sciendo

Management Systems in Production Engineering

2024, Volume 32, Issue 2, pp. 252-264

Date of submission of the article to the Editor: 11/2023
Date of acceptance of the article by the Editor: 04/2024

DOI 10.2478/mspe-2024-0025

ANALYSIS EFFECT OF PARAMETERS OF GENETIC ALGORITHM ON A MODEL FOR OPTIMIZATION DESIGN OF SUSTAINABLE SUPPLY CHAIN NETWORK UNDER DISRUPTION RISKS

Atiya Al-Zuheri
University of Technology, Baghdad

Hussein S. Ketan
University of Warith Al Anbiyaa, Karbala

Layla L. Alwan
Imam Ja'afar Al-Sadiq University, Baghdad

Abstract:
Over the last decade, our world exposed to many types of unpredictable disasters (recently Coronavirus). These disasters have clearly shown the uncertainty and vulnerability of supply chain systems. Also, it confirmed that adopting Just-in-Time (JIT) strategy to reduce the logistic chain cost may lead to inbuilt complexity and risks. Efficient tools are therefore needed to make complexity optimized supply chain decisions. Evolutionary algorithms, including genetic algorithms (GA), have proven effective in identifying optimal solutions that address the trade-offs between total supply chain cost and carbon emissions regulatory policy represented by carbon tax charges. These solutions pertain to the design challenges of supply networks exposed to potential disruption risks. However, GA have a set of parameters must be chosen for effective and robust performance of the algorithms. This paper aims to set the most suitable values of these parameters that used via GA – ased optimization cost and risk reduction model in firms using a JIT as a delivery system. The model has been conceptualized for addressing the design complexities of the supply chain, referred to as SCRRJITS (Simultaneous Cost and Risk Reduction in a Just-in-Time System). A complete analysis of the different parameters and operators of the algorithm is carried out using design of experiments approach. The algorithm performance measure used in this study is convergence of solutions. The results show the extent to which the quality of solution can be changed depending on selection of these parameters.

Key words: *genetic algorithm, supply chain networks, genetic operators, disruption risks*

INTRODUCTION

Supply chain systems management is receiving increasing attention in the current global corporate and competitive envirionment [1]. This heightended focus compelled academics, industries and governments to earnestly consider enhancing the performance and sustainability of these systems [2]. A pivotal aspect of this enhancement is integrating environmental and social concerns into the industrial processes within supply chains. However, a significant challenge persists in implementing alternatives that foster sustainable communities, driving substantial changes in the economic, environmental and social dimensions. This is essential for ensuring long – term success in the development of sustainable communities [3]. Consequently, it is crucail to make decisions that prioritize sustainability in the design of supply chain systems.

Supply chains exerts substantial environmental impacts, contributing to over 80% of greenhouse gas emissions. Additionally, they account for over 90% of the effects on air, land, water, biodiversity, and geological resources. According to [4], aside from water vapor and methane, carbon dioxide stands out as one of the primary gases contributing significantly to gas emissions. Among greenhouse gas emissions, carbon dioxide holds the utmost importance due to its profound impact on the environment. Carbon dioxide emissions are prevalent in both the transportation and manufacturing sectors. The implementation of a carbon tax policy has proven effective in reducing emissions [5]. This research considers the carbon tax as a

© 2024 Author(s). This is an open access article licensed under the Creative Commons BY 4.0 (https://creativecommons.org/licenses/by/4.0/)

representation of the environmental dimension of sustainability, while also incorporating its economic dimension by factoring it into the total cost of the product.

Traditionally, supply chain design models primarily aimed cost reduction without factoring carbon emissions. However, this approach has shifted in recent years. Many contemporary studies now prioritize environmentally friendly production methods, incoporating carbon emissions into their consideration and thereby enhancing the overall cost – effectiveness [6].

Designing supply chain network for the production flow is characterized by its complexity due to numerousness, variety and interconnections [7]. To address complex problems, optimization techniques are valuable resources for researcher and practitioners who work with optimization in real world settings. In recent times, optimization has garnered significant attention, emerging as a pivotal concern within the domain of supply chain management. Meta-heuristic optimization techniques have had the widest application in solving problems surrounding supply chain management issues [8]. With minimizing total delivery cost in mind, these approaches targeted all activities necessary to design a network and enable firms meet demand, including transportation and distribution networks, site locations and structures, and network configuration [9]. Combinational optimization problems in supply chain network design are often considered NP-hard problems which need metaheuristic that can cope with the increased complexity of real-life applications in facility location and distribution systems of products.

For such optimization problems, numerous intelligent algorithms have been developed such as TABU search [10, 11], simulated annealing [12, 13], and genetic algorithm (GA) [14, 15, 16, 17, 18, 19]. Among these approaches, GA finds widespread usage [20, 21]. Increasing the complexity of the model requires increasing the efficiency of solution approaches. In this case may still a need to adequately consider any approach parameters that influence achieving the optimal solution obtained by these approaches [22]. GA optimization process divides into two phases. In the first phase, appropriate basic parameters are selected to explore the impact of using these parameters at different values on GA performance. In the second phase, the results from the first phase are to obtain the optimal solution of the original solution [23]. The performance of a GA is greatly affected by selecting the convenient values for these parameters. This selection can impact improving performance of GA in the quality of results obtained and convergence rate when compared with unturned parameters setting. This issue is initially addressed in our current research work. Since GA performance is tightly depended on the values of its parameters (such as crossover probability, mutation probability, and population size and others) to use in searching process of GA, the aim of this paper is analysing the effect of those parameters on the optimal solution to the design problem in the green supply chain network. Consequently, the end target is to find out the appropriate combination of these parameters which compromises between quality and complexity.

The remainder of this paper is structured as follows. Section 2 starts with a review of the previous research dedicated to tuning parameters of algorithms that were used in optimization of SCM design network. The proposed optimization model is presented in section 3. Next, in section 4 we present and analyse the experimental results of the key parameters' setting in an illustrate case study, to illustrate that the effectiveness of GA relays on the selection of its parameters. Finally, a conclusion of this research and further research recommendation are outlined in section 5.

LITERATURE REVIEW

Several studies have investigated the impact of varying parameters in metaheuristic algorithms utilized for optimizing supply chain network design. Naturally, GA "evolves" the best solution using parameters that they need to a good selection in order to obtain the best possible performance for solving the addressed problem. The basic parameters comprise: population size (N), crossover probability (P_C), mutation probability (P_m), and maximum number of generations (G_{max}). This could potentially empower the algorithm to explore solutions within the problem space rapidly, producing near -optimal solutions. In this regard, Syarif et al. [24] are also the others to propose MILP to address the problem of multi-stage fixed charge transportation problem. A spanning tree-based Genetic Algorithm (GA) approach has been applied to solve this problem. In that study, the value of both crossover and mutation rates were fixed at 0.4 and 0.2, respectively, and the value of population size was set to be 100. To gain more insight into the proposed algorithm, the researchers conducted three numerical experiments by altering the population size to address the given problem. Drawing from the acquired results, their conclusion was based on the recognition that the solution space for larger problems is immensely vast. Consequently, they emphasized the necessity of conducting experiments with appropriate values for both population size and the maximum number of generations. This is can ensure the chances that can lead to the optimal solution.

The MILP was also part of Pishvaee et al. [13] research, as they used it to obtain a reverse logistic network design in which the costs of transportation and operation are minimal. To attain the optimal solution, a hybrid approach incorporating a novel neighborhood search and a simulated annealing method is introduced. This study uses four distinct cooling rates in its analysis. It was clear from the results that the standard deviation increases with the increase in the problem size. To evaluate the efficacy of the proposed algorithm, a fixed standard deviation rate was adopted. Additionally, in order to gauge the impact of varying cooling rates, several statistical tests were employed. The results indicated that only two particular cooling rates had an influence on the computation time and gaps.

In the extended iteration of the two-stage transportation problem, initially presented by Gen et al. [25], the main

goal was to minimize the total cost. As a methodological solution, a genetic algorithm using priority-based encoding has been proposed. Within this approach, a novel crossover technique referred to as weight mapping crossover (WMX) was introduced. Simulation experiments were conducted in two stages. The aim of the first stage was to observe the impact of different combinations of crossover and mutation operators on the performance of the GA. Also, the experiments were set to identify the best combination of the proposed GA operators that include eight possibilities whereas the rates of both mutation and crossover of are two and four respectively. In the second stage, each of the three test problems was subjected to three experiments in order to understand how the performance of the proposed GA is affected by varying population size and number of generations. As statistical analyzes indicate, the average performance of the priority-based genetic algorithm exhibits enhancement with variations in both population sizes and the number of generations. As a result, the authors summarized it; that the improvement in the quality of the solution increases with the increase in the population size and the number of generations, and that the quality of the solution is associated with the increase in the computation time.

Li and Dong [11] introduced a mixed-integer linear programming (MILP) model capable of simultaneously managing forward and reverse distributions within a supply network, specifically catering to end-of-life computer products. Aiming this purpose and based on tabu search algorithm on initial value, the researchers used memetic algorithm. The outcomes demonstrated that the number of iterations had negligible impact on the performance of the proposed algorithm in finding optimum solutions to the five problems presented in that research. Add to that, through their results, it was found that the optimal solution can be reached with only 20 iterations.

Zandieh et al. [26] presented the desirable function approach for solving a multi-response problem. The primary objective was to determine the optimal parameter values for a genetic algorithm, tabu search and simulated annealing method. The experiments were conducted in a two-stage process. In the initial stage of the study, the focus was on establishing the appropriate parameter levels for each algorithm through Taguchi analysis. The second stage included identifying the parameters that significantly impact the performance of the proposed algorithm.

Wnag and Hsu [19] introduced a closed loop supply chain network model with genetic algorithm that uses a spanning-tree-based. In that study, they had fixed the values of rates of crossover and mutation at 0.4 and 0.2. In relation to the population size, they explored different numerical values to assess its impact concerning the problem's scale. Several conditions, including number of generations to convergence, computational time and the fitness convergence, had an important impact in determining the optimal number of the population size. Among these considered conditions, fitness convergence is appeared when GA run produce chromosomes have the same goodness score, in other words; same fitness value. For termination condition of GA, the authors set two conditions. Firstly, they selected to stop running of GA when the fitness value reaches 10 and there is no any improvement whatever the number of iterations. Secondly, the maximum number of generations is set to 750. The results indicated that the increasing in the population size although it improves slightly the accuracy level of the solution of large size problem, but the time taken to achieve that slight improvement will be significant. Accordingly, they concluded that it was not sufficient to use a large population size for large-scale problem.

Khorshidian et al. [27] applied GA on the one-machine just-in-time scheduling problem. The algorithm was employed with a nonlinear model characterized by integer variables. To evaluate the effectiveness of the algorithm parameters, multiple test problems were executed. They investigated the performance of GA using four rates of crossover and mutation, three population size, and two maximum number of generations. The Taguchi technique is used for designing experiments to investigate how these parameters affect GA performance on this specific problem. The obtained results for these parameters were chosen as default values to be used for further evaluation.

In Xu et al. [28] study, the authors explored parameter settings in applying genetic algorithms to address continuous network design problems (CNDP), which are structured as bi-level programming models. They performed a sensitivity analysis using a "one at a time" approach to evaluate the effect of different parameters. Their analysis revealed that population size significantly affects the solution, whereas the individual effects of crossover probability and mutation probability are relatively less pronounced than the combined effects of both. In a subsequent work, Sadeghi et al. [29], the researchers applied a non-dominated sorting genetic algorithm-II (NSGA-II) with carefully tuned parameters to optimize a hybrid problem involving vendor-managed inventory (VMI) and redundancy allocation within supply chain context management.

In order to obtain maximum flexibility and efficiency in the integrated design of forward/reverse logistics network, Behmanesh & Pannek [30] introduced a Memetic Algorithm featuring innovative population generation technique. The algorithm was designed to discover the optimal design solution for a substantial scale problem. In that study, the authors highlighted the effect of different GA parameters including on algorithm performance. From the experiments that were conducted, the study revealed that choosing a larger population size, a higher number of local search iterations, and an increased crossover rate contributed to enhancing solution quality. However, it was noted that despite these improvements, the computational time remained considerably high.

Tavana et al. [31] addressed the problem of designing a three-stage supply chain network (SCN) within a single product system. To address this NP-hard problem, they introduced two hybrid metaheuristic approaches: Genetic Algorithm-Variable Neighborhood Search (GA-VNS) and Variable Neighborhood Search-Simulated Annealing

(VNS-SA). The study implemented a robust parameter precision and operator setting methodology using the Taguchi experimental design method, using multiple random test problems. Performance evaluations and comparisons were performed across various problem sizes, revealing that the GA-VNS approach demonstrated superior robustness and outperformed other competing approaches.

In 2020, Guderzian et al. [32] presented a pioneering hybrid approach, merging particle swarm optimization and genetic algorithm techniques to attain Pareto solutions for the sustainable medicine supply chain network design. To fine-tune the critical algorithm parameters and determine optimal settings for significant factors, the study used the Taguchi method. Numerical experiments yielded results confirming the superior reliability of the proposed solution algorithm compared to other approaches. In addition, the research included a series of sensitivity analyses, shedding light on the model's responsiveness to changes in input parameters.

Duffuaa & Mohammed [33] presented three distinct meta-algorithms designed to address large-scale multi-objective supply chain network design problems. These algorithms draw inspiration from tabu search, genetic algorithms, and simulated annealing, each of which aims to identify near-optimal global solutions. The development process included design, coding, testing, and fine-tuning of their parameters. The results of the study showed that the tabu search algorithm outperformed the other two alternatives, both in terms of the percent of domination and computation time. On the other hand, the simulated annealing solutions outperformed in terms of their diversity, representing a notable strength of this approach. Pan & Shan [34] developed a mixed-integer nonlinear programming model designed to address the complex multi-level, multi-product, multi-period location inventory routing problem (LIRP) within the perishable products supply chain network (PPSCN). To effectively address this NP-hard problem, PAN used a hybrid approach involving genetic algorithm (GA) and multi-population genetic algorithm (MPGA). Fine-tuned input parameters were studied using the Taguchi experimental design method, recognizing the significant impact of these parameters on the performance of heuristic algorithms. Extensive experimentation across various scales revealed that the hybrid MPGA with VNS (Variable Neighbor Search) showed superior performance, as demonstrated by experimental results.

Based on the issues presented in the above literature review, one can conclude that in the most decision systems proposed to solve the problem, not all algorithm parameters are investigated when considering effect of these parameters on the perform searching to get a sound solution. Generally, under proper parametric values and using sufficient iteration number, it is supposed to get an optimal solution. Hence, based on this research limitation, in this paper, research aims are as follows:

- To ensure that the values of the basic parameters are suitable for the proposed GA which can apply to obtain simultaneously reducing costs and risks in problem solutions for green SCN design which adopts JIT concept as a delivery system,
- Illustrating the effectiveness of the proposed GA in obtaining meaningful solutions to such a complex problem which under study.

A real case study is used to assist the above aims. This work explores how GA obtained basic parameters could be set to obtain high efficiency when solving optimization problem in this real case study which regards to design of green logistic network adopting a JIT approach, and the total cost minimization of the final product is a basic rule used by producer.

THE PROPOSED OPTIMISATION MODEL

The studied supply chain system and its considerations

It is often believed that the terms "green" and "sustainable" are synonymous with each other, but this is not accurate. “Going green” typically encompasses only the environmental aspect, whereas sustainability entails a comprehensive evaluation that consideers the social, economic and environmental impacts of a product or organization [35]. This research focuses on sustainability examing both the economic and environmental dimensions: seeking cost reduction while addressing the carbon emmision.

For the overall optimization of both costs and service levels, making organizations more responsive and efficient is the top goal of supply chain management. This has given rise to many ideas aimed at developing new cooperation strategies that would strengthen the synergy between the actors in the supply chain and reduce costs in the supply chain. Among these cooperation strategies, there should be a flexibility in the use of the logistics services provided, whether local or external, to avoid the disruption that may occur in the logistics chains through the sharing of resources and decisions.

The proposed optimization model in this paper was applied to sequencing logistic operations designed for simple assembly process of a hollow-shaft electric motor. To produce a finalized product, the motor assembly involves a sequence of nearly identical operations for twenty-five individual components (NP = 25). In the given case example, aiming for a target average inventory, it was assumed that the production system relies on a network of suppliers, consisting of eleven external suppliers (N_{SE} = 11), to provide the raw materials needed to manufacture the end products. Supply chain that relays on blend of suppliers (external and local) is more resilient. External suppliers may be more cost savings, but they may raise a number of issues not easy to overcome; i.e., disruption. Thus, in this context, the approach to address this situation typically involves local sourcing, which is represented by the utilization of seven domestic suppliers as a local backup (N_{SLB} = 7). Although local sourcing reduces supply chain risks, short delivery and lead times, it results with a higher cost. The assembly system follows a Just-In-Time (JIT) approach, which synchronizes the quantities of component obtained from both local and external suppliers directly with production schedules, as detailed in Table 1.

Additionally, Table 1 furnishes the weight (in kilograms) of the items listed in the bill of materials required for crafting a single electric motor. The efficiency-oriented structure of the production system includes five distinct processes.

Table 1

Key parameters of supply chain problem

Part No.	Weight (kg)	Supplier type					
		Local Backup Supplier			External Supplier		
		Supplier No. S_{LB}	Lead Time (*LT*) Days	Distance to Required Raw Materials (v) (Km)	Supplier no. S_E	Lead Time (*LT*) Days	Distance to Required Raw Materials (v) (Km)
1	3.1	1	4	350	1	24	5000
2	2.6	1	4	350	1	24	5000
3	0.16	2	6	500	2	32	5000
4	3.2	1	4	350	1	24	5000
5	0.76	3	3	300	3	18	7500
6	0.12	4	5	400	4	38	6000
7	2.3	4	5	400	4	38	6000
8	5.9	4	5	400	5	42	6500
9	0.24	4	5	400	5	42	6500
10	0.76	3	3	300	3	18	7500
11	0.21	2	6	500	2	32	5000
12	2.6	5	2	250	6	28	5000
13	1.3	5	2	250	7	35	8000
14	0.16	5	2	250	7	35	8000
15	0.29	5	2	250	6	28	5000
16	0.16	3	3	300	9	20	3500
17	0.26	6	8	500	8	45	4000
18	0.12	2	6	500	2	32	5000
19	0.14	6	8	500	8	45	4000
20	0.26	3	3	300	9	20	3500
21	0.14	6	8	500	8	45	4000
22	0.24	7	7	600	10	28	5000
23	0.14	7	7	600	10	28	5000
24	0.26	7	7	600	10	28	5000
25	0.26	7	7	600	11	21	4000

The company has allocated five workers (w_1, w_2, w_3, w_4, and w_5) to oversee these operations, whereby each worker is responsible for managing a specific process. The daily shift duration (N_h) is a fixed period from 9:00 AM to 5:00 PM, encompassing eight hours, and this schedule applies from Monday through Friday. Each worker receives a fixed hourly wage (C_{wi}) of 14 monetary units (MU/hour). Utilities cost C_u is estimated as 10 percent of the raw material cost. In practice, external and local suppliers have to offer quantity discount as incentive to the production system managers and this results in decreased cost per unit of products or materials. For purchasing a greater number of raw materials, the supplier (both; local or external) applies quantity discount price around 5 to 14 percent. Constraints are imposed on the daily production scheduling process, which decide the quantity to be 70 units per day. In normal circumstances, the raw materials to be procured from regular, external suppliers *SE*, and the local backup supplier *SLB* only serves when these external suppliers may suffer disruption risks.

Based on the inventory theory, it is well known that the order lead time of a supplier directly affects the production system schedules. Lead time variability poses a real risk which can cause production to halt entirely. The end user or the customer, who is intended to use the finished product (the electrical motor in our case), can purchase it at 485 MU. Additional information concerning the necessary data for implementing the proposed model in this case example can be found in El Dabee et al. [36].

Problem statement

In most of the assembly plants in the world and to reduce the inventory costs, deliveries are organized according based on JIT approach which guarantees instantaneously replenishing the raw materials in the system. The SCN of the production system includes multiple external suppliers are generally offered their materials at a competitive price. Subsequently, costs related to direct raw inventory, which involves items, subassemblies, and supplies, specifically used to make the fished product, will not be taken into account. In general, supply chain disruptions have even more-direct than general disruption, since occurrence of any unexpected failure in one stage of the SCN can affect the entire production system and, in the worst case, bring it to a standstill. In most cases, disruption risks are consistently of an external nature and have a low probability of occurrence, making them challenging to predict. These risks encompass events such as economic crises, adverse weather conditions, the spread of viruses such as the Coronavirus, natural disasters, man-made threats, or combinations of various other risk factors. But if they do happen, then their consequences, as mentioned above, are more serious than those related to operational risks – such as changes in demand or in production times. After the disruption has occurred and in order to stabilize the SCN and control the disruptions in the direct response, the reactive instruments are used immediately which involve the shift toward local backup suppliers. Considering local can often come involve higher prices than when the firms were to explore external suppliers. Consequently, the proposed optimization model incorporates multiple scenarios comprising order for a predefined qua ntity of input materials from both external and local suppliers. These scenarios are executed through four basic modes of transportation. These modes are shipment by waterways, railways, roadways, and airways, and each of these well-handled transport modes has unique benefits.

The JIT system, while designed to minimize costs by maintaining minimal inventory onsite to ensure the smooth flow of the manufacturing process, leads to heightened usage of transport vehicles. This increased transportation affects the organization's sustainable environmental performance [37]. In this research, where the focus on the environmental dimension of sustainability, and given that the transportation sector stands out as one of the biggest emitters of greenhouse gas emissions, selecting the appropriate transportation mode within the supply chain is

necessary. As previously elucidated, each type of transportation mode has its distinct carbon emissions, making careful consideration essential.

Mathematical formulation of the model

The indices, parameters, and decision variables are denoted using the notations provided in the appendix of El Dabee et al. [36]**.** For further insight into these notations, readers are directed to El Dabee's research [36]. The proposed model aims to minimize the overall product cost, risk impact within JIT systems (C_T), and carbon tax within the supply chain network (C_{tax}). This objective can be formulated as follows:

$$Minimize\ C_{Total} = \sum(C_T + C_{tax}) \quad (1)$$

Formulas (2) to (8) provided in the formulas in the appendix are employed to calculate the diverse costs linked to the total supply chain cost. Formula (2) evaluates the procurement costs of materials "C_{RM}" from different suppliers. The worker cost "C_W," representing wages paid to employees for their tasks within an organization per time unit, is determined using formula (3). Formula (4) calculates the utilities cost "C_U" across the entire supply chain. The overall product cost within the supply chain system is computed using formula (5). For comprehensive insights into the calculations, syntax, and meanings of the six primary cost categories contributing to the total production cost, El Dabee et al.'s [36] research offers in-depth details. The costs are: Ordering Cost "C_O", Holding Cost "C_H", Purchasing Cost "C_p", Transportation Cost "C_{tr}", Duties Cost "C_D", Transfer Price Cost "TP".

With respect to carbon emissions in the supply chain, formula (2) calculates the overall carbon emissions that take place during the transportation of materials from suppliers to customer zones.

C_E=Σ (quantity of raw materials measured in tonnes or volume) × distance to the source of necessary raw materails (measured in kilometers) × emmision factor for transport mode or vechile type (measured in kilograms of CO_2 equivalent per tonne or volume per kilometer):

$$C_{Ei} = Q_{Mi} \times v_i \times E_{fmi} \quad (2)$$

The CO_2 emission for producing one product is the sum of CO_2 emissions for each raw material's *i* quantity needed in each patch to fulfill the regular weekly production (measured in units). The emission factor for the type of transportation mode used for raw material shipping is represented by E_{fmi}. v_i represents the destination traveled by the required raw materials. Therefore, the total CO2 emmisions to produce one product are:

$$C_E = \sum_{i=1}^{N_P} Q_{Mi} \times v_i \times E_{fmi} \quad (3)$$

According to the DEFRA guidelines for companies on GHG emissions [38], the default CO2 emission factors for raw material shipping vary depending on the mode of transportation. For road transport using petrol and diesel, the emission factor is 2.31. For LPG fuel, it is 1.51. For rail, air, and shipping transportation modes, the emission factors are 0.03, 0.57, and 0.06 respectively. In this research, a moderate fee level of 25 m.u per ton of CO_2 emitted is assumed to quantify the cost of carbon emissions associated with logistic operations. Therefore, the total carbon tax associated with transport operations at the SCN is:

$$C_{tax} = C_E \times 25 \quad (4)$$

GA application in optimization of SCRRJITS design

Genetic algorithm (GA) is a search-based optimization technique that is inspired by Charles Darwin's theory of natural evolution [39]. Because GA emulates the evolutionary processes, it is therefore an evolutionary algorithm in which the strongest elements become stronger while the weakest elements are eliminated. In the realm of business practices, genetic algorithms are utilized to optimize solutions for numerous real-life applications, spanning supply chains, financial markets, manufacturing, healthcare and insurance. But the application of this algorithm does not guarantee that they can find the optimal solution to the addressed problem. Nonetheless, experimental evidence indicates that this approach is capable of generating solutions that closely approximate the optimal solution. Furthermore, it achieves this competitive performance within a reasonable amount of time when compared to alternative combinatorial optimization algorithms. The genetic algorithm (GA) encompasses three basic genetic operations: selection, crossover, and mutation. To initiate the GA for the purpose of seeking an optimal solution to the problem, an initial population is formed by generating a set of random individuals. Subsequently, these individuals within the population undergo evaluation and are assigned fitness values. This evaluation is facilitated by an operator that assesses the performance of individuals, assigning scores to them according to their proficiency in the designated task (fitness value). From this pool, the two most exceptional individuals are selected based on their fitness levels, with higher fitness favoring greater chances of selection. When the procedure of the selection process has been carried out, it is followed by applying crossover to pairs of individuals selected at random. Through this process of combining their genetic information, one or more offspring are generated as a result. This outcome can be regarded as the formation of a new population. The process of random mutations typically occurs after crossover application to the selected off-spring. After the completion of selection process, recombination, and mutation, the subsequent population is subjected to evaluation. This iterative process continues until the desired solution is attained or until the predefined number of generations is reached [40]. Figure 1 illustrates the system workflow diagram of the GA process that is used to determine the optimal design of SCRRJITS which concurrently aids minimizing the cost of the finished product and also the cost originating from potential risk occurrence. This process is iteratively repeated to produce new generations until satisfactorily solution is found or termination condition is achieved, such as the maximum number of generations. Here, the described approach in figure1 consists of three major design decisions. Firstly, the candidate solutions (individuals or chromosomes) are represented as strings of binary digits (1s and 0s). Secondly, an evaluation function (known as the

fitness function) is specified to evaluate how close an obtained solution to the optimum solution of the desired problem. Lastly, setting the GA operators value to specify how the individuals are logically combined. The GA has been formulated for integrate manufacture – supplier problem jointly decides the optimal order quantity for every echelon in the supply chain. Let us assume we have a problem has n variables, and the structure representation of a chromosome – as a solution to this problem- is considered as $X = (X_1+X_2+X_3.....+X_n)$. Here in our addressed problem, in the chromosome, we have four genomes (X_1, X_2, X_3, and X_4) – fixed variable length, and each one represents a main decision variable and the levels of there are 34. This study consider variable X_1 represents the multiple external suppliers (N_{SELB}) used to provide the raw materials which are 11 suppliers (genes) with two levels. As X_1 gets the value 1, *SE* secures raw materials and C_{TP} is calculated using formula (7) in the appendix. When X_1 is equal to 0, *SE* is disrupted, and C_{PT} is computed using formula (8) provided in the appendix.

When X_1 takes the value 0, the *SE* encounters a disruption, and the C_{TP} calculation is performed using formula (8) found in the Appendix. X_2 represents the customer's daily demand (*dp*) for the final product, with a single demand represented by a gene spanning 210 levels (*dp* = 1, 2,..., 210). X_3 refers to the critical transportation measurement (*tm*) of raw materials, which are transported using four different transport modes (*m* = 1, 2, 3, 4) involving 11 resources (genes) at 4 distinct levels. Lastly, X_4 signifies the quantity of raw materials (*QM*) ordered in each path necessary for the weekly production of the final product. This involves 11 suppliers (genes) and spans 7 levels (*QM* = 350, 700, 1050, 1400, 1750, 2100, 2450). was developed using the Java programming language and subsequently executed on a PC equipped with an Intel®Core™ i5 – 3210M processor operating at speed of 2.5 GHz. The system was accompanied by 4GB of RAM. For chromosome representation, this study uses real – valued numbers in GA handling population of possible solutions for solving this problem. As a result, each solution is represented through a chromosome, which is just an abstract representation. As step by step guide on how GA works is is shown in Figure 1.

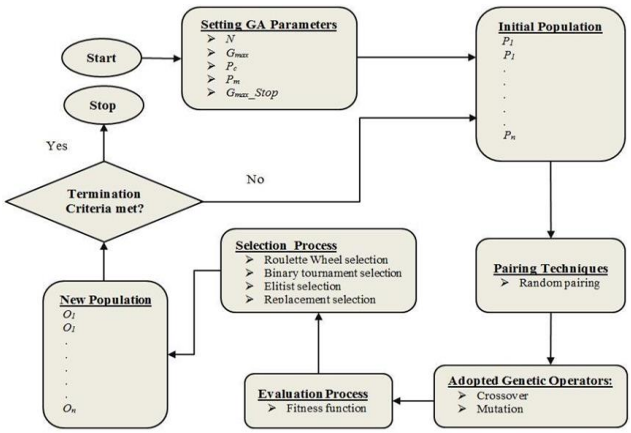


Fig. 1 The GA structure for optimizing SCRRJITS design

Designing experiments for optimizing SCRRJITS using the proposed GA

Designing experiments for the basic parameter exploration in the proposed GA

The basic parameters within the genetic algorithm (GA), such as crossover rate (P_C), mutation rate (P_m), population size (*N*), and maximum generations (G_{max}), play a pivotal role in the problem-solving process. Hence, the undertaking of computational experiments becomes imperative for discerning the optimal values for these components. These experiments are conducted to find out the impact of these parameters on the GA's performance in finding the optimal solution for the problem under investigation. To ascertain the appropriate values of these parameters in the proposed genetic algorithm, two levels were chosen for each parameter, as shown in Table 2.

Table 2
Chosen levels for basic parameters in the GA

No.	Parameter	Level numbers	Setting
1	Crossover rate (P_C)	2	0.2, 0.8
2	Mutation rate (P_m)	2	0.2, 0.8
3	Population size (N)	2	100, 400
4	Maximum generations (G_{max})	2	1000, 5000

Table 3 presents the computational results derived from averaging the results of 10 runs that include the basic parameters of the proposed genetic algorithm applied to solve the supply chain network design problem introduced in Section 3.1. The outcomes displayed in Table 3 includes the parameter averages (P_C, P_m, *N*, and G_{max}) for each experiment, along with the best and average values of the fitness function (*F.F* and *F.F*(*Ave*)), the minimum and average total costs (*CT* and *CT*(*Ave*)), average values of the fitness function Maximum and average fitness function obtained from 10 runs (F.F and F.F(Ave)), the average convergence generations (*C.G*), and the average values of the minimum and average total costs (*CT* and *CT*(*Ave*)), respectively. It is clear from the results listed in Table 3 that the appropriate rate of the values of the basic parameters that can be used to find optimal solution or near-optimal solution to the problem under study are P_C = 0.8, P_m = 0.2, *N* = 400 and G_{max} = 5000.

An analysis of variance (ANOVA) technique was used to evaluate the effect of the basic parameters of the proposed genetic algorithm on the objective function, with a particular focus on minimizing the total cost within the proposed model. Its goal is to identify the optimal solution to the problem at hand. In the existing body of literature, ANOVA has been widely adopted as an analytical method for determining significance probabilities (P-values) associated with each parameter.

Table 3

Performance summary – average values from 10 runs of basic GA parameters

Exp. No.	P_c	P_m	N	G_{max}	F.F	F.F (Ave)	C_T	C_T (Ave)	Average of F.F	Average of F.F (Ave)	Average of C.G	Average of C_T	Average of C_T (Ave)
1	0.2	0.8	100	1000	0.2271	0.2264	439.50	440.68	0.2270	0.2218	257.70	439.51	450.63
2	0.2	0.8	400	5000	0.2271	0.2226	439.50	448.16	0.2270	0.2200	335.20	439.50	454.02
3	0.2	0.8	400	1000	0.2271	0.2263	439.50	440.99	0.2270	0.2220	167.50	439.50	450.13
4	0.2	0.8	100	5000	0.2271	0.2204	439.50	452.73	0.2270	0.2217	208.90	439.50	450.16
5	0.2	0.2	100	1000	0.2270	0.2218	439.50	449.81	0.2270	0.2227	498.80	439.54	448.25
6	0.2	0.2	400	5000	0.2271	0.2219	439.50	449.73	0.2270	0.2233	395.30	439.53	446.84
7	0.2	0.2	400	1000	0.2271	0.2250	439.50	443.38	0.2270	0.2211	269.70	439.50	451.98
8	0.2	0.2	100	5000	0.2271	0.2223	439.50	448.78	0.2270	0.2200	263.60	439.50	454.03
9	0.8	0.8	100	1000	0.2271	0.2270	439.50	439.59	0.2270	0.2256	128.30	439.52	442.37
10	0.8	0.8	400	5000	0.2271	0.2269	439.50	439.66	0.2270	0.2264	429.80	439.50	440.76
11	0.8	0.8	400	1000	0.2271	0.2209	439.50	451.75	0.2270	0.2243	98.10	439.50	444.94
12	0.8	0.8	100	5000	0.2271	0.2269	439.50	439.70	0.2270	0.2246	95.50	439.50	444.32
13	0.8	0.2	100	1000	0.2271	0.2253	439.50	442.91	0.2270	0.2265	186.10	439.55	440.56
14	0.8	0.2	400	5000	0.2271	0.2267	439.50	440.19	0.2270	0.2240	631.10	439.50	445.62
15	0.8	0.2	400	1000	0.2271	0.2260	439.50	441.59	0.2270	0.2268	84.00	439.50	440.01
16	0.8	0.2	100	5000	0.2271	**0.2268**	439.50	**439.84**	0.2270	**0.2268**	**69.90**	439.50	**439.96**

Table 4 shows the impact of each parameter on the results acquired through applying the proposed GA in the given example. It seemed clear that each of P_m, N, and Gmax had an important influence on the performance of GA, as indicated by their P-values being less than or approximately equal to 0.05. These p-values indicate that varying the values of these independent variables has substantial effects the dependent variables. However, Pc exhibits no influence on the GA's performance. This observation potentially presents challenges in finding the optimal solution through the application of the proposed GA. Consequently, there is no possibility of enhancing its performance by changing the crossover rate Pc. This limitation arises from the dominance of certain chromosomes in the process after a limited number of generations. To compare the outcomes obtained each case, the program was executed with distinct values of the basic parameters in the experiments, namely P_C = 0.8, P_m = 0.2, N = 400 and G_{max} = 5000. The following section provides a detailed analysis of the model when different values were assigned to each parameter.

Table 4

Factorial ANOVA experiment for basic parameters

Parameter effect	Sum of squares	*Df*	Mean squares	F value	*P*- value	Significance
Pc vs. C_T	5.50E-05	1	5.70E-05	4.76E-02	8.29E-01	x
Pm vs. C_T	4.44E-03	1	4.44E-03	3.79E+00	5.34E-02	x
N vs. C_T	1.24E-02	1	1.23E-02	1.10E+01	1.21E-03	√
Gmax vs. C_T	4.44E-03	1	4.44E-03	3.79E+00	5.34E-02	x
Pc & Pm vs. C_T	4.49E-03	2	2.25E-03	1.91E+00	1.52E-01	x
Pc & N vs. C_T	1.23E-02	2	6.17E-03	5.47E+00	5.11E-03	√
Pc & Gmax vs. C_T	4.49E-03	2	2.25E-03	1.91E+00	1.52E-01	x
Pm & N vs. C_T	1.67E-02	2	8.36E-03	7.60E+00	7.58E-04	√
Pm & Gmax vs. C_T	8.88E-03	2	4.44E-03	3.86E+00	2.32E-02	√
N & Gmax vs. C_T	1.67E-02	2	8.36E-03	7.60E+00	7.58E-04	√
Pc, Pm & N vs. C_T	2.94E+03	3	9.80E+02	7.64E+00	1.34E-04	√
Pc, Pm & Gmax vs. C_T	2.94E+03	3	9.81E+02	7.65E+00	1.34E-04	√
Pm, N & Gmax vs. C_T	1.19E+02	3	3.98E+01	2.72E-01	8.46E-01	x
Pc, Pm N & Gmax vs. C_T	2.12E-02	4	5.31E-03	5.81E-03	1.02E-03	√

Extended experimental investigations into the basic parameters of the proposed GA

As a general guide, ANOVA analysis was carried out on the results of the experiments performed on different settings for the basic parameters of the proposed GA to address the problem of designing the supply chain network system, as elaborated in Section 3.1. Therefore, additional experiments were conducted using varied values for the basic parameters within the proposed GA in order to ascertain their optimal configurations that would lead to the optimal solution to the problem under investigation. This process involves varying the values of one parameter while keeping the others constant.

Table 5 provides an overview of the results across different values of these parameters, including data on the number of generations, minimum total cost, and average total cost. Furthermore, Figure 2 provides a visual representation illustrating the evolutionary progress of crossover rate, mutation rate, population size, and maximum generations as they converge towards the minimization of the total cost of the final product. The results, as presented in Table 5 and Figure 2, unequivocally indicate that a crossover rate of 0.8 outperforms rates of 0.2, 0.4, 0.6, and 0.9 in achieving the optimal solution for this problem.

Table 5

Outcome analysis across five variations of crossover rate, mutation rate, population size, and maximum generations values

Basic parameter	Levels	Generations	Total minimum cost (*CT*)	Total average cost (*CT(Ave)*)
Crossover rate (P_C)	0.2	233	440.0013	443.1827
	0.4	128	440.0013	440.5657
	0.6	116	440.0013	440.7462
	0.8	89	440.0013	440.1792
	0.9	318	440.0013	440.0941
Mutation rate (Pm)	0.1	209	440.0013	441.8799
	0.2	61	440.0013	443.0519
	0.4	95	440.0013	440.1863
	0.6	283	440.0013	440.0941
	0.8	404	440.0013	455.9879
Population size (N)	100	308	440.0013	443.6439
	200	190	440.0013	439.8309
	300	98	440.0013	439.86
	400	61	440.0013	441.0706
	500	73	440.0013	440.1255
Maximum generations (G_{max})	1000	110	440.0013	441.4865
	2000	576	440.0013	439.5991
	3000	154	440.0013	465.8236
	4000	160	440.0013	441.7281
	5000	75	440.0013	439.8388

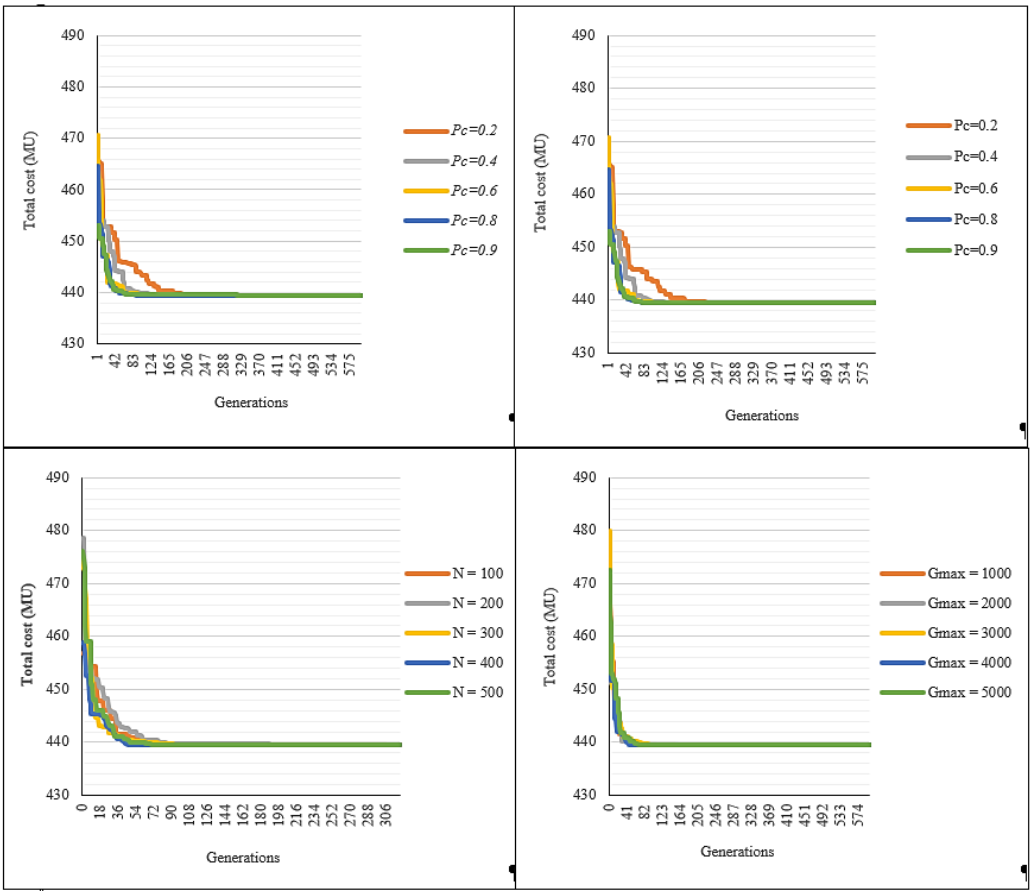


Fig. 2 Analyzing the influence of crossover rates (Pc), mutation rates (Pm), population size (N), and maximum generation rates (Gmax) on convergence towards the minimum total cost in the final product

Similarly, a mutation rate of 0.2 exhibits the most superior algorithmic performance among the available alternatives (0.1, 0.4, 0.6, and 0.8) for attaining the lowest total manufacturing cost, and this achievement is realized within a limited number of generations. It is essential to note, however, that a higher P_m value does not guarantee the identification of the optimal solution for the SCRRJITS optimization problem. Impressively, a population size of N = 400 reveals the optimal solution to the problem in a mere 60 generations. It is noteworthy that a maximum generation value of 5000 surpasses values of 1000, 2000, 3000, and 4000 in reaching the optimal solution for the problem at hand.

Analyzing the outcomes presented in Figure 2 reveals a noticeable difference in the time taken to attain the optimal solution. Specifically, the maximum generation value of 5000 demonstrates significantly quicker convergence compared to values 1000, 2000, 3000 and 4000 generations. This highlights the importance of employing a sufficiently large maximum generation number to ensure the desired genetic diversity. A comprehensive summary of the aforementioned experiments, showcasing the optimal combinations of baseline parameters GA, for the presented illustrative case study, is presented in Table 6.

Table 6
Input parameters for the GA

Parameter	Rate
Crossover rate (P_c)	0.8
Mutation rate (P_m)	0.2
Population size (N)	400
Maximum generations (G_{max})	5000
Generation stop (G_{max}_Stop)	30000

These carefully selected values are chosen to optimize concurrent cost risk reduction in JIT systems (SCRRJITS).

Computational findings and analysis for SCRRJITS optimization

The GA presented in this paper is implemented utilizing the optimal basic parameters values obtained from prior experiments (as listed in Table 6) aimed solving the optimization problem of concurrent cost - risk reduction through the adoption of a JIT (SCRRJITS) approach.

Identifying the optimal selection method for the proposed GA

The proposed genetic algorithm evaluates four distinct selection techniques: Roulette Wheel, Binary Tournament, Elite, and Replacement methods. Each method is executed 10 times to ascertain the optimal solution for diminishing total costs of the final product and mitigating risks within short-term JIT systems. A comparative analysis of these four selection methods is conducted to pinpoint the most appropriate approach among them, utilizing the GA parameters outlined in Table 7. "Iter" indicates the count of iterations necessary to identify the optimal solution. Beyond this stage, the GA is unable to discover a better solution.

Table 7
Outputs of the GA for the four selection methods

Method	Iter.	Time (S)	d_p	Cpt	C_R	CT-max	CT-ave	F.F$_{max}$	F.F$_{ave}$
RW	90	47.2	210	418.573	20.93	439.5013	446.8472	0.227014	0.223667
BT	122	47.0	210	418.573	20.93	439.5013	446.8472	0.227014	0.223667
ELIT	110	46.9	210	418.573	20.93	439.5013	442.1773	0.227014	0.225643
REP	227	47.1	210	418.573	20.93	439.5013	440.1363	0.227014	0.226687

Table 7 displays the average metrics, including best iterations, computational time, customer demand, product cost, risk cost, total cost (both maximum and average), and fitness function (both maximum and average) for each selection method. The results underscore the dominance of the replacement selection method compared to the alternatives. This method allows the proposed GA to sustain population diversity and navigate the solution space effectively. Notably, the replacement selection method ensures the continuous propagation of the best-performing chromosome to subsequent generations.

Assessing genetic operators' efficacy in the proposed GA

The impact of crossover and mutation operator rates on the performance of the proposed GA has been examined by employing various values of these rates to identify the most suitable configuration of them to address the undertaken problem. Both crossover and mutation operations generate new chromosomes. crossover produces a new chromosome equal to $N \times P_C$ offspring, while the mutation generates $N \times P_m$ offspring for each generation. This study chooses the following values for both crossover rate (P_C) and mutation rate (P_m): 0.2, 0.4, 0.6, 0.8, and 1.0. For each of these values, the proposed genetic algorithm (GA) is run 10 times to ascertain the optimal solution that minimizes the total cost of the final product while taking into account the implications of risks within the JIT system and adhering to a predefined timeframe. Figure 3 provides a comparison across 10 runs for different crossover rate values and their corresponding average total cost. It is evident that the highest number of generations is achieved when P_C = 0.8 and P_m = 0.2. In this scenario, consists of 320 offspring (400×0.8) resulting from crossover, and an additional 80 offspring (400×0.2) produced through mutation operation with a rate of 0.2. Comparing 10 generation runs of different crossover rates and their impact on average total cost reveals a notable pattern: the best average

crossover rate corresponds to the minimum average total cost is 0.8, as depicted in Figure 3. As stated earlier above, the assumption is that P_C + P_m equals constant. Consequently, when employing a low crossover rate, the proposed GA would necessitate a higher mutation rate. This combination might result in restricted exploration stemming from preceding generations. On the other hand, opting for a high crossover rate and a low mutation rate could lead to increased similarity between offspring and their parents. This similarity could lead the proposed GA to converge quickly toward the optimal fitness function, even after a limited number of iterations.

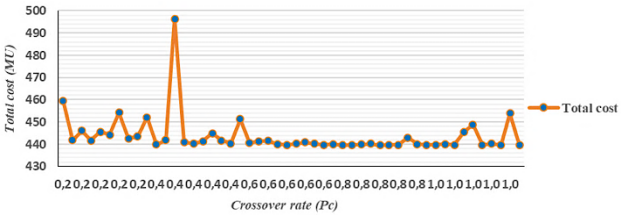


Fig. 3 Comparing 10 generation runs of different crossover rates and their impact on average total cost

Optimizing Solutions: the quest for optimal outcomes in the Proposed GA

By implementing the GA parameters as detailed in Table 8, the proposed genetic algorithm effectively achieves the optimal solution, resulting in the minimization of total production costs and the mitigating of risks in short-term JIT systems. The optimal solution is attained following 252 generations. Table 8 displays the optimal chromosome configuration, while Table 8 provides comprehensive results from the genetic algorithm, including the number of iterations, time requirements, client demand, and various cost categories.

Table 8

The optimal chromosome and the output of GA achieved via replacement selection method

N_{SELB}										d_P	t_m									Q_M									
1	0	0	0	1	0	1	0	1	0	210	1	3	4	2	1	3	2	4	1	3	4	1	1	1	1	1	1	1	1	1	1

Iter.	*Time (S)*	d_{fi}	C_O	C_H	C_P	C_W	C_D	*TP*	C_W	C_U	C_{pt}	C_R	C_T
252	47.29	210	6.953	9.919	314.961	36.26	2.919	2.235	8.0	37.325	418.573	20.928	439.501

Figure 4 visually represents the average and best cost values for all chromosomes with respect to the number of iterations.

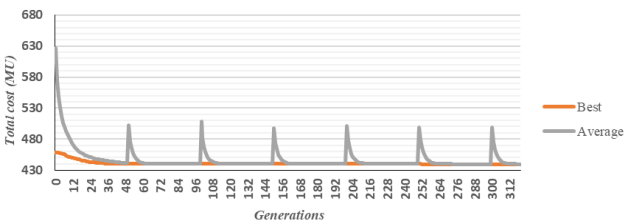


Fig. 4 Best and average total final product cost values

The evident fluctuations are attributed to the population's variability arising from applied injection strategy. This demonstrates the effectiveness of the crossover operator in generating new offspring that can explore different directions within the search space. This capability enables the proposed GA to break free from the local optimal areas and enhance its ability to reach a more globally optimal solution.

CONCLUSION AND FURTHER RESEARCH

The effective design of a sustainable supply chain system encompasses two major dimensions: environmental and economic considerations. Furthermore, such a design should possess the capability to adeptly mitigate and manage potential distribution risks. Within this framework, the research community has developed multiple models aimed at optimizing the intricate design of these systems. Despite the advancements in SCM design knowledge, conventional approaches employed for this purpose have not consistently yielded success. This is primarily due to lack of comprehensive attention directed towards the complexities inherent in the key drivers across the entire logistics chain. Genetic algorithms have emerged as a promising approach capable of explicitly addressing the complexity of existence in large space solutions. However, the efficacy of a GA largely hinges on the parameter values chosen for its operations, which encompasses crossover and mutation probabilities, population size, maximum number of generations, and selection method. In this research, a real-coded genetic algorithm was employed to address the design challenge of a supply chain system. This approach, known as SCRRJITS (Simultaneous Cost Risk Reduction in Just-in-Time Production Systems), focuses on mitigating cost-related risks while implementing a JIT approach in production systems. Utilizing the GA framework, the chromosome representation was tailored to generate feasible solutions exclusively, thereby by reducing computational time within each generation. To demonstrate the practical application of the developed GA, a supply chain case study involving a basic assembly process for a hollow shaft electric motor was presented. This served to showcase the efficiency of the solution algorithm and its potential to address real-world complexities in the supply chain design.

The basic parameters of the proposed genetic algorithm (GA), namely P_C (crossover rate), P_m (mutation rate), N (population size), and G_{max} (maximum number of generations), were subjected to ANOVA analysis to evaluate their effect on the objective function of the developed model. experimental studies were conducted, involving manipulation of each variable's value while maintain others fixed, aiming to determine the appropriate parameter values for resolving the challenge of concurrent cost risk reduction in JIT systems. To form a subset from the initial pool, four selections methods – the Roulette Wheel, the Double Tournament, Elitist, and Substitution – were identified and evaluated. This assessment aimed to identify the appropriate selection method for the devised GA approach. The acquired results underwent through analysis and discussion to elucidate the efficacy of the proposed approach, both in its general assembly and its specific criteria, in achieving the optimal solution for the identified problem. In summary, the superiority of the developed GA with its chosen base parameters compared to the

traditional GA utilizing untuned parameters in addressing SCRRJITS design problem is evident in terms of convergence generations. Based on the findings of this research, there is a potential to enhance the quality of the solution quality by employing the Taguchi approach for experimenting with the GA parameters.

This could replace the current method of relying on the researcher's personal experience, as done in this research. Additionally, avenues for further research are available, such as extending the investigation into various problems domains within the SCRRJITS context, each with distinct structural parameter configurations. Moreover, future research could delve into exploring the interplay between numerical and structural parameters to gain deeper insights into their interactions.

REFERENCES

[1] M.C. Cooper, L.M. Ellram. "Characteristics of supply chain management and the implications for purchasing and logistics strategy". *The International Journal of Logistics Management*, vol. 4 no. 2, 1996, pp. 13-24.

[2] C.R. Carter, D.S. Rogers, T.Y. Choi. "Toward the theory of the supply chain". *Journal of Supply Chain Management*, vol. 51 no. 2, 2015, pp. 89-97.

[3] L. Bals, W.L. Tate. "Sustainable supply chain design in social businesses: advancing the theory of supply chain". *Journal of Business Logistics*, vol. 39 no. 1, 2018, pp. 57-79.

[4] M. Etminan, G. Myhre, E.J. Highwood, K.P. Shine. "Radiative forcing of carbon dioxide, methane, and nitrous oxide: A significant revision of the methane radiative forcing". *Geophysical Research Letters*, vol. 43, 2006, pp. 12614-12623.

[5] R.I. Mogos, M.D. Negescu-Oancea, S. Burlacu, V.A. Troaca. "Climate change and health protection in European union". *European Journal of Sustainable Development*, vol. 10, no. 3, 2021, pp. 97-108.

[6] B. He, Y. Liu, L. Zeng, S. Wang, D. Zhang, Q. Yu. "Product carbon footprint *across sustainable supply chain*", *Journal of Cleaner Production*, vol. 241, no. 11, 2019, p. 118320.

[7] C. Bode, S.M. Wagner. "Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions". *Journal of Operations Management*, vol. 36, 2015, pp. 215-228.

[8] C.A. Silva, T.A. Runkler, J.M. Sousa, J.M.S. Da Costa. "Optimization of logistic processes in supply-chains using metaheuristics". *Proceedings of the Progress in Artificial Intelligence. EPIA 2003*, Lecture Notes in Computer Science, vol. 2902, 2003.

[9] T. Paksoy, C-T Chang. "Revised multi-choice goal programming for multi-period, multi-stage inventory controlled supply chain model with popup stores in Guerrilla marketing". *Applied Mathematical Modelling*, vol. 34, no.11, 2010, pp. 3586-3598.

[10] C.S. Sung, S.H. Song. "Integrated service network design for a cross-docking supply chain network". *Journal of the Operational Research Society*, vol. 54, no. 12, pp. 2003, 1283-1295.

[11] D.-H. Lee, M. Dong. "A heuristic approach to logistics network design for end-of-lease computer products recovery". *Transportation Research Part E: Logistics and Transportation Review*, vol. 44, no. 3, 2008, pp. 455-474.

[12] V. Jayaraman, A. Ross. "A simulated annealing methodology to distribution network design and management". *Journal of Operational Research*, vol. 144, no. 3, 2003, pp. 629-645.

[13] M.S. Pishvaee, K. Kianfar, B. Karimi. "Reverse logistics network design using simulated annealing". *The International Journal of Advanced Manufacturing Technology*, vol. 47, no. 1-4, 2010, pp. 269-281.

[14] B. Dengiz, F. Altiparmak, A.E. Smith. "Local search genetic algorithm for optimal design of reliable networks". *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 3, 1997, pp. 179-188.

[15] F. Altiparmak, M., Gen, L. Lin, T. Paksoy. "A genetic algorithm approach for multi-objective optimization of supply chain networks". *Computers & Industrial Engineering*, vol. 51, no. 1, 2006, pp. 196-215.

[16] J. B. Jo, L. Yinzhen, M. Gen. "Nonlinear fixed charge transportation problem by spanning tree-based genetic algorithm". *Computers & Industrial Engineering*, vol. 53, no. 2, 2007, pp. 290-298.

[17] H. Min, H. Ko. "The dynamic design of a re verse logistics network from the perspective of third-party logistics service providers". *International Journal of Production Economics*, vol. 113, no. 1, 2008, pp. 176-192.

[18] G. Kannan, S. Pokharel, P.S. Kumar. "A hybrid approach using ISM and fuzzy TOPSIS for the selection of reverse logistics provider, *Resources, Conservation & Recycling*, Vol. 54, No. 1, 2009, pp. 28-36.

[19] H.F. Wang, H.F., H.W. Hsu. "A closed-loop logistic model with a spanning-tree based genetic algorithm". *Computers & Operations Research*, vol. 37, no. 2, 2010, pp. 376-389.

[20] W. Liu, X. Li, N. Luo, X. Chen. "Common grounding optimization for CVRP*". Proceedings of the IEEE 8th Conference on Industrial Electronics and Applications (ICIEA)*, Melbourne, VIC, 2013, pp. 1755-1758.

[21] B. Rabta, R. Schodl, G. Reiner, J. Fichtinger. "A hybrid analysis method for multi-class queueing networks with multi-server nodes". *Decision Support Systems,* vol. 54, no.4, 2012, pp. 1541-1547.

[22] M.T Melo, S. Nickel, F. Saldanha-Da-Gama. "Facility location and supply chain management – a review". *European Journal of Operational Research*, vol. 196, no. 2, 2009, pp. 401-412.

[23] H. Lee, Y. Fan. "An Adaptive real-coded genetic algorithm". *Applied Artificial Intelligence*, vol*.* 16, no.6, 2002, pp. 457-486.

[24] A. Syarif, Y. Yun, M. Gen. "Study on multi-stage logistic chain network: a spanning tree-based genetic algorithm approach". *Computers & Industrial Engineering*, vol. 43, no. 1-2, 2002, pp. 299-314.

[25] M. Gen, F. Altiparmak, L. Lin. "A genetic algorithm for two stage transportation problem using priority-based encoding". *OR Spectrum*, vol. 28, no. 3, 2006, pp. 337-354.

[26] M. Zandieh, M. Amiri, B. Vahdani, R. Soltani. "A robust parameter design for multi-response problems". *Journal of Computational and Applied Mathematics*, vol. 230, no. 2, 2009, pp. 463-476.

[27] H. Khorshidian, N. Javadian, M. Zandieh, J. Rezaeian, K. Rahmani. "A genetic algorithm for JIT single machine scheduling with preemption and machine idle time", *Expert Systems with Applications*, vol. 38, no. 7, 2011, pp. 7911-7918.

[28] M. Xu, J. Yang, Z. Gao. "Parameters sensitive analyses for using genetic algorithm to solve continuous network design problems". *Procedia – Social and Behavioral Sciences*, vol. 43, 2012, pp. 435-444.

[29] J. Sadeghi, S. Sadeghi, S.T.A. Niaki. "A hybrid vendor managed inventory and redundancy allocation optimization problem in supply chain management: AnNSGA-II with tuned parameters". *Computers & Operations Research*, Vol. 41, No. 1, 2014, pp. 53-64.

[30] E. Behmanesh, J. Pannek. "The effect of various parameters of solution methodology on a flexible integrated supply chain model, *Mathematical Problems in Engineering*, vol. 2018.
[31] M.M. Tavana, F.J. Santos-Arteaga, A. Mahmoodirad, S. Niroomand, M. Sanei. "Multi-stage supply chain network solution methods: hybrid metaheuristics and performance measurement". *International Journal of Systems Science: Operations & Logistics*, vol 5, no. 4, 2018, pp. 356-373, 2018.
[32] F. Goodarzian, H. Hosseini-Nasab, M.B. Fakhrzad. "A multi-objective sustainable medicine supply chain network design using a novel hybrid multi-objective metaheuristic algorithm". *International Journal of Engineering*, vol. 33, no. 10, 2020, pp. 1986-1995.
[33] S.O. Duffuaa, A. Mohammed. "Performance evaluation of meta-heuristic algorithms for designing multi-objective multi-product multi-echelon supply chain network". *Soft Computing*, vol. 27, 2022, pp. 12223-12248.
[34] L. Pan, M. Shan, L. Li. "Optimizing perishable product supply chain network using hybrid metaheuristic algorithms". *Sustainability*, vol.15, no. 13, 2023, pp. 1-21.
[35] A.R.W Ananda, P. Astuty, Y.C. Nugroho. "Role of green supply chain management in embolden competitiveness and performance: Evidence from Indonesian organizations". *International Journal of Supply Chain Management,* Vol. 7, No. 5, 2018, pp. 437-442.
[36] F. El Dabee, R. Marian, Y. Amer. "A novel optimization model for simultaneous cost-risk reduction in multi-suppliers just-in-time systems". *Journal of Computer Science*, vol. 9, no.12, 2013, pp. 1778-1792.
[37] J.C. Melo, B.S. Bezerra, F.B. Souza. "An analysis of JIT from the perspective of environmental sustainability". Revista GEPROS, 17, no. 2, 2022, pp. 111-135.
[38] C. Kauffmann, C. Tébar Less, D. Teichmann. "*Corporate Greenhouse Gas Emission Reporting: A Stocktaking of Government Schemes*." OECD Working Papers on International Investment, OECD Publishing, 2012.
[39] M. Gen, R. Cheng. *Genetic algorithms and engineering design,* John Wiley & Sons, Inc*,* 1997.
[40] C.R. Reeves, J.E., Rowe. *Genetic Algorithms: Principles and Perspectives: A Guide to GA Theory*. New York: Kluwer, 2003.

Atiya Al-Zuheri (corespondig author)
Department of Production Engineering and Metallurgy
University of Technology-Iraq
Baghdad, Iraq
e-mail: atiya.a.jiryo@uotechnology.edu.iq

Hussein S. Ketan
College of Engineering
University of Warith Al Anbiyaa
Karbala, Iraq
e-mail: hussein.ke@uowa.edu.iq

Layla L. Alwan
Imam Ja'afar Al-Sadiq University
Baghdad, Iraq
e-mail: layla.lateef@sadiq.edu.iq