AI-Driven Optimization Approach Based on Genetic Algorithm in Mass Customization Supplying and Manufacturing

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***Abstract*—Numerous artificial intelligence (AI) techniques are currently utilized to identify planning solutions for supply chains, which comprise suppliers, manufacturers, wholesalers, and customers. Continuous optimization of these chains is necessary to enhance their performance. Manufacturing is a critical stage within the supply chain that requires continuous optimization. Mass Customization Manufacturing is one such manufacturing type that involves high-volume production with a wide variety of materials. However, genetic algorithms have not been used to minimize both time and cost in the context of mass customization manufacturing. Therefore, we propose this study to present an artificial intelligence solution using genetic algorithm to build a model that minimizes the time and cost which associated with mass customized orders. Our problem formulation is based on a real-world case, and it adheres to expert descriptions. Our proposed optimization model incorporates two strategies to solve the optimization problem. The first strategy employs a single objective function focused on either time or cost, while the second strategy applies the multi-objective function NSGAII to optimize both time and cost simultaneously. The effectiveness of the proposed model was evaluated using a real case study, and the results demonstrated that leveraging genetic algorithms for mass customization optimization outperformed expert estimations in finding efficient solutions. On average, the evaluation revealed a 20.4% improvement for time optimization, a 29.8% improvement for cost optimization, and a 25.5% improvement for combined time and cost optimization compared to traditional expert optimization.**

Keywords—Mass customization manufacturing; metaheuriatic search; genetic algorithm; optimization; supply chain management

I. Introduction

Technological breakthroughs often give rise to new and persistent optimization dilemmas. To address these real-world challenges, metaheuristics (MHs), characterized as versatile and general-purpose methods, have been suggested as effective tools [1]. Metaheuristic optimization is focused on resolving real-world optimization problems by employing a range of metaheuristic algorithms, such as genetic algorithms, particle swarm optimization, bee algorithms, ant colony optimization, and memetic algorithms. Supply chain management poses a formidable task in the domain of continuous optimization using the power of metaheuristic optimization. It involves the simultaneous minimization of time, cost, and distance, or the maximization of quality and profit, as dictated by the problem's specifications. A supply chain is a cohesive group of organizations that are interconnected through the flow of materials, information, logistics, and finances. Each organization within this collective consists of enterprises responsible for manufacturing raw materials and components and offering services such as distribution, storage, wholesale, and retail. The ultimate customers are regarded as the concluding segment within this chain [2]. Typically, a supply chain encompasses diverse facilities such as suppliers of raw materials, manufacturers, warehouses, wholesalers, retailers, distribution hubs, and customers. The movement of materials and information occurs within and between these organizations [3].

In simpler terms, the supply chain comprises diverse components working together in a network that commences with raw material manufacturing and culminates in its shipment to storage facilities, distribution centers, and ultimately ensuring customer satisfaction [4]. The optimization of the supply chain network holds great importance when it comes to minimizing time and cost or maximizing profit. One area that requires particular attention is the manufacturing component of the supply chain. Manufacturing strategies, including make to stock, make to order, engineer to order, and mass customization, play a significant role in this regard. Mass customization revolves around producing a diverse array of products in large volumes. However, executing mass customization orders successfully poses various challenges, with a major focus on formulating a compelling value proposition that ensures customers' utmost satisfaction [5, 6], which creates the need for the optimization of the complete value creation process, the other challenge and the important one is that the mass customized products usually consume time and cost money more than the standard manufacturing forms.

In order to optimize the manufacturing lines inside the manufacturing floor, it is required to minimize the time and the cost of producing mass customized products which is the objective of this paper. The objective is not only the optimization of selecting the suitable manufacturing operations, but also the selection of proper or suitable supplier that help in minimizing time and cost. One of the AI methods for reaching this objective is genetic algorithms (GA). This includes formulating the supplying and manufacturing of mass customization processes as an optimization problem, in addition to applying two optimization strategies, single objective time and cost separately, and multi-objective time and cost together.

The core motivation behind our proposed model is to apply genetic algorithms for the optimization of supply and manufacturing processes for mass-customized products. After constructing the model and implementing genetic algorithms, we observed substantial improvements, including a 20% reduction in time, a 30% reduction in cost, and a 25% reduction in both time and cost when compared to estimations provided by experts and consultants. This paper is structured into six sections. Section II provides an overview of existing research in the domains of supply chains and mass customization optimization from diverse viewpoints. Section III is the proposed model, followed by a discussion of Genetic Algorithms will be illustrated in the Section IV. Section V encompasses the discussion of results. The conclusions are detailed in the Section VI, and the presentation of future research directions in Section VII.

II. Related Work

Mass customization entails a highly complex supply chain with distinct features that can be classified into two key branches. The first branch encompasses the intricate relationship between the random information provided by clients' orders and the supply chain partners. This connection often gives rise to numerous scheduling conflicts and introduces dynamic or random elements into the process. The second aspect revolves around the collaborative benefits and the inherent risks within this intricate environment [7]. Therefore, this paper aims to investigate how to effectively manage these characteristics, analyze the advantages and risks associated with collaboration in mass customization, and present previous research on supply chain optimization, mass customization manufacturing and the application of GA either in supply chain or mass customization optimization in next three separate sections.

A. Supply Chain Optimization

The escalating global population and the increased demand for food, especially in aquaculture [8], have led to a surge in research focusing on the food supply chain. One notable study in this domain presented an innovative bi-objective and multi-period mathematical model for a closed-loop supply chain (CLSC) specifically tailored to the fish industry. The model is designed by using the multi-objective Keshtel algorithm (MOKA), NSGA-II, and MOSA. In addition, the Taguchi method is applied to harmonize these meta-heuristics to reach higher performance, and the ε-constraint method is used to solve small-sized problems to validate them. The results showed that the exact method cannot solve large-sized problems. The solutions are compared in terms of different performance metrics. Also, a case study with a trout CLSC in the north of Iran is investigated. The results and the case study showed that the implemented model can be applied to the suggested solution approach. The focal point of the food supply chain model mentioned is to enhance the chain's performance, prioritizing improvements regardless of time or cost implications.

A supply chain optimization problem could decide where to locate and relocate mobile and modular production units to convert biomass waste to energy [9]. Both deterministic and two-stage stochastic designs were introduced, accounting for the inherent uncertainty of how much and where biomass is produced. The framework was applied to case studies analyzing the states of Minnesota and North Carolina. Results from both states were that mobile production modules lead to reduce supply chain cost around 1–4%, or millions of dollars per year. Furthermore, this framework shows the benefit of mobile modules as a means of protection against uncertainty. Authors in that model directed their contribution to save cost by choosing the best location of the production units regardless the time.

A blood supply chain network (BSCN) [10] was formulated to minimize the total cost of the supply chain system for demand and transportation costs. The network stages considered for modeling was containing of blood donation clusters, major laboratory centers, permanent and temporary blood transfusion centers, and blood supply hubs. Other goals included determining the optimal number and location of potential facilities, optimal allocation of the flow of goods between the selected facilities and determining the most suitable transport route to distribute the goods to customer areas in uncertainty conditions. Given that the model was implemented by using NP-hard, the MFGO algorithm to solve the model with a priority-based solution. The results of the experiments' design showed the higher efficiency of the MFGO algorithm than the PSO algorithm in obtaining efficient solutions. Also, the mean of the objective function in robust approach was more than the one in the deterministic approach, while the standard deviation of the first objective function in the robust approach was less than the one in the deterministic approach at all levels of the uncertainty factor. In BSCN model time was not a factor in optimization process.

A location-inventory optimization model for supply chain (SC) configuration was presented in [11]. It included a supplier, several distribution centers (DCs), and several retailers. Customer demand and replenishment lead time were considered to be stochastic. Two classes of customer orders, priority and ordinary, were assumed based on their demand. The goal was to find the optimal locations for DCs and their inventory policy simultaneously. For this purpose, a two-phase approach based on queuing theory and stochastic optimization was developed. In the first phase, the stock level of DCs was modeled as a Markov chain process and is analyzed, while in the second phase, a mathematical program was used to determine the optimal number and locations of DCs, the assignment of retailers to DCs, and the order quantity and safety stock level at DCs. As solving this problem was NP-hard, a hybrid Genetic Algorithm (GA) was developed to make the problem computationally tractable. In location-inventory optimization model, the time and destination were considered to be factors in optimization process which were two dependable factors regardless the cost of the destination.

In time of pandemic (COVID 19), a novel multi-objective optimization model for the vehicle routing problem from suppliers of raw material to manufacturer were introduced within the realm of a factory-is-a-box framework [12]. The key objective is the minimization of both the cumulative cost incurred while traversing network edges and the total cost accrued by visiting network nodes. This solution approach incorporates a specialized multi-objective hybrid metaheuristic algorithm that explicitly incorporates problem-specific characteristics. This model's primary objective was to optimize vehicle routing for raw material delivery to the manufacturer. In contrast, our proposed model is dedicated to optimizing the entire supply chain for raw materials and the manufacturing process, particularly for mass customization products.

B. Mass Customization Optimization

This section presents some authors who handled the manufacturing and mass customization manufacturing optimization. For optimizing manufacturing problems, a literature review was done to focus on reconfigurable manufacturing systems (RMS) optimization. This literature was classified in two scenarios. The first scenario, different optimization problems uprising in RMS were introduced and discussed. The second classification scenario presented solution approaches used to solve these problems. This work was intended to help scientists identify potential research areas in the domain of optimization for RMS. This literature showed the optimization process for reconfigurable manufacturing systems using different techniques such as mathematical programming (MP) models [13, 14], dynamic programming [15, 16], meta-heuristics [17] and heuristics [18]. RMS optimization concerned of maximizing the profit or quality or minimizing the cost regardless the time which is considering in our research. On the other hand, Mass Customization Manufacturing (MCM), existing research fingered to optimization.

A research was pointed to the fourth industrial revolution and the digital transformation of consumer marketplaces and its need in manufacturers to reshape their business models to deal with the continuous changing in customer needs and market fluctuations [19]. Currently, manufacturers are tending toward product variation strategies and more customer oriented methods to keep the competitive advantage in the Industry 4.0 environment, and mass customization is among the most famous implemented business models. Under such circumstances, an economical material supply to assembly lines has become a significant concern for manufacturers. Consequently, the proposed study concerned about optimizing the material supply to mixed-model assembly lines that contributed to the overall production cost efficiency, mainly by decreasing both the material holding and material transportation costs across production lines, while satisfying certain constraints. Given the complexity of the problem, a new two-stage heuristic algorithm is applied in such study to enable a cost-efficient delivery. To evaluate the efficiency and effectiveness of the proposed heuristic algorithm, a set of test problems were solved and compared versus the best solution found by a commercial expert. The results of the comparison reveal that the proposed heuristic offered reasonable solutions, thus presenting huge opportunities for production cost efficiency and manufacturing sustainability under the mass customization viewpoint. As seen, that research focused on minimizing the cost only without putting the factor of time into consideration.

The current global unpredictable market is characterized by increasing demand for highly customized products [20]. To thrive in this scenario, it becomes necessary to establish a closer interaction between product and manufacturing system, keeping the main focus on the customer. This paper presented a Modular Product Design (MPD) as a best strategy to produce a large product variety. MPD's configuration stage represented a key step for mass customization because it allows customers to be integrated into the value-creation process. Reconfigurable Manufacturing Systems (RMS) appear to be the most suitable manufacturing system to manufacture mass customized products due to their ability to be quickly reconfigured, adjusting their production capacity and functionality to fit new market demands. Pointing to integrate single customer needs with the decisions taken for the product and manufacturing process, this paper suggested a new 0-1 nonlinear integer programming model to optimize the configuration of modular products and RMS, driven by individual customer requests. A genetic algorithm based approach was proposed to solve this model, and its parameters were tuned with a two-full factorial design. A case study of customizable office chairs was used to illustrate the proposition, and several scenarios of customer requirements and RMS configurations were presented. Results showed that varying initial machines' configurations could highly affect the process plan and the total manufacturing costs; but, there was no confirmation that changes in initial design of configurations caused weighty effects. In summary, this work confirmed the relevance of integrating modular product and RMS configuration decisions for decreasing costs of producing mass-customized products. In RMS model, time was not considered in the optimization process.

A distributed approach for smart production management in a cellular manufacturing system was presented for offering mass-customized products [21]. This approach was based on three decision stages: factory-stage (master planning module), shop floor stage (bidding system) dealing with unexpected actions, and cell stage. The approach integrated planning, scheduling, and material handling allocation while considering real-time data from the supply chain. A mathematical model for factory-stage planning was proposed with two sequence-based resolution approaches implemented on two meta-heuristics, NSGAII and SMPSO.

C. Genetic Algorithm with Supply Chain Management and Mass Customization Manufacturing

A literature review of the application of GA on supply chain management (SCM) was published [22]. It consists of several complex processes and each process is equally important to maintain a successful supply chain. The literature review contained the eight processes of supply chain as given by Council of SCM Professionals. This literature review illustrated that there are no contributions of applying bi-objective function of minimizing the time and cost together which we focused on in our proposed model.

On the other hand, some models were designed to solve the problem of optimization of manufacturing sector [23].

However, very few models that concerned about mass customized manufacturing. Moreover, a few numbers of these models were implemented using genetic algorithm and no models were implemented using bi-objective function of minimizing time and cost in such sector [24, 25].

It was proven regarding the related work section that there were infrequently highlighted points in the optimization process in supply chain management, mass customization manufacturing and using genetic algorithm in these two fields. The following section will discuss the proposed model which takes into consideration what was neglected previously in the related work.

III. The Proposed Model

This research focuses on creating a model that integrates cost and time considerations in the optimization of mass customization. It emphasizes the collaboration between suppliers and manufacturers involved in the supply chains for mass customized products. The primary goal is to identify the most effective combinations of these entities to achieve desired objectives. To accomplish this, the study suggests the utilization of evolutionary algorithms, which are ideal for generating suitable combinations and yielding favorable results.

The suggested solution is based on using the evolutionary algorithms especially genetic algorithms to optimize the best scenario of selecting the best supplier, best operation type (either manual or automatic) and best number of manufacturing lines in order to minimize time, cost or both in a mass customized order. The definition of the mathematical formulation of the objective functions designed to obtain the optimal solution or scenario will be clarified in next paragraphs. Fig. 1 clarifies some abbreviations that will be used in the mathematical model of the proposed problem.

Before commencing a comprehensive explanation of our mathematical model, it's essential to recognize the importance of considering specific manufacturing rules. These rules play a critical role in clarifying the methods for calculating time and cost, and they are informed by the collective expertise of consultants. These rules are:

- Automatic Time = Manual Time/2.
- Automatic Manufacturing Cost = 1.6 * Manual Manufacturing Cost.

According to real-world manufacturing metrics, manual manufacturing consumes double the time of automated manufacturing, while the average cost of the automated process is 1.6 times that of manual manufacturing.

Generally, the mathematical formulation for the optimization process is being built according to an objective function and constrains that controls this function. Here, the suggested solution was divided into three choices according to the order demander priority. The customer may need to minimize the time only, cost only, or both of them. Table I illustrates the objective functions and the constraints of each priority. Within the context of the cost objective function, we come across TotSC, or total supply cost, which is subject to the influence of numerous variables such as supplier selection, category, color, and operation type. These factors are collectively evaluated to ascertain the overall cost. In the following three paragraphs, we will illustrate the three objective functions specified in Table I, encompassing a breakdown of their individual terms.

MLQ_n = Manufacturing Line Quantity for n (n: 1, 2, 3,..etc.)
MLT = Manufacturing Lead Time.
ML= Manufacturing Line.
SLT= Supplying Lead Time.
TotLT: Total Lead Time.
TotSC: Total Supplying Cost
TotMC: Total Manufacturing Cost
TotC: Total Cost.
SCO: Supplying Cost Order
TQ: Total Quantity
Op: Operation Type

Fig. 1. Abbreviations.

TABLE I. Objective Functions and Constraints

Priority	Objective Function	Subject to
Time	Min (Y) = $\sum MLT + SLT$	$1 \leq Order \leq 3$ $1000 \leq TQ \leq 6000$ $0 \leq Op \leq 1$ $1 \leq Supplier \leq 2$
Cost	Min (Y) = $\sum TotSC + TotMC + Overhead$	$1 \leq Order \leq 3$ $1000 \leq TQ \leq 6000$ $0 \leq Op \leq 1$ $1 \leq Color \leq 12$ $1 \leq Size \leq 2$ $1 \leq Supplier \leq 2$
Time and Cost	Min (Y) = 0.5($\sum (TotSC + TotMC + Overhead)$) + 0.5($\sum(MLT + SLT)$)	$1 \leq Order \leq 3$ $1000 \leq TQ \leq 6000$ $0 \leq Op \leq 1$ $1 \leq Color \leq 12$ $1 \leq Size \leq 2$ $1 \leq Supplier \leq 2$

When discussing the Time objective function, MLT, representing manufacturing lead time covering all phases of the manufacturing process (including assembly, painting, and packaging) is a key factor. Notably, manufacturing lines employing automatic processes outperform their manual counterparts in terms of time efficiency. In our model where the priority is for minimizing the time only, the quantity is distributed equally over the four manufacturing lines, so the time consumed is equal to any of manufacturing line. Furthermore, SLT, denoting supplying lead time, relates to the time required to deliver the components from two distinct suppliers, with Supplier A exhibiting superior delivery speed compared to Supplier B. In our model Supplier A takes half time of Supplier B. So, the total time will be MLT+SLT.

Within the context of the cost objective function, we come across TotSC, or total supply cost, which is subject to the influence of numerous variables such as supplier selection, category, color, and operation type. These factors are collectively evaluated to ascertain the overall cost.Conversely, TotMC, denoting total manufacturing cost, is predominantly governed by the choice between manual and automatic operation modes distributed over manufacturing lines, with manual operations being the more cost-efficient alterna additionally, there exists an overhead factor, representing a fixed monetary addition to the unit cost, covering various expenses like utilities (electricity, water, maintenance), and labor.

The third objective function can be regarded as a consolidation of the two objective functions discussed above. Nonetheless, in any multi-objective function, it is crucial to assign weights to individual terms during the optimization process. In this scenario, we have opted for an equal allocation of 50% weight to both time and cost, signifying their equal importance. Under these conditions, the quantity is allocated among the four manufacturing lines as detailed below:

- ML1 = Automatic = 2/5 from the Total Quantity.
- ML2= Manual = 1/5 from the Total Quantity.
- ML3= Manual = 1/5 from the Total Quantity.
- ML4= Manual = 1/5 from the Total Quantity.

This division into fifths is based on the principle that the automatic line processes double the quantity of the manual line within the same time interval.

Now that we have clarified the terms associated with each objective function in Table I, it's time to provide a comprehensive explanation of our model.

The suggested model consists of three scenarios of mass customization optimization process. The model depends on entering five inputs which are quantity, color, category, size, sub-size, and priority. The priority input is the key of which objective function will be executed.

Fig. 2 illustrates the inputs, GA processing and the output of these scenarios.

The suggested model has five inputs:

- Color: Black, Silver, White, Red, Blue, Green, Red, Brown, Pink, Purple, Golden, or Yellow.
- Category: Mountain, Tour, Road, or Folded bikes.
- Size: Child or Adult.
- Sub – Size: Small, Medium, or Large.
- Priority: Time only, Cost only, or Both.

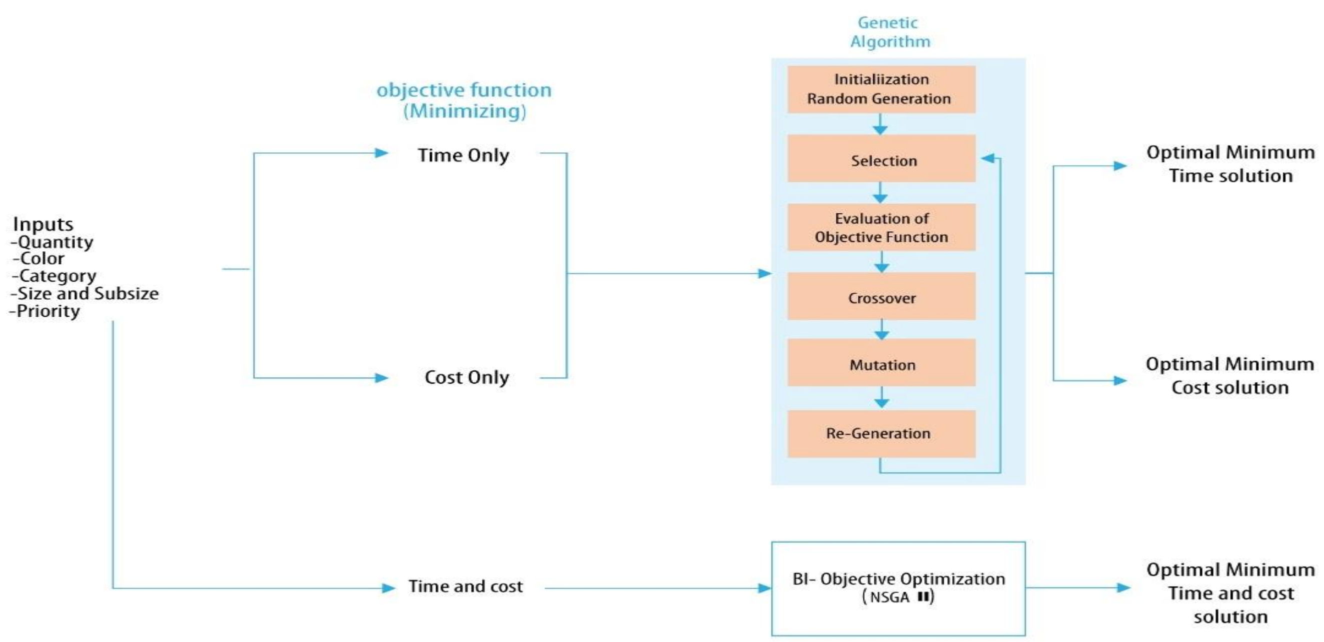


Fig. 2. The suggested optimization model.

The customer requests his/her order by determining the above inputs. However, the values of each input are limited which is considered as constrains in genetic algorithm point of view. These constraints (see Table I) are:

- Quantity : $1000 \leq TQ \leq 6000$
- Color: $1 \leq$ Color ≤ 12
- Category: $1 \leq$ Category ≤ 4
- Size: $1 \leq$ Size ≤ 2
- Sub-Size: $1 \leq$ Sub-Size ≤ 3
- Priority: Time, Cost, or Both.

From manufacturer side, there three values must be clarified which are the operation type, number of manufacturing lines and which supplier will supply the material. These values are:

- Operation Type (Op): Manual or Automatic.
- Supplier: A or B

The customer may request up to 3 different orders per one request. In addition, there are three constrains for optimization process but from the manufacturer side which are:

- Operation Type : $1 \leq Op \leq 2$
- ML=4
- Supplier = $1 \leq$ Supplier ≤ 2

The customer requests will be optimized using genetic algorithm to find the optimal solution of minimized time, cost or both of them. The proposed model is using two techniques of GA. For time only and cost only, single objective optimization technique is being used, while for both time and cost bi-objective optimization techniques is being implemented. Next section will explain the genetic algorithm and how the proposed model is being implemented by it.

IV. Genetic Algorithm

In recent times, meta-heuristic algorithms have gained significant popularity for addressing complex real-world challenges across various domains including engineering, manufacturing, economics, healthcare, and politics. Among these algorithms, the genetic algorithm (GA) stands out as a widely recognized approach, drawing inspiration from the process of biological evolution. Meta-heuristics can be categorized into two groups: single-solution based and population-based meta-heuristics [24]. GA falls into the category of population-based meta-heuristic algorithms.

The new populations are produced by iterative procedure of genetic operators on individuals existing in the population. The chromosome structure, selection, crossover, mutation, and evaluation of objective function computation are the basic elements of GA [24]. The GA chromosome representation and GA operators (Selection, Crossover and Mutation) will be explained and how GA was applied on the proposed solution.

A. Chromosome Representation

Genetic Algorithm draws inspiration from the evolutionary process, selecting elite solutions (chromosomes) for optimal outcomes in the search space. Chromosome in GA represents a solution and it is also called individual. Each chromosome consists of many genes according to the solution parameter.

The chromosome of our proposed solution consists of five genes. Fig. 3 represents the chromosome which represents the form of solution that the manufacturer will execute. First gene describes the supplier group that suits to the objective function. Rest of genes is the manufacturing lines (MLi) and if it will operate automatically or manually according to the objective function as well.

Supplier Group	**ML1 (A/M)**	**ML2 (A/M)**	**ML3 (A/M)**	**ML4 (A/M)**

Fig. 3. The chromosome representation.

In the first gene of the Supplier Group, there are two categories. The first category is associated with higher expenses but faster raw material deliveries; whereas the second category offers cost savings but slower material delivery. The subsequent genes in the sequence represent the manufacturer's internal manufacturing lines. When these lines operate manually, manufacturing time increases but cost decreases.

Conversely, automatic operation reduces manufacturing time but increases cost. Within genetic algorithms, there are two terms called "genotype" and "phenotype" which signify the relationship between the proposed genetic chromosomes and their actual chromosomes post-processing. In the realms of artificial intelligence optimization and computer science, these two terms are fundamentally interchangeable. Hence, there is no inherent difference, eliminating the necessity to define a distinct ratio between them.

B. Selection Process

Selection is a first feature to go forward of finding the nearest solution, which commonly services Evolutionary Computation (EC) [26]. In general, there are many selection techniques in GA, such as roulette wheel, tournament, rank, Boltzmann, and stochastic universal sampling [24]. The most usable technique and it is used in the proposed solution is roulette wheel selection (RWS). It works on selecting specific solutions that will share in forming the next generation. It gives each solution or individual of the recent generation the probability to be selected in the next generation according to its proportionality to the objective function value [27].

C. Crossover

It is one the GA operators that is done between two chromosomes called parents by choosing randomly either single point or multiple points to swap what beyond these chosen point(s) [28]. The result of the crossover process is new modified chromosomes called off-springs. Fig. 4 describes the implementation of crossover types in the suggested solution. It describes a single crossover implementation and a multi crossover implementation in the proposed solution.

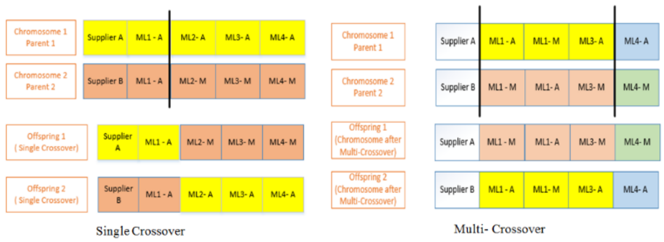


Fig. 4. Crossover operator single crossover, multi crossover.

D. Mutation

Mutation is another operator that keeps the genetic variety and diversity from one population to the succeeding population [29]. It is performed by choosing at least one or more genes randomly and changing their values. The value of the objective function is then recalculated. Fig. 5 gives an example of mutation process by choosing a random gene and changing its value according to the proposed solution.

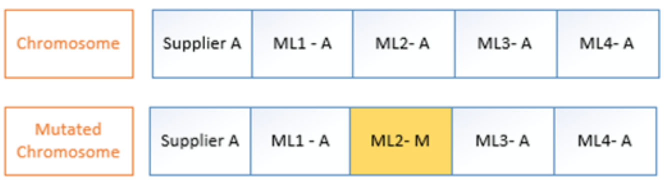


Fig. 5. Applying mutation operator

The steps of implementing the GA can be clarified through the pseudo-code as shown in Fig. 6.

Parameter(s): C- set of Chromosomes

Output: super-offspring of set C

Initialization:
$t \leftarrow 0$
Initialize I_t *to random individuals from* C^*
Evaluate the solution objective value
while *stop criterion not met*
Do
  Select individuals from I_t
  Crossover individuals
  Mutate individuals
  Re- Evaluate the solution objective value
  $I_{t+1} \leftarrow$ *new created individuals*
  $t \leftarrow t + 1$
End Do
return (*super-offspring derived from best individual in* I_t)

Fig. 6. Genetic algorithm pseudocode.

V. Discussion and Results

To the best of our knowledge, this is the first study to solve the problem through applying the optimization methodology; moreover, the problem was formulated mathematically according to the real manufacturing case, and according to the consultants inside the manufacturer and experts in mass customization manufacturing field. So, they are our reference and benchmark in our proposed study. In a practical case study focused on a mass customization bicycle manufacturer, the proposed model was put into action. Customers had the option to place orders for bicycles in diverse categories, sizes, and colors, as previously mentioned. Moreover, they were able to order bicycles in large quantities.

The objective is to optimize the combination of supplying and manufacturing processes from the manufacturer to execute the orders in minimum time, minimum cost or both to achieve the customer goal. The three mathematical models and GA were implemented using MATLAB [30]. Two of these mathematical models used the single objective GA.

However, the third model was implemented using NSGAII technique [31] to solve the multi-objective optimization problem. Table II illustrates the values of each parameter used in GA implementation. Each genetic algorithm code asks for assigning values of 4 main parameters. These parameters are population size [24], number of generations, crossover rate and mutation rate.

Each objective function is tested on three different quantities 2000, 3500 and 5500 bicycles with different categories, colors, sizes and sub-sizes. Table III illustrates the enhancement of solutions in form of enhancement of GA generations.

The results in Table III shows the modifications of solutions for time only and cost only columns versus the number of generations. While the last column shows the modifications of time and cost together over the number generations using NSGAII technique. In bi-objective function mode, time is being represented in Y-axis and cost is in X-axis. In Table III, the graphs in each row determine the values of the most optimum time, cost or time and cost with every round of generation (100 rounds) until reaching the minimum optimum solution.

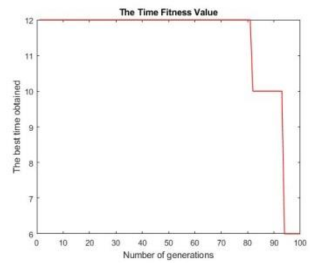
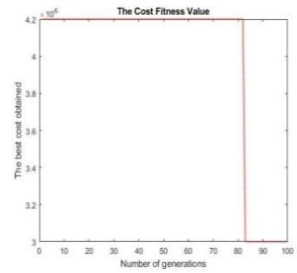
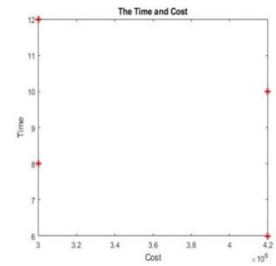
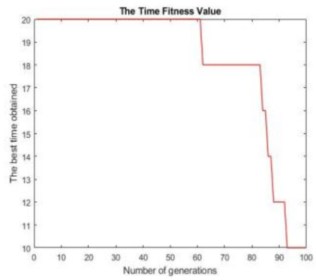
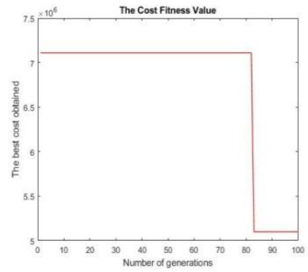
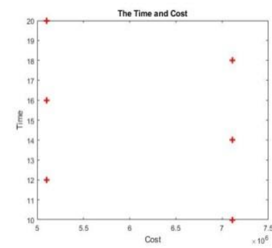
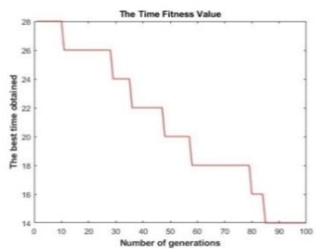
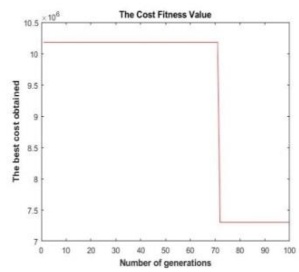
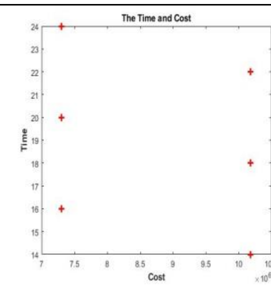
When examining the time column graphs, it becomes evident that values are progressively minimized with each generation. Conversely, the cost column experiences abrupt reductions, primarily because cost is subject to fixed prices determined by various factors, leading to the characteristic sharp curve.

After the observation of 100 solutions per each iteration, eight forms of solutions were noticed but different objective function values. Fig. 7 presents these forms of these solutions (chromosomes that mentioned in Fig. 3).

TABLE II. GA Parameter Setting

Parameter	Value
Population Size	100
Number of Generation	100
Crossover Rate	0.85
Mutation Rate	0.01

TABLE III. ENHANCEMENT OF GA GENERATIONS FOR THREE DIFFERENT CASES

Quantity	Time	Cost	Time and Cost
2000			
3500			
5500			

Solution 1	Supplier A	ML1 - A	ML1- A	ML3- A	ML4- A
Solution 2	Supplier B	ML1 - A	ML1- A	ML3- A	ML4- A
Solution 3	Supplier A	ML1 - A	ML1- A	ML3- A	ML4- M
Solution 4	Supplier B	ML1 - A	ML1- A	ML3- A	ML4- M
Solution 5	Supplier A	ML1 - A	ML1- A	ML3- M	ML4- M
Solution 6	Supplier B	ML1 - A	ML1- A	ML3- M	ML4- M
Solution 7	Supplier A	ML1 - M	ML1- M	ML3- M	ML4- M
Solution 8	Supplier B	ML1 - M	ML1- M	ML3- M	ML4- M

Fig. 7. Forms of solutions.

The evaluation of the results involved consulting production management experts in the bicycle manufacturing industry. Their estimations, obtained using traditional computation techniques, were compared with the outcomes generated by GA and NSGAII, as shown in Table IV. The table presents numerical data for three different cases, each involving different quantities. The evaluation considered time, cost, and a combination of both for each quantity. The results section of the table includes the expert estimation, GA results, and the percentage improvement achieved by our proposed models over the expert estimation. The findings clearly indicate that treating time and cost as a multi-objective functions leads to optimal results. Additionally, it was observed that higher quantities ordered corresponded to greater enhancements achieved through GA.

The expert estimations documented in Table IV are cited in order to facilitate a comparison between our GA-generated results and the authentic data stored within the database of a prominent bicycle manufacturer.

Table V illustrates the average of enhancement percentage of GA and NSGAII versus the experts estimates.

TABLE IV. SAMPLE OF NUMERIC RESULTS

Solution Forms	Time (Week)			Cost ($x10^6$)			Time (Week) and Cost ($x10^6$)					
	Expert Estimation	GA Result	%	Expert Estimation	GA Result	%	Expert Estimation		NSGAII Result		%	
							Time	Cost	Time	Cost	Time	Cost
	Quantity : 2000 Bicycles											
Solution 1	**8**	**6**	**25**	**6.3**	**4.2**	**33.3**	**8**	**6.3**	**6**	**4.2**	**25**	**33.3**
Solution 2	**10**	**6**	**40**	**5.9**	**3**	**49.1**	**10**	**5.9**	**8**	**3**	**20**	**49.1**
Solution 3	**9**	**6**	**33.3**	**5.5**	**4.2**	**23.6**	**9**	**5.5**	**6**	**4.2**	**33.3**	**23.6**
Solution 4	**11**	**10**	**9.1**	**5.1**	**3**	**41.2**	**11**	**5.1**	**8**	**3**	**27.3**	**41.2**
Solution 5	**10**	**10**	**0**	**4.7**	**4.2**	**10.6**	**10**	**4.7**	**10**	**4.2**	**0**	**10.6**
Solution 6	**12**	**10**	**16.6**	**4.4**	**3**	**31.8**	**12**	**4.4**	**12**	**3**	**0**	**31.2**
Solution 7	**11**	**10**	**9.1**	**4.3**	**4.2**	**2.4**	**11**	**4.3**	**10**	**4.2**	**9.1**	**2.3**
Solution 8	**13**	**12**	**7.7**	**3.5**	**3**	**14.3**	**13**	**3.5**	**12**	**3**	**7.7**	**14.3**
Quantity : 3500 Bicycles												
Solution 1	**14**	**10**	**28.5**	**11.5**	**7.11**	**38.2**	**14**	**11.5**	**10**	**7.1**	**28.6**	**38.3**
Solution 2	**16**	**12**	**25**	**10.0**	**5.1**	**49**	**16**	**10.0**	**12**	**7.1**	**25**	**29**
Solution 3	**16**	**12**	**25**	**9.8**	**7.11**	**27.4**	**16**	**9.8**	**12**	**5.1**	**25**	**48**
Solution 4	**18**	**14**	**22.2**	**9.2**	**5.1**	**44.5**	**18**	**9.2**	**14**	**5.1**	**22.2**	**44.6**
Solution 5	**20**	**16**	**20**	**8.6**	**7.11**	**17.3**	**20**	**8.6**	**14**	**7.1**	**30**	**17.4**
Solution 6	**20**	**18**	**10**	**7.8**	**5.1**	**34.6**	**20**	**7.8**	**16**	**7.1**	**20**	**9**
Solution 7	**22**	**18**	**18.2**	**7.2**	**7.11**	**1.4**	**22**	**7.2**	**18**	**5.1**	**18.2**	**29.2**
Solution 8	**24**	**20**	**16.6**	**5.6**	**5.1**	**9**	**24**	**5.6**	**20**	**5.1**	**16.7**	**8.9**
Quantity : 5500 Bicycles												
Solution 1	**20**	**14**	**30**	**17.5**	**10.1**	**42.3**	**20**	**17.5**	**14**	**10.2**	**30**	**41.7**
Solution 2	**22**	**16**	**27.2**	**16.3**	**7.3**	**55.2**	**22**	**16.3**	**16**	**7.3**	**27.3**	**55.2**
Solution 3	**24**	**18**	**25**	**15.5**	**10.2**	**34.2**	**24**	**15.5**	**18**	**10.2**	**25**	**34.2**
Solution 4	**26**	**20**	**23.1**	**14.3**	**7.2**	**49.6**	**26**	**14.3**	**20**	**7.3**	**23.1**	**49**
Solution 5	**28**	**22**	**21.4**	**13.5**	**10.3**	**23.7**	**28**	**13.5**	**22**	**10.2**	**21.4**	**24.4**
Solution 6	**30**	**24**	**20**	**12.3**	**7.2**	**41.5**	**30**	**12.3**	**24**	**7.3**	**20**	**40.7**
Solution 7	**32**	**26**	**18.8**	**11.5**	**10.3**	**10.4**	**32**	**11.5**	**24**	**10.2**	**25**	**11.3**
Solution 8	**34**	**28**	**17.6**	**10.5**	**7.2**	**31.4**	**34**	**10.5**	**24**	**7.3**	**29.4**	**30.5**

TABLE V. GA AND NSGAII AVERAGE OF REFINEMENT PERCENTAGE

Quantity	2000	3500	5500	Total Average
Time	17.6%	20.7%	22.9%	20.4
Cost	25.8%	27.7%	36.03%	29.8
Time and Cost	20.5%	25.6%	30.5%	25.5

VI. CONCLUSION

In this paper, a genetic-based approach was introduced for the supply and manufacturing of mass customization products. The approach integrated the supply and manufacturing phases to achieve the best possible solution with minimal time and cost.

The study presented two techniques utilizing Genetic Algorithms: one for solving single objectives of time and cost, and another for optimizing both objectives simultaneously using the multi-objective NSGAII.

Experimental results, including numerical and graphical analyses, demonstrated the significant improvements of the proposed approach compared to traditional factory methods. On average, the proposed model enhances time optimization by 20.4%, cost optimization by 29.8%, and both time and cost optimization by 25.5%.

VII. FUTURE WORKS

Optimization constitutes a vast and dynamically evolving field that accommodates numerous artificial intelligence technologies. In the context of our planning model, we have the flexibility to refine and tailor it further by adopting novel hybrid heuristics and metaheuristic search techniques, including adaptive algorithms, self-adaptive algorithms, or combinations of existing methods. Moreover, our future work includes exploring the potential of applying machine learning as an optimizer within our model. On a parallel front, the domain of supply chain optimization offers a rich landscape for exploration. We aim to extend the horizons of optimization by considering the comprehensive optimization of the entire supply chain network, employing new evolutionary algorithms, machine learning, and deep learning approaches.

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