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An Integrated Decision Making Model for Manufacturing Cell Formation and Supplier Selection

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Abstract

Optimization of the complete manufacturing and supply process has become a critical ingredient for gaining a competitive advantage. This article provides a unified mathematical framework for modeling manufacturing cell configuration and raw material supplier selection in a two-level supply chain network. The commonly used manufacturing design parameters along with supplier selection and a subcontracting approach are incorporated into our mathematical model. To the authors' knowledge, there is no single model which integrates all of these attributes simultaneously. A sensitivity analysis is also performed to study the effects of this integration. An efficient meta-heuristic based on Genetic Algorithm (GA) search procedure is employed to effectively solve the model in medium and large scales. We improve the GA search mechanism by proper combination of linear programming optimization technique and GA in a cooperative framework. Computational results show that our hybrid solution technique can find satisfactory solutions in a timely manner.

Keywords

Cellular manufacturing, supplier selection, linear programming, genetic algorithm.

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Introduction

Group Technology (GT) is an innovative theory in management that attempts to solve the trade-off between efficiency and flexibility of a system by decomposing it into smaller easily manageable subsystems. Cellular Manufacturing System (CMS) is known as the most important derivative of the GT principles in industrial applications. Wemmerlov and Johnson (1997) discussed the reasons for the creation of manufacturing cells. The main reasons are lower throughput time, work in process inventory, response time to customer order, higher manufacturing flexibility, better quality, supervision and utilization of resources.

Typically, the CMS design includes four stages of cell formation, group layout, group scheduling, and resource allocation. For more information and detailed review, one can refer to Wu et al. (2007). In this article, we concentrate on the first stage in the design of a CMS that is cell formation and due to its direct impact on the establishment of an effective CMS, has been a topic with considerable amount of research in the related literature. At the conceptual level, cell formation deals with clustering machines and parts into machine cells and part families and its primary goal is to form independent manufacturing cells. In the last decades, many different procedures have been employed to tackle the Cell Formation Problem (CFP). An overview and discussion on some of these procedures can be found in Papaioannou and Wilson (2010). Mathematical programming models and methods are powerful tools to formulate and solve the CFP and its variants. However, since the CFP is known as NP-hard problem, the exact solution approaches are not able to find effective solutions in a timely manner for real-size problems. Thanks to the ability to cope with the complexity of this type, meta-heuristic algorithms are more suitable approaches to solve larger CFPs.

Supplier selection is an extremely critical decision for purchase managers, since appropriate selection of suppliers can considerably reduce the purchase cost and strengthen corporate competitiveness. Production system design and component supplier selection were being considered as two separate decisions for several decades until the requirements have been identified recently for an integrated approach. Integrating production and supply functions facilitates comprehensive and accurate decision-making process. Generally, the competitive advantage for a company can only be obtained by simultaneous optimization of functions that are in logical association with each other. Successful integration of CMS design and supplier selection related issues addresses the cell formation to obtain optimal or effective solutions in view of corporate overall operation. As reported in Paydar et al., (2014), simultaneous consideration of cellular manufacturing and supplier selection will lower production cost while keeping procurement cost low, and it also provides a rapid response for customer orders.

Exact methods and heuristics (i.e., in particular meta-heuristics) have been usually regarded as two independent approaches. In this article, we develop a scheme for hybridizing an exact method based on Linear Programming (LP) with a nature-inspired meta-heuristic, Genetic Algorithm (GA), for solving the integrated cell formation and supplier selection problem. GA is a stochastic global search technique which mimics the mechanism of the evolution of living beings, that is natural selection, inheritance and variation. Each individual is interpreted as a viable solution for the problem at hand. GA selects the best individuals in each generation and combines them to create a new population. Two major problems arise when GA is used to solve optimization problems with continuous decision variables. The first problem is the generation of a high proportion of infeasible solutions in the initial population and evolutionary stages which considerably slows down the optimization process. The second problem is that since GA searches the continuous intervals completely to find the best value, it does not guarantee the quality of the final solution. On the other hand, LP is the most preferred method to search inside the continuous spaces. One of the initial assumptions of LP is divisibility in which the values of decision variables can be fractions. The synergy effect provided by the integration and cooperation of LP and GA, can facilitate the search process. As a matter of fact, when optimization problem involves both discrete and continuous variables, the search space can be divided into two subspaces, corresponding to the two kinds of decision variables. In this framework, the LP embedded GA can be structured in such a manner that GA searches within the subspace of discrete variables and the LP searches over the continuous subspace.

In the presented paper, a unified mathematical model for integrating manufacturing cell configuration and raw material supplier selection in a two-level Supply Chain (SC) network with an extensive coverage of important design attributes is presented. An efficient hybrid solution approach is also proposed to effectively solve the model. The aim of our hybrid approach is to join the strength of GA search procedure and LP optimization technique in a cooperative framework. The main contributions of this research are as follows:

- We propose a new unified mathematical model for the generalized CFP and supplier selection in CMS.
- We consider various design attributes including alternative process routings, operation sequences, part demands, processing times, machine capacity, machine duplication, etcetera, and a subcontracting approach.
- We use the top three indicators for supplier selection (i.e., quality, delivery and purchase price) in our integrated model.
- We utilize LP within GA framework in order to create an advanced search procedure.

Literature Review

Conventional approaches of the cell formation seek to find machine clusters and part families based on a 0-1 machine-part incidence matrix. Many researchers addressed the CFP using this binary input data. Of them, Mahdavi et al. (2009) proposed a mathematical model and a GA for the CFP based on the cell utilization concept. Paydar and Saidi-Mehrabad (2013) formulated a fractional (linear) model to the CFP to maximize the grouping efficacy in case the number of cells is not predetermined. Noktehdan et al. (2016) presented a league championship algorithm for the CFP based on grouping efficacy and provided a real-world industrial case.

It is very important to take into account the production design factors for modeling and simulating the real factory situation. However, it may increase the model complexity and consequently the computation time. Jayaswal and Adil (2004) incorporated operation sequence in their mathematical model for the CFP with alternative routings, cell size constraints, production volume, and machine redundancy considerations. Wu et al. (2009) developed a hybrid algorithm employing the Simulated Annealing (SA), together with the GA mutation operator for the design of cell configuration in which multiple process routings for parts can be planned. Rabbani et al. (2017) presented a new mathematical model for the CFP considering different design parameters such as inventory, subcontracting and especially backorder. They used GA and discrete particle swarm optimization techniques to manage the complexity of the model.

Rao and Mohanty (2003) identified the necessity of integrating manufacturing systems and SC system. They noted that the traditional sequential procedure for making CMS strategic decisions and CMS design decisions results in sub-optimal SC designs. Schaller (2008) developed a mathematical model and a TS procedure for the integrated SC and cell design problem. Saxena and Jain (2012) suggested an integrated model of dynamic CMS and SC design that can be customized individually or in combination for operational, tactical and strategic decisions. Paydar and Saidi-Mehrabad (2015) developed a bi-objective possibilistic programming model which incorporates dynamic virtual CFP and SC. They also provided a case study which illustrates the applicability of the model. Alaei and Davoudpour (2016) applied a revised multi-choice goal programming for the integrated virtual CMS and SC design. They mainly considered location-allocation decisions and multi-period production planning under demand and capacity uncertainties. In another work, Alaei and Davoudpour (2017) developed a robust optimization model for SC-CMS management. The objective considered in their study includes the total cost of SC design, exceptional elements and labor salary.

Supplier selection has become a crucial part of SC management.

Although several studies have been carried out on the quantitative modeling for supplier selection in production systems, little attention was given so far to supplier selection in CMSs. Benhalla et al. (2011) proposed a single-period integrated mixed-integer non-linear model for supplier selection and multiple plant CMS design on active factories. They also provided several numerical examples to illustrate the cost-effectiveness of the integrated model. Paydar et al. (2014) developed a robust optimization model to integrate cell formation, machine layout, and supplier selection. The objective function of their model is to minimize the total cost of intracellular and intercellular movements, machinery, inventory, and procurement. Heydari et al. (2017) developed a unified fuzzy mixed-integer LP model to make the cell formation and supplier selection decisions simultaneously. They investigated the relationship between production and purchasing functions in CMS with respect to product quality considerations and the fuzzy nature of defect rate and demand data. Table 1 presents a summary of previous studies in the area of SC-CMS design.

Whereas previous studies on the integration of CMS with supplier selection have focused on the utility of this integration, presented approaches suffer from a large number of constraints and decision variables which limit the application of these approaches only to some small cases. In this article, we fill this gap by designing a hybrid meta-heuristic based on GA and LP for solving large-scale industrial cases. Different from previous studies on the problem formulation, we additionally consider more manufacturing and supply attributes to increase its applicability.

Problem Hypotheses and Mathematical Model

Hypotheses

Consider a two-echelon SC with two or more competing suppliers and one manufacturer. The integrated approach is considered for concurrently making the cell formation and supplier selection decisions; thus, we are faced with two implicitly interrelated decisions including:

Table 1.A summary of Related Literature

Study	CMS decision(s)	SC decision(s)	objective function(s)	Solving method
Schaller (2008)	cell configuration	multi-plant location + multi-market allocation	Min. total cost	Meta-heuristic (TS)
Benhalla et al. (2011)	cell configuration + routing selection	supplier selection	Min. total cost	Mathematical programming (branch and cut)
Paydar et al. (2014)	cell configuration + machine layout	supplier selection	Min. total cost	Mathematical programming (robust optimization)
Paydar and Saidi-Mehrabad (2015)	cell configuration	supplier selection + multi-market allocation	1. Min. total cost 2. Min total value of grouping efficacy	Mathematical programming (revised multi-choice goal programming)
Aalaei and Davoudpour (2016)	cell configuration + subcontracting + labor assignment	multi-plant location + multi-market allocation	Min. total cost	Mathematical programming (Benders' decomposition)
Aalaei and Davoudpour (2016)	cell configuration + subcontracting + labor assignment	multi-plant location + multi-market allocation	1. Min. total cost 2. Min. exceptional elements	Mathematical programming (revised multi-choice goal programming)
Aalaei and Davoudpour (2017)	cell configuration + labor assignment	multi-plant location + multi-market allocation	Min. total cost	Mathematical programming (robust optimization)
Heydari et al. (2017)	cell configuration + routing selection + lot sizing optimization with part quality consideration	supplier selection	Min. total cost	Fuzzy mathematical programming
This paper	cell configuration + routing selection + subcontracting	supplier selection (single sourcing strategy)	Min. total cost	Hybrid meta-heuristic (GA-LP)

Supplier selection

At the first echelon, there are a number of component suppliers for each type of required items. The manufacturer as a buyer has pre-evaluated all suppliers according to various criteria such as management and strategy, financial status, performance history, geographical location, capacity, etcetera, and now needs to further assess the qualified suppliers for ultimate selection based on quantitative criteria including quality, delivery, and purchase price.

Close working with a few good suppliers yields an effective purchasing function (Akinc, 1993). It is recommended that a single supplier should be selected to make a long-term supplier-manufacturer relationship and enhance the service quality (Qi, 2007). For this purpose, the single sourcing strategy is employed by purchasing department. Treleven and Schweikhart (1988) defined the single sourcing as the complete fulfillment of all corporate requirements for a particular raw material from one supplier by choice. In this manner, the purchase managers should decide for each component type, which supplier is the best choice to supply whole of the required items.

Cell formation design

At the second echelon, there is one manufacturer with cellular layout consisting of a number of multi-purpose machines with limited capacities that should be placed in a pre-determined number of manufacturing cells for processing required operations of a number of parts. The demand is constant and predefined. Machines can be replicated. The maximum and minimum cell sizes are given in terms of number of machines. The required operations of a part can be processed on different routings with different time and cost values. Subcontracting approach can be used as a tool to reduce machine unused capacity and unit product cost. In subcontracting, some of the required final products are provided from the outside of the manufacturing company to meet the market demand. However, in order to develop in-house skills and to cope with intrinsic constraints on subcontracting (i.e., unfulfilled orders, poor quality products, decreasing compatibility of innovation, etc.) management determines an upper bound for quantities of parts to be subcontracted.

Mathematical Model

The integrated problem is formulated as an effective non-linear mixed-integer programming model to make the cell formation and supplier selection decisions concurrently.

Indexing sets

C	Cell index, $c = 1, 2, ..., C$
M	Machine index, $m = 1, 2, ..., M$
P	Part index, $p = 1, 2, ..., P$
O	Operation index, $o = 1, 2, ..., O_p$
T	Component index, $t = 1, 2, ..., T$
S	Supplier index, $s = 1, 2, ..., S_t$

Parameters

D_p	Demand of part type p.
a_{opm}	1, if oth operation of part p can be processed on machine m; 0, otherwise.
PT_{opm}	Time to process the oth operation of part p on machine m.
SC_p	Subcontracting cost per part p.
AC_m	Acquisition cost of machine m.
OC_m	Operating cost of machine m per unit time.
TC_m	Time capacity of one unit of machine m.
IMC_p	Intercellular material handling cost per unit of part p.
AMC_p	Intracellular material handling cost per unit of part p
LS_c	Lower size limit for cell c.
US_c	Upper size limit for cell c.
UB_p	Upper bound for subcontracting proportion of part type p.
CR_{tp}	Consumption rate of component t for producing one unit of part type p.
FC_{st}	Fixed cost of selecting sth supplier of component t.
PC_{st}	Unit sale price of sth supplier of component t.
RR_{st}	Reject rate of sth supplier of component t.
LD_{st}	Lead time delay for sth supplier of component t.
UPC_t	Unit penalty cost for quality deficiency of component t.
UDC_t	Unit delay cost of component t.

Decision variables

N_{mc}	Number of machines type m assigned to cell c.
Z_{opmc}	1, if oth operation of part p can be processed on machine m

in cell c; 0, otherwise.

V_{st} 1, if sth supplier of component t is selected; 0, otherwise.

x_p Proportion of the total demand of part type p to be produced inside the manufacturing plant (i.e., $x_p.D_p$ shows the production volume of part type p).

y_t Procurement quantity of component t.

Objective function and constraints

Minimize OF=

$$\sum_{c=1}^{C}\sum_{m=1}^{M} AC_m \times N_{mc} + \sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{o=1}^{O_p} OC_m \times PT_{opm} \times x_p \times D_p \times Z_{opmc}$$

$$+\frac{1}{2}\times\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{o=1}^{O_p-1} IMC_p \times x_p \times D_p \times \left|\sum_{m=1}^{M} Z_{o+1,pmc} - \sum_{m=1}^{M} Z_{opmc}\right|$$

$$+\frac{1}{2}\times\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{o=1}^{O_p-1} AMC_p \times x_p \times D_p \times (\sum_{m=1}^{M}\left|Z_{o+1,pmc} - Z_{opmc}\right| -$$

$$\left|\sum_{m=1}^{M} Z_{o+1,pmc} - \sum_{m=1}^{M} Z_{opmc}\right|)$$

$$+\sum_{p=1}^{P} SC_p \times (1 - x_p) \times D_p + \sum_{t=1}^{T}\sum_{s=1}^{S_t} FC_{st} \times V_{st} + \sum_{t=1}^{T}\sum_{s=1}^{S_t} PC_{st} \times y_t \times V_{st}$$

$$+\sum_{t=1}^{T}\sum_{s=1}^{S_t} RR_{st} \times UPC_t \times y_t \times V_{st} + \sum_{t=1}^{T}\sum_{s=1}^{S_t} LD_{st} \times UDC_t \times y_t \times V_{st} \quad (1)$$

Subject to:

$$\sum_{p=1}^{P}\sum_{o=1}^{O_p} PT_{opm} \times x_p \times D_p \times Z_{opmc} \le TC_m \times N_{mc} \qquad \forall m,c \qquad (2)$$

$$\sum_{m=1}^{M} N_{mc} \ge LS_c \qquad \forall c \qquad (3)$$

$$\sum_{m=1}^{M} N_{mc} \le US_c \qquad \forall c \qquad (4)$$

$$\sum_{c=1}^{C}\sum_{m=1}^{M} a_{opm} \times Z_{opmc} = 1 \qquad \forall o,p \qquad (5)$$

$$Z_{opmc} \leq a_{opm} \qquad \forall o,p,m,c \qquad (6)$$

$$1 - x_p \leq UB_p \qquad \forall p \qquad (7)$$

$$\sum_{s=1}^{S_t} y_t \times V_{st} \times (1 - RR_{st}) = \sum_{p=1}^{P} CR_{tp} \times x_p \times D_p \qquad \forall t \qquad (8)$$

$$\sum_{s=1}^{S_t} V_{st} = 1 \qquad \forall t \qquad (9)$$

$$N_{mc} \in \{0,1,2,3,\ldots\} \qquad \forall m,c \qquad (10)$$

$$Z_{opmc}, V_{st} \in \{0,1\} \qquad \forall o,p,m,c \qquad (11)$$

$$x_p \leq 1 \qquad \forall p \qquad (12)$$

$$x_p, y_t \geq 0 \qquad \forall p,t \qquad (13)$$

The objective function given in Equation (1) seeks to minimize machine acquisition cost, machine operating cost, intercellular movements cost, intracellular material handling cost, final product subcontracting cost, component supplier selection fixed cost, component procurement cost, component quality deficiency penalty cost, and component lead time delay penalty cost, respectively. Constraint (2) guarantees that the time capacity of a machine in a cell does not exceed the upper bound. Constraints (3) and (4) specify the minimum and maximum cell sizes according to the user defined lower and upper bounds. Equation (5) ensures that a specific operation of a part is processed on just one machine in one cell. Constraint (6) ensures that each part operation is assigned to a machine only when this machine can process the corresponding job. Constraint (7) guarantees that the proportion of total demand of each part type which is subcontracted does not exceed the pre-determined upper bound. Equation (8) is related to the quantity of components of each type with desirable quality that should be procured. Equation (9) allocates each component type to only one supplier. Finally, constraints (10)-(13) denote the decision variables types.

Linearized model

Although, off-the-shelf optimization software packages have an ability to solve complicated non-linear mathematical programming models, in some cases, converge to local optimal solutions. Moreover, there are difficulties to solve the problems of this type, in a reasonable amount of computational time. Therefore, to ensure that the global optima will be reliably discovered, linearization is necessary. The second, seventh, eighth, and ninth terms of the objective function and the Constraints (2) and (8) because of being the product of decision variables and also third and fourth terms of the objective function because of the existence of absolute expression and multiplication to another decision variable are cases in which the proposed model is non-linear. To linearize the second term of the objective function and Constraint (2), the product terms $x_p \times Z_{opmc}$ are rewritten by:

$$x_p \times Z_{opmc} = w_{opmc} \tag{13}$$

Moreover, these auxiliary constraints are added:

$$w_{opmc} \geq x_p + Z_{opmc} - 1 \qquad \forall o, p, m, c \tag{14}$$

$$w_{opmc} \leq x_p \qquad \forall o, p, m, c \tag{15}$$

$$w_{opmc} \leq Z_{opmc} \qquad \forall o, p, m, c \tag{16}$$

Such that w_{opmc} is a non-negative variable.

Similarly, the seventh, eighth, ninth terms of the objective function and Constraint (8) can be linearized by introducing non-negative variable u_{st}. The transformation equation is as follows:

$$y_t \times V_{st} = u_{st} \tag{17}$$

Where the following new constraints are added:

$$u_{st} \geq y_t + BPN \times V_{st} - BPN \qquad \forall s, t \tag{18}$$

$$u_{st} \leq y_t \qquad \forall s, t \tag{19}$$

$$u_{st} \leq BPN \times V_{st} \qquad \forall s, t \tag{20}$$

The Constraint (5) and the binary nature of decision variable z_{opmc} confine the absolute expressions to take a binary value. Hence, to linearize the third term of the objective function, at the first step we introduce a binary variable z^{1}_{opc} where the transformation equation is as follows:

$$\left|\sum_{m=1}^{M} Z_{o+1,pmc} - \sum_{m=1}^{M} Z_{opmc}\right| = Z^{1}_{opc} \tag{21}$$

Moreover, the following auxiliary constraints are added:

$$\sum_{m=1}^{M} Z_{o+1,pmc} - \sum_{m=1}^{M} Z_{opmc} \leq Z^{1}_{opc} \qquad \forall o,p,c \tag{22}$$

$$-\sum_{m=1}^{M} Z_{o+1,pmc} + \sum_{m=1}^{M} Z_{opmc} \leq Z^{1}_{opc} \qquad \forall o,p,c \tag{23}$$

Next, to transform the product term $x_p \times Z^{1}_{opc}$ we introduce the following continuous variable:

$$x_p \times Z^{1}_{opc} = k^{1}_{opc} \tag{24}$$

Where the below sets of constraints are added:

$$k^{1}_{opc} \geq x_p + Z^{1}_{opc} \qquad \forall o,p,c \tag{25}$$

$$k^{1}_{opc} \leq x_p \qquad \forall o,p,c \tag{26}$$

$$k^{1}_{opc} \leq Z^{1}_{opc} \qquad \forall o,p,c \tag{27}$$

To linearize the fourth term of the objective function, at the beginning, the mentioned term should be segregated as follows:

$$\frac{1}{2} \times \sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{o=1}^{O_p-1} AMC_p \times x_p \times (\sum_{m=1}^{M} \left|Z_{o+1,pmc} - Z_{opmc}\right|)$$
$$-\frac{1}{2} \times \sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{o=1}^{O_p-1} AMC_p \times x_p \times (\left|\sum_{m=1}^{M} Z_{o+1,pmc} - \sum_{m=1}^{M} Z_{opmc}\right|) \tag{28}$$

$$= \frac{1}{2} \times \sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{o=1}^{O_p-1}\sum_{m=1}^{M} AMC_p \times x_p \times \left|Z_{o+1,pmc} - Z_{opmc}\right|$$
$$-\frac{1}{2} \times \sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{o=1}^{O_p-1} AMC_p \times x_p \times (\left|\sum_{m=1}^{M} Z_{o+1,pmc} - \sum_{m=1}^{M} Z_{opmc}\right|) \tag{29}$$

Linearization procedure for the second term of (29) is similar to the third term of the objective function as mentioned above. To linearize the first term of (29) we define a binary variable Z^{2}_{opmc} as follows:

$$\left|Z_{o+1,pmc} - Z_{opmc}\right| = Z^{2}_{opmc} \tag{30}$$

Where the following constraints are added:

$$Z_{o+1,pmc} - Z_{opmc} \leq Z^{2}_{opmc} \qquad \forall o,p,m,c \tag{31}$$

$$-Z_{o+1,pmc} + Z_{opmc} \leq Z^{2}_{opmc} \qquad \forall o,p,m,c \tag{32}$$

Then we introduce the following continuous variable:

$$x_{p} \times Z^{2}_{opmc} = k^{2}_{opmc} \tag{33}$$

Where the below constraints are added:

$$k^{2}_{opmc} \geq x_{p} + Z^{2}_{opmc} \qquad \forall o,p,m,c \tag{34}$$

$$k^{2}_{opmc} \leq x_{p} \qquad \forall o,p,m,c \tag{35}$$

$$k^{2}_{opmc} \leq Z^{2}_{opmc} \qquad \forall o,p,m,c \tag{36}$$

Numerical Illustration with Global Optimization Experience

To validate the proposed mathematical model a comprehensive numerical example is solved by branch-and-cut method using GAMS software CPLEX 12 solver on a PC including an Intel® Core™ i7 @2.40 GHz CPU and 8 GB of RAM. This example consists of five part types, five machine types and five component types in which for each component type there are at most five suppliers. Each part has three operations. All parts' operations are processed in three fairly independent manufacturing cells with the lower size of 2 and the upper size 7. In addition, the upper bound of subcontracting proportion of total demand is considered equal to 0.5 for each part type. Other input parameters are in Tables 2 to 4. The last four columns of Table 2 contain unit intracellular movement, intercellular movement, and subcontracting costs and also the demand volume of each part that is shown in the last column. In this table, the last three rows show the machine acquisition cost, machine operating cost, and machine time capacity in hours, respectively. The required processing time for each part operation on eligible machines is also given in Table 2. For example, consider the first operation of Part Type 1 that can be processed either on Machine Type 1 in 0.54 h or on Machine Type 5 in 0.45 h.

Table 3 presents the bill of material identifying the consumption rate of each component type in one unit of each part type. Table 4 shows the suppliers' information including the fixed cost of supplier selection, procurement and transportation cost, reject rate and lead time delay for each component type presented by each supplier. Moreover, the unit quality deficiency and lead time delay penalty costs for all of the component types are assumed to be equal to 9 and 3, respectively.

After linearization, this model consists of 1075 variables under the considered example; 535 of them are discrete variables. Moreover, the corresponding number of constraints is equal to 2391. The output of software is in Tables 5 and 6, and the optimal objective function value is 219999.8. The cell configuration is shown in Table 5. Manufacturing cells are specified as rectangular shapes and the numbers within cells represent the required operations of parts as numbered. For example, Operation 1 of Part Type 3 must be processed by Machine Type 4 in Cell 3, Operation 2 by Machine Type 2 in Cell 2, and Operation 3 by Machine Type 1 in Cell 2, respectively. Therefore, producing one unit of Part Type 3 inside the manufacturing plant requires one intercellular movement and one intracellular movement. As is clear from Table 5, Cell 1 consists of two units of Machine Type 4 and one unit of Machine Types 3 and 5. The demand of Part Type 2 is entirely satisfied by internal production in Cell 1 and the demand of Part Type 4 is satisfied partially by internal production in Cell 1 and partially by subcontracting. Cell 2 includes one quantity of Machine Types 1, 2, 5. Part Type 5 entirely and Part Type 3 partially are allocated to this manufacturing cell. Finally, 641 units of total demand of Part Type 1 are allocated to Cell 3 including one quantity of Machine Types 2, 4, 5 and remained 59 units are subcontracted.

Table 2.Machine and Part Information

Part	Operation	Machine					AMC_p	IMC_p	SC_p	D_p
		M1	M2	M3	M4	M5				
P1	Opr1	0.54				0.45	2	5	77	700
	Opr2		0.67							
	Opr3			0.50	0.31					
P2	Opr1				0.95		2	5	69	650
	Opr2	0.40				0.30				
	Opr3			0.32		0.63				
P3	Opr1				0.67		2	5	65	600
	Opr2		0.42	0.20		0.50				
	Opr3	0.35								
P4	Opr1	0.47		0.35			2	5	61	650
	Opr2		0.74			0.54				
	Opr3		0.60		0.60					
P5	Opr1		0.18				2	5	73	700
	Opr2	0.25	0.55		0.33					
	Opr3				0.9	0.60				
AC_m		250 0	240 0	230 0	2500	260 0				
OC_m		8	6	7	8	7				
TC_m(h)		400	430	410	450	420				

Table 3.Bill of Material

		Component				
		T1	T2	T3	T4	T5
Part	P1	2	0	1	0	1
	P2	0	2	0	0	1
	P3	0	2	1	2	0
	P4	0	1	0	2	1
	P5	2	0	2	0	0

Table 4 .Supplier Information

Component	Supplier	FC_{st}	PC_{st}	RR_{st}	LD_{st}
T1	S1	750	5	0.20	3
	S2	800	7	0.13	2
	S3	640	8	0.10	1
	S4	700	7	0.17	1
T2	S1	700	4	0.15	3
	S2	950	7	0.10	1
	S3	800	10	0.10	0
	S4	750	5.5	0.12	2
	S5	850	5	0.10	2
T3	S1	900	4.5	0.11	0
	S2	850	5	0.12	0
	S3	720	2.5	0.20	2
	S4	800	2.5	0.19	2
	S5	790	3	0.15	1
T4	S1	800	4	0.10	1
	S2	770	6.5	0.13	0
	S3	950	3	0.15	3
T5	S1	650	4.5	0.19	2
	S2	860	7	0.17	1

Table 5.Optimal Cell Formation

		Part				
	Machine type (quantity)	**P2**	**P4**	**P3**	**P5**	**P1**
Cell1	M3 (1)	3	1			
	M4 (2)	1	3			
	M5 (1)	2	2			
Cell2	M1 (1)			3	2	
	M2 (1)			2	1	
	M5 (1)				3	
Cell3	M2 (1)					2
	M4 (1)			**1**		3
	M5 (1)					1
	Internal production	650	416	300	700	641
	Subcontracting	–	234	300	–	59

Table 6.Optimal Procurement Decision

Component	**T1**	**T2**	**T3**	**T4**	**T5**
Selected supplier	S3	S3	S1	S1	S2
Procurement quantity	2981	2574	2631	1592	2058

Table 6 represents the optimal procurement decision in the proposed integrated mathematical model. For instance, 2631 units of component Type 3 are required that all of them are provided by the first supplier of this component.

In order to demonstrate the effects of incorporating supplier selection into CMS decisions, a comparative analysis is made. To this end, the proposed example is solved according to the conventional two-phase procedure in which at the first phase, optimal cell configuration is determined and then at the second phase, suppliers are selected on the basis of the obtained cell formation. Comparing Tables 5 and 7 reveals the differences between the proposed integrated approach and the conventional two-phase procedure from the perspective of optimal cell configuration. For example, the demand of Part Type 1 in the integrated approach is satisfied partially by internal production in Cell 3 and partially by subcontracting. However, Part Type 1 in the conventional two-phase procedure is assigned to Cell 1 along with Part Type 2 and it also requires one intercellular movement. Cell 3 includes one quantity of Machine Types 2, 4, 5 in the integrated approach. However, in the conventional two-phase procedure Cell 3 includes one quantity of Machine Type 3 and two quantities of machine Type 2. The results also show that the total cost corresponding to the proposed integrated approach accompany by nearly 2.01% cost saving as compared with the conventional two-phase procedure. In systems of such size, even a small percentage reduction in total cost by applying an integrated approach can be valuable for the overall competitiveness.

Table 7.Optimal Cell Formation in the Conventional Two-Phase Procedure

		Part				
	Machine type (quantity)	P2	P1	P3	P5	P4
Cell1	M3 (1)	3				
	M4 (2)	1	**3**			
	M5 (1)	2				
Cell2	M1 (1)			3	2	
	M2 (2)		2	2	1	
	M4 (1)			1		
	M5(2)		1		3	
Cell3	M2 (2)					2, 3
	M3 (1)					1
	Internal production	650	700	600	700	641
	Subcontracting	–	–	–	–	9

The Suggested Hybrid Solution Approach

The algorithmic steps of LP embedded GA are represented in the flow chart given in Figure 1. Moreover, the detailed description of the main components for implementing LP embedded GA, as a solution approach to the integrated cell formation and supplier selection problem, is proposed in the following.

Solution Representation

The first stage in any GA implementation is to design a suitable chromosomal structure. Each chromosome is a string of genes taken from a predefined alphabet. In the case of the integrated problem under consideration, the chromosome structure consists of three sections corresponding to the discrete decision variables N_{mc}, Z_{opmc} and V_{st}. Figure 2 illustrates the schematic structure of chromosomes for the proposed numerical example. In this figure, the first section, labeled "Cells", specifies the machine configuration. For example, the term of $N_{52} = 3$ means that the number of Machine Type 5 in Cell 2 is equal to 3. The second section, labeled "Parts", indicates the operation assignment of the parts to manufacturing cells and also to machines. For example, the term of $CI_{31} = 3$ means that Operation 3 of Part Type 1 is assigned to Cell 3. The gene related to the assignment of an operation of a part to a machine type is named MI_{op}. For example, the term of $MI_{31} = 4$ means that Operation 3 of Part Type 1 is assigned to Machine Type 4. In order to avoid infeasible solutions, the machine assigned to process a specified operation should be a member of machines on which the considered part operation can be processed. Finally, the third section in the chromosome structure, labeled "Components", is associated with the supplier selection process. In this section, the gene SI_t takes an index related to the selected supplier of each component type. For example, the term $SI_3 = 5$ means that 5th supplier of component Type 3 is selected for procurement.

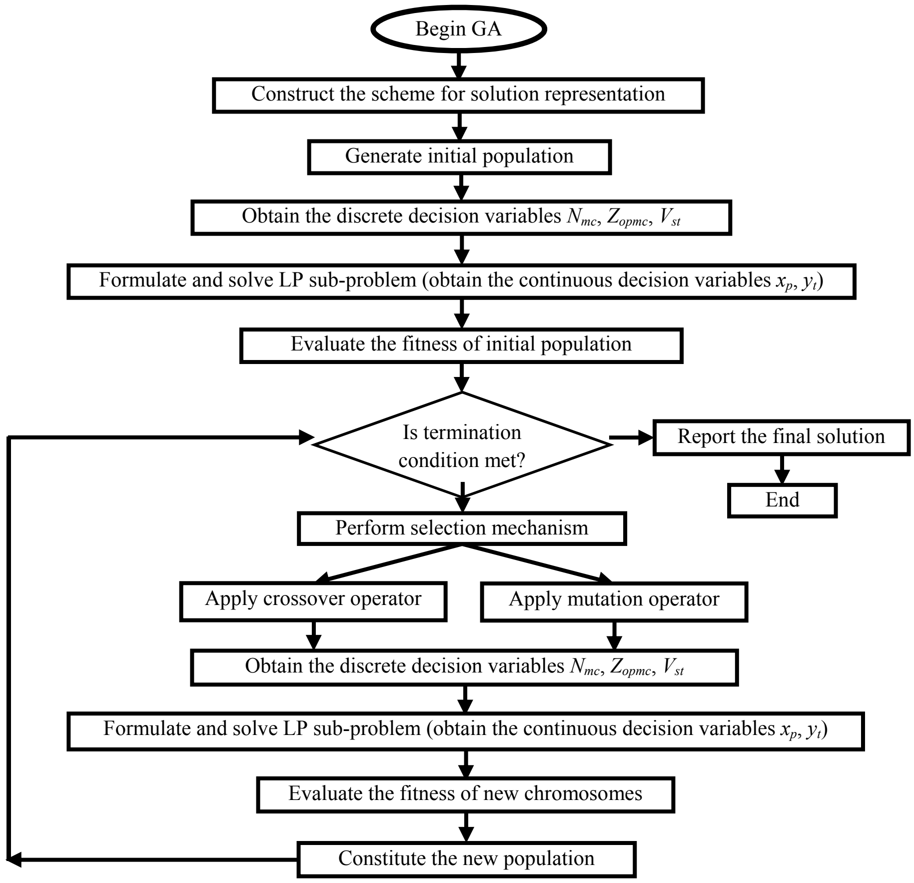

Fig. 1. LP embedded GA framework

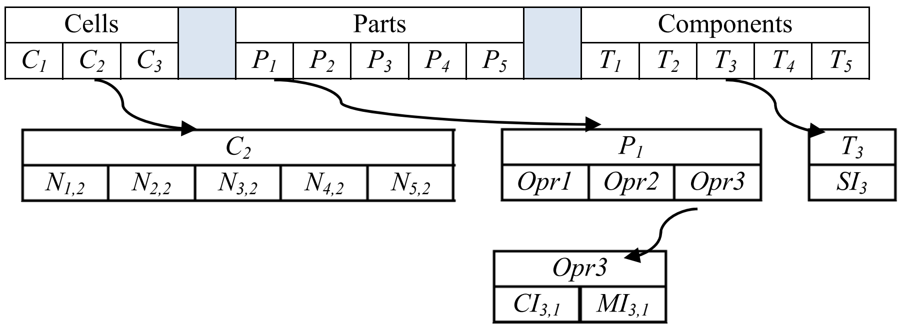

Fig. 2. Chromosome structure

Generating Initial Population

The procedure used here is to randomly generate initial population and consequently to satisfy the constraints in (5), (6), and (9). In fact, these randomly generated solutions satisfy all the constraints involving only the discrete variables, except the cell size constraints which are being taken care by the penalty manner.

Solving LP Sub-Problem

By eliminating all of the constraints and objective function terms involving only the discrete variables, the following LP sub-problem is formulated. In this formulation by fixing the values of the discrete variables there is no need for linearization. Determination of discrete variables not only simplifies the mathematical model by reducing the number of constraints and variables, but also facilitates the LP search procedure by removing all integer and binary variables.

Minimize OF_{LP}=

$$\begin{aligned}
&\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{o=1}^{O_p} OC_m \times PT_{opm} \times x_p \times D_p \times Z_{opmc} \\
&+\frac{1}{2}\times\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{o=1}^{O_p-1} IMC_p \times x_p \times D_p \times \left|\sum_{m=1}^{M} Z_{o+1,pmc} - \sum_{m=1}^{M} Z_{opmc}\right| \\
&+\frac{1}{2}\times\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{o=1}^{O_p-1} AMC_p \times x_p \times D_p \times \Big(\sum_{m=1}^{M}\left|Z_{o+1,pmc} - Z_{opmc}\right| - \\
&\left|\sum_{m=1}^{M} Z_{o+1,pmc} - \sum_{m=1}^{M} Z_{opmc}\right|\Big) \\
&+\sum_{p=1}^{P} SC_p \times (1-x_p) \times D_p + \sum_{t=1}^{T}\sum_{s=1}^{S_t} PC_{st} \times y_t \times V_{st} \\
&+\sum_{t=1}^{T}\sum_{s=1}^{S_t} RR_{st} \times UPC_t \times y_t \times V_{st} + \sum_{t=1}^{T}\sum_{s=1}^{S_t} LD_{st} \times UDC_t \times y_t \times V_{st}
\end{aligned} \tag{37}$$

Subject to:

$$\sum_{p=1}^{P}\sum_{o=1}^{O_p} PT_{opm} \times x_p \times D_p \times Z_{opmc} \le TC_m \times N_{mc} \qquad \forall m, c \tag{38}$$

$$1 - x_p \le UB_p \qquad \forall p \tag{39}$$

$$\sum_{s=1}^{S_t} y_t \times V_{st} \times (1 - RR_{st}) = \sum_{p=1}^{P} CR_{tp} \times x_p \times D_p \qquad \forall t \tag{40}$$

$$x_p \le 1 \qquad \forall p \tag{41}$$

$$x_p, y_t \ge 0 \qquad \forall p, t \tag{42}$$

The objective of the LP sub-problem is to minimize the sum of the operating cost, intercellular and intracellular movements cost, final product outsourcing cost, component variable procurement cost, component quality deficiency penalty cost, and lead time delay penalty cost, subject to the constraints in (2), (7)-(8) and (12)-(13). These constraints were renumbered as (38)-(42).

Fitness Function

As seen from Equation (43) below, the fitness of a given solution in the algorithm is equal to the objective function value of the main model plus two penalty terms. The penalty manner is used to penalize solutions which violate the constraints. The model objective function is comprised of the objective function value of the LP sub-problem, machine acquisition cost, and component supplier selection fixed cost. The first penalty term controls the cell size constraints and the second one is related to infeasible LP sub-problems. The factors PF_{cs} and PF_{LP} were used to scale these penalty terms. These factors are easily determined by a preliminary trial-and-error process.

$$FF = \text{model objective function} + PF_{cs} \times \sum_{c=1}^{C} max \left\{ 0, (LS_c - \sum_{m=1}^{M} N_{mc}), (\sum_{m=1}^{M} N_{mc} - US_c) \right\} + PF_{LP} \times \begin{cases} 1; & \text{If the corresponding LP sub-problem is infeasible.} \\ 0; & \text{otherwise.} \end{cases} \quad (43)$$

Selection Mechanism

The purpose of selection mechanism is to provide a situation in which the fittest individuals have more chance to be selected and to produce new offspring. Roulette wheel is one of the standard selection mechanisms in GA and other evolutionary algorithms. Each individual, on the basis of its fitness value, receives a probability of being selected. We modify the conventional Roulette wheel mechanism as follows:

$$RF_j = \frac{FF_j - (\min_{i \in population} FF_i)}{(\max_{i \in population} FF_i) - (\min_{i \in population} FF_i)} \quad (44)$$

Where RF_j is the relative fitness value of individual j and FF_i is the absolute fitness value of individual i in the population.

Genetic Operators

A new filial generation of individuals is created by crossover and mutation operators. Crossovers combine the features of the two parents so that by iteratively applying these operators, the genes of good chromosomes are appearing more and more in the population. Unlike crossovers, mutation operators try to make indiscriminate changes in single randomly selected individuals. This provides an opportunity to diversify search direction and to escape from local optimums. We developed six types of crossover operators in our GA. These are (1) simple crossover, (2) "Cells" swap crossover, (3) "Parts" swap crossover, (4) "Components" swap crossover, (5) single-cell swap crossover, and (6) single-part-type swap crossover. We also applied four different types of mutation, called the (1) cell-machine mutation, (2) part-operation-cell mutation, (3) part-operation-machine mutation, and (4) component-supplier mutation. For more information on these operators we refer to Defersha and Chen (2008).

Computational Results

We arrange 10 randomly generated instances to evaluate different aspects of our algorithm. Problems' dimensions data, number of constraints and number of discrete and continuous variables are given in Table 8. The instance number 2 in Table 8 is that which was presented above in Section 4. The meta-heuristic was also compiled in MATLAB R2014a.

The main parameters of GA, namely, the number of generations, population size, crossovers rates and mutations rates, control the behavior of the algorithm. In this study, a plan of experiments based on Taguchi technique with three levels for each parameter was executed to calibrate the hybrid GA parameters, while a L9 (3^ 4) orthogonal array is taken into account.

Table 8.Problem Dimension Data, Number of Constraints and Variables

Instance number	Dimensions						Number of constraints	Number of variables	
	Number of parts	Number of machines	Number of cells	Maximum number of operations	Number of components	Maximum number of suppliers for each		Discrete	Continues
1	5	4	3	2	5	4	1348	302	310
2	5	5	3	3	5	5	2391	535	540
3	7	4	3	3	6	4	2730	603	614
4	6	6	3	3	6	6	3370	756	760
5	7	7	3	3	6	8	4512	1014	1016
6	8	8	3	3	9	6	5804	1302	1305
7	10	7	3	4	7	9	8460	1884	1890
8	15	11	4	3	10	8	19117	4264	4255
9	18	14	3	4	11	9	28781	6405	6402
10	20	17	4	3	13	8	38444	8572	8547

Table 9 shows the candidate levels for each parameter. These values were determined by preliminary tests. The experiments of the Taguchi design and the corresponding response values are shown in Table 10.

The response value for each experiment in the last column of the Taguchi design table is the average of OF values of three consecutive runs with the hybrid GA. In order to determine the optimum levels of process parameters, Taguchi uses a statistical performance measure called Signal to Noise (SN) ratio. For the design problem under consideration, the smaller is the better case of Taguchi's SN ratio selected. Table 11 presents details of analyzing the statistical experimental results by Minitab software.

The response graph of SN ratio is also given in Figure 13. In this figure, the optimum level for each process parameter is the one with the highest value of SN ratio. Accordingly, the third level of a number of generations (50), the third level of population size (60), the third level of crossover rate (0.7), and the first level of mutation rate (0.05), are selected. The estimated values of all GA parameters for small, medium and large size problems are given in Table 12. It is expected that larger values for these control parameters will increase the computational burden without noticeable improvement in solution quality.

Table 9.Control Parameters and Their Levels

Parameter	Range	Level 1 (low)	Level 2 (medium)	Level 3 (high)
Number of generations	30- 50	30	40	50
Population size	20- 60	20	40	60
Crossovers rate	0.5- 0.7	0.5	0.6	0.7
Mutations rate	0.05- 0.15	0.05	0.10	0.15

Table 10.L9 Orthogonal Array of Taguchi Design of Experiments

Experiment	Coded levels				Decoded levels				Response
	A	B	C	D	Number of gen.	Pop. size	Cross. rate	Mute. rate	Avg. Fitness values
1	1	1	1	1	30	20	0.5	0.05	228393.7
2	1	2	2	2	30	40	0.6	0.10	226786.4
3	1	3	3	3	30	60	0.7	0.15	224802.5
4	2	1	2	3	40	20	0.6	0.15	226856.6
5	2	2	3	1	40	40	0.7	0.05	223458.9
6	2	3	1	2	40	60	0.5	0.10	223811.5
7	3	1	3	2	50	20	0.7	0.10	225439.4
8	3	2	1	3	50	40	0.5	0.15	222890.7
9	3	3	2	1	50	60	0.6	0.05	222246.6

Table 11.Results of Implementing Taguchi Design of Experiments

Response table for SN ratios (smaller is better)					Response table for means					Response table for standard deviations				
Level	A	B	C	D	Level	A	B	C	D	Level	A	B	C	D
1	-107.107	-107.116	-107.044	-107.031	1	226661	226897	225032	224700	1	*	*	*	*
2	-107.032	-107.019	-107.055	-107.057	2	224709	224379	225297	225346	2	*	*	*	*
3	-106.986	-106.990	-107.027	-107.038	3	223526	223620	224567	224850	3	*	*	*	*
Delta	0.121	0.126	0.028	0.026	Delta	3135	3276	730	646	Delta	*	*	*	*
Rank	2	1	3	4	Rank	2	1	3	4	Rank	2.5	2.5	2.5	2.5

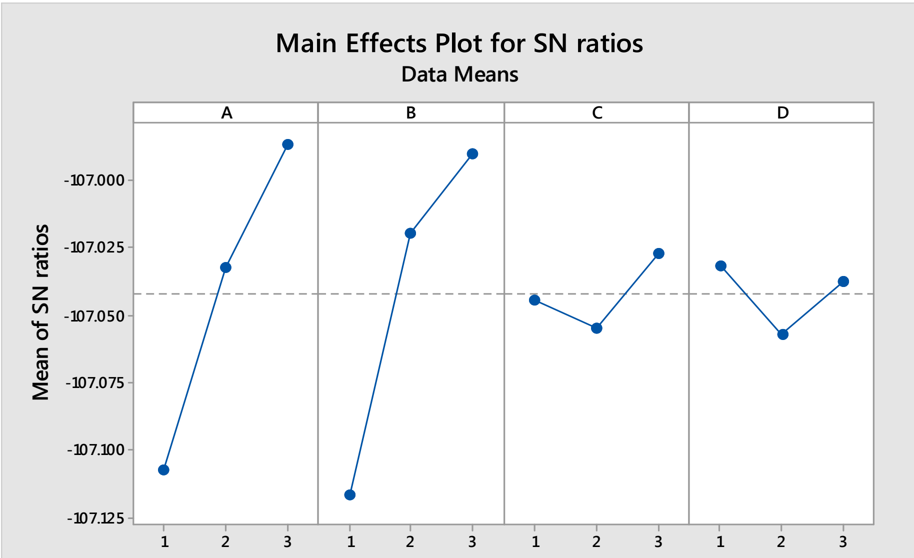

Fig. 3. SN ratio from Taguchi design of experiments

The results of solving the problems by branch and cut method on GAMS software package and the proposed LP embedded GA are given and compared in the last five columns of Table 12. As can be seen from this table, the GAMS software has only solved the small-size problems in a reasonable time. However, problems 6-10 cannot be solved in an acceptable time using GAMS software, because of the large number of constraints and variables. Therefore, we limit runtime to 50 hours for problems 6-7 and 100 hours for problems 8-10 to save computational work and report the best obtained solution.

The relative difference between objective function values obtained by the two methods is represented as Gap in Table 12. In the case of Problem 1, the LP embedded GA has obtained the globally optimal solution. The solutions obtained by the LP embedded GA for test Problems 2-5 show that in the worst case, the solution gap between the proposed hybrid approach and the global optima obtained by GAMS software is about 1.49%. This result verifies the validity of our proposed GA-based method.

However, because of the computational complexity, the proposed model cannot be optimally solved within 50 hours or even longer for problems 6-7 and 100 hours for problems 8-10. As seen in Table 12, even for unsolvable problems in a reasonable time by GAMS software, the gap between the objective function values of the proposed LP embedded GA heuristic approach and the best obtained by the branch and cut exact method in the worst case is around 4.01%. This shows the proposed approach is capable to find near-optimal solutions for large-scale problems. Moreover, a computational time obtained by LP embedded GA for these problems is largely better than those obtained by GAMS software and it can be concluded that the proposed hybrid approach is efficient from the amount of computational time point of view.

Conclusions

In traditional manufacturing systems, designing production facilities and selecting component suppliers are two separate decisions. In this paper, an integrated approach was adopted to analyze, since production and purchasing functions are interrelated and interact with each other in view of corporate overall operation. A novel mixed-integer non-linear programming model was developed to make production and procurement decisions in generalized CFP and supplier selection process, simultaneously. Benhalla et al. (2011), Paydar et al. (2014), and Heydari et al. (2017) also focused on the development of quantitative models for integrated supplier selection and CMS design.

Table 12.Comparison of LP Embedded GA and GAMS Solutions

Instance number	Number of chromosome's gens	GA parameters				OF value		Time		Gap (%)
		Number of generations	Population size	Crossovers rate	Mutations rate	GAMS	LP embedded GA	GAMS	LP embedded GA	
1	37	50	60	0.7	0.05	203404.1	203404.1	00:00:25	00:01:52	0
2	50	50	60	0.7	0.05	219999.8	221444.9	00:02:09	00:02:24	0.66
3	60	50	60	0.7	0.05	307635.8	309468	00:10:38	00:03:02	0.6
4	60	50	60	0.7	0.05	271829.7	275876.9	01:01:20	00:04:49	1.49
5	69	80	100	0.8	0.15	265407.9	269175.5	09:57::46	00:16:55	1.42
6	81	80	100	0.8	0.15	302484.4	314262.9	50:00:00	00:17:58	3.89
7	108	80	100	0.8	0.15	435344.4	445588.5	50:00:00	00:23:51	2.35
8	144	125	150	0.9	0.1	580053.4	603291.2	100:00:00	01:06:04	4.01
9	197	125	150	0.9	0.1	723399.6	730878.4	100:00:00	01:46:09	1.03
10	201	125	150	0.9	0.1	683693.5	689722.6	100:00:00	02:09:30	0.88

This paper contributes to the literature by incorporating various manufacturing design attributes such as alternative process routings, operation sequences, part demands, processing times, machine capacity, machine duplication, etcetera along with supplier selection and a subcontracting approach. To our knowledge, this is the first time that a single model addresses all these features simultaneously.

We linearized the non-linear formulation of our proposed model by a special procedure. The validation of the model was illustrated by solving a comprehensive numerical example. The Generalized Algebraic Modeling Systems software package is able to solve the small-size problems efficiently. However, the proposed model is NP-hard and for medium-size and large-size problems cannot be solved by off-the-shelf optimization software packages in a reasonable amount of computational time. Hence, we applied a hybrid heuristic based on combining GA and LP. As far as we know, this is the first heuristic approach for real-world integrated cell configuration and supplier selection problems. A number of numerical experiments were performed to verify the good ability of the hybrid solution procedure. Computational results illustrated the efficiency of the proposed technique in obtaining effective solutions.

The proposed mathematical model is still open for incorporating other features, such as machine layout, machine closeness, machine utilization, workload balancing, worker assignment and worker training, multi-plant location, considering additional tiers of the SC, introducing uncertainty in part demand, machine availability and cost coefficients, multi-objective optimization, that will be left for future research. As a solution method, we developed the LP embedded GA to cope with the complexity of the problem. In this direction, employing other solution approaches based on integrating an exact method with other meta-heuristics such as SA, TS, as well as different hybrid meta-heuristic algorithms so as to attain even better results can also be taken into account.

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