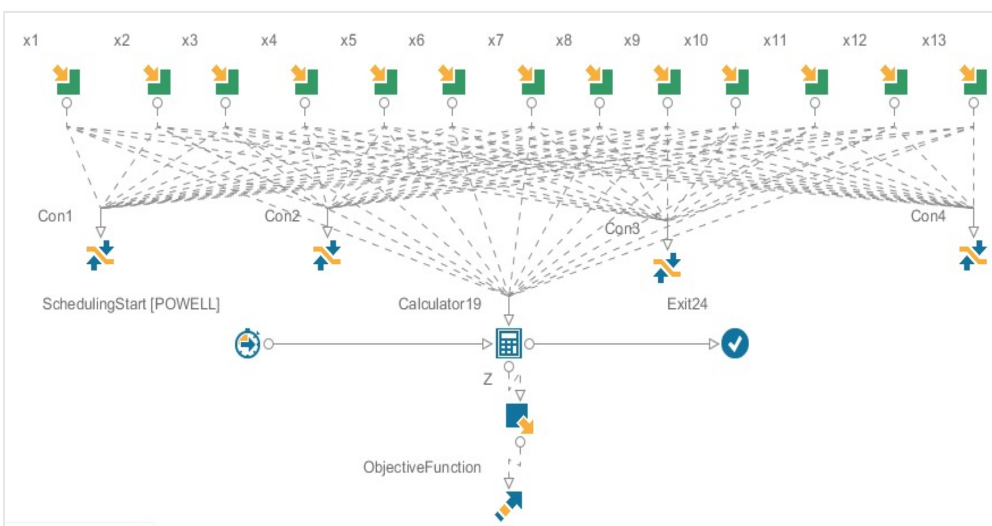

Figure 4.17. The Workflow of Model Using POWELL Algorithm

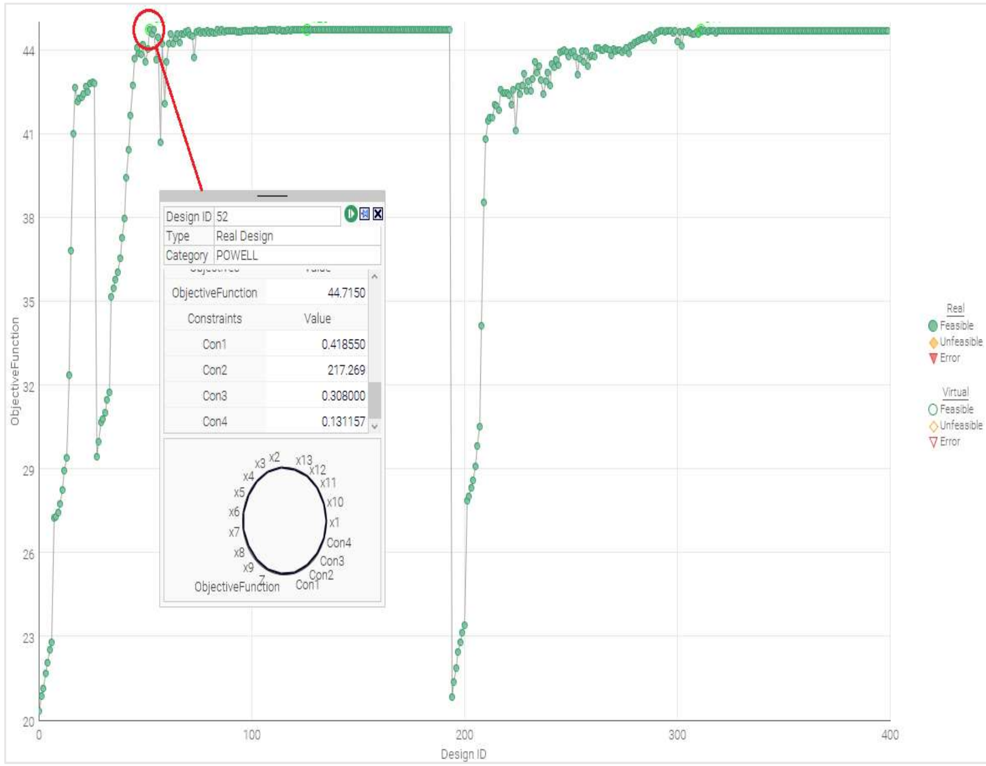

Figure 4.18. The Optimal Solution of Objective Function Using POWELL Algorithm

We also trained RSM, which is trained upon a design of experiment (DOE), based on three algorithms: statistical models (Kriging), and classical models (stepwise regression & Polynomial singular value decomposition), as shown in Table 4.6. This table shows that the best value of the selected validation criterion is represented by the stepwise regression model based on five performance indexes including mean absolute error, mean relative error, mean normalized error, R-Squared, and Akaike information criterion.

Table 4.5. The Optimal Solution of Model Using POWELL Algorithm

Design ID	Algorithm	Phase	Objective Function
111	POWELL	Evolution	44.7140
113	POWELL	Evolution	44.7146
114	POWELL	Evolution	44.7063
119	POWELL	Evolution	44.7138
122	POWELL	Evolution	44.7149
125	POWELL	Evolution	44.7146
126	POWELL	Evolution	44.7150
130	POWELL	Evolution	44.7144
132	POWELL	Evolution	44.7141
133	POWELL	Evolution	44.7140
135	POWELL	Evolution	44.7150
137	POWELL	Evolution	44.7149
138	POWELL	Evolution	44.7147

Table 4.6. Model Training Using RSM Algorithm for POWELL Algorithm

RSM	Mean Absolute Error	Mean Relative Error	Mean Normalized Error	R-squared	AIC
Statistical Model (Kriging)	2.69335	0.0973642	0.112909	0.0283381	927.573
Stepwise Regression	$9.11271e^{-14}$	$2.56839e^{-15}$	$3.82018e^{-15}$	1.00000	-4740.98
Polynomial singular value decomposition	$1.06271e^{-13}$	$2.93362e^{-15}$	$4.45501e^{-15}$	1.00000	-4725.43

4.1.2.4 The Optimal Solution Using NSGA-II Algorithm

Non-dominated Sorting Genetic Algorithm (NSGA) is one of the optimization algorithms used to solve optimization problems. This algorithm is a powerful algorithm for solving complex optimization problems. In this research, we also use this algorithm to solve the optimization problem. Then, we compare the result of this algorithm with some other powerful optimization algorithms to determine which algorithm has the best optimized solution and satisfactory results. Figure 4.19 shows the workflow of a model created using the NSGA-II algorithm.

We ran the model for 400 iterations to get the optimal solution. Figure 4.20 shows the best design iteration for the optimal solution. It indicates that the best optimal solution is indicated by shaded area as shown in Table 4.7. The best optimal objective function is 41.7237. In addition, the optimal solution for all decision variables is also indicated as shown in Table 4.7. As shown in Figure 4.20, all design iterations are feasible.

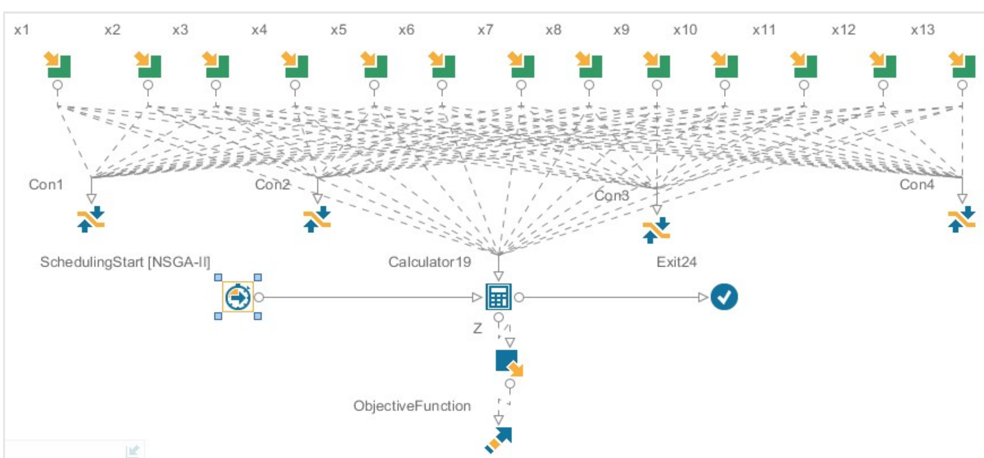

Figure 4.19. The Workflow of Model Using NSGA-II Algorithm

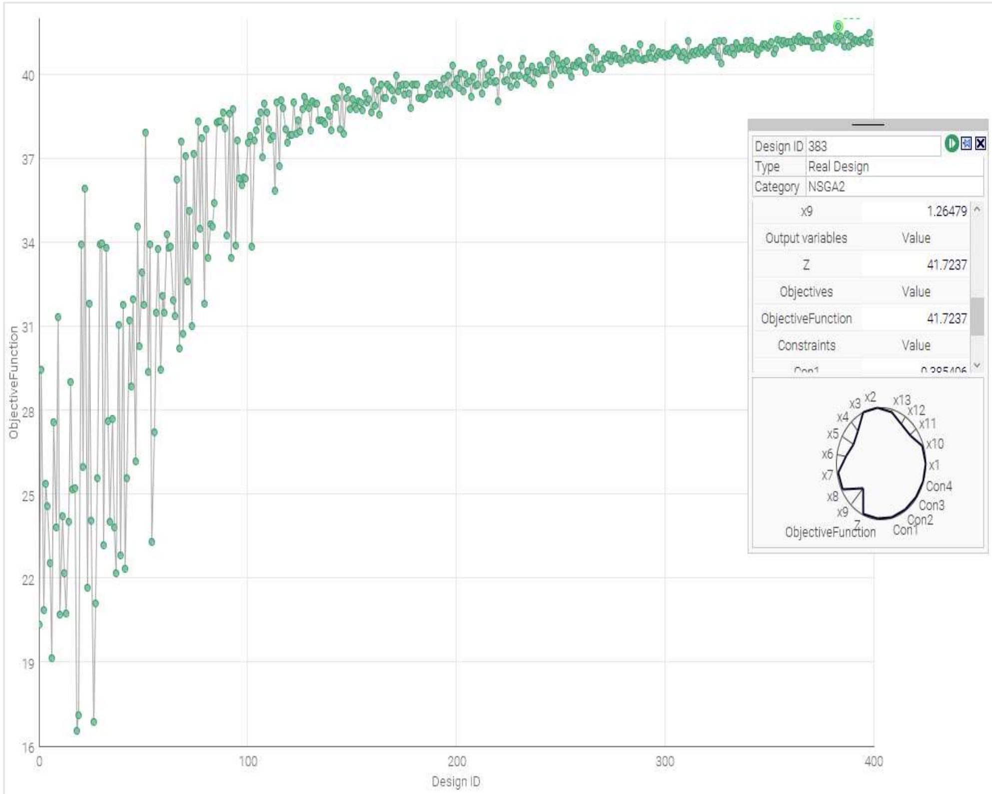

Figure 4.20. The Optimal Objective Function Using NSGA-II Algorithm

We also trained RSM, which is trained upon a design of experiment (DOE), based on three algorithms: statistical models (Kriging), and classical models (stepwise regression & Polynomial singular value decomposition), as shown in Table 4.8. This table shows that the best value of the selected validation criterion is represented by the stepwise regression model based on five performance indexes including mean absolute error, mean relative error, mean normalized error, R-Squared, and Akaike information criterion.

Table 4.7. The Optimal Solution of Model Using NSGA-II Algorithm

Design ID	Algorithm	Phase	Objective Function
373	NSGA-II	Evolution	41.0207
375	NSGA-II	Evolution	40.9793
376	NSGA-II	Evolution	41.2270
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
385	NSGA-II	Evolution	41.2187
390	NSGA-II	Evolution	41.1389
393	NSGA-II	Evolution	41.1625
394	NSGA-II	Evolution	41.2324
396	NSGA-II	Evolution	41.3074

Table 4.8. Model Training Using RSM Algorithm for NSGA Algorithm

RSM	Mean Absolute Error	Mean Relative Error	Mean Normalized Error	R-squared	AIC
Statistical Model (Kriging)	0.00202892	$9.09292e^{-05}$	$9.11119e^{-05}$	0.999997	-151.658
Stepwise Regression	$1.53211e^{-14}$	$5.41118e^{-16}$	$6.88018e^{-16}$	1.00000	-4950.94
Polynomial singular value decomposition	$5.18252e^{-14}$	$1.46569e^{-15}$	$2.32730e^{-15}$	1.00000	-4852.45

4.1.2.5 The Optimal Solution Using Firefly Algorithm

Another objective of this research was to determine the capability of a metaheuristic algorithm, based on the FA, to optimize production line operations so that a bottling company can maximize its profits. The model was solved using the FA to test the efficiency of the latter and to compare the results of meta-heuristic algorithms. The main objective was to identify the appropriate limited resources required to gain maximum profit. MATLAB was used to run the model using the FA. The result demonstrates that the FA can be considered a powerful tool in solving the model and gaining maximum profits when compared with other meta-heuristic algorithms. The profit obtained by the FA is greater than that obtained by other meta-heuristic algorithms which indicates that the FA is the best algorithm for solving this model.

The results reveal that the FA is recommended because the company is able to gain the optimal solution at minimal production costs, as shown in Figure 4.21.

Therefore, the FA offers the best solution when compared with other meta-heuristic algorithms used, as shown in Figure 4.21. The optimal solution for the objective function of each algorithm is shown in Figure 4.22.

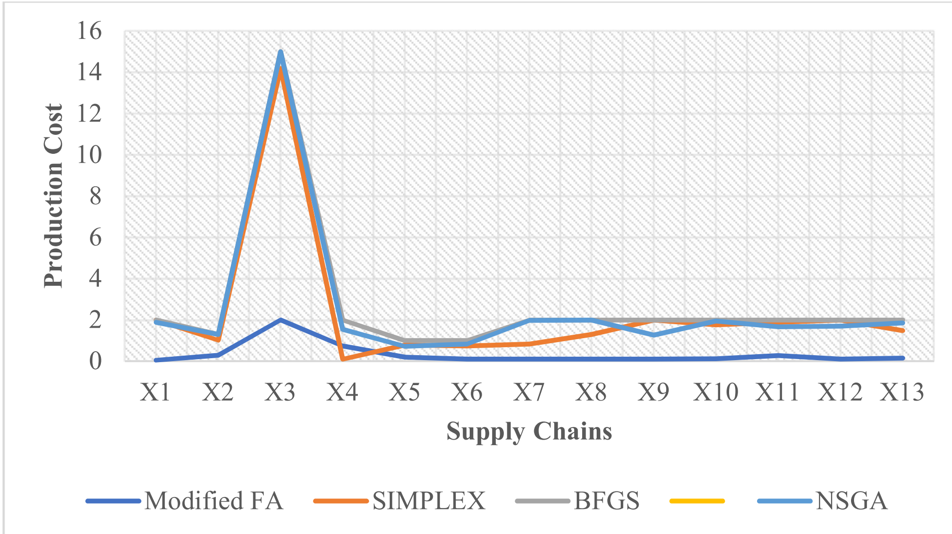

Figure 4.21. The Best Solution for Each Supply Chain Obtained by Meta-Heuristic

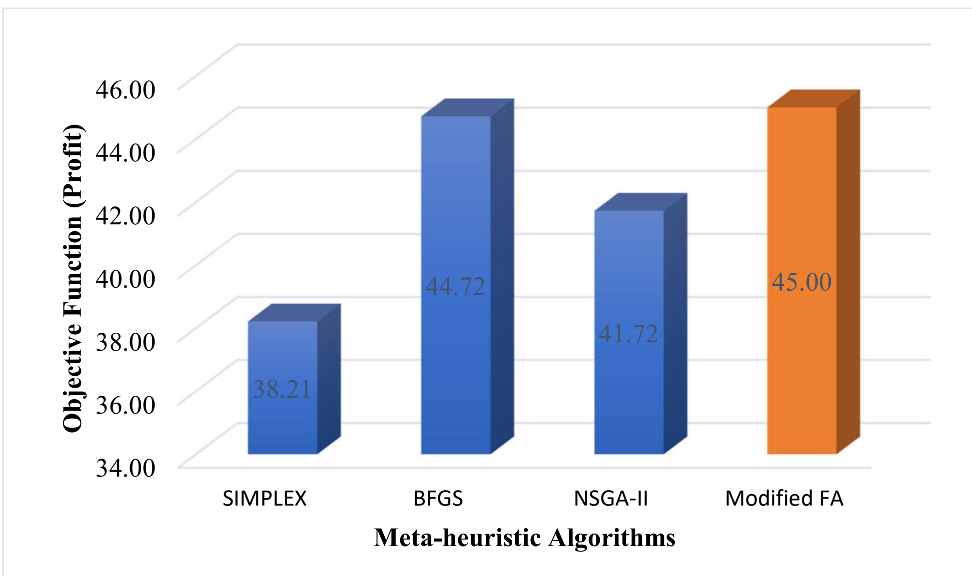

Figure 4.22. The Objective Function of each Algorithm

CHAPTER FIFE

CONCLUSION AND FUTURE WORK

5.1 Conclusion

In this section, we concluded that the proposed algorithm was applied to solve optimization problems related to supply chain networks under risks of failure in supply and demand uncertainty based on the balance between exploitation and exploration. In this research, we developed a model for a stochastic approach considering the demand is stochastic. In this research, a meta-heuristic algorithm based on the firefly algorithm, was applied to solve the model of a multi-stage supply chain network under risk of failure. The aim of the multi-objective function of the model is to minimize the total expected transportation cost, and penalty costs associated with shortage of products and unmet demand, and to maximize the profit of the proposed supply chain networks. The sensitivity analysis was applied by changing the values of significant parameters and keeping the others.

This research also introduced the ability of the firefly algorithm to obtain the best results for optimization problems (maximization or minimization). Two case studies were used to explore these methods. The first, a piping company, which produces three kinds of pipes, in which the objective for this case was to minimize the total expected costs of the supply chain network. The second, a steel company, which produces various kinds of steels, had the objective of maximizing the profit and minimizing production cost.

To test the efficiency of the firefly algorithm, the model was run using other optimization algorithms and the results of algorithms were compared. Using the firefly algorithm enables the company to achieve a higher profit and lower production cost when compared with other meta-heuristic algorithms.

In this research, we also showed the applicability of a meta-heuristic algorithm based on the firefly algorithm using two different programs including buying and stocking to track the limited number of orders and the limited stock for products and raw materials. The problem was developed as a multi-objective function to optimize multi-stage supply chain networks under risks of failure to determine the applicability of a corporation strategy between supply chains 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.

Finally, 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 modified firefly algorithm has the capability to deliver a higher number of shipments when compared with the standard firefly algorithm.

A meta-heuristic algorithm based on the firefly algorithm was used due to the flexibility of value sets for the upper and lower limits of the decision variables of the proposed model. A similar study using different factors related to other supply chain network problems can be conducted in further research.

5.2 Future Work and Limitations

There are some interesting points which we intend to investigate in future work which includes:

- While this research focuses on the applicability of meta-heuristic algorithms to solve the problems with Multi-Objective Supply Chain Problems (MOSCP), this research can be extended as future research in developing a model for a Single Objective Supply Chain Problems (SOSCP) and solve it using meta-heuristic algorithms.
- The modified FA was employed in this research using Linear Programming (LP) with a multi-objective function; this research can be extended for applying the modified algorithm using other models, such as Mixed-Integer Linear Program (MILP) model, Mixed-Integer Program (MIP), and Single Integer Program (SIP) with a single-objective supply chain network.
- While the model considered in this research was to minimize the total expected costs of supply chain networks, this research can be extended to develop a model for minimizing the delivery time of products.
- This research can be also extended by considering other important factors such as delivery time between collaborative suppliers that support the same raw materials of products, the distance between supply chains, and different stages of supply chain networks, using the modified firefly algorithm based on different settings of the modified parameters.

APPENDIX A
MODEL VALIDATION USING SIMPLEX ALGORITHM

Table. A.1

Design ID	Algorithm	Phase	Feasible	Objective Function
5	SIMPLEX	DOE	true	2.90E+01
12	SIMPLEX	DOE	true	1.96E+01
18	SIMPLEX	Evolution	true	3.50E+01
19	SIMPLEX	Evolution	true	3.59E+01
25	SIMPLEX	Evolution	true	3.41E+01
28	SIMPLEX	Evolution	true	3.54E+01
32	SIMPLEX	Evolution	true	3.67E+01
34	SIMPLEX	Evolution	true	3.72E+01

APPENDIX B
MODEL VALIDATION USING BFGS ALGORITHM

Table. B.1

Design ID	Objective Function	FEASIBLE	Validation ALGORITHM
2	2.07E+01	true	BFGS
6	2.07E+01	true	BFGS
7	2.07E+01	true	BFGS
9	2.07E+01	true	BFGS
12	2.07E+01	true	BFGS
13	2.07E+01	true	BFGS
22	3.14E+01	true	BFGS
23	3.14E+01	true	BFGS
33	3.46E+01	true	BFGS
35	3.46E+01	true	BFGS
46	3.70E+01	true	BFGS
57	4.47E+01	true	BFGS
68	4.47E+01	true	BFGS
97	4.38E+01	true	BFGS
101	4.47E+01	true	BFGS
102	4.47E+01	true	BFGS
103	4.47E+01	true	BFGS
107	4.47E+01	true	BFGS
113	2.41E+01	true	BFGS
115	2.41E+01	true	BFGS
126	3.13E+01	true	BFGS
127	3.13E+01	true	BFGS
132	3.13E+01	true	BFGS
135	3.13E+01	true	BFGS
136	3.13E+01	true	BFGS
137	3.13E+01	true	BFGS
159	3.66E+01	true	BFGS
160	3.66E+01	true	BFGS
170	3.85E+01	true	BFGS
171	3.85E+01	true	BFGS
181	3.85E+01	true	BFGS
194	4.47E+01	true	BFGS
204	3.05E+01	true	BFGS
205	3.05E+01	true	BFGS
206	3.05E+01	true	BFGS
208	3.05E+01	true	BFGS

Design ID	Objective Function	FEASIBLE	Validation ALGORITHM
215	4.02E+01	true	BFGS
223	4.02E+01	true	BFGS
229	4.44E+01	true	BFGS
230	4.44E+01	true	BFGS
234	4.44E+01	true	BFGS
237	4.44E+01	true	BFGS
238	4.47E+01	true	BFGS
244	4.47E+01	true	BFGS
247	4.47E+01	true	BFGS
251	4.47E+01	true	BFGS
260	2.98E+01	true	BFGS
264	2.98E+01	true	BFGS
268	3.99E+01	true	BFGS
273	3.99E+01	true	BFGS
277	3.99E+01	true	BFGS
280	4.31E+01	true	BFGS
294	4.47E+01	true	BFGS
298	4.47E+01	true	BFGS
300	4.47E+01	true	BFGS
302	4.47E+01	true	BFGS
313	2.14E+01	true	BFGS
314	2.14E+01	true	BFGS
318	2.14E+01	true	BFGS
324	3.31E+01	true	BFGS
327	3.31E+01	true	BFGS
334	3.31E+01	true	BFGS
336	3.62E+01	true	BFGS
340	3.62E+01	true	BFGS
341	3.62E+01	true	BFGS
342	3.62E+01	true	BFGS
344	3.62E+01	true	BFGS
346	3.62E+01	true	BFGS
349	3.62E+01	true	BFGS
350	4.47E+01	true	BFGS
354	4.47E+01	true	BFGS
362	4.47E+01	true	BFGS
367	2.64E+01	true	BFGS

APPENDIX C

MODEL VALIDATION USING POWELL ALGORITHM

Table. C.1

Design ID	Objective Function	FEASIBLE	POWELL (VALIDATION)
2	2.12E+01	true	POWELL
6	2.28E+01	true	POWELL
7	2.72E+01	true	POWELL
9	2.75E+01	true	POWELL
12	2.90E+01	true	POWELL
13	2.94E+01	true	POWELL
22	4.27E+01	true	POWELL
23	4.25E+01	true	POWELL
33	3.18E+01	true	POWELL
35	3.55E+01	true	POWELL
46	4.41E+01	true	POWELL
57	4.07E+01	true	POWELL
68	4.46E+01	true	POWELL
97	4.47E+01	true	POWELL
101	4.47E+01	true	POWELL
102	4.47E+01	true	POWELL
103	4.47E+01	true	POWELL
107	4.47E+01	true	POWELL
113	4.47E+01	true	POWELL
115	4.47E+01	true	POWELL
126	4.47E+01	true	POWELL
127	4.47E+01	true	POWELL
132	4.47E+01	true	POWELL
135	4.47E+01	true	POWELL
136	4.47E+01	true	POWELL
137	4.47E+01	true	POWELL
159	4.47E+01	true	POWELL
160	4.47E+01	true	POWELL
170	4.47E+01	true	POWELL
171	4.47E+01	true	POWELL
181	4.47E+01	true	POWELL
194	2.09E+01	true	POWELL
204	2.86E+01	true	POWELL
205	2.91E+01	true	POWELL
206	2.98E+01	true	POWELL
208	3.41E+01	true	POWELL

Design ID	Objective Function	FEASIBLE	POWELL (VALIDATION)
223	4.26E+01	true	POWELL
229	4.26E+01	true	POWELL
230	4.29E+01	true	POWELL
234	4.32E+01	true	POWELL
237	4.24E+01	true	POWELL
238	4.29E+01	true	POWELL
244	4.35E+01	true	POWELL
247	4.40E+01	true	POWELL
251	4.39E+01	true	POWELL
260	4.38E+01	true	POWELL
264	4.40E+01	true	POWELL
268	4.40E+01	true	POWELL
273	4.40E+01	true	POWELL
277	4.39E+01	true	POWELL
280	4.43E+01	true	POWELL
294	4.47E+01	true	POWELL
298	4.46E+01	true	POWELL
300	4.43E+01	true	POWELL
302	4.41E+01	true	POWELL
313	4.47E+01	true	POWELL
314	4.47E+01	true	POWELL
318	4.46E+01	true	POWELL
324	4.47E+01	true	POWELL
327	4.47E+01	true	POWELL
334	4.47E+01	true	POWELL
336	4.47E+01	true	POWELL
340	4.47E+01	true	POWELL
341	4.47E+01	true	POWELL
342	4.47E+01	true	POWELL
344	4.47E+01	true	POWELL
346	4.47E+01	true	POWELL
349	4.47E+01	true	POWELL
350	4.47E+01	true	POWELL
354	4.47E+01	true	POWELL
362	4.47E+01	true	POWELL
367	4.47E+01	true	POWELL
369	4.47E+01	true	POWELL
371	4.47E+01	true	POWELL
374	4.47E+01	true	POWELL

APPENDIX D

MODEL VALIDATION USING NSGA-II ALGORITHM

Table. D.1

Design ID	Objective Function	FEASIBLE	ALGORITHM (VALIDATION)
2	2.09E+01	true	NSGA2
6	1.92E+01	true	NSGA2
7	2.76E+01	true	NSGA2
9	3.13E+01	true	NSGA2
12	2.22E+01	true	NSGA2
13	2.08E+01	true	NSGA2
22	3.59E+01	true	NSGA2
23	2.17E+01	true	NSGA2
33	2.76E+01	true	NSGA2
35	2.77E+01	true	NSGA2
46	2.62E+01	true	NSGA2
57	3.38E+01	true	NSGA2
68	3.76E+01	true	NSGA2
97	3.61E+01	true	NSGA2
101	3.78E+01	true	NSGA2
102	3.38E+01	true	NSGA2
103	3.77E+01	true	NSGA2
107	3.70E+01	true	NSGA2
113	3.58E+01	true	NSGA2
115	3.67E+01	true	NSGA2
126	3.88E+01	true	NSGA2
127	3.92E+01	true	NSGA2
132	3.90E+01	true	NSGA2
135	3.84E+01	true	NSGA2
136	3.83E+01	true	NSGA2
137	3.82E+01	true	NSGA2
159	3.87E+01	true	NSGA2
160	3.98E+01	true	NSGA2
170	3.91E+01	true	NSGA2
171	4.00E+01	true	NSGA2
181	3.96E+01	true	NSGA2
194	3.98E+01	true	NSGA2
204	4.00E+01	true	NSGA2
205	3.97E+01	true	NSGA2
206	3.98E+01	true	NSGA2
208	3.99E+01	true	NSGA2

Design ID	Objective Function	FEASIBLE	ALGORITHM (VALIDATION)
234	4.01E+01	true	NSGA2
237	3.97E+01	true	NSGA2
238	4.01E+01	true	NSGA2
244	4.05E+01	true	NSGA2
247	4.00E+01	true	NSGA2
251	4.04E+01	true	NSGA2
260	4.03E+01	true	NSGA2
264	4.06E+01	true	NSGA2
268	4.02E+01	true	NSGA2
273	4.07E+01	true	NSGA2
277	4.06E+01	true	NSGA2
280	4.09E+01	true	NSGA2
294	4.10E+01	true	NSGA2
298	4.07E+01	true	NSGA2
300	4.07E+01	true	NSGA2
302	4.07E+01	true	NSGA2
313	4.08E+01	true	NSGA2
314	4.07E+01	true	NSGA2
318	4.08E+01	true	NSGA2
324	4.12E+01	true	NSGA2
327	4.04E+01	true	NSGA2
334	4.11E+01	true	NSGA2
336	4.10E+01	true	NSGA2
340	4.09E+01	true	NSGA2
341	4.12E+01	true	NSGA2
342	4.10E+01	true	NSGA2
344	4.07E+01	true	NSGA2
346	4.10E+01	true	NSGA2
349	4.10E+01	true	NSGA2
350	4.10E+01	true	NSGA2
354	4.12E+01	true	NSGA2
362	4.12E+01	true	NSGA2
367	4.12E+01	true	NSGA2
369	4.12E+01	true	NSGA2
371	4.09E+01	true	NSGA2
374	4.14E+01	true	NSGA2
384	4.13E+01	true	NSGA2
385	4.12E+01	true	NSGA2
389	4.14E+01	true	NSGA2

APPENDIX E

MODEL TRAINING AND VALIDATION USING BFGS

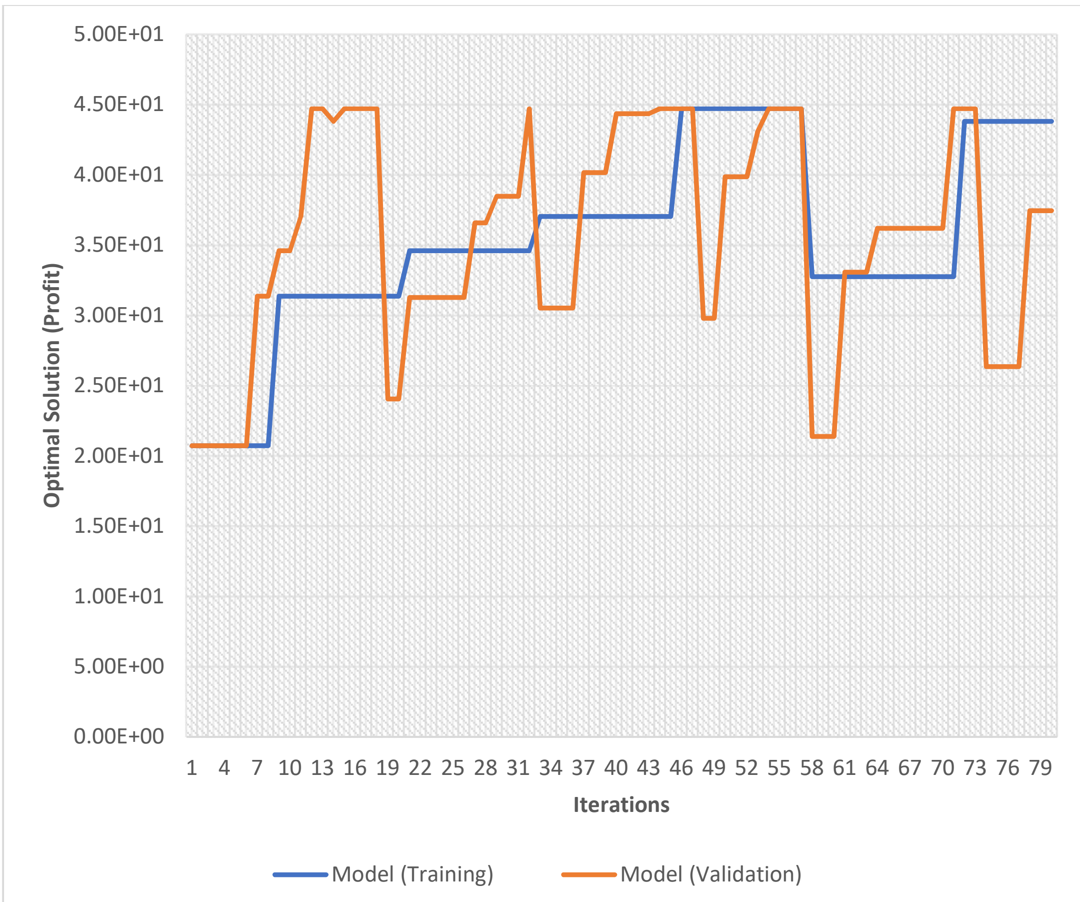

Figure E.1: Model Training and Validation Using BFGS

APPENDIX F

MODEL TRAINING AND VALIDATION USING POWELL

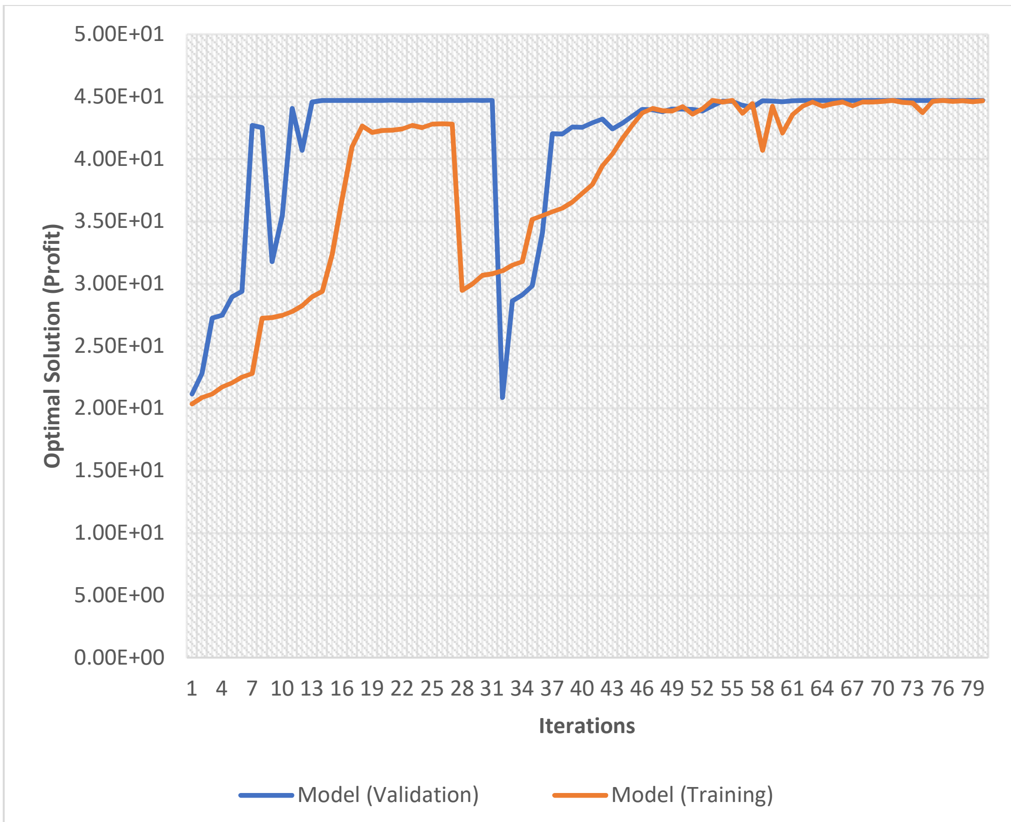

Figure F.1: Model Training and Validation Using POWELL

APPENDIX G

MODEL TRAINING AND VALIDATION USING NSGA

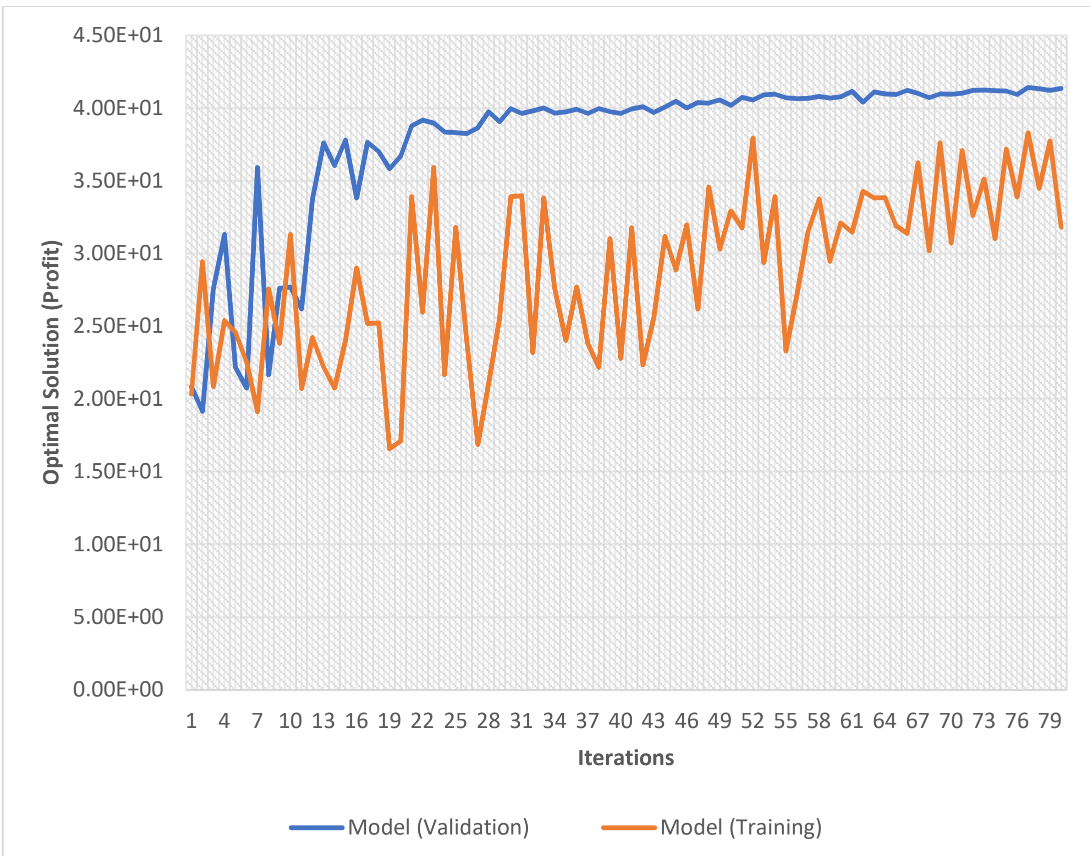

Figure G.1: Model Training and Validation Using NSGA

APPENDIX H

PUBLICATIONS

PUBLICATIONS

Altherwi, A., Zohdy, M., Olawoyin, R., and Alwerfalli, D. (2020). "A Modified Firefly Algorithm for Global Optimization of Supply Chain Networks". In *Proceedings of the 5th NA International Conference on Industrial Engineering and Operations Management* (pp.1174 -1188).

Altherwi, A. (2020). "Application of the Firefly Algorithm for Optimal Production and Demand Forecasting at Selected Industrial Plant". *Open Journal of Business and Management*, 8, 2451-2459.

Altherwi, A., & Nezamoddini, N. (2019), "Game Theory Modeling of Collaborative Supply Chains," *In Proceedings of Industrial & Systems Engineering Research Conference*, Orlando, FL, United States.

Altherwi, A., & Alwerfalli, D. (2020). "A Modified Firefly Algorithm for Global Optimization of Collaborative Supply Chain Networks Under Stochastic Demand". In *Proceedings of the 2nd African International Conference on Industrial Engineering and Operations Management* (pp.1726 -1745).

Altherwi, A., & Hijry, H. (2016). "Implementation of a Statistical Process Control System for a selected industrial plant". In *Proceedings of the International Conference on Industrial Engineering and Operations Management* (pp. 23-25).

REFERENCES

[1] Yang, X. S. (2010). *Nature-inspired metaheuristic algorithms*. Luniver press.

[2] Simon, D. (2013). *Evolutionary optimization algorithms*. John Wiley & Sons.

[3] Talbi, E. G. (2009). *Metaheuristics: from design to implementation* (Vol. 74). John Wiley & Sons.

[4] Shen, Z. J. M., Coullard, C., & Daskin, M. S. A joint location-inventory model. *Transportation Science*, *37*(1), 2003.

[5] Qi, L., Shen, Z. J. M., & Snyder, L. V. (2010). The effect of supply disruptions on supply chain design decisions. *Transportation Science*, *44*(2), 274-289.

[6] Liu, S., Moizer, J., Megicks, P., Kasturiratne, D., & Jayawickrama, U. (2014). A knowledge chain management framework to support integrated decisions in global supply chains. *Production Planning & Control*, *25*(8), 639-649.

[7] Gu, Q. L., & Gao, T. G. (2012). Joint decisions for R/M integrated supply chain using system dynamics methodology. *International journal of production research*, *50*(16), 4444-4461.

[8] Hsieh, C. C., Chang, Y. L., & Wu, C. H. (2014). Competitive pricing and ordering decisions in a multiple-channel supply chain. *International Journal of Production Economics*, *154*, 156-165.

[9] Li, D., & O'Brien, C. (1999). Integrated decision modelling of supply chain efficiency. *International journal of production economics*, *59*(1-3), 147-157.

[10] Vernimmen, B., Dullaert, W., & Engelen, S. (2007). Schedule unreliability in liner shipping: origins and consequences for the hinterland supply chain. *Maritime Economics & Logistics*, *9*(3), 193-213.

[11] Wang, S., & Meng, Q. (2011). Schedule design and container routing in liner shipping. *Transportation Research Record*, *2222*(1), 25-33.

[12] Notteboom, T. E. (2006). The time factor in liner shipping services. *Maritime Economics & Logistics*, *8*(1), 19-39.

[13] Dietrich, B. L., & Wittrock, R. J. (1996). *U.S. Patent No. 5,548,518*. Washington, DC: U.S. Patent and Trademark Office.

[14] Tang, O., & Grubbström, R. W. (2002). Planning and replanning the master production schedule under demand uncertainty. *International journal of production economics*, *78*(3), 323-334.

[15] Nehring, M., Topal, E., & Little, J. (2010). A new mathematical programming model for production schedule optimization in underground mining operations. *Journal of the Southern African Institute of Mining and Metallurgy*, *110*(8), 437-446.

[16] Göthe-Lundgren, M., Lundgren, J. T., & Persson, J. A. (2002). An optimization model for refinery production scheduling. *International Journal of Production Economics*, *78*(3), 255-270.

[17] Riepshoff, R. D., & Klinefelter, P. (2014). *U.S. Patent No. 8,655,705*. Washington, DC: U.S. Patent and Trademark Office.

[18] Peng, S., Jia, L., Xu, J., Zhang, C., Li, Q., & Han, E. (2020). The production schedule optimization of a multilayer superposed CBM system: An experimental study. *Powder Technology*, *373*, 99-108.

[19] Tambe, P. P., & Kulkarni, M. S. (2015). A superimposition-based approach for maintenance and quality plan optimization with production schedule, availability, repair time and detection time constraints for a single machine. *Journal of Manufacturing Systems*, *37*, 17-32.

[20] Chang, Y. C., Li, V. C., & Chiang, C. J. (2014). An ant colony optimization heuristic for an integrated production and distribution scheduling problem. *Engineering Optimization*, *46*(4), 503-520.

[21] Karterakis, S. M., Karatzas, G. P., Nikolos, I. K., & Papadopoulou, M. P. (2007). Application of linear programming and differential evolutionary optimization methodologies for the solution of coastal subsurface water management problems subject to environmental criteria. Journal of hydrology, 342(3-4), 270-282.

[22] Tsai, J. F., Lin, M. H., & Hu, Y. C. (2008). Finding multiple solutions to general integer linear programs. European Journal of Operational Research, 184(2), 802-809.

[23] Koné, O., Artigues, C., Lopez, P., & Mongeau, M. (2013). Comparison of mixed integer linear programming models for the resource-constrained project scheduling problem with consumption and production of resources. Flexible Services and Manufacturing Journal, 25(1-2), 25-47.

[24] Poli, R., Kennedy, J., & Blackwell, T. (2007). Particle swarm optimization. Swarm intelligence, 1(1), 33-57.

[25] Kashan, A. H. (2014). League Championship Algorithm (LCA): An algorithm for global optimization inspired by sport championships. Applied Soft Computing, 16, 171-200.

[26] Gandomi, A. H., Yang, X. S., & Alavi, A. H. (2013). Cuckoo search algorithm: a metaheuristic approach to solve structural optimization problems. Engineering with computers, 29(1), 17-35.

[27] Ezugwu, A. E., & Prayogo, D. (2019). Symbiotic organisms search algorithm: theory, recent advances, and applications. *Expert Systems with Applications*, 119, 184-209.

[28] Karaboga, D., & Akay, B. (2009). A comparative study of artificial bee colony algorithm. Applied mathematics and computation, 214(1), 108-132.

[29] Selvi, V., & Umarani, R. (2010). Comparative analysis of ant colony and particle swarm optimization techniques. International Journal of Computer Applications, 5(4), 1-6.

[30] Shi, Y. (2004). Particle swarm optimization. IEEE connections, 2(1), 8-13.

[31] Karaboga, D. (2005). *An idea based on honey bee swarm for numerical optimization* (Vol. 200, pp. 1-10). Technical report-tr06, Erciyes university, engineering faculty, computer engineering department.

[32] Khalifehzadeh, S., & Fakhrzad, M. B. (2019). A Modified Firefly Algorithm for optimizing a multi-stage supply chain network with stochastic demand and fuzzy production capacity. Computers & Industrial Engineering, 133, 42-56.

[33] Xiao, L., Shao, W., Liang, T., & Wang, C. (2016). A combined model based on multiple seasonal patterns and modified firefly algorithm for electrical load forecasting. Applied energy, 167, 135-153.

[34] Memari, A., Ahmad, R., Akbari Jokar, M. R., Rahim, A., & Rahman, A. (2019). A new modified firefly algorithm for optimizing a supply chain network problem. Applied Sciences, 9(1), 7.

[35] Yang, X. S. (2009, October). Firefly algorithms for multimodal optimization. In *International symposium on stochastic algorithms* (pp. 169-178). Springer, Berlin, Heidelberg.

[36] Apostolopoulos, T., & Vlachos, A. (2010). Application of the firefly algorithm for solving the economic emissions load dispatch problem. *International journal of combinatorics*.

[37] Mukherjee, I., & Ray, P. K. (2006). A review of optimization techniques in metal cutting processes. *Computers & Industrial Engineering*, *50*(1-2), 15-34.

[38] Madić, M., & Radovanović, M. (2014). Optimization of machining processes using pattern search algorithm. *International Journal of Industrial Engineering Computations*, *5*(2), 223-234.

[39] Carlyle, W. M., Montgomery, D. C., & Runger, G. C. (2000). Optimization problems and methods in quality control and improvement. *Journal of Quality Technology*, *32*(1), 1-17.

[40] Yang, T., & Chou, P. (2005). Solving a multiresponse simulation-optimization problem with discrete variables using a multiple-attribute decision-making method. *Mathematics and Computers in simulation*, *68*(1), 9-21.

[41] Venter, G. (2010). Review of optimization techniques. *Encyclopedia of aerospace engineering*.

[42] Jayal, A. D., Badurdeen, F., Dillon Jr, O. W., & Jawahir, I. S. (2010). Sustainable manufacturing: Modeling and optimization challenges at the product, process, and system levels. *CIRP Journal of Manufacturing Science and Technology*, *2*(3), 144-152.

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

[44] Stecke, K. E. (1983). Formulation and solution of nonlinear integer production planning problems for flexible manufacturing systems. *Management science*, *29*(3), 273-288.

[45] Saxena, L. K., & Jain, P. K. (2011). Dynamic cellular manufacturing systems design—a comprehensive model. *The International Journal of Advanced Manufacturing Technology*, *53*(1-4), 11-34.

[46] Zimmermann, A., Rodriguez, D., & Silva, M. (2001). A two-phase optimization method for Petri net models of manufacturing systems. *Journal of Intelligent Manufacturing*, *12*(5-6), 409-420.

[47] Nouira, I., Frein, Y., & Hadj-Alouane, A. B. (2014). Optimization of manufacturing systems under environmental considerations for a greenness-dependent demand. *International Journal of Production Economics*, *150*, 188-198.

[48] Wilcox, R., Nikolaidis, S., & Shah, J. (2013). Optimization of temporal dynamics for adaptive human-robot interaction in assembly manufacturing. *Robotics*, *8*, 441.

[49] Gong, J., & You, F. (2018). A new superstructure optimization paradigm for process synthesis with product distribution optimization: Application to an integrated shale gas processing and chemical manufacturing process. *AIChE Journal*, *64*(1), 123-143.

[50] Olivares-Benitez, E., Ríos-Mercado, R. Z., & González-Velarde, J. L. (2013). A metaheuristic algorithm to solve the selection of transportation channels in supply chain design. *International Journal of Production Economics*, *145*(1), 161-172.

[51] Bottani, E., Murino, T., Schiavo, M., & Akkerman, R. (2019). Resilient food supply chain design: Modelling framework and metaheuristic solution approach. *Computers & Industrial Engineering*, *135*, 177-198.

[52] Castillo-Villar, K. K. (2014). Metaheuristic algorithms applied to bioenergy supply chain problems: theory, review, challenges, and future. *Energies*, *7*(11), 7640-7672.

[53] Moncayo-Martínez, L. A., & Zhang, D. Z. (2011). Multi-objective ant colony optimisation: A meta-heuristic approach to supply chain design. *International Journal of Production Economics*, *131*(1), 407-420.

[54] Cardona-Valdés, Y., Álvarez, A., & Pacheco, J. (2014). Metaheuristic procedure for a bi-objective supply chain design problem with uncertainty. *Transportation Research Part B: Methodological*, *60*, 66-84.

[55] Sahebjamnia, N., Fathollahi-Fard, A. M., & Hajiaghaei-Keshteli, M. (2018). Sustainable tire closed-loop supply chain network design: Hybrid metaheuristic algorithms for large-scale networks. *Journal of cleaner production*, *196*, 273-296.

[56] Memari, A., Ahmad, R., Akbari Jokar, M. R., Rahim, A., & Rahman, A. (2019). A new modified firefly algorithm for optimizing a supply chain network problem. *Applied Sciences*, *9*(1), 7.

[57] Atabaki, M. S., Khamseh, A. A., & Mohammadi, M. (2019). A priority-based firefly algorithm for network design of a closed-loop supply chain with price-sensitive demand. *Computers & Industrial Engineering*, *135*, 814-837.

[58] Shu, T., Gao, X., Chen, S., Wang, S., Lai, K. K., & Gan, L. (2016). Weighing efficiency-robustness in supply chain disruption by multi-objective firefly algorithm. *Sustainability*, *8*(3), 250.

[59] Khalifehzadeh, S., Fakhrzad, M. B., Mehrjerdi, Y. Z., & Hosseini_Nasab, H. (2019). Two effective metaheuristic algorithms for solving a stochastic optimization model of a multi-echelon supply chain. *Applied Soft Computing*, *76*, 545-563.

[60] Sababha, M., Zohdy, M., & Kafafy, M. (2018). The enhanced firefly algorithm based on modified exploitation and exploration mechanism. *Electronics*, *7*(8), 132.