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A two-stage stochastic supply chain scheduling problem with production in cellular manufacturing environment: A case study

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Abstract. An integrated decision in supply chain is a significant principle for proper competition in today's market. This paper proposes a novel mathematical model in a two-stage supply chain scheduling to make a coordination between procurement and manufacturing activities. The supply chain scheduling along with the production approach of cellular manufacturing under demand, processing time, and transportation time uncertainties makes business environment sustainably responsive to the changing needs of customers. Uncertainties are formulated by queuing theory. In this paper, a new mixed-integer nonlinear programming formulation is used to determine types of vehicles to carry raw materials, suppliers to procure, priority of each part in order to process, and cell formation to configure work centers. The goal is to minimize total tardiness. A linearization method is used to ease tractability of the model. A genetic algorithm is developed due to the NP-hard nature of the problem. The parameters of the genetic algorithm are set and estimated by Taguchi's experimental design. Numerous test problems are employed to validate the effectiveness of the modeling and the efficiency of solution approaches. Finally, a real case study and a sensitivity analysis are discussed to provide significant managerial insights and assess the applicability of the proposed model.

1. Introduction

Nowadays, the intensifying pressure of competition in the market has forced manufacturers to pay attention to all steps, from raw materials to finished products. Managing the material flow from supplier to customer as a unified system rather than a sequence of independent actions is the fundamental philosophy behind the supply chain management [1]. The purpose is connecting procurement activities, distribution network, and marketplace to manufacturing process in terms of making a unified decision. Therefore, customers are serviced at the upper level and lower cost and manufacturers are getting competitive advantage through both cost reduction and product augmentation [2,3]. Supply chain scheduling is looking for coordination between different parts of a supply chain. The collaboration among procurement, production, and transportation

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plays a key role in the supply chain scheduling. Therefore, supply chain scheduling is essential to improve the efficiency and effectiveness of a supply chain. In practical terms, it is significant in industries such as automobile, electronics, and aviation owing to the fact that the production activities of these industries are decentralized [4]. This field is becoming more popular due to energy saving and reduction of fuel consumption [5]. In general, the collaboration among suppliers, shipping fleets, and manufacturer leads to customer satisfaction and it is achievable by selecting the right supplier and proper shipping fleet to cooperate along with choosing a rational production approach.

Raw materials provide one or more suppliers; therefore, manufacturers require deciding which supplier to choose. Consequently, one of the significant components of the supply chain scheduling is choosing the right supplier. Given that raw material costs constitute the main part amongst the costs of finished products, it is an important factor to gain market share amongst competitors. Based on a review of the related literature, supplier selection has received visible attention by researchers [6–11]. Thus, supplier selection is considered as one of the most important measures for manufacturers in order to preserve a strategically competitive position. This leads to procuring the right quantity of raw materials with right quality at the right time and sensible cost.

Another important component of the supply chain scheduling is selecting the right manufacturing approach. The right manufacturing approach is reactive to the changing requests and demands of customers and it tackles their challenges looking for high-quality, low-cost products. Furthermore, it will deal with fluctuating demands through a fair speed of adaptation and sufficient production of goods. Group technology has been experienced all over the world as a manufacturing system philosophy owing to its flexibility and adaptability [12]. Cellular Manufacturing (CM) is the usage of the group technology concepts for shop floor layout design and firm reconfiguration. The CM provides flexibility for producing new products while affecting the declining production lead-time [13,14]. Manufacturers have transformed traditional production configurations, such as job shop and flow shop, to new ones like CM. The CM utilizes the positive features of job shop (e.g., flexibility and variety) and flow shop (e.g., efficiency and production volume) [15,16]. Also, the CM does not enforce manufacturers to necessarily invest in capital assets like Flexible Manufacturing Systems (FMS) in order to achieve flexibility. The CM includes processing a group of similar parts on a specified set of machines or manufacturing processes [17]. The application of the CM leads to numerous important benefits, e.g., reducing material handling cost, setup time duration, work-in-process inventory, and throughput time but also improve quality and simplify scheduling [18,19]. A successful design of the CM must incorporate Cell Formation (CF) and cell management. CF as a component of the CM contains the process of categorizing the parts with similar processing necessities or design characteristics into part families and assigning machines to machine cells [20]. Each part family should make a production in a machine cell. Nevertheless, parts may be manufactured in more than one cell, in practice. Cell management relates to planning subjects such as scheduling and sequencing of operations. Scheduling involves scheduling of each part within each cell [21] and sequencing concerns the order of operations behind each machine [22].

Manufacturers must take uncertainties seriously to enhance the sustainability of their business in today's competitive market. Uncertainty management will allow manufacturers to escalate their performance efficiently and effectively [23]. Such uncertainties associated with the entire supply chain include uncertain demand, transfer time of shipping fleet, the delivery lead-time of suppliers, material handling time, operation time on machines in the factory, and so on. With regard to these uncertainties, manufacturers can be resiliently responsive about their customers.

This research aims to make an integrated decision in the entire supply chain under uncertainties by reducing total tardiness in order to enhance competitive features. To this end, the three following steps are considered concurrently. First, supplier selection is made amongst suppliers to procure raw materials based on distance and delivery lead-time, facilitating the reduction of the major costs of finished products and delay. Second, use of CM as a manufacturing approach contributes to a reduction in delay and material handling cost in advance due to its nature. In addition, improvements in the CF and cell management reduce the material handling time and the resource consumption, respectively, which in turn decreases delay. Third, this centralized decision enhances the sustainability of decision regarding demand, transfer time of shipping fleet, and processing time under uncertainty. These uncertainties make the integrated decision more realistic. Since any production plan is based on customers' demand. In most business environments, future demand is partly known in the best condition and occasionally is not clear at all [24]. Also, the transfer time of shipping fleet and processing time are uncertain because of traffic congestion, machine breakdown, and some unexpected events. Therefore, considering the mentioned uncertainties is essential to obtain a reliable solution. Overall, this integrated decision under uncertainties ensures customer goodwill owing to good quality and low price of products along with sustainability. Hence, the question concerns how to make this integrated decision including various delivery lead-times of suppliers, speeds of shipping fleets, configurations of cells, priorities of parts behind machines, and inter-cell movements of parts under uncertainties of demand, transfer time of shipping fleet, and processing time. Therefore, in compliance with the scope of this research, the literature review covers the two following areas. First, supply chain scheduling due to the coordination of suppliers, shipping fleets, and manufacturer was studied. Second, the selected manufacturing approach was reviewed to realize how researchers consider the priorities and inter-cell movements of parts along with the configurations of cells in the CM.

2. Literature review

2.1. The supply chain scheduling

Supply chain scheduling encourages decision-makers in different stages of a supply chain to make coordinated decisions and raise efficiency. It was presented for the first time by Hall and Potts [25]. They studied various scheduling problems in which one supplier delivers materials to some manufacturers and the deliverers take products to customers. The above authors minimized the objective function, i.e., the total scheduling and delivery cost, using numerous classical scheduling objectives such as a sum of completion times, maximum lateness, and number of late jobs. Owing to the applicability of this field, researchers have continued to make use of supply chain scheduling. Some of the most relevant researches are presented in the following. Selvarajah and Steiner [26] studied a two-stage supply chain in order to find the optimal job sequence, number of batches, and batch sizes to meet customer demand. They assumed the amount of delivery cost to be dependent on each delivered batch. A single supplier produces multiple products with a single machine and utilizes a setup in case of changing from one product to another. Objective function minimizes the sum of total inventory holding costs and the batch delivery costs from the viewpoint of the supplier. The scheduling problem that considers both production and job delivery simultaneously was studied by Wang and Cheng [27]. They considered machine availability, as well. Their assumption was that one vehicle would be available to deliver jobs at a fixed transportation time to a distribution center. Minimization of the arrival time for the last delivery batch to the distribution center is considered as the objective function. Production and transportation scheduling were integrated by Zegordi and Beheshti Nia [28] in a two-stage supply chain. They also assigned orders to the suppliers. The first stage contains numerous suppliers distributed in different geographic regions, while the second stage consists of vehicles with different speeds and transportation capacities that transported jobs from the supplier to a manufacturing firm. The objective function of their paper was the minimization of makespan (i.e., the maximum completion time of all jobs). A two-phase mixed integer linear programming model was presented by Yimer and Demirli [29] for a build-to-order supply chain system to optimize material procurement, components of production, assembling of products, and distribution scheduling. First, they decomposed the problem into two phases. The first phase comprised assembly and distribution scheduling of customizable products. The second phase included production and procurement planning. The objective function of the first-phase model was the total cost for the assembling of products and distribution-subsystem, and the objective function of the second-phase model was the total cost including the components of production and procurement subsystem. Zegordi et al. [30] conducted a study in the context of a two-stage supply chain environment for the scheduling of products and vehicles. The first stage of this attempt consisted of suppliers with different production speeds, while the second stage included vehicles with different speeds and transportation capacities to carry products from suppliers to a manufacturing company. Also, products have different batching sizes to occupy the capacity of a vehicle. The objective function minimized the makespan of the whole output products for all jobs. Steinrücke [31] discussed a real-life problem of a global aluminum supply chain network containing three supply chain stages. In each stage of the aluminum supply chain network, numerous members are involved that are located at various sites worldwide. The materials among supply chain stages are transferred by a global shipping firm. The production capacities and transportation capacities differ from site to site. The proposed model of the above author minimized the total costs in order to coordinate production operations with material flows within the supply chain. Production and transportation costs along with bonus payments for early deliveries to final customers are considered in the total costs. Maheut et al. [32] proposed a model for operations of lot-sizing and scheduling, which included an assignment and sequencing in the supply chain of an international company. The company produced and delivered made-to-order products through numerous distributed assembly plants geographically. The objective function minimized the sum of the storage costs, the stroke execution costs, and those costs associated with sequencing strokes. The stroke is a similar concept to the Resource-Task Networks to consider purchase, transport, and production alternatives in the supply chain. Wang et al. [33] presented an integrated scheduling problem for a single item in a make-to-order supply chain system with one supplier. Also, their supply chain system was considered to be one capacitated transporter, one customer, and a single machine in the production stage. Their nonliner model minimized the sum of setup, delivery, and inventory costs. Moreover, an intermediate inventory was assumed as a buffer to balance the production rate and the transportation speed. Ma et al. [34] investigated scheduling of production with shipping information simultaneously. Manufacturing model assumes a factory located in one place and customers are overseas. They considered a manufacturing model along with shipping. Objective function minimized the earliness and tardiness, which consisted of storage, shipment, and tardiness. Hajiaghaei-Keshteli et al. [35] formulated the coordination problem of production and rail transportation. They developed a mathematical model to deliver orders from a facility to the warehouses. The model optimized both production schedule and the rail transportation allocation of orders to available transportation capacities and also, identified the sequence and completion time of these orders. Destinations and capacities of trains differed. This model minimized the total cost including delivery earliness, delivery tardiness, and transportation. Cheng et al. [36] studied two-stage supply chain scheduling problems to optimize production and distribution of products. They assumed the processing of a batch to be non-preemptive until all jobs in the batch were finished and machine capacity was limited. The finished jobs were categorized by the manufacturer and delivered to the customer by its own vehicles. Two types of machine configuration, including single machine and parallel machines, were explored. The goal was to minimize the time of production and delivery. Pei et al. [37] concentrated on a two-stage supply chain scheduling problem in an aluminum production. The extrusion factory of the supplier and the transportation from the supplier to the manufacturer were the first stage, and the aging factory of the manufacturer was the second stage. A serial batching machine and a parallel batching machine process jobs in the first stage and the second stage, respectively. Meanwhile, only one vehicle transports jobs between two firms. The machines and vehicle have the specified capacity, and all jobs are processed as non-preemptive in each batch. Their mixed integer programming model minimizes makespan. Cheng et al. [38] considered the scheduling of production and distribution for manufacturers. Machines with a specified capacity process batches and jobs have constant sizes in the production stage. Jobs are clustered into batches and the processing of each batch cannot be stopped until all its jobs are finished. All deliveries are transferred by a third-party logistic provider and vehicles have a specified transportation capacity. The objective function minimizes the total cost of production and distribution. Pei et al. [39] discussed the preemptive scheduling problem in a two-stage supply chain. The first stage is production stage where jobs are first divided into batches and then, they are processed on a limited serial batching machine. There is a possibility for two situations to occur: (a) all jobs are available at time zero and (b) they arrive with a release time. In the second stage, i.e., customer stage, a single vehicle carries each batch to a customer. The vehicle capacity was constant and it was equal to machine capacity. Objective function is to minimize the makespan of both problems. Assarzadegan and Rasti-Barzoki [40] presented a mathematic model to study due date assignment, production scheduling, and outbound distribution scheduling, simultaneously. The model minimized the costs including maximum tardiness, due date assignment, and delivery for a single machine. Hassanzadeh and Rasti-Barzoki [41] investigated the supply chain scheduling and vehicle routing problem in order to reduce the consumption of resources and energy as well as tardiness penalty. They solved a bi-objective mathematical model to find a proper assembly sequence, assignment of orders to vehicles, and vehicle routing in order to reduce resource consumption. The first objective function is minimization of the total tardiness cost and the second one minimizes the total amount of resources. Noroozi et al. [42] studied the coordination of order acceptance, batch delivery, and transportation. Orders were accepted or rejected based on distribution cost, capacity, tardiness cost, and sales revenue of each order. Single machine produces several products scheduled in the production stage of supply chain. Then, products are batched and shipped to a respective customer by vehicles in the distribution stage. When the number of vehicles to carry products is less than required, it is important to use third-party logistics. The number of vehicles and their capacity belonging to the firm are constant in the customer stage. Objective function maximizes the difference between revenue from accepted orders and costs of tardiness and transportation. Wang et al. [43] investigated the integrated production and distribution scheduling problem and multiple-trip vehicle routing problem with time windows and uncertain travel times. They considered a processing site with parallel machines to produce a number of jobs and finished jobs are distributed by a fleet of identical vehicles, in which demand of customers remains known for each job. Jobs are assigned to the machines and the processing sequence of the jobs is determined on each machine in the production stage. Moreover, the completed jobs are assigned to the delivery vehicles and the vehicle routing is determined in the customer stage. The objective function minimizes the travel cost and penalty cost due to tardiness. Tang et al. [4] studied a multi-factory supply chain scheduling in a collaborative manufacturing mode by considering transportation and production concurrently. They took into account the urgency of various orders via a delivery time window with respect to the least production and slack time. The objective function of their mixed integer programming model minimizes the sum of inventory cost, production cost, and the penalty costs of tardiness and early completion. Aminzadegan et al. [5] presented a two-stage supply chain scheduling problem including two types of customers and one manufacturer. Providing that the tardiness penalty is paid by the manufacturer, the first customer admits tardiness in delivery of orders, while the second customer does not admit the tardy orders. Manufacturer uses one machine and at any given moment, the machine can process one order at most. Each order is processed uninterruptedly. Objective function minimizes the sum of costs consisting of resource allocation, tardiness penalty, and batch delivery for the first customer and it, also, reduces the total number of tardy orders for the second customer.

2.2. The CM

The CM has been widely studied in the literature and some of the most relevant pieces will be given as follows. Arkat et al. [44] presented two mathematical models in order to investigate the design of the CM system. First, the CF and cellular layout problems were solved simultaneously to minimize the total movement costs due to the optimized cell configuration and the layout of the machines on the shop floor. Second, the cellular scheduling problem was solved based on the found solution in the first model as a job shop scheduling problem with the objective function of minimizing the total completion time of parts. They demonstrated the impact of considering cellular scheduling on the CM system design. Pasupuleti [45] employed a methodology for detailed scheduling of all jobs in the CM systems with the given part families, the number of machines for each type of machine, and machine cells. The processing sequences of jobs, processing and setup times, and due dates were considered along with different dispatching rules, i.e., first come first serve, shortest processing time, longest processing time, earliest due date, and least slack in their methodology. The methodology allocates jobs for each type of machine in each cell along with producing detailed schedules for each job. The considered dispatching rules are evaluated in terms of different performance measures such as the makespan, mean flow time, mean lateness, and mean tardiness. Arkat et al. [46] investigated three major decisions of the CM including the CF, the layout of machines, and the scheduling of operations concurrently. They proposed a multi-objective mathematical model whose first objective function minimizes the total transportation cost of parts while the second one minimizes the makespan. Kesen and Güngör [47] discussed the job scheduling problem with lot-streaming strategy in virtual manufacturing cells. A virtual CM system includes a group of machines dedicated to the production of a part family, but machines do not have to be close to each other, i.e., they can be in different places on the shop floor physically. Each job has its own processing sequences and there is a set of machines to process any operation of each job. They developed a mixed integer linear programming formulation that considers machine assignments, starting times, and the sub-lot sizes of operations. Objective function was to minimize the makespan given that machines were distributed through the facility and traveling times between each pair of machines were taken into account. Eguia et al. [48] investigated the CF and the scheduling of part families. A mixed integer linear programming model was employed whose objective function minimized production costs. These costs are related to the reconfigurable machine tools between two sequential families and the under-utilization of machine resources while producing families. Solimanpur and Elmi [49] proposed a mixed integer linear programming model for the cell scheduling problem in order to minimize the makespan. They considered the bottleneck machines and exceptional parts as well as processed parts in multiple cells in this model, because duplicated machines reduce intercellular movements. Taouji Hassanpour et al. [50] explored the scheduling problem of jobs in virtual CM systems. Also, they assumed that there were multiple jobs with different manufacturing processing routes. Objective function minimized the sum of two weighed objectives including tardiness and total traveling distance. Saravanan and Karthikeyan [51] addressed the scheduling optimization problem of CM systems which consisted of different manufacturing cells. First, Rank Order Clustering Method was employed to identify and group into cells in order to optimize scheduling for different types of products in the job-shop environment. Second, an optimization procedure was presented for sequencing jobs to be processed in the machine cells. Objective function minimized the penalty cost when the due dates were not met. Fahmy [52] presented a mixed integer linear programming model to formulate and solve combined CF, group layout, and group scheduling decision problem to design the CM system. Their model took into account intercellular and intracellular transportation times and sequence-dependent setup time to determine the optimal CF, candidate positions for machines within cells, distances between these positions and between cells to obtain the optimal group layout, and scheduling of parts on machines, simultaneously. Objective function minimized the mean flow time. Halat and Bashirzadeh [53] studied the problem of operation scheduling by considering the sequence-dependent family setup time, exceptional elements, and intercellular transportation time in the CM systems concurrently. They proposed an integer linear programming model that considered all aspects of the problem with the objective function of minimizing the makespan. Liu and Wang [54] grouped multi-functional machines and multi-skilled workers and assigned them to cells. They presented a nonlinear integer mathematical model, which simultaneously integrated the CF and task scheduling with the dual-resource constrained setting. Objective function minimized the makespan. Egilmez et al. [55] studied the family and job sequencing problem in the CM, where family splitting amongst cells was allowed. Each job was assumed to have an individual due date and each family required a setup before jobs in that family can be processed. This creates a natural conflict between meeting due dates of jobs and reducing total setup time. Objective functions minimized the total tardiness and the number of tardy jobs in a multi-objective mathematical model. Rafiei et al. [56] investigated the CF problem and group scheduling simultaneously in the presence of sequence-dependent setups in a job shop layout. They proposed a mixed integer nonlinear program to cover issues with the objective function of minimizing the costs of operations and movement of both intercellular and intracellular paths simultaneously in a single-period setting. Liu et al. [57] investigated the CM system under a dual-resource constrained setting by considering the CF and task scheduling, concurrently. They presented a nonlinear 0-1 integer programming to minimize intercellular material handling cost, the fixed costs of machines and worker, and the operating costs of machines and workers. Also, they considered multi-functional machines, multi-skilled workers, and operation sequence. Deliktas et al. [58] proposed four nonlinear multi-objective models that dealt with a flexible job shop scheduling problem in the CM environment. They considered exceptional parts, intercellular movements and transportation times, sequence-dependent family setup time, and recirculation; a part may visit a machine or work center more than once. The objective function minimized the makespan. Feng et al. [59] discussed a dynamic cellular scheduling problem with machine sharing; a machine might belong to more than one cell and flexible routes. The makespan and the total workload were minimized by the multi-objective mathematical model. Machines were assigned different cells and the sequence of operations for each part was determined in this model simultaneously. Feng et al. [60] integrated the CF with the scheduling problem in the presence of substitute process routings, reentrant parts, duplicate machines, and variable cell number. They minimized total completion time in order to form machine groups, determine cell number, generate optimal production schedule, and choose a suitable machine for each operation. Forghani and Fatemi Ghomi [61] designed and configured a CM system integrating the CF, group layout, and cell scheduling. They configured cells considering classical and virtual cells. The classical cell configuration arranged machines within cells and located them on the shop floor. Likewise, the virtual cell configuration was employed to locate machines on the shop floor. They attempted to minimize the weighted sum of average cycle time and total handling costs in the presence of substitute processing routes.

In Table 1, a brief review of the relevant pieces in the literature in comparison with this research is presented. The type of supply chain stage, the scheduled component of supply chain, the uncertain component of supply chain, objective function, and solution method are determined in each research. To the best of authors' knowledge, a two-stage supply chain scheduling along with the CM in the production stage under uncertainties formulated by queuing theory has not been presented in the literature. In this paper, significant aspects of supply chain scheduling along with the CM are considered to minimize total tardiness. In order to formulate this integrated decision, a mathematical model is presented. The modeling approaches of supply chain management include economic, deterministic analytical, stochastic, and simulation models [62]. Moreover, uncertainty in the CM could be classified according to the three approaches: stochastic programming, fuzzy programming, and robust optimization. In this research, a stochastic supply chain scheduling along with a stochastic CM in the production stage is presented. The interval between two successive arrivals of demand, processing time on machines, and transportation time of vehicles are uncertain. Queuing theory is employed to formulate the uncertainties. Queuing theory formulates simple models by incorporating randomness and comparatively few data, while it is a powerful analytical tool [63]. Besides, a Genetic Algorithm (GA) owing to the discreteness of decision variables is used to handle the complexity of the proposed model.

According to hierarchical decisions of the supply chain, decisions are categorized into four time horizons. Their order from a longer horizon to a shorter horizon includes strategic planning, tactical planning, operational planning, and operational execution planning. When moving from the strategic planning to the operational execution planning, the horizon of decisions is shortened [64]. Moreover, this paper uses the queuing theory approach in the steady state for modeling and thus, the decision horizon is longer than operational planning. Then, the horizon of the decision in this research is tactical planning. The main contributions of this paper are as follows:

- The problem considers the CF problem, cellular scheduling problem, transportation between the

Table 1. The summary of literature and comparison with this research.

	No.	Authors	Year	Supply chain stages	Scheduled component	Uncertain component	Objective function	Solving method
Supply chain scheduling	1	Hall and Potts [25]	2003	S & M-S, M &C	S &M		1-Min TCT 2-Min $L_{\max}$ 3-Min NLJ	H
	2	Selvarajah and Steiner [26]	2006	M & C	M		Min C(INV+TTD)	H
	3	Wang and Cheng [27]	2007	M & C	M		Min $C_{\max}$	H
	4	Zegordi and Beheshyi Nia [28]	2009	S & M	M & T		Min $C_{\max}$	DGA
	5	Yimer and Demirli [29]	2010	M & W	M & T		1-Min C(OP+DC+TTD) 2-Min C(FI+OP)	GA & MM
	6	Zegordi et al. [30]	2010	S & M	T		Min $C_{\max}$	GGA
	7	Steinrücke [31]	2011	S, M & C	M & T		Min C(OP+TTD+DE)	RFH
	8	Maheut et al. [32]	2012	S,M & C	M		Min C(INV+OP+FI)	–
	9	Wang et al. [33]	2013	M, W &C	M & T		Min C(OP+TTD+INV)	–
	10	Ma et al. [34]	2013	M & W	M & T		Min C(WS+TTD+DC+TT)	TLGA
	11	Hajiaghaei-Keshteli et al. [35]	2014	M & C	M		Min C(DE+TT+TTD)	GA, SA,H & MM
	12	Cheng et al. [36]	2015	M & W	M & T		Min TI(OP+TTD)	H
	13	Pei et al. [37]	2015	S & M	S & M		Min $C_{\max}$	H
	14	Cheng et al. [38]	2015	M & C	M		Min C(OP+TTD)	H(ACO/H)
	15	Pei et al. [39]	2015	M & C	M & T		Min $C_{\max}$	H
	16	Assarzadegan and Rasti-Barzoki [40]	2016	M & C	M & T		Min C($T_{\max}$+DA+TTD)	AGA & PSA
	17	Hassanzadeh and Rasti-Barzoki [41]	2017	M & C	M & T		1-Min C(TT) 2-Min C(OP+TTD)	VNSGA-II & NSGA-II
	18	Noroozi et al. [42]	2018	M & C	M & T		Max RO-C(TT+TTD)	H(PSO/GA)
	19	Wang et al. [43]	2019	M & C	M & T	T	Min C(TTD+TT)	MA
	20	Tang et al. [4]	2019	M & C	M		Min C(INV+OP+TJ+DE)	HACO, GA, ACO & IM-ACO
	21	Aminzadegan et al. [5]	2019	M & C	M		Min C(RA+TT+BD+TNTO)	MM, AGA, ALO & H
Cellular manufacturing system	22	Arkat et al. [44]	2012	M	M		1-Min C(Intr+Inte)2-Min TCT	GA & MM
	23	Pasupuleti [45]	2012	M	M		1-Min $C_{\max}$ 2-Min M(FT) 3-Min M(LA) 4-Min M(TJ)	H
	24	Arkat et al. [46]	2012	M	M		1-Min C(Intr+Inte)2-Min $C_{\max}$	PGA
	25	Kesen and Güngör [47]	2012	M	M		Min $C_{\max}$	GA
	26	Eguia et al. [48]	2013	M	M		Min C(OP)	TS
	27	Solimanpur and Elmi [49]	2013	M	M		Min $C_{\max}$	NTS
	28	Taouji Hassanpour et al. [50]	2014	M	M		Min W(TT+Intr+Inte)	SA, GA & MM
	29	Saravanan and Karthikeyan [51]	2015	M	M		Min C(TT)	PSO & GA
	30	Fahmy [52]	2015	M	M		Min M(FT)	MM
	31	Halat and Bashirzadeh [53]	2015	M	M		Min $C_{\max}$	GA & MM
	32	Liu and Wang [54]	2016				Min $C_{\max}$	H(SA)
	33	Egilmez et al. [55]	2016	M	M		1-Min TT 2-Min NTJ	MM & GA
	34	Rafiei et al. [56]	2016	M	M		Min C(OP+ Inte+ Intr)	H(SA/GA) & MM
	35	Liu et al. [57]	2016	M	M		Min C(Inte+FI+OP)	DBFA
	36	Deliktas et al. [58]	2017	M	M		Min $C_{\max}$	MM
	37	Feng et al. [59]	2018	M	M		1- Min $C_{\max}$ 2- Min TW	TCGA, MM & GA
	38	Feng et al. [60]	2019	M	M		Min TCT	IGA & MM
	39	Forghani and Fatemi Ghomi [61]	2020	M	M		Min W (C(TTD)+M(CT))	MM, GA, SA & MA
		This research		S & M	M	T & M	Min TCT	GA & MM

**Notes: Dash (-) means two types of a problem were investigated and stages are named based on [1].
Supplier: S, Manufacturer: M, Customer: C, Transportation: T, and Warehouse or Distributer:
W Objectives are numbered in multi-objective models and independent models individually.
Functions used in the objectives are named such as The weighed function: W(),The time function: TI(),The cost function: C(), and The mean function: M(). Moreover, terms in the objectives named such as; makespan: Cmax, total workload: TW, intercellular movement: Inte, intracellular movement: Intr, fixed costs: C(FI), costs of operations: C(OP), total tardiness: TT, the number of tardy jobs: NTJ, flow time: FT, tardiness of each job: TJ, total travelling distance: TTD, mean lateness: M(LA), the total completion time: TCT, revenue of orders: RO, maximum tardiness: Tmax, Due date assignment cost per extended time: C(DA), delivery earliness cost: C(DE), warehouse storage cost: C(WS), distribution center storage cost: C(DC), inventory cost: C(INV), maximum lateness: Lmax, number of late jobs: NLJ, resource allocation cost: C(RA), batch delivery cost: C(BD), the total number of tardy orders cost: C(TNTO), cycle time: CT A hybrid algorithm is shown as H() in which algorithms are put inside parentheses. The solving methods are named such as; mathematical modeling: MM, genetic algorithm: GA, three-layer chromosome genetic algorithm: TCGA, discrete bacteria foraging algorithm: DBFA, simulated annealing: SA, Particle Swarm Optimization: PSO, Tabu search algorithm: TS, nested tabu search algorithm: NTS, proposed genetic algorithm: PGA, heuristic: H, memetic algorithm: MA, Non-dominated Sorting Genetic Algorithm II: NSGA-II, Variable Neighborhood Search based Non-dominated Sorting Genetic Algorithm II: VNSGA-II, Adaptive Genetic Algorithm: AGA, Parallel Simulated Annealing algorithm: PSA, ant colony optimization method: ACO, two-level genetic algorithm: TLGA, relax-and fix heuristics: RFH, gendered genetic algorithm: GGA, dynamic genetic algorithm: DGA, improved ant colony algorithm: IM-ACO, Ant Lion Optimization: ALO, improved genetic algorithm: IGA.

manufacturer and suppliers, and supplier selection in one mathematical model;

- Processing time of each machine, the demand of parts, and the transportation time of vehicles are uncertain;
- The cellular scheduling problem is usually investigated individually while it affects the CF as presented in the literature review. They are formulated in this research simultaneously;
- A GA is presented to tackle the complexity of the model and solve the problem within a logical time.

The rest of the article is arranged as follows: in Section 2, the statement and assumptions of the problem, the notation of the model, and the mathematical model are discussed. Linearization of the model is described in Section 3. Section 4 describes the developed solution approach. In Section 5, computational results are presented including a number of numerical results and the detailed analysis of the spare parts manufacturer for automobiles in order to examine the strength and performance of the proposed mathematical model. Finally, conclusions are discussed in Section 6.

3. Problem description

In this section, a non-liner model is presented for the supply chain with two stages. The first stage includes transportation and procurement; the vehicles with different speeds transport raw materials in transportation component of supply chain. The second component of the first stage includes suppliers with different delivery lead-times. The second stage is a factory. In the factory, machines group into cells and parts behind machines are prioritized for processing. Figure 1 illustrates the problem.

A stochastic CF problem in the production stage is described, in which the processing time of parts on machines is uncertain. The proposed model minimizes the total tardiness to form the best cells, leading to increase in the number of parts processed in intra-cell and inter-cell movements of parts.

As mentioned earlier, queuing theory is used for formulating the problem. In this paper, three steps are taken to answer a demand and queuing systems are used in each step. The first step includes the order time interval of parts by a customer to load raw materials from a supplier in the vehicle, in which the $M/M/\infty$ queuing system is used (see, Figure 2). Demand is

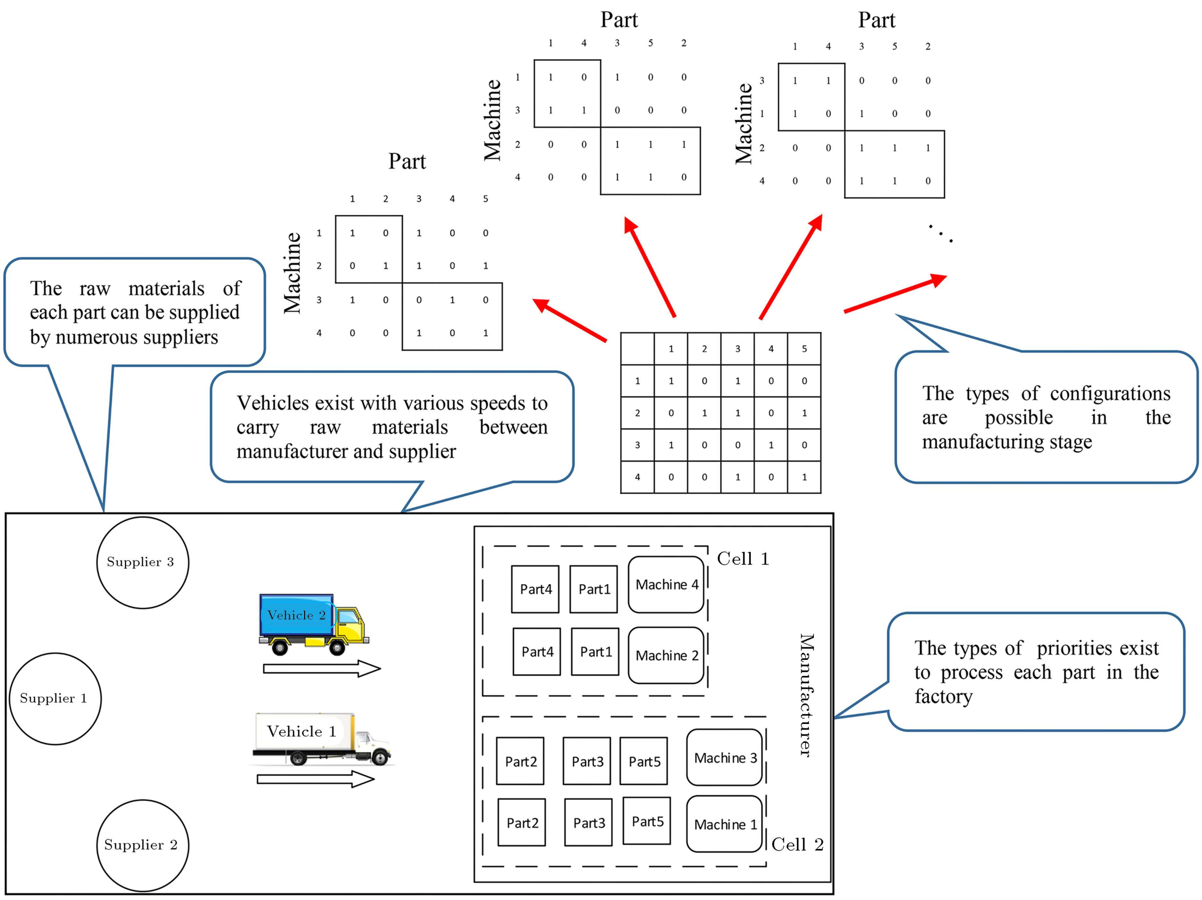

Figure 1. Illustration of the proposed problem.

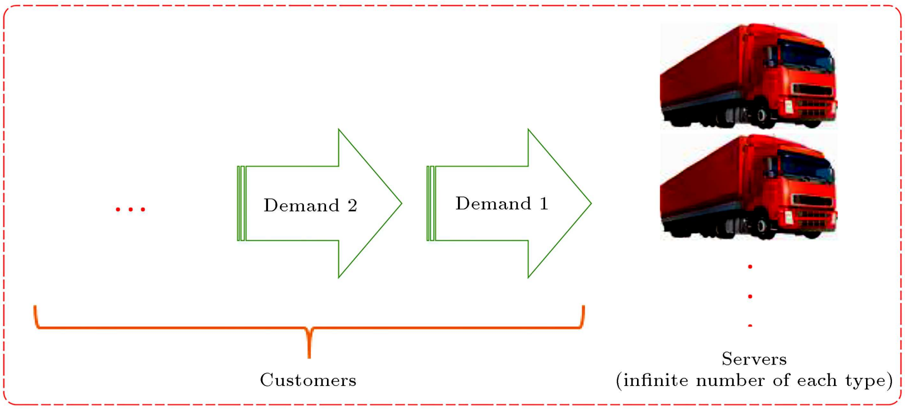

Figure 2. Queuing system for the first step.

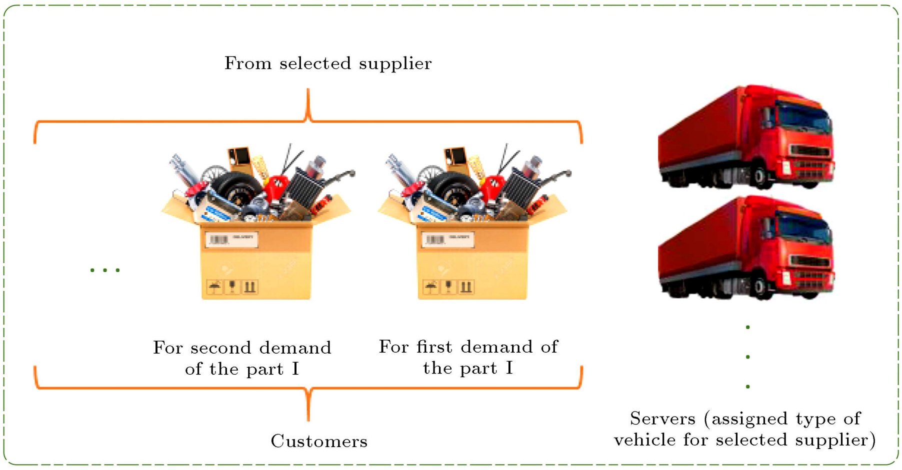

Figure 3. Queuing system for the second step.

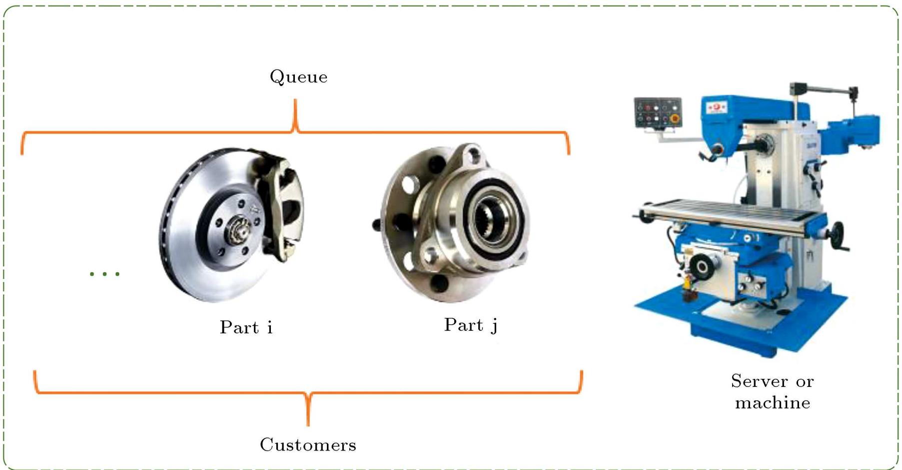

Figure 4. Queuing system for the third step.

represented as a customer in this queuing system. Of note, the loading time is ignored. The second step involves the respective supplier to the manufacturer, according to which the $M/M/\infty$ queuing system is used. Raw materials of each part are considered as a customer (see Figure 3). Meanwhile, the vehicle as a server is assumed in both $M/M/\infty$ queuing systems. The last step involves the interval that raw materials receive in the factory to produce the finished parts. $M/M/1/\infty/PR$ queuing system is incorporated in this step (see, Figure 4) where each part as a customer and each machine as a server are assumed. Based on these concepts, the arrival rate for each queuing system is less than the service rate for these queuing systems. Then, the arrival rate is equal to the output rate for each queuing system and the inter-arrival times in three queuing systems are distributed exponentially.

As mentioned earlier, the transportation component in the first stage is assumed to be the $M/M/\infty$ queuing system, in which the first M means the inter-arrival time described by the exponential distribution, the second M indicates the service time defined by the exponential distribution, and ∞ represents the number of servers that is infinite. The production stage is assumed as the $M/M/1/\infty/PR$ queuing system. The definition of the first three symbols is given in the $M/M/\infty$ queuing system. The rest of symbols are the restriction on system capacity and the queue discipline, respectively. The fourth symbol indicates no restriction on the system capacity. PR, which is a type of queue disciplines, means that customers with the highest priorities are chosen for service ahead of those with lower priorities, independent of their time of arrival into the system. There are two more refinements possible in priority situations: preemptive and non-preemptive. In this paper, non-preemptive refinement is assumed. It means that there is no interruption and the highest-priority customer goes straight to the head of the queue to wait its turn. Meanwhile, each machine as a server and each part as a customer are considered where servers should provide service for customers.

As mentioned earlier, the transportation component is assumed as a queuing system, in which there are an unlimited number of services because the infinite number of vehicles is available. The number of vehicles is unlimited, whereas there are a certain number of vehicle types. Each type of vehicles has a constant speed. Demand for part i arrives with rate λ_i where one of the vehicles with the rate μ_v picks up raw materials from the respective supplier. The average waiting time in the system is $\frac{1}{\mu_v}$, as well. Meanwhile, the return route from supplier to the manufacturer is considered the same queuing system. It should be mentioned that each supplier only produces raw materials of certain part. In the production stage, parts of the kth priority arrive at a single channel queue according to the Poisson process with rate $\lambda_k (1 \le k \le N)$ and these parts wait on a first-come, first-served basis within their relevant priorities. It should be noted that the smaller number for k shows the higher priority. Also, the service distribution for the kth priority is exponential with mean $\frac{1}{\mu_k}$. Meanwhile, the average waiting time in queue for the i-priority part in the production stage is defined as follows (for further detail of the queuing system in this section, see [65]):

$$W_q^{(i)} = \frac{\sum_{k=1}^{N} \frac{\rho_k}{\mu_k}}{(1-\sigma_{i-1})(1-\sigma_i)}, \tag{1}$$

where $\rho_k = \frac{\lambda_k}{\mu_k}$ $1 \le k \le N$ is called utilization factor, $\sigma_k = \sum_{i=1}^{k} \rho_i$, $\sigma_0 = 0$, and the system is stationary for $\sigma_N < 1$.

Index

i	Index of parts $i = 1, 2, \ldots, P$
j, u	Index of machines $j, u = 1, 2, \ldots, M$
v	Index of types of vehicles $v = 1, 2, \ldots, V$
s	Index of suppliers $s = 1, 2, \ldots, S$
p, r	Index of priorities $p, r = 1, 2, \ldots, N$
o	Index of operations $o = 1, 2, \ldots, O_i$
k	Index of cells $k = 1, 2, \ldots, C$

Parameters

R_{is}	Delivery lead-time of supplier s for part i
λ_i	Demand rate of part i for a given planning horizon
μ_{ji}	Mean service rate of machine j for part i
μ'_{vs}	Mean service rate of vehicle v for supplier s
L	A sufficiently large number
O_i	The number of operations for part i
$M_{\max}$	The largest number of machines permitted for each cell
d_i	The due date of part i
a_{ioj}	1 if the operation o of part i is processed on machine j and 0 otherwise
τ	Inter-cell movement time of each part to be processed on required machines

Decision variables

c_{1i}	Mean completion time of raw materials for part i, the interval between the order time of part i by a customer and loaded vehicle(s) ready to carry raw materials (first component of the first stage)
c_{2i}	Mean procurement time of raw materials for part i from the order time of part i by a customer to arrival time in the manufacturer (first stage)
c_{3i}	Mean completion time of part i (from the order time of part i to the finished part)
SU_{si}	1 if part i is supplied by supplier s and 0 otherwise
G_{vi}	1 if part i is picked up by vehicle v and 0 otherwise

PR_{ip} 1 if part i assigned to priority p and 0 otherwise

y_{jk} 1 if machine j assigned to cell k and 0 otherwise

4. Model formulation

The queuing system in the manufacturer must be stable, i.e., the service rate must be necessarily more than the arrival rate. Hence, the number of used parameters in the mathematical model consider the stability condition of the queuing system related to the manufacturer. The stabilizing Eq. (2) is elaborated in this subsection. The following equation avoids the infinite queue length behind each machine:

$$\sum_{i=1}^{P} \frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}} < 1 \forall j. \tag{2}$$

The mathematical model is formulated below:

$$\min Z = \sum_{i=1}^{P} \max\{0, c_{3i} - d_i\}. \tag{3}$$

The objective function (3) minimizes the total mean tardiness.

s.t.:

$$\sum_{s=1}^{S} SU_{si} = 1 \qquad \forall i. \tag{4}$$

Constraint (4) guarantees that each part must be assigned to one supplier.

$$SU_{si} \leq L \times R_{is} \qquad \forall s, i. \tag{5}$$

Constraint (5) is the reason why one supplier is selected out of existing suppliers with the production capability of raw materials for part i (i.e., $R_{is} > 0$).

$$\sum_{v=1}^{V} G_{vi} = 1 \quad \forall i. \tag{6}$$

Constraint (6) ensures that each part is assigned to one type of vehicles.

$$c_{1i} \geq \sum_{s=1}^{S}\sum_{v=1}^{V} \frac{1}{\mu'_{vs}} SU_{si} G_{vi} \quad \forall i. \tag{7}$$

As mentioned above, the waiting time for $M/M/\infty$ queuing system is mean service time. Then, Constraint (7) shows that the mean completion time of raw materials for each part in the relevant supplier (i.e., c_{1i}) is at least equal to the mean service time of the vehicle.

$$\sum_{i=1}^{P} PR_{ip} = 1 \quad \forall p, \tag{8}$$

$$\sum_{p=1}^{N} PR_{ip} = 1 \quad \forall i. \tag{9}$$

Constraints (8) and (9) assign each priority to one part.

$$c_{1i} \geq \sum_{s=1}^{S} R_{is} SU_{si} \qquad \forall i. \tag{10}$$

Constraint (10) ensures that the mean completion time of raw materials in the respective supplier for each part is longer than the delivery lead time in the case of the same supplier.

$$c_{2i} \geq c_{1i} + \sum_{s=1}^{S}\sum_{v=1}^{V} \frac{1}{\mu'_{vs}} G_{vi} SU_{si} \qquad \forall i. \tag{11}$$

Constraint (11) guarantees that the mean procurement time of raw materials is longer than the mean completion time of raw materials in the respective supplier plus mean transportation time from the respective supplier to the manufacturer for each part.

$$\sum_{k=1}^{C} y_{jk} = 1 \qquad \forall j. \tag{12}$$

Constraint (12) ensures that each machine is assigned only to one cell.

$$\sum_{j=1}^{M} y_{jk} \leq M_{\max} \qquad \forall k. \tag{13}$$

Constraint (13) ensures that the maximum number of machines will not exceed a certain value of $M_{\max}$. Constraint (14) is shown in Box I. Constraint (14) indicates that the mean completion time of part i (i.e., c_{3i}) is summation of the mean procurement time of raw materials for part i (i.e., c_{2i}), the mean waiting time of part i in the manufacturer stage, and inter-cell movement time of part i. The mean waiting time of each part in the manufacturer stage includes two terms. The first term in the parentheses indicates the mean waiting time of p-priority part in queue behind machine j.

Term $[\frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}}]$ represents the utilization factor of machine j to process part i, in which term $\sum_{o=1}^{O_i} a_{ioj}$ indicates the number of operations of part i on machine j. The utilization factor machine j for processing p-priority part is obtained by multiplying term $[\frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}}]$ by PR_{ir}. Therefore, term σ_{p-1} in Eq. (1) is equal to:

$$\sum_{r=1}^{(p-1)} \left(\sum_{i=1}^{P} \left(\left[\frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}} \right] \times PR_{ir} \right) \right)$$

and it is rewritten to term,

$$\sum_{i=1}^{P} [\frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}}] (\sum_{r=1}^{(p-1)} PR_{ir})$$

$$c_{3i} \geq c_{2i} + \sum_{j=1}^{M} \sum_{p=1}^{N}$$

$$\left(\frac{\sum_{i=1}^{P} \frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{(\mu_{ji})^2}}{\left(1 - \sum_{i=1}^{P} \left[\frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}}\right] \left(\sum_{r=1}^{(p-1)} PR_{ir}\right)\right) \left(1 - \sum_{i=1}^{P} \left[\frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}}\right] \left(\sum_{r=1}^{p} PR_{ir}\right)\right)} + \sum_{i=1}^{P} \frac{PR_{ip} \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}} \right)$$

$$PR_{ip} + \sum_{j=1}^{M} \sum_{\substack{u=1 \\ u \neq j}}^{M} \sum_{k=1}^{C} \sum_{o=1}^{(O_i-1)} \tau \left(a_{ioj} y_{jk}\right) \left(a_{i(o+1)u} \left(1 - y_{uk}\right)\right) \qquad \forall i. \tag{14}$$

Box I

in Constraint (14). The second term in the parentheses of the mean waiting time of each part in the manufacturer stage is the mean processing time for p-priority part on machine j. Ultimately, the sum of two terms in the parentheses of the mean waiting time of each part is multiplied by PR_{ip}, which means the mean waiting time of part i to be processed on machine j. The third term of Constraint (14) means that if the next operation of a certain part is processed in another cell, it gives rise to the inter-cell movement of the same part. It should be noted that the intra-cell movement time is neglected.

$$SU_{si}, G_{vi}, PR_{ip}, y_{jk} \in \{0, 1\},$$

$$c_{1i}, c_{2i}, c_{3i} \geq 0 \qquad \forall s, i, v, p, j, k, o. \tag{15}$$

Constraint (15) defines the ranges of the decision variables.

In the following, the stabilizing Constraint (2) is explained. The utilization factor for each machine in the manufacturer stage must be less than 1 to avoid instability of the queuing system. Furthermore, the utilization factor for machine j, ρ_j, is equal to the arrival rate divided by service rate [65]. Also, the arrival rate of machine j is $\sum_i \lambda_i$, because the part arrival time to process on machine j is equivalent to the minimization of the arrival time of parts needed to be processed on machine j. Moreover, the inter-arrival time between two successive parts has exponential distribution; then, the minimization of the part arrival time to process has an exponential distribution with parameter $\sum_i \lambda_i$. Ultimately,

$$\rho_j = \sum_{k=1}^{C} \frac{\sum_{i=1}^{P} \sum_{o=1}^{O_i} \lambda_i a_{ioj} y_{jk}}{\mu_{ji}} \qquad \forall j,$$

is rewritten using Eq. (12), $\sum_{k=1}^{C} y_{jk} = 1 \quad \forall j$, to find Constraint (2).

5. Linearization

The proposed model is a nonlinear mathematical model. Hence, three steps are used to linearize the proposed model. In the first step, the objective function (3) is linearized by defining a new variable $CDI_i \geq 0$, which is equal to $\max_i \{0, c_{3i} - d_i\}$. Constraints (18) and (19) are added to the proposed model for the linearization of the objective function (3). In the second step, a new binary variable SUG_{svi} is replaced by $SU_{si} \times G_{vi}$ for the linearization of Constraints (7) and (11), and Constraints (21) and (22) are added to the proposed model. In the third step, Constraint (14) is broken down into four segments for linearization. First, the mean waiting time of p-priority part in the queue behind machine j is linearized by introducing variable $WT_{jp} \geq 0$, which is equal to Eq. (16) as shown in Box II. The new auxiliary variables

$$WT_{jp} = \frac{\sum_{i=1}^{P} \frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{(\mu_{ji})^2}}{\left(1 - \sum_{i=1}^{P} \left[\frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}}\right] \left(\sum_{r=1}^{(p-1)} PR_{ir}\right)\right) \left(1 - \sum_{i=1}^{P} \left[\frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}}\right] \left(\sum_{r=1}^{p} PR_{ir}\right)\right)} \qquad \forall j, p. \tag{16}$$

Box II

$Q_{jpir} \geq 0$, $DPR_{i(qq)(tt)} \in \{0,1\}$, $WPR_{jpi(qq)(tt)} \geq 0$, $TPR_{qtr'r''} \in \{0,1\}$, $WTPR_{jpqtr'r''} \geq 0$, $WR_{jpi} \geq 0$, $SPR_{i'i''pr} \in \{0,1\}$, and $WSPR_{jpi'i''r} \geq 0$ are presented in order to linearize Eq. (16). Also, the relevant Constraints (24)–(45) are added. Second, the mean processing time for part i on machine j is obtained via multiplying the mean processing time for p-priority part on machine j by PR_{ip}. It is linearized by defining the new variable $MPR_{i'ip} \in \{0,1\}$ that is equal to $PR_{i'p} \times PR_{ip}$ and adding Constraints (46) and (47) to the proposed model. Third, the third term of Constraint (14), i.e., the inter-cell movement time of parts, is linearized. New variable $ty_{juk} \in \{0,1\}$ is defined and Constraints (48) and (49) are added. Fourth, Constraint (14) is replaced by Constraint (50). Finally, the linearization of the mathematical model based on the direct decision variables is presented as follows:

$$\min Z = \sum_{i=1}^{P} CDI_i, \tag{17}$$

s.t.:

$$CDI_i \geq 0 \qquad \forall i \tag{18}$$

$$CDI_i \geq c_{3i} - d_i \qquad \forall i, \tag{19}$$

Constraints (4)–(6):

$$c_{1i} \geq \sum_{s=1}^{S}\sum_{v=1}^{V} \frac{1}{\mu'_{vs}} SUG_{svi} \qquad \forall i, \tag{20}$$

$$SUG_{svi} - SU_{si} - G_{vi} + 1.5 \geq 0 \qquad \forall s, v, i, \tag{21}$$

$$1.5SUG_{svi} - SU_{si} - G_{vi} \leq 0. \qquad \forall s, v, i. \tag{22}$$

Constraints (8)–(10):

$$c_{2i} \geq c_{1i} + \sum_{s=1}^{S}\sum_{v=1}^{V} \frac{1}{\mu'_{vs}} SUG_{svi} \qquad \forall i. \tag{23}$$

Constraints (12) and (13):

$$WT_{jp} - 2\sum_{i=1}^{P}\left(\left(\frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}}\right)\left(\sum_{r=1}^{p} Q_{jpir}\right)\right),$$

$$+\sum_{i=1}^{P}\left(\left(\frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}}\right)^2\left(\sum_{r=1}^{p} Q_{jpir}\right.\right.$$

$$\left.\left.+2\sum_{tt=1}^{p}\sum_{qq=1}^{tt-1} WPR_{jpi(qq)(tt)}\right)\right)$$

$$+\,2\sum_{t=1}^{P}\sum_{q=1}^{t-1}\left(\left(\frac{\lambda_q \sum_{o=1}^{O_i} a_{qoj}}{\mu_{jq}}\right)\left(\frac{\lambda_t \sum_{o=1}^{O_i} a_{toj}}{\mu_{jt}}\right)\right.$$

$$\left.\sum_{r'=1}^{P}\sum_{r''=1}^{P} WTPR_{jpqtr'r''}\right)$$

$$+\sum_{i=1}^{P}\left(\frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{\mu_{ji}}\right) WR_{jpi}$$

$$-\sum_{i'=1}^{P}\sum_{i''=1}^{P}\left(\left(\frac{\lambda_{i'} \sum_{o=1}^{O_i} a_{i'oj}}{\mu_{ji'}}\right)\right.$$

$$\left.\left(\frac{\lambda_{i''} \sum_{o=1}^{O_i} a_{i''oj}}{\mu_{ji''}}\right)\sum_{r=1}^{p} WSPR_{jpi'i''r}\right)$$

$$= \sum_{i=1}^{P} \frac{\lambda_i \sum_{o=1}^{O_i} a_{ioj}}{(\mu_{ji})^2} \qquad \forall j, p, \tag{24}$$

$$Q_{jpir} = WT_{jp} \times PR_{ir} \qquad \forall j, p, i; r = 1, 2, \ldots, p,$$

$$Q_{jpir} \leq L \times PR_{ir} \qquad \forall j, p, i, r, \tag{25}$$

$$Q_{jpir} \leq WT_{jp} \qquad \forall j, p, i, r, \tag{26}$$

$$Q_{jpir} \geq WT_{jp} - (1 - PR_{ir}) \times L \qquad \forall j, p, i, r, \tag{27}$$

$$DPR_{i(qq)(tt)} = PR_{i(qq)} \times PR_{i(tt)},$$

$$\forall i;\ qq = 1, 2, \ldots, (tt-1);\ tt = 1, 2, \ldots, p,$$

$$DPR_{i(qq)(tt)} - PR_{i(qq)} - PR_{i(tt)} + 1.5 \geq 0$$

$$\forall i;\ qq = 1, 2, \ldots, (tt-1);\ tt = 1, 2, \ldots, p, \tag{28}$$

$$1.5DPR_{i(qq)(tt)} - PR_{i(qq)} - PR_{i(tt)} \leq 0$$

$$\forall i;\ qq = 1, 2, \ldots, (tt-1);\ tt = 1, 2, \ldots, p, \tag{29}$$

$$WPR_{jpi(qq)(tt)} = WT_{jp} \times DPR_{i(qq)(tt)}$$

$$\forall j, p, i;\ qq = 1, 2, \ldots, (tt-1);\ tt = 1, 2, \ldots, p,$$

$$WPR_{jpi(qq)(tt)} \leq L \times DPR_{i(qq)(tt)}$$

$$\forall i;\ qq = 1, 2, \ldots, (tt-1);\ tt = 1, 2, \ldots, p, \tag{30}$$

$$WPR_{jpi(qq)(tt)} \leq WT_{jp}$$

$$\forall i;\ qq = 1, 2, \ldots, (tt-1);\ tt = 1, 2, \ldots, p, \tag{31}$$

$$WPR_{jpi(qq)(tt)} \geq WT_{jp} - \left(1 - DPR_{i(qq)(tt)}\right) \times L$$

$$\forall i; qq = 1, 2, \ldots, (tt-1); tt = 1, 2, \ldots, p, \tag{32}$$

$$TPR_{qtr'r''} = PR_{qr'} \times PR_{tr''}$$

$$\forall r', r'';\ t = 1, 2, \ldots, P;\ q = 1, 2, \ldots, (t-1),$$

$$TPR_{qtr'r''} - PR_{qr'} - PR_{tr''} + 1.5 \geq 0$$

$$\forall r', r''; \; t=1,2,\ldots,P; \; q=1,2,\ldots,(t-1), \quad (33)$$

$$1.5TPR_{qtr'r''} - PR_{qr'} - PR_{tr''} \leq 0$$

$$\forall r', r''; \; t=1,2,\ldots,P; \; q=1,2,\ldots,(t-1), \quad (34)$$

$$WTPR_{jpqtr'r''} = WT_{jp} \times TPR_{qtr'r''}$$

$$\forall r', r = 1,2,\ldots,p; \forall t = 1,2,\ldots,P;$$

$$\forall q = 1,2,\ldots,(t-1); \; \forall q, p,$$

$$WTPR_{jpqtr'r''} \leq L \times TPR_{qtr'r''}$$

$$\forall j; p; q; t; r'; r'', \quad (35)$$

$$WTPR_{jpqtr'r''} \leq WT_{jp} \qquad \forall j; p; q; t; r'; r'', \quad (36)$$

$$WTPR_{jpqtr'r''} \geq WT_{jp} - (1 - TPR_{qtr'r''}) \times L$$

$$\forall j; p; q; t; r'; r'', \quad (37)$$

$$WR_{jpi} = WT_{jp} \times PR_{ip} \quad \forall j; p; i,$$

$$WR_{jpi} \leq L \times PR_{ip} \qquad \forall j; p; i, \quad (38)$$

$$WR_{jpi} \leq WT_{jp} \qquad \forall j; p; i, \quad (39)$$

$$WR_{jpi} \leq WT_{jp} - (1 - PR_{ip}) \times L \qquad \forall j; p; i, \quad (40)$$

$$SPR_{i'i''pr} = PR_{i'p} \times PR_{i''r}$$

$$\forall i'; \; i'' = 1,2,\ldots,P; \; \forall p; \; \forall r = 1,2,\ldots,p,$$

$$SPR_{i'i''pr} - PR_{i'p} - PR_{i''r} + 1.5 \geq 0$$

$$\forall i', i'' = 1,2, \; \ldots, P; \; \forall p; \forall r = 1,2,\ldots,p, \quad (41)$$

$$1.5SPR_{i'i''pr} - PR_{i'p} - PR_{i''r} \leq 0$$

$$\forall i', i'' = 1,2,\ldots,P; \forall p; \forall r = 1,2,\ldots,p, \quad (42)$$

$$WSPR_{jpi'i''r} = WT_{jp} \times SPR_{i'i''pr}$$

$$\forall j; \; p; \; \forall i', \; i'' = 1,2,\ldots,P,$$

$$WSPR_{jpi'i''r} \leq L \times SPR_{i'i''pr}$$

$$\forall j; p; \forall i', i'' = 1,2,\ldots,P, \quad (43)$$

$$WSPR_{jpi'i''r} \leq WT_{jp}$$

$$\forall j; p; \; \forall i', i'' = 1,2,\ldots,P, \quad (44)$$

$$WSPR_{jpi'i''r} \geq WT_{jp} - (1 - SPR_{i'i''pr}) \times L$$

$$\forall j; p; \forall i', i'' = 1,2,\ldots,P, \quad (45)$$

$$MPR_{i'ip} - PR_{i'p} - PR_{ip} + 1.5 \geq 0$$

$$\forall i, i' = 1,2,\ldots,P; \quad \forall p = 1,2,\ldots,N, \quad (46)$$

$$1.5MPR_{i'ip} - PR_{i'p} - PR_{ip} \leq 0$$

$$\forall i, i' = 1,2,\ldots,P; \quad \forall p = 1,2,\ldots,N, \quad (47)$$

$$ty_{juk} = y_{jk} \times y_{uk} \quad \forall u, j, k, \quad u \neq j,$$

$$ty_{juk} - y_{jk} - y_{uk} + 1.5 \geq 0 \qquad \forall u, j, k, \quad u \neq j, \quad (48)$$

$$1.5ty_{juk} - y_{jk} - y_{uk} \leq 0 \qquad \forall u, j, k, \quad u \neq j, \quad (49)$$

$$c_{3i} \geq c_{2i} + \sum_{j=1}^{M} \sum_{p=1}^{N} \Bigg(WR_{jpi} + \sum_{i'=1}^{P} \frac{MPR_{i'ip} \sum_{o=1}^{O_i} a_{i'}oj}{\mu_{ji'}} \Bigg) + \sum_{j=1}^{M} \sum_{\substack{u=1 \\ u \neq j}}^{M} \sum_{k=1}^{C} \sum_{\substack{k'=1 \\ k=k'}}^{C} \sum_{o=1}^{(O_i-1)} \tau_{kk'} a_{ioj} a_{i(o+1)u} ty_{jukk'} \qquad \forall i. \quad (50)$$

6. Solution approach

The NP-hardness of the CF problem was already proved by some researchers [66] and [67]. Hence, our more general problem is NP-hard, as well. One of well-known methods to solve such problems is meta-heuristic algorithms. Besides, the discreteness of decision variables motivates to choose GA among meta-heuristic algorithms to solve the mentioned problem. An overview of our framework is illustrated in Figure 5.

The structure of solution or so-called chromosome in the GA is in the form of a matrix with 1 row and $3 \times P + M$ (M is the number of machines and P is the number of parts) columns. The structure of chromosome is illustrated in Figure 6. The first p (index for the number of parts) arrays of the matrix are filled with the assigned type of vehicles to transport. The second p arrays of the matrix are selected as the suppliers to produce raw materials of parts. The next m (index for the machine number) positions of the matrix are filled by the assigned cell number so that each machine can be located only in one cell. The last p arrays of the matrix are the priorities of parts, where each part is assigned to only one priority.

6.1. Population initialization

Initial population is generated as a set of feasible solutions. Steps of the initial solutions are shown in Figure 7.

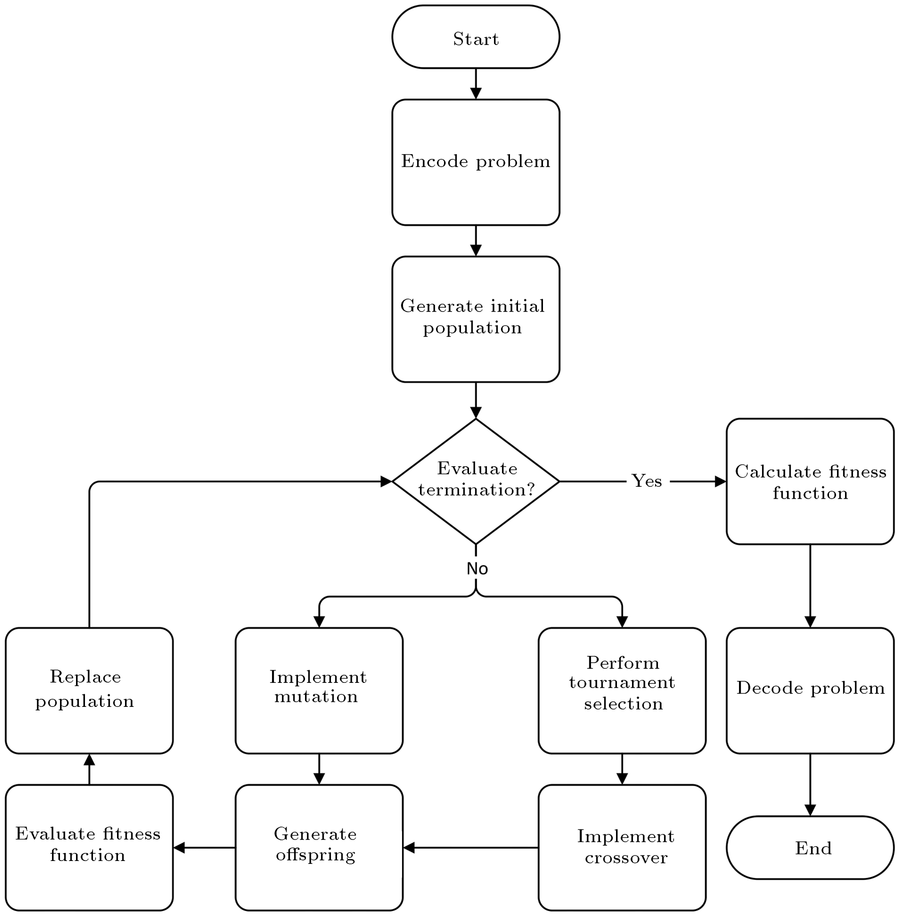

Figure 5. The GA framework.

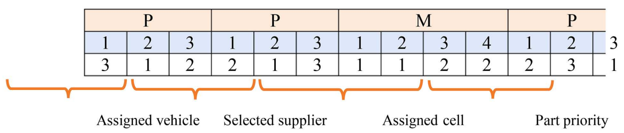

Figure 6. A sample solution representation.

6.2. Fitness function

A fitness function measures the chromosomes in the population. A fraction or whole of the better chromosomes is chosen for the next iteration generation. The objective function of the proposed model is the fitness function in this research. Of note, the new generation is called offspring or children in the GA and each chromosome respects all the constraints of the proposed model.

6.3. Selection method

Tournament selection is the selection strategy in the proposed algorithm. It selects the fittest chromosomes from the current generation for use in the next generation. First, a certain number of chromosomes are chosen randomly. Second, a tournament is run among them based on fitness function. Finally, the best one is selected that moves on to be used in the crossover operator. When the tournament size is large, it is possible that chromosomes with weak fitness functions compete with stronger ones.

6.4. Crossover operator

A crossover operator replaces data from two parents and generates children from them. These children inherit some segments from their parents. In this paper, a one-point crossover is chosen among crossover mechanisms to generate children. An example based on our solution structure is presented to clarify the mechanism of one-point crossover in Figure 8. It should be noted that the last segment of chromosome, involving the priorities of parts, is not considered as the crossover mechanism. The one-point crossover replaces genes of parents with each other to generate children from both parents.

6.5. Mutation operator

Mutation keeps one or more genes from current generation to the next. A single-point mutation operator is used in this research. A random number between 1 and $3 \times P + M$ is generated for the mutation operator. If the number is between 1 and $2 \times P + M$, the selected

Step 1: Set $r = 1$ (population index) and identify population of chromosomes $\rightarrow pop$;
Step 2: Set $i = 1$ (index for the array number in the chromosome) $0 < i \leq 3 \times P + M$;
Step 3: If "$i \leq P$";
3-1: Generate a random integer between 1 to $V \rightarrow X(i)$ (X is the chromosome and $X(i)$ is i^{th} position of the matrix or the chromosome) and go to sub-step 3-2;
3-2: $i \leftarrow i+1$ and go back to step 3;
Else go to step 4;
Step 4: If "$i \leq 2 \times P$";
4-1: Select randomly among suppliers with production capability of raw materials for the respective part $\rightarrow X(i)$, and go to sub-step 4-2;
4-2: $i \leftarrow i+1$ and go back to step 4;
Else go to step 5;
Step 5: Set *the number of machines inside each cell* $= 0$ and go to step 6;
Step 6: If "$i \leq 2 \times P + M$";
6-1:Generate a random integer between 1 to $C \rightarrow d$, and go to sub-step 6-2;
6-2: If "the number of assigned machines to cell $d \leq M_{max}$";
6-2-1: (The number of machines inside the cell d) + 1 $\rightarrow$ (the number of machines inside the cell d) and $X(i) \leftarrow d$. Then, go to sub-step 6-4;
6-3: Else $i = 2 \times P + 1$, set *the number of machines inside each cell* $= 0$. Then, go back to step 6;
6-4: $i \leftarrow i+1$ and go back to step 6;
Else, go to step 7;
Step 7: Generate randomly a permutation with P elements and fill positions from $X(i)$ to $X(i+P)$. Go to step 8;
Step 8: If "$pop < r$";
8-1: $r \leftarrow r+1$ and go back step 2;
Else, "End";

Figure 7. Steps for generating the initial population.

Table 2. The candidates and obtained values for the GA parameters.

	Problem scale					
	Small		Medium		Large	
Factor	**Candidates**	**Obtained**	**Candidates**	**Obtained**	**Candidates**	**Obtained**
Maximum iteration	{40,50,60,70}	40	{200,250,300,350}	250	{300,350,400,450}	300
Population size	{30,40,50,60}	30	{500,550,600,650}	550	{600,650,700,750}	600
Mutation probability	{0.2,0.3,0.4,0.5}	0.2	{0.3,0.4,0.5,0.6}	0.5	{0.3,0.4,0.5,0.6}	0.3
Tournament size	{2,3}	2	{2,3}	2	{2,3}	2
Crossover probability	{0.2,0.3,0.4,0.5}	0.3	{0.4,0.5,0.6,0.7}	0.6	{0.2,0.3,0.4,0.5}	0.2

gene will be changed into another one with relative features. For instance, if the number is less than P, then another vehicle is replaced. As mentioned earlier, the chromosome has 4 segments. The last segment is a permutation of parts. Therefore, if the number is larger than $2 \times P + M$, then another gene in this segment is selected randomly to swap places. Figure 9 clarifies the mechanism of the single-point mutation.

7. Computational results

Taguchi method is performed to set parameters since the efficiency of the meta-heuristics algorithms depends toughly on parameters. The importance of each setting parameter and the interactions between them are estimated by this technique. It should be noted that the test problems are categorized into three groups including small, medium, and large scales. The test problems 2, 5, and 8 are selected from examples to cover different scales. After conducting a number of tests, a range of data are assumed for each parameter of the GA to estimate an appropriate value (see, Table 2). The results of the Taguchi experiment show small-, medium-, and large-scale experiments, in order.

Nine test problems presented in Table 3 are considered to evaluate the adequacy of the model and the performance of the GA. The small-scale test problems were selected from the literature [44,68], and the rest of test problems were generated randomly. The proposed model and GA were coded in the Lingo 12.0 and MATLAB 2013a, respectively. They were solved on a computer featuring 2.99 GB RAM and core i5 with 2.50 GHz processor.

The test problems were solved by Branch and

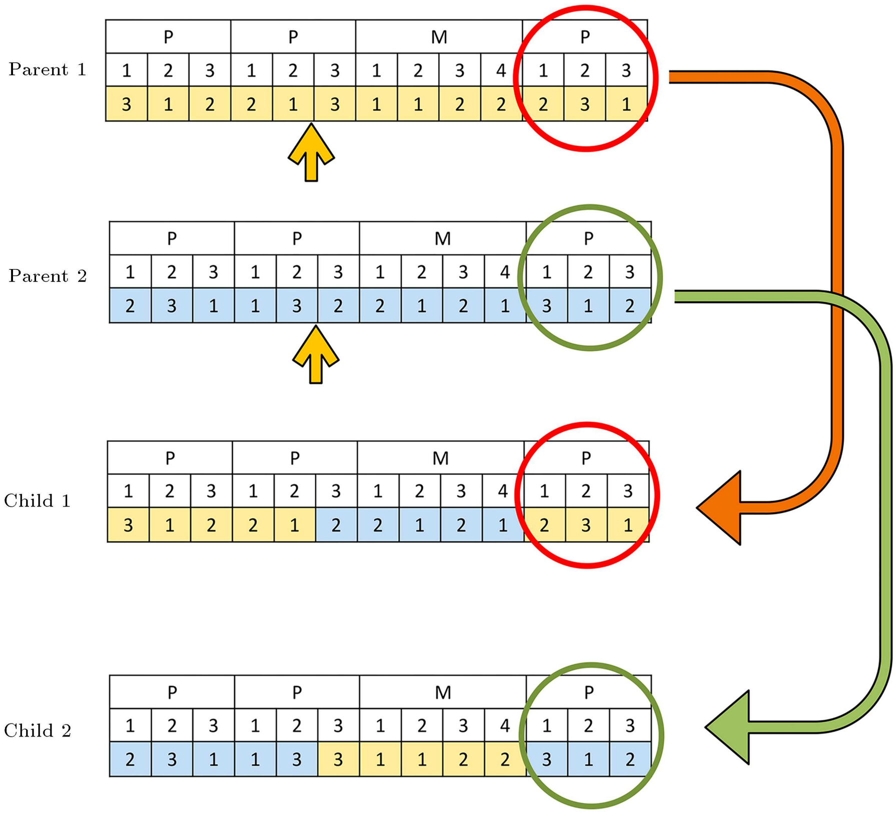

Figure 8. The offspring resulting from crossover between Parents 1 and 2.

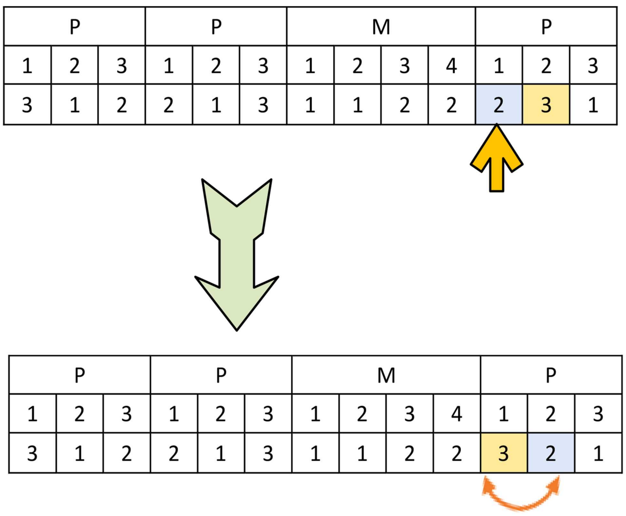

Figure 9. The mutated solution resulting from applied mutation.

Bound (B&B) of Lingo software and the GA. Then, the results of them are compared with each other in Table 3. Large-scale test problems were allowed to run for 5400 s or 1.5 h. Each test problem was run 3 times by the GA; then, the average of solutions in Z_{ave} and the best solution in Z_{best} were reported. According to the tutorial of Lingo software, F_{best} is the best value of the objective function that has been ever found and F_{bound} is the objective function of dual model obtained through the primary model. If F_{bound} is equal to F_{best}, the objective function achieves the global optimal solution. Furthermore, for large-scale test problems, if Z_{ave} or Z_{best} is between F_{bound} and F_{best}, it means that the GA obtained a better solution than the B&B of Lingo software. Moreover, if the GA achieves F_{bound} in the proposed model, the global optimal solution will be obtained, because F_{bound} is the least possible amount of the objective function for the primary model obtained by the B&B of Lingo software. Using these concepts, it is worth noting that suitable metrics are essential, which can provide a base for comparing results and claiming to obtain reliable solutions. In this manner, Standard Deviation (SD) is used. The small value of SD means that the GA can provide reliable solutions.

The results of the GA and the B&B of Lingo software are shown in Table 3. The results illustrate that for the small-scale problems, the B&B of Lingo software and the GA reach the same results except problem 3 with small deviation. The B&B of Lingo software and the GA are in good agreement for the medium-scale problems in Table 3. The results depict that the GA can provide a better solution to the large-scale problems (see, Figure 10). The B&B of Lingo software consumes and requires much more time than the GA. In addition, the SD of solutions is small, as shown in Table 3, which means that the GA can provide

Table 3. The results obtained from the B&B of Lingo software and the GA.

Problem no.	P	M	C	$M_{\max}$	V	S	B&B			GA			
							F_{best}	F_{bound}	TB&B (s)	Z_{ave}	Z_{best}	SD	TGA (s)
1	4	3	2	2	3	12	0	0	6	0	0	0	0
2	4	4	2	3	3	12	0	0	11	0	0	0	0
3	5	5	2	3	7	15	0	0	112	8.51	0	7.1	0
4	5	11	3	4	5	15	0.8267	0.8267	1471	2	0.8267	1.1	78
5	5	12	4	4	8	15	0.0	0.0	1556	0.7	0.0	0.9	112
6	5	14	2	7	5	15	0.0602	0.0602	3433	2.3	0.4156	1.8	70
7	5	20	5	5	7	15	6.2	0.0	5400	9.9	1.8132	5.8	185
8	5	23	6	4	6	15	75.5	0.0	5400	0.0	0.0	0.0	40
9	5	25	7	4	8	15	38.6673	0	5400	0.0	0	0.0	60

Table 4. The machines assigned to cells.

	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5
Machines	{3,5,8,17,19,25}	{1,10,15,20,21,23}	{2,6,18}	{4,11,12,13,14}	{7,9,16,22,24}

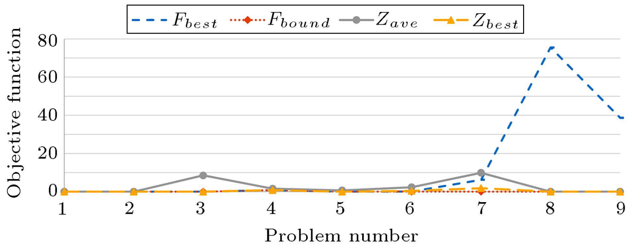

Figure 10. The comparison of the performances of the GA and B&B of Lingo software.

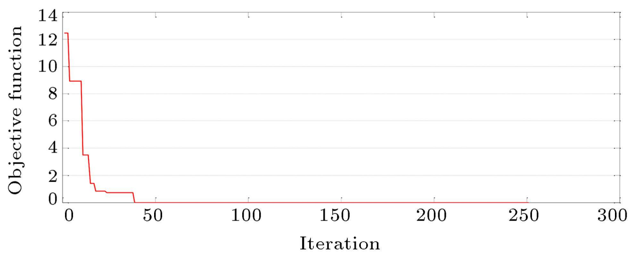

Figure 11. The convergence of the GA for test problem 5.

reliable solutions. Figure 11 shows the minimization process for the test problem 5 using the GA.

7.1. A case study

The model was applied to a spare parts manufacturer for automobiles located in Tehran, Iran. In this case, the cell number was five; $M_{\max}$ was six; four types of spare parts for automobiles produced in the manufacturer; eight suppliers supplied raw materials of parts; five vehicle types were available to carry raw materials; inter-cell movement time of each part was 10, and machines were assigned to five cells. The rest of the case information is presented in Appendix A.

The following results were obtained by solving the case study. The vehicle type 1 was assigned to carrying the raw materials of all parts; the raw materials of parts 1 to 4 were supplied by suppliers 1, 7, 2, and 8, respectively; the priorities of parts 1 to 4 were 1, 4, 3, and 2 in order to be processed on machines, and Table 4 shows assigned machines to cells.

Each row in each cell shows the queue of parts in Figure 12 in order to be processed on the respective machine based on the solution. In addition, each part in the queue waits to be processed based on its priority.

There can be more than one type of parts in each queue. However, this idea is rejected because the figure looks messy. Each type of parts is shown by a certain shape and the process flow of each part can be followed by the numbers on the inside of shapes. According to the figure, the number of inter-cell movements is less than intra-cell movements, proving the high performance of the proposed model. As is clear, the main factor in the configuration of cells is $M_{\max}$, which prevents more than six machines in each cell.

7.2. Sensitivity analysis

This case study was considered for sensitivity analysis of the proposed model to highlight important managerial insights such as coordination of supply chain. The delivery lead time of candidate suppliers (R_{is}) for part 4 was changed and the other parameters were kept fixed to analyze the effect of change on the mean waiting and inter-cell movement time of part 4. The behavior of the model was investigated by multiplying R_{4s} for all candidate suppliers by different numbers (X). How the mean waiting and inter-cell movement time behave are depicted in Figure 13. As X increased,

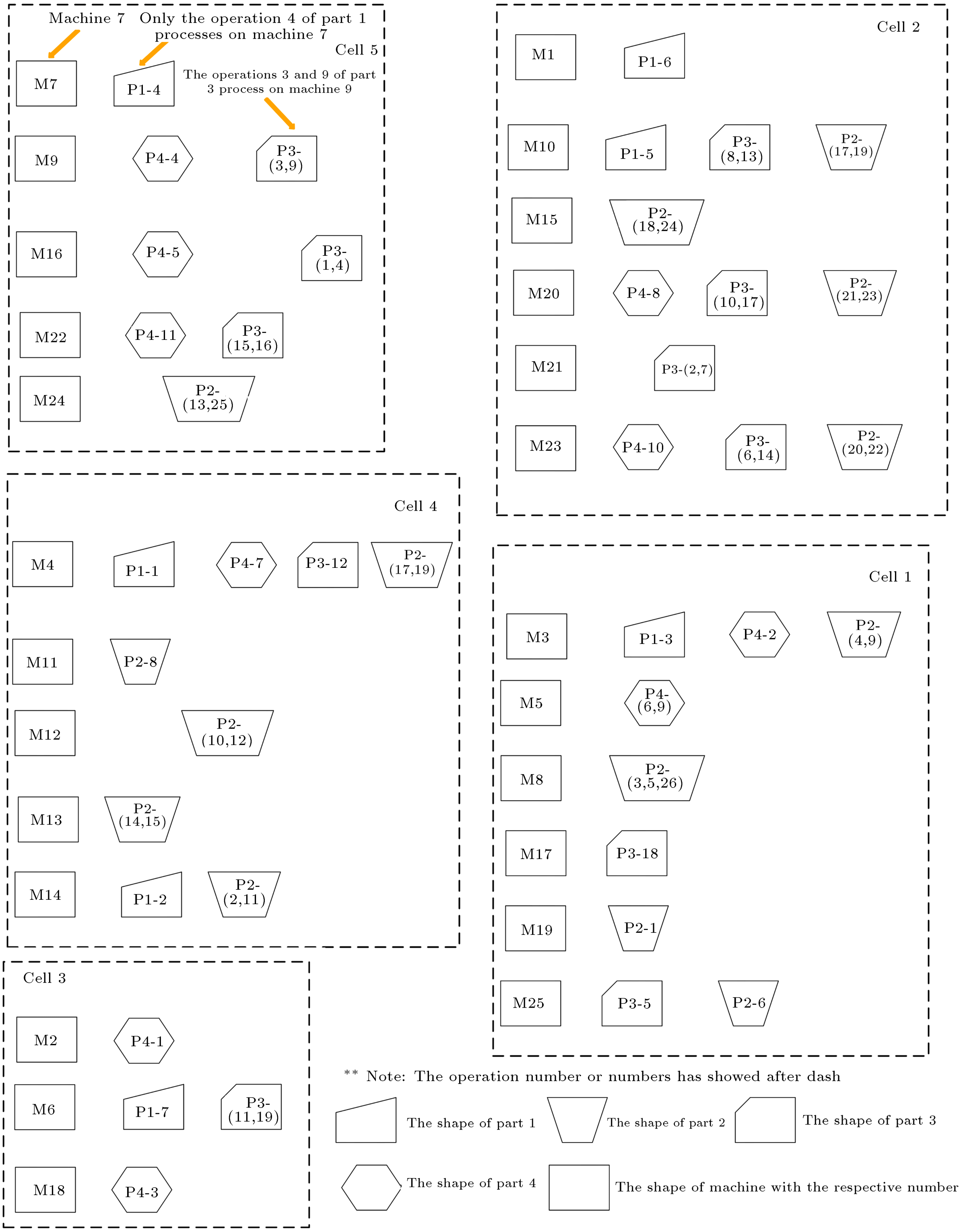

Figure 12. Detailed solution of the case study.

the mean waiting time was reduced, leading to the reduction of the priority of part 4, because the mean waiting time impacted on the delay. Increasing the delivery lead time of candidate suppliers for part 4 not only affected the mean waiting time, but also inter-cell movement time. Therefore, it reduced the inter-cell movement time by trying to assign all operations of part 4 in one cell. In addition, it may not decrease the mean waiting and inter-cell movement time for part 4 simultaneously as X increases. However, the

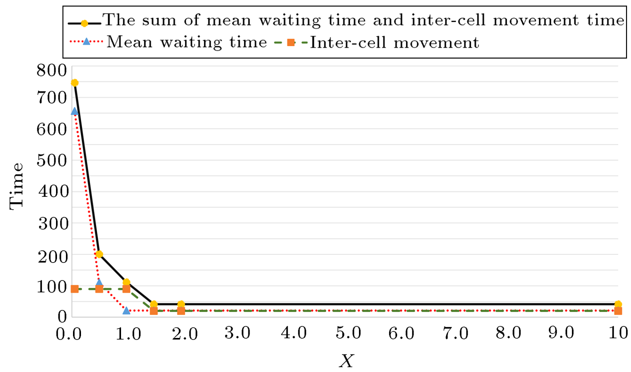

Figure 13. The behavior of inter-cell movement, mean waiting time, and the sum of both with varying delivery lead times of candidate suppliers for part 4.

mentioned increase in the delivery lead time reduced the total mean waiting and inter-cell movement time for part 4. In case of increase in X, the extent of this reduction was the shortest total mean waiting and inter-cell movement time for part 4 in order to reduce the delay in this part.

The results showed that increase in the delivery lead time of candidate suppliers for the specific part increased would cause a reduction in the sum of mean waiting and inter-cell movement times for that part, until there would be no delay for the other parts. This reduction in the mean waiting and inter-cell movement time for the specific part may increase the mean waiting time or inter-cell movement time of the other parts. This may occur due to the fact that the model attempts to assign all operations of the specific part in one cell and push other parts out of the cell. All parts must be operated on the same machine(s). In addition, this might increase the mean waiting time of parts other than the specific part so that the specific part takes a short mean waiting time.

8. Conclusion

In this study, a two-stage supply chain scheduling was presented. The first stage, supply, involved vehicles with various speeds for transporting raw materials and suppliers with different delivery lead-times. Production, the second stage, involved investigating the assignment of machines to cells and the assignment of priority to each part to be processed on the relevant machine. In other words, the Cell Formation (CF) problem along with the scheduling of each part within cells was studied. In this paper, demand, processing time on machines, and the transportation time of vehicles had an exponential distribution. A novel mixed-integer nonlinear mathematical model was developed with the queuing theory framework to find the mentioned issues based on the minimization of total tardiness as the objective function. In order to find exact solutions, the nonlinear mathematical model was linearized. A Genetic Algorithm (GA) was developed to cope with such an NP-hard problem. Moreover, Taguchi's experimental design method was employed to set the proper values for the parameters of the GA to improve its performance. The performances of the model and the GA were tested by solving test problems with different sizes. The GA solved all the test problems within a very short period of computational time. However, the linearized mathematical model, which was coded using Lingo software, could not provide an optimal solution to the large scale test problems within 1.5 h. The proposed mathematical model was employed in a real case. The acquired results demonstrated that the proposed model could find the best suppliers to procure, vehicles to transport, machines to assign to cells, and the priority of each part to be processed on the relevant machine, simultaneously. As an attained managerial insight, the sensitivity analysis of the proposed model showed that increase in the delivery lead time of candidate suppliers for the specific part might cause a reduction in mean waiting and inter-cell movement time for the same part. For future research, it is recommended that the capacity of vehicles, routes for a fleet of vehicles, and inventory models be considered in order to ensure more realistic results.

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Appendix

The initial dataset of the factory is shown in Tables A.1 to A.3. The first row in Table A.1, the candidate suppliers, indicates suppliers with the production capability of raw materials for each part. Also, the delivery lead-time of each supplier is presented in the paren-

Table A.1. Detailed data of candidate suppliers, demand rate, and due date.

	Part 1	Part 2	Part 3	Part 4
Candidate suppliers (delivery lead-time)	{1(720),5(1440)}	{3(4320),7(2160)}	{2(2880),6(3600)}	{4(3600),8(720)}
Demand rate	0.5900	0.5580	0.3090	0.4050
Due date	900	2600	3200	1000

Table A.2. The mean service rate of machines.

	Part 1	Part 2	Part 3	Part 4
Machine 1	17.1429	–	–	–
Machine 2	–	–	–	0.5746
Machine 3	5.9406	2.1429	–	2.1201
Machine 4	2.9126	4.5872	1.7143	3.0769
Machine 5	–	–	-	1.7746
Machine 6	4.3796	–	1.0782	–
Machine 7	3.2432	–	–	–
Machine 8	–	2.2447	–	–
Machine 9	–	-	0.9091	1.994
Machine 10	6	4.5872	1.7143	5.4545
Machine 11	–	2.5641	–	–
Machine 12	–	4.4346	–	–
Machine 13	–	1.1669	–	–
Machine 14	3.352	1.9868	–	–
Machine 15	–	1.4061	–	–
Machine 16	–	–	1.1719	1.7411
Machine 17	–	–	3.5294	–
Machine 18	–	–	–	4.2857
Machine 19	–	5.2678	–	–
Machine 20	–	4.5872	1.8182	3.0769
Machine 21	–	–	0.7426	–
Machine 22	–	–	1.0782	2.6087
Machine 23	–	4.5872	1.7143	5.4545
Machine 24	–	1.5436	–	–
Machine 25	–	2.7273	0.4637	–

Table A.3. The mean service rate of vehicles to transport raw materials from suppliers.

	Supplier 1	**Supplier 2**	**Supplier 3**	**Supplier 4**	**Supplier 5**	**Supplier 6**	**Supplier 7**	**Supplier 8**
Vehicle 1	0.0087	0.0085	0.0084	0.0078	0.0084	0.0077	0.0077	0.0083
Vehicle 2	0.0072	0.0069	0.0066	0.0065	0.0068	0.0064	0.0058	0.0065
Vehicle 3	0.0068	0.0066	0.0061	0.0058	0.0062	0.0057	0.0056	0.0060
Vehicle 4	0.0064	0.0063	0.0060	0.0057	0.0060	0.0056	0.0056	0.0058
Vehicle 5	0.0083	0.0079	0.0074	0.0072	0.0077	0.0072	0.0066	0.0073

thesis. The second and third row show the demand rate and due date of each part, respectively. Table A.2 presents the mean service rate of each machine for each part. Finally, the mean service rate of each vehicle for each supplier is shown in Table A.3.

Biographies

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