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Designing an Integrated Production/Distribution and Inventory Planning Model of Fixed-life Perishable Products

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Abstract

This paper aims to investigate the integrated production/distribution and inventory planning for perishable products with fixed life time in the constant condition of storage throughout a two-echelon supply chain by integrating producers and distributors. This problem arises from real environment in which multi-plant with multi-function lines produce multi-perishable products with fixed life time into a lot sizing to be shipped with multi-vehicle to multi-distribution-center to minimize multi-objective such as setup costs between products, holding costs, shortage costs, spoilage costs, transportation costs and production costs. There are many investigations on production/distribution planning area with different assumptions. However, this research aims to extend this planning by integrating an inventory system in which for each distribution center, net inventory, shortage, *FIFO* system and spoilage of items are calculated. A mixed integer non-linear programming model (*MINLP*) is developed for the considered problem. Furthermore, a genetic algorithm (*GA*) and a simulated annealing (*SA*) algorithm are proposed to solve the model for real size applications. Also, Taguchi method is applied to optimize parameters of the algorithms. Computational characteristics of the proposed algorithms are examined and tested using *t*-tests at the 95% confidence level to identify the most effective meta-heuristic algorithm in terms of relative percentage deviation (*RPD*). Finally, Computational results show that the *GA* outperforms *SA* although the computation time of *SA* is smaller than the *GA*.

Keywords: Production/distribution and inventory planning, Perishable product, Multi-objective, Mixed integer non-linear programming, Genetic algorithm.

1. Introduction

In the real world, many goods are spoiled and cannot be used after a period of the time. So, it is necessary to consider the duration of storage to keep perishable goods. For example, it is essential to note to the expiration date to purchase and maintain drugs. On the other hand, some products lose their properties after a while without having changes in their appearance. For example, long-term storage of foods in the freezer causes to miss their vitamins and nutrients although their appearance has not changed. Also, there are types of products which are excluded after a period of the time despite having suitable quality for using. For example, consider different fashion clothing. With the changing fashion, the numbers of old-fashioned clothing customers are reduced. So, these clothes are sold with discount or are not sols. Also, there are other items such as soy sauce, spices etc. which they will have a higher value with the passage of the time. So, attention to the type of product and its characteristics is important for maintenance of items.

Liu and Shi (1999) categorized perishability and deteriorating inventory models into two major groups; namely, finite lifetime models and decay models. The Finite lifetime models assume a limited lifetime for each product, while the Decay models deal with inventory that diminishes continuously with the passage of the time. Furthermore, the finite lifetime can be generally classified into two subcategories; namely, fixed finite lifetime and random finite lifetime. In the former case, products may be retained in stock for some fixed time after which they must be discarded and in the latter case, items are discarded when they spoil and time to spoilage is uncertain.

This research is motivated by a practical problem in which a set of plants with limited production lines are producing perishable products with fixed life times that should be delivered to a set of distribution centers by a set of capacitated vehicles. Distribution centers have different deterministic demands with limited capacity.

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The problem is formulated as a Mixed Integer Non-linear Programming (*MINLP*) model. This model used several features of the formulations previously studied by Amorim et.al (2012, 2013) and the method used by Pauls-Worm et al. (2014) for applying *FIFO* policy. The model is extended to account for shortage, spoilage, *FIFO* system and net inventory in a production and distribution planning in which perishable products are delivered by multi-vehicles to capacitated warehouses of distribution centers. Further, a genetic algorithm (*GA*) as well as a simulated annealing (*SA*) algorithm are presented for large scales of the considered problem.

The main contributions of this paper can be summarized as follows: (i) Proposing a *MINLP* formulation for the production and distribution planning problem within the food industry, (ii) Developing an approach that combines the inventory system advantages with a production and distribution planning model, and (iii) proposing two meta-heuristic algorithms to a real world production and distribution planning problem for perishable products.

This paper is organized as follows. In the next section, brief survey of relevant literature is given in which a review of available literature will lead us to conclude that the candidate problem in this research has not been studied. Section 3 gives a detailed description of the problem and presents the proposed *MINLP* model. Introducing the two meta-heuristic algorithms are presented in Section 4. Section 5 includes computational results. Finally in Section 6, some conclusions and future research directions are cited.

2. Literature Review

The integrated Production and Distribution Problem (*IPDP*) has received remarkable attention during the past two decades. A rich literature has been initiated and recently some more complicated problems were built up on stochastic and nonlinear models were studied (e.g., Chen et al.,2009; Farahani et al.,2012). Hunter and Van Buer (1996) are among the pioneers who studied *IPDP*s on serving multiple products to multiple customers. Their models incorporated vehicle routing options and were studied using real data from a newspaper company. Lee and Chen (2001) proved that general *IPDP*s are *NP*-hard except a few cases which are pseudo- polynomial time solvable. Their study established a milestone on the considerations of transportation capacity issues in *IPDP*s.

Armstrong et al. (2008) and Geismar et al. (2008) proposed *IPDP*s on perishable products so that the no-wait condition becomes necessary for the limited product life time once after being processed. The former considered customer-specified delivery time windows, and the latter investigated vehicle routing options. Both studies employed only one production and delivery batch instead of multiple ones; furthermore, truck capacity is not a constraint in either research. Viergutz and Knust (2012) studied the same problem of Armstrong. et al. (2008), and utilized mate- heuristic. Also, they developed the scenario by permitting delays of the production start time and variable production and distribution sequences.

Yang and Wee (2003) extended a mathematical model for multi-item production lot sizing for perishable items in *JIT* environment. They considered both the lot-splitting of material from the supplier to producer and the lot-splitting of finished goods from producer to multiple buyers. Eksioglu and Jin (2006) investigated a planning model that integrates production, inventory and transportation decisions in a two-stage supply chain for perishable products with fixed shelf time. They proposed a mixed integer linear programming (*MILP*) formulation for the problem. Also, a primal-dual heuristic is developed that provides lower and upper bounds. Ahuja etal.(2007) studied a two-stage logistic network similar to that of Eksioglu and Jin (2006) with additional production and inventory capacity constraints.

Bilgen and Günther (2010) studied an integrated production and distribution planning model with setup family and transportation. They introduced the block planning concept for short-term scheduling of setup families, and proposed mixed-integer linear optimization model for two sub models, production planning and distribution planning. Also, they considered two transportation modes, full truckload and less than truckload for the delivery of final goods from the plants to distribution centers. Yan et al. (2011) developed an integrated production and distribution model for a deteriorating item in a two-echelon supply chain. Furthermore, they assumed some limitations concerning perishability and the supplier's production batch size is restricted to an integer multiple of the discrete delivery lot quantity to the buyer. They aimed to minimize the total system cost.

Amorim et al. (2012) discussed the importance of integrating the analysis for a production and distribution planning problem dealing with perishable products. The logistic setting of their operational problem is multi-product, multi-plant, multi-distribution-center and multi-period. Based on the block planning concept, they developed models for two types of perishable products: with fixed shelf-life and with loose shelf-life. They presented an integrated and a decoupled production and distribution planning model for each of these cases, and afterwards compared the two different approaches. In addition, their research aim to minimized total costs, namely: production costs, transportation costs and spoilage costs.

Also, Amorim et al. (2013) studied an integrated production and distribution planning problem in which multi-production line produce multi-perishable product to be delivered in a certain route by identical fixed capacity vehicles to a set of customers. They proposed two formulations for two cases. The first formulation models the operational integrated production and distribution problem that only considers batching of orders and the second formulation extends the first one by considering the sizing of the lots. Then they compared both models under different terms. Pauls-Worm et al. (2014) developed a *MILP* model for the practical production planning problem of a food producer facing a non-stationary erratic demand for a perishable product with a fixed life time under *FIFO* issuing policy and a service level approach.

Chen et al. (2009) presented a model that considers stochastic demand for multiple products subject to perishability. The production environment does not consider setups between products and the delivery function is assured by a set of capacitated vehicles, however, the vehicle operating costs are disregarded. Kanchanasuntorn and Techanitisawad (2006) presented an approximate periodic model for fixed-life perishable products. They investigated the effect of product perishability and retailers' stock out policy on system total cost, net profit, service level, and average inventory level in a two-echelon inventory–distribution system.

Production–inventory model was developed for a deteriorating item over a finite planning horizon by Sana et al. (2004). They solved the model by using the box complex algorithm. For an extensive review on perishable items in production/distribution and inventory models, the reader is referred to the works of Amorim et al. (2013) and Karaesmen et al. (2011).

3. Problem Definition and Mathematical Formulation

The proposed mathematical model in this paper is developed on the following assumptions and notations: There are number of plants p=1,…,p having a set of multi-function parallel lines l=1,…, l that produce multi-perishable products k=1,…, k with a limited capacity to be delivered to a set of distribution centers c=1,..,c. Products are shipped with multi-vehicle m=1,…,m with a limited capacity. Setup time between two products is assumed and dependent on the sequence of production. Products have a fixed lifetime. The planning horizon is formed of several macro periods d=1,…, dd (weeks), that each of them consists of the number of micro periods s=1,.., ss (days). Products are produced daily and are maintained in the plant storage and at the end of each week are shipped to the distribution centers. The distances between the plants and the distribution centers are small enough so that the product is delivered on the same day at the end of week. Thus, the decrease of freshness during the transportation is considered to be negligible. Products can be transported between any pair production plant–*DC*. The capacity of distribution centers and vehicles are limited. Plants have Temporary storage without the maintenance cost. Maintenance cost of the item is respect to the stock inventory at distribution centers. The product lifetime is determined by week and it is assumed to be more than a week. The spoiling of products occurs in distribution centers warehouses. On the other hand, no items spoil in plants. The spoiled products cannot be repaired or replaced. Demand in any time period is certain, deterministic and negative. Products inventory balance at distribution centers are updated at the end of each week according to the production output from the various lines at the plants, the transportation quantities, and the given external demand. Shortage of demand is allowed and it's lost sales. Demand that cannot be fulfilled in one period is backlogged in the next period. The outputs of items at distribution centers are according to *FIFO* system in which the first produced items are issued first. For convenience and without loss of generality, the initial inventory level is set to zero.

The purpose is to minimize the total system costs, including the setup cost, production, decay, shortage, maintenance and transportation, simultaneously. A simple graphical interpretation of the problem is shown in Figure 1.

Figure 1 demonstrates the product flow from plants to distribution centers by using vehicles and the correspondent demand and spoilage. The figure shows a weekly planning horizon and the inventory which is carried connecting the sequential planning horizons. Furthermore, as Figure 1 represents, products are produced daily (s=1,…, ss) and are maintained in the temporary warehouse of plant, and at the end of each week (d=1,…, dd) are shipped to the distribution centers. The optimization process output includes production planning (sequence of products) on the parallel lines, the number of produced and shipped goods, the number of spoiled items, the net inventory and inventory shortage, so that the total costs of system are minimized.

3.1. Indices

l	Production lines
k, k'	Products
d	Macro-periods (week)
s	Micro-periods (day)
p	Production plants
m	Vehicle
c	Distribution centers (DCs)
b	Age of products

3.2. Parameters

dd	The last of macro period
cap_{ld}	Capacity (time) on production line l available in macro period d
a_{lk}	Capacity consumption (time) needed to produce one unit of product k on line l
pc_{klp}	Production costs of product k (per unit) on line l in plant p
$set_{kk'lp}$	Sequence dependent setup cost (time) for a change-over from product k to product k' on line l in plant p
$tset_{kk'lp}$	Setup time for a change- over from product k to product k' on line l in plant p

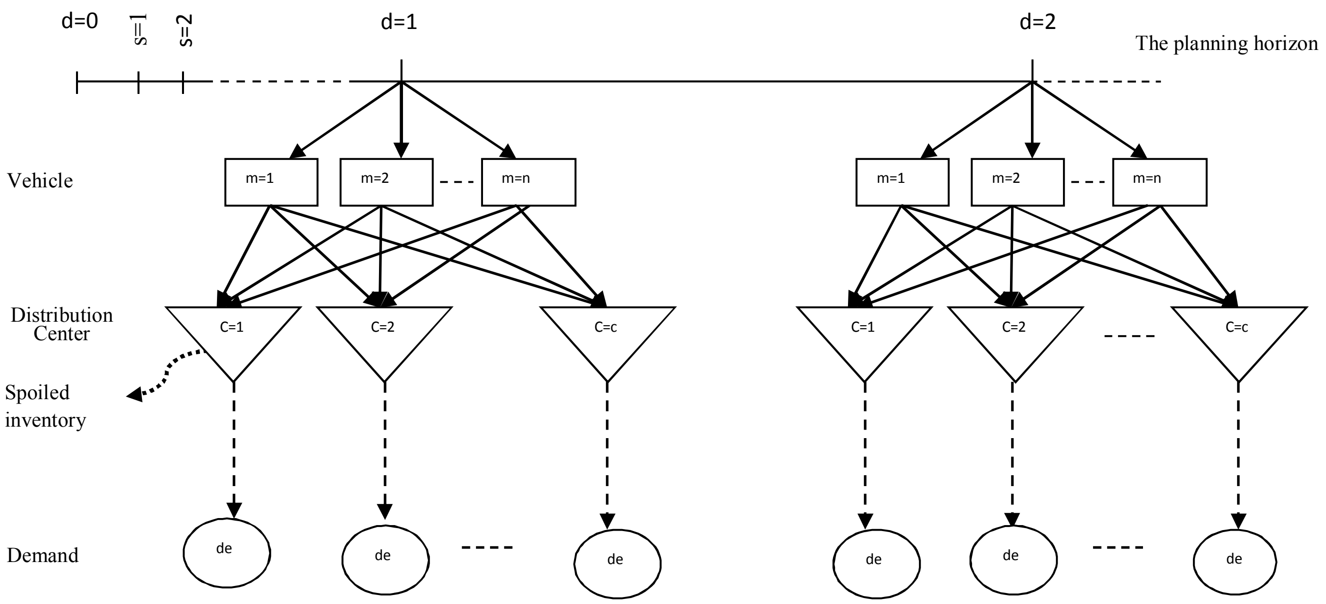


Fig.1. Graphical interpretation of the problem statement.

sc_k Cost associated with the spoilage per unit of product k

L_k Lifetime of product k

sp_k Cost associated with the shortage of one unit of product k

tc_{pmc} Cost for transporting one item of production plant p with vehicle m to DC c

h_{kc} Holding cost for product k at DC c

fp_k Occupied Space for one unit of product k

f_c Available space at DC c

vc_m Available space in vehicle m

de_{kdc} Demand for product k at the end of macro-period d at DC c (units)

3.3. Decision variables

q_{klpsd} Quantity of product k produced on line l of plant p in micro-period s of macro period d (units)

y_{klpsd} Equals1, if product k is produced on line l of plant p in micro-period s of macro period d; otherwise 0

B_{kdc} Quantity of stock of product k that spoils at the end of macro- period d at DC c (units)

$z_{kk'lpsd}$ Equals 1, if a change-over from product k to product k' takes place on line l of plant p in micro-period s of macro period d; otherwise 0

x_{kmdpc} Quantity of product k shipped by vehicle m from production plant p to DC c at the end of macro-period d (units)

I_{kbdc} Inventory of product k with age b at the end of macro period d at DC c

Iv_{kdc} Inventory of product k at the end of macro period d at DC c

Sh_{kdc} Shortage of product k at the end of macro period d at DC c

3.4. The proposed mathematical model

Objective function:

$$Min\,Z = \sum_{k,k',l,p,s,d} set_{kk'lp}.z_{kk'lpsd} + \sum_{k,d,c} h_{kc}.Iv_{kdc} + \sum_{k,d,c} sp_k.Sh_{kdc} + \sum_{k,d,c} sc_k\,.B_{kdc} + \sum_{p,m,k,d,c} tc_{pmc}.x_{kmdpc} + \sum_{k,l,p,s,d} pc_{klp}.q_{klpsd} \quad (1)$$

Subject to:

$$q_{klpsd} \le \left(\frac{cap_{ld}}{a_{lk}}\right).y_{klpsd} \qquad \forall\, k,l,p,s,d \quad (2)$$

$$\sum_{k,k',s} tset_{kk'lp}.z_{kk'lpsd} + \sum_{k,s} a_{lk}.q_{klpsd} \le cap_{ld} \qquad \forall\, l,p,d \quad (3)$$

$$\sum_{k} y_{klpsd} = 1 \qquad \forall\; l,p,s,d \quad (4)$$

$$z_{kk'lpsd} \ge y_{klpsd} + y_{k'lp(s-1)d} - 1 \qquad \forall\, k,k',l,p,s,d, \quad (5)$$

$$y_{klp0d} = 0 \qquad \forall\, k,l,p,d \quad (6)$$

$$\sum_{l,s} q_{klpsd} = \sum_{c,m} x_{kmdpc} \qquad \forall\, k,p,d \quad (7)$$

$$\sum_{k} fp_k\,.Iv_{kdc} \le f_c \qquad \forall\, d,c \quad (8)$$

$$\sum_{k} fp_k\,.x_{kmdpc} \le vc_m \qquad \forall\, m,p,c,d \quad (9)$$

$$\sum_{b=1}^{L_k} I_{kbdc} = \sum_{b=1}^{L_k-1} I_{kb,d-1,c} + \sum_{m,p} x_{kmdpc} - de_{kdc} \qquad \forall\, k,c,d \quad (10)$$

$$I_{k1dc} = \sum_{m,p} x_{kmdpc} - \max\{0, de_{kdc} - \sum_{b=1}^{L_k-1} I_{kb,d-1,c}\} \quad \forall k,c,d \quad (11)$$

$$I_{kbdc} = I_{k,b-1,d-1,c} - \max\{0, de_{kdc} - \sum_{i=b}^{L_k-1} I_{ki,d-1,c}\} \quad \forall k,c,d,b = 2,\dots,L_k \quad (12)$$

$$I_{k0dc} = 0 \quad \forall k,c,d \quad (13)$$

$$I_{kbdc} = I^{+}_{kbdc} - I^{-}_{kbdc} \quad \forall k,d,b,c \quad (14)$$

$$I^{+}_{kbdc} \times I^{-}_{kbdc} = 0 \quad \forall k,d,b,c \quad (15)$$

$$Iv_{kdc} = \sum_{b=1}^{L_k} I^{+}_{kbdc} \quad \forall k,d,c \quad (16)$$

$$Sh_{kdc} = \sum_{b=1}^{L_k} I^{-}_{kbdc} \quad \forall k,d,c \quad (17)$$

$$B_{kdc} \geq I_{kb,d-1,c} \quad \forall k,c,d,b = L_k+1,\dots,dd \quad (18)$$

$$I^{+}_{kbdc}\ ,\ I^{-}_{kbdc}\ ,\ Iv_{kdc}, Sh_{kdc}, q_{klpsd}, x_{kmdpc}, B_{kdc} \geq 0; \quad I_{kbdc} \in free; \ z_{kk'lpsd}, y_{klpsd} \in \{0,1\} \quad (19)$$

In the above formulation, the objective function (1) aims to minimize setup costs between products, holding costs, shortage costs, spoilage costs, transportation costs and production costs.

Constraints (2) and (3) are concerned with the capacity of the production line (available time). Constraint (2) ensures that a product can only be produced if there exists a setup for it. Constraint (3) is satisfied when in every line l of macro period d the sum of setup time and production time becomes less than available time. In other word, the makespan of the plant at each planning period should not be greater than the corresponding total available time.

Constraint (4) ensures that on each line just one product can be produced simultaneously. Constraint (5) specifies linking between setup states and changeover indicators for products. Constraint (6) sets the initial configuration of the lines.

Constraint (7) ships the products to the distribution centers which means the sum of the Quantity of product k produced in plant p in all micro-period s of macro period d to be the same with the quantity of product k of plant p transferred to the various distribution centers by any vehicles at the end of macro period d.

Constraints (8) and (9) are related to the capacity of distribution centers and vehicles, respectively. In constraint (10), the inventory levels of all ages of product k at distribution center c at the end of macro period d are balanced. The inventory of product k at the end of macro period d is determined by the ending inventory of the previous period d-1 of ages b=1,…, L_k-1 of product k plus the quantities received of product k via the various vehicles in macro period d minus the corresponding external demand in the respective macro period.

Constraints (11) and (12) are concern with the *FIFO* policy. They ensure that demand is fulfilled first by the oldest products in stock and then successively by the younger products. Variable I_{kbdc} denotes the inventory level of product k with age b at the end of period d. Products that are delivered at the end of period d have age b=1 at the end of correspondent period. Product k of age L_k at the end of a period is not carried over to the next period, because it is out-dated; inventory I_{kbdc} of age L_k at the end of period d is considered waste. Constraint (13) necessitate that the starting inventory level of all ages of each product is equal to zero.

Constraints (14) and (15) present the relationship between the two auxiliary variables in which I^{+}_{kbdc} and I^{-}_{kbdc} are inventory level and shortage backlog, respectively. Constraints (16) and (17) compute the inventory level and backlogging of shortage of all ages of product k at the end of macro period d. Constraint (18) represents the quantity of stock of product k which spoils in macro period d at distribution center c. Finally, Constraint (19) provides the logical binary, free and non-negative necessities for the decision variables.

3.5. Sensitivity analysis

Sensitivity analysis is a technique used to determine how different values of an independent variable will impact a particular dependent variable under a given set of assumptions. This technique is used within specific boundaries that will depend on one or more input variables. Here, a hypothetical example is considered for evaluating importance of variable used in the proposed mathematical model.

In this example, s=1, d=3, k=2, p=1, l=1, m=1 and c=1, where s represents the micro period (day), d displays the macro periods (weeks), k represents types of the products, p denotes the plants, l represents the product lines, m is the vehicles and the distribution centers is c. In Tables 1–5 the remainder data of the hypothetical example is given.

Table1
Total available time to produce in macro period d

1	2	3
4000	4000	4000

Table2
Demands of products in each macro period

k \ d	1	2	3
1	15	5	40
2	100	50	60

Table3
Available space at *DC*, available space in vehicle and Cost for transporting one item

f	*vc*	*tc*
10000	6000	1.5

Table 4
Costs and setup times of line

k	*set*	*tset*
1 →2	3	0.5
2 →1	2.5	1

Table5
The values of other parameters

fp	*h*	*sc*	*pc*	*sp*	*b*	*a*
0.25	1.5	0.75	2	1	2	0.6
0.4	1	1	1.5	0.5	2	0.8

This example is solved by lingo 9. According to the obtained results, parameters of demand (de), Production cost(pc), spoilage cost(sc), shortage cost (sp)and capacity consumption (time) needed to produce one unit (cap) are effective on the variables of the model. Here, the changes of the quantity of product (q), the inventory of product (Iv) and the shortage of product (Sh) are evaluated. In each step, the values of these parameters are multiplied by half, one, two and four. Then, the changes of the variables are examined. Results obtained are shown in the following figures.

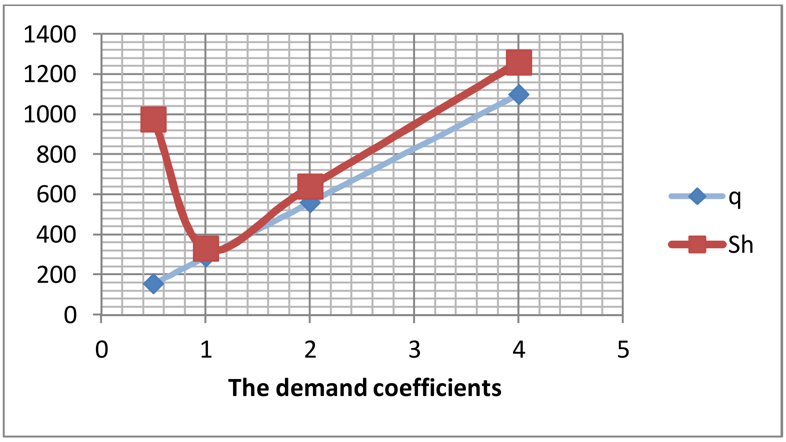


Fig. 2. The effect of demand on the quantity of product and the inventory of product.

It can be observed, by increasing the demand (de), the quantity of product (q)and the inventory of product (Iv)are increased.

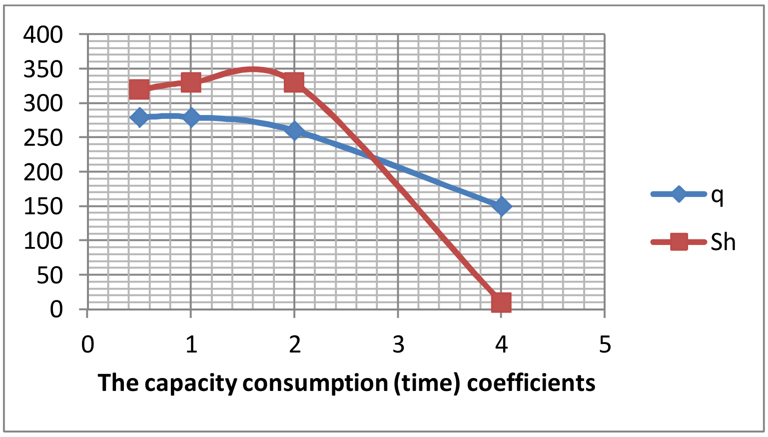


Fig.3. The effect of capacity consumption (time) needed to produce one unit on the quantity of product and the inventory of product.

In this example, the range of this parameter is between (0, 100]. Although the small values don't have much effect on the considered variables, reaching the values to the end of the interval cause to decrease the quantity of product and the inventory of product.

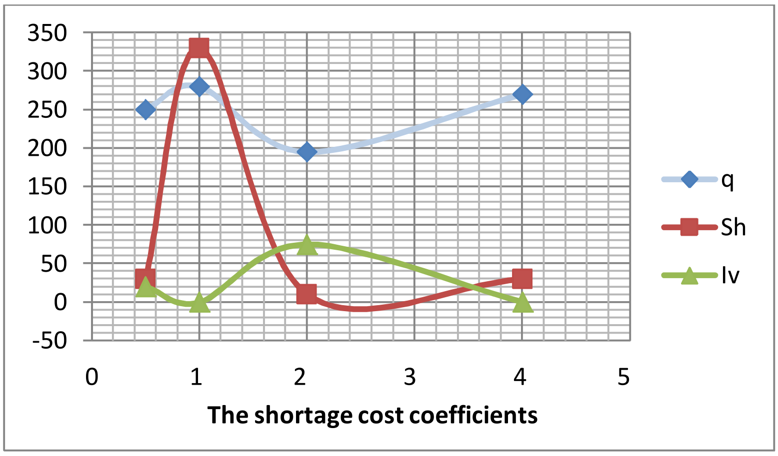


Fig.4. The effect of shortage cost on the quantity of product, the inventory of product and the shortage of product.

The small quantity of shortage cost (sp)causes to decrease the net inventory $(sh)$and increase the shortage(Iv). If the value of the shortage cost reaches to infinity then the quantity and inventory of product will increase and the shortage of product will reach to zero.
The small values of other parameters such as production cost (pc), holding cost $(h)$and transportation cost (tc)have little effect on these variables. If these parameters reach to infinity afterwards the quantity of product will decrease.

4. Solution Methods

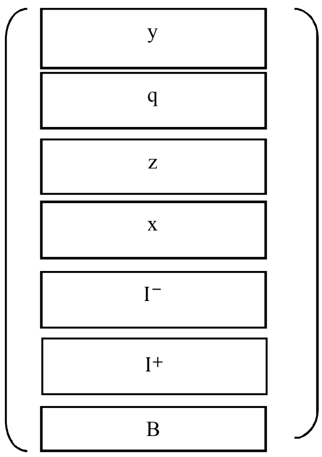
As we mentioned earlier, most general cases of *IPDP*s examined in the literature are *NP*-hard in the strong sense. In this case, a meta-heuristic may be a more practical approach. A meta-heuristic uses certain well-known characteristics of a problem to produce an approximate solution rather than try to find a perfect solution.
Hence, two meta-heuristics; namely, a genetic algorithm (*GA*) and a simulated annealing (*SA*) algorithm are proposed to solve the problem for real size application in a reasonable computation times.

4.1. Genetic algorithm

The genetic algorithm (*GA*) has received considerable attention regarding its potential as an optimization technique for many complex problems. It was first proposed by Holland (1975). *GA* starts with an initial population of random solutions. Each individual or chromosome in the population represents a solution to the problem. Chromosomes evolve through successive generations. In each generation, chromosomes are evaluated by a measure of fitness and those with smaller fitness values have higher probabilities of being selected to produce offspring through the crossover and the mutation operations. The crossover operator merges two chromosomes to create offspring which inherit features from their parents. The mutation operator produces a spontaneous random change in genes to prevent premature convergence. The methodology of the proposed *GA* is as follows:

4.1.1. Chromosome presentation

Mapping solution characteristics in the format of chromosome string is one of the important steps of any *GA* implementation. The proposed model has two types of variables, zero or one and integer. Each chromosome is a matrix which has $(k \times 7)$ rows and $(l \times p \times s \times d \times m \times c)$ columns, so that k represents types of the products, l represents the product lines, p denotes the plants, s represents the micro period (day), d displays the macro periods (weeks), m is the vehicles and the distribution centers is c. This matrix is shown in Figure 5.



Chromosome =

Fig 5. Chromosome illustration

4.1.2. Generation of initial population

Generation an initial population of *N* chromosomes that *N* equivalent to population size is the first step for implementing *GA*.

4.1.3. Fitness function

After the generation of new population, fitness value of each chromosome is calculated. In this problem, the fitness value and the objective function are the same. The chromosome with best objective function is determined as the most appropriate chromosome.

4.1.4. Crossover operator

According to the constraints, all of the decision variables are calculated using y and q. Therefore, we cannot apply the crossover and the mutation operators on them. If these operations were applied on them, not feasible areas will be produced. So, these operators are done on y and q. To form offspring, a two-point crossover operator is utilized so that two points are selected on the parent organism strings, and everything between the two points is swapped between the parent organisms, rendering two child organisms.

4.1.5. Mutation operator

In mutation, the solution may change entirely from the previous solution. Hence *GA* can come to better solution by using the mutation. Mutation occurs during evolution according to a probability. This probability should be set low. If it is set too high, the search will turn into a primitive random search. In this problem, the method of mutation operator is based on selecting the random elements.

4.2. Simulated annealing algorithm

Simulated Annealing method (*SA*) was introduced in the 80s and due to its simplicity and efficiency has had a significant impact on solving combinatorial optimization problems (Kirkpatrick et al., 1983). This method is based on the statistical mechanics that in it the cooling process is done by the heating and slow cooling of a substance in order to achieve a rigid crystalline structure. This algorithm simulates the changes of melt system energy according to a cooling process in order to achieve a stable equilibrium state. This algorithm enables to accept the answers with superior quality. The purpose of this method is escaping from the local optimum point and delaying the premature convergence. *SA* goes to a new neighborhood solution by starting from a random initial answer in each successive repetition. It utilizes a control parameter which is called temperature to determine the probability of accepting a non-improving solution.
In this algorithm, the solutions are acceptable that cause to improve the objective function; otherwise, the neighbors will be accepted with the possibility that depend on the current temperature and the rate of change in the objective function ΔE (Kirkpatrick et al., 1983).
ΔE represents the difference in the objective function (energy) between the obtained present and neighbor solution. Whatever the algorithm continues, probability of acceptance such a displacement is less. In this paper, the procedures which generate neighborhood solution based on a random search are as follows:

- An element of the matrix (x) is replaced with other element of it. Therefore, the Matrices (B and I) changed and Matrices (y, q and z) remain unchanged.
- An element of the matrix (q) is replaced with other elements. In line with this, the Matrices (B and I) changed and Matrices(y, z) remain unchanged.
- An element of the matrix (y) is randomly chosen. If this element was zero, it would convert to one and if this element was one, it would convert to zero. Thus, all of the variables will change.
- All elements of the matrix (x) are changed. Therefore Matrices (B and I) changed and Matrices (y, q and z) remain unchanged.
- All elements of the matrix (q) are changed. Therefore matrixes (x, B, I) changed and matrixes (y, q, z) remain unchanged.
- All elements of the matrix (y) are changed. Therefore all of the variables changed.

The use of these procedures depends on the number of neighbors to be divided between them.

4.2.1. The method of changing initial temperature

Temperature is one of the parameters which it is involved in the acceptance or rejection of the changes in the objective function. The initial value of the temperature must be chosen such that a large number of adverse responses are accepted in the early stages. This method is doing for providing the possibility of changes and further development. The number of iterations during the annealing process depends on the relative initial temperature. Of course, there are many ways where the initial temperature is assumed to be a large number.

4.2.2. The method of changing temperature

One of the major aspects associate with the process of annealing is the temperature changes during the implementation of the *SA* algorithm. In fact, the temperature is likely to accept the worse solution. Because when the temperature is too high, a lot of bad answers will be accepted. Therefore, they will get out of the local optimum point. Conversely, when the temperature is low, the probability of being in a local optimum is high. There are distinctive cooling ratios used in the *SA* literature. In this paper, the decreasing temperature as follows:

$$T_k = \alpha \times T_{k-1} \qquad 0 < \alpha < 1 \tag{20}$$

4.2.3. Selected responses acceptance mechanism

In the *SA*, the randomly generated neighbor solution becomes a new solution if it improves the objective function; otherwise the probability of accepting non-improving movements in each temperature is calculated according to the following equation:

$$p = e^{\frac{-\Delta E}{kT}} \tag{21}$$

So that, k is called Boltzmann constant, T is a temperature parameter in the current iteration and ΔE is measure to which neighbor solution become worse from the current solution. We create a random number r between 0 and 1 and then we compare it with p. If the random number was smaller than p, we would accept solution; otherwise another neighborhood will be chosen.

4.2.4. Stop condition

Several types of stopping criteria have been proposed for *SA*. Some of them are as follows:

- To reach a final temperature
- The total number of steps that must be done
- The total number of accepted change during the annealing process (Total number of iterations)
- The number of rejected changes in the total iterations has reached to specific amount.

In this algorithm, the first mode is used in which temperature becomes less than 1 or a solution whose objective value is zero is found.

4.3. Parameter setting

The setting of parameters of meta-heuristic algorithms are directly related to their performance. An appropriate initial parameter setting has a significant impact on the solving progress, such as the exploitation or exploration rate of the search space, and consequently the quality of the solution. In this paper, we apply the Taguchi method to determine the values of the parameters of the *GA* and the *SA*. This method uses a transformed response function which has been defined to Signal-to-noise ratio for accurate statistical analysis of the results. In this study, after several pretests, we set each of these parameters at three levels. Test problems were made of variable sizes. Each scenario runs 5 times. The best values of the parameters in the *GA* and the *SA* are shown in Table 6.

Table 6
parameter setting of *GA* and *SA*

GA	*SA*
Iteration number is 250	Initial temperature is 220
Population size is 60	Iteration number in each temperature is 25
Mutation rate is 0.2	Cooling ratio (α) is 0.87
Crossover rate is 0.7	

5. Computational Results

In this section, we evaluate the performance of meta-heuristics algorithms. Hence, after setting of algorithms' parameters, problems with different sizes are solved and the results of the algorithms are compared with each other in terms of computation times and relative percentage deviation (*RPD*). Problems are categorized in tree cases, namely; small, medium and large. In the small-sized problems, the parameters *l, p, s, d, m, c, k* which respectively denote the number of product lines, the number of factories, the number of micro periods (day), the number of macro periods (week), the number of vehicles, the number of distribution centers and products are considered between 1 and 3. In the medium-sized problems, the mentioned parameters are considered between 1 and 5 and finally in the large-sized problems these parameters are considered between 1 and 10.

For each category 15 instances are considered. So, the total numbers of test problems are 45. The meta-heuristics algorithms are coded in MATLAB 10 and all the computational experiments were performed on a laptop with Intel core due 2 GHz and 2.5 GB memory. Each test problem runs for 5 times. So, the total runs are equal to 45×5×2=450. The computational results are summarized in Table 7. For each test case, the T_{avg}, the mean and the best solutions of the proposed meta-heuristics are given, where T_{avg} denotes median of the computation times, mean denotes the average of solution and best denotes the best solution in 5 times running algorithm.

Also, in order to compare the efficiency of the proposed *GA* and *SA*, the relative percentage deviation (*RPD*) is applied. The *RPD* computes in this fashion:

$$RPD = \frac{Heuristic\ solution - Best\ heuristic\ solution}{Best\ heuristic\ solution} \times 100 \tag{22}$$

For each group size, the *RPD* values are computed and shown in Table 7. Also, the *RPD* values and the computation times of the *GA* and the *SA* algorithms are depicted in Figures 3 and 4, respectively. Furthermore, in order to make better comparisons between the proposed meta-heuristics, relative percentage deviation means plot with least significant difference (*LSD*) intervals at a 95% confidence level are tested and shown in Fig 8.

Table 7
Computational results for small-to-large size problems.

Category	Instance number	GA				SA			
		T^a_{avg}	mean	best	*RPD*	T^a_{avg}	mean	best	*RPD*
Small-sized problems	1	16.2	432	432	0%	13.7	434.4	432	0.555%
	2	28.3	660.8	652	1.349%	17.1	662.6	652	1.625%
	3	46.7	1233.2	1230	0.260%	28.9	1255.5	1230	2.073%
	4	42.1	847.3	843	0.510%	25.4	859.2	843	1.921%
	5	65.8	581.5	573	1.483%	41.5	580.3	573	1.273%
	6	94.9	922.5	901	2.386%	77.6	914.5	901	1.498%
	7	68.5	675.2	674	0.178%	40	678	674	0.593%
	8	133.2	625.7	615	1.73%	91.8	618.6	615	0.585%
	9	152.7	847.9	843	0.581%	107.3	861.3	843	2.170%
	10	138.2	951	951	0%	93.6	965.5	951	1.524%
	11	93.6	544.6	539	1.038%	75.2	552.8	539	2.560%
	12	114.1	1176.1	1163	1.126%	81.5	1165.3	1163	0.197%
	13	123.8	762	746	2.144%	86.1	746	746	0%
	14	147.8	433.5	427	1.522%	101.4	438.5	427	2.693%
	15	185.2	732.7	720	1.763%	128.7	735.5	720	2.152%
Average		**96.74**		**753.933**	**1.072%**	**67.32**		**753.933**	**1.428%**
Medium-sized problems	16	287.1	1832.3	1763	3.930%	275.6	1873.1	1768	6.245%
	17	439.5	1903.4	1854	2.664%	326.2	1934.5	1862	4.341%
	18	383.3	2178.5	2101	3.688%	271.5	2214.3	2101	5.392%
	19	558.9	2454.6	2378	3.221%	432.7	2467.8	2391	3.776%
	20	261.7	3754.5	3618	4.611%	161.3	3753.1	3589	4.572%
	21	373.4	1653.7	1572	5.197%	258.9	1671.4	1572	6.323%
	22	429.5	2481.8	2434	2.257%	321.4	2613.7	2427	7.692%
	23	345.3	2864.1	2785	2.179%	234.7	2954.3	2803	5.397%
	24	454.8	3581.3	3431	4.380%	334.1	3671.9	3431	7.021%
	25	384.2	1866.9	1778	5%	272.6	1861.5	1778	4.696%
	26	557.5	4811.5	4659	3.273%	429.3	4843.2	4677	3.953%
	27	351.4	3421.4	3278	5.209%	237.4	3467.4	3252	6.623%
	28	688.5	4395.7	4256	3.282%	531.4	4482.4	4271	5.319%
	29	568.1	2771.6	2636	5.144%	435.5	2785.3	2654	5.663%
	30	645.9	3022.8	2974	1.640%	517.1	3082.7	2998	3.655%
Average		**448.60**		**2767.8**	**3.712%**	**335.98**		**2771.6**	**5.378%**
Large-sized problems	31	1745.2	15803.2	14682	4.231%	929.4	16121.3	14741	9.803%
	32	1836.7	18906.3	17531	4.992%	956.2	19325.4	17531	10.235%
	33	2321.6	13741.4	12833	4.740%	1264.5	13962.5	12833	8.801%
	34	2465.2	21146.1	19767	4.953%	1375.3	21948.9	20231	11.038%
	35	1986.4	26132.7	24874	5.060%	1131.3	27232.7	24992	9.482%
	36	2628.2	19771.6	18395	4.765%	1516.6	19871.6	18463	8.027%
	37	2534.3	27893.3	26439	4.365%	1476.2	28848.3	26482	9.112%
	38	2764.8	16828.1	15381	5.507%	1540.7	17135.1	15381	11.404%
	39	2965.7	12933.5	12258	3.646%	1772.5	13471.5	12189	10.521%
	40	2544.5	18215.8	17321	5.165%	1479.8	18912.6	17387	9.188%
	41	2826.1	23683.9	21794	6.377%	1662.9	23648.3	21915	8.508%
	42	2949.1	29421.7	27285	6.731%	1691.4	30121.3	27348	10.395%
	43	2867.2	15792.3	14847	4.346%	1677.1	16422.8	14847	10.613%
	44	3154.3	20858.4	19129	6.426%	1831.7	20742.5	19312	8.434%
	45	3273.6	24521.6	22517	4.388%	1882.2	23856.2	22437	6.325%
Average		**2590.86**		**19003.5**	**5.046%**	**1479.18**		**19072.6**	**9.459%**

[a] T_{avg} (second).

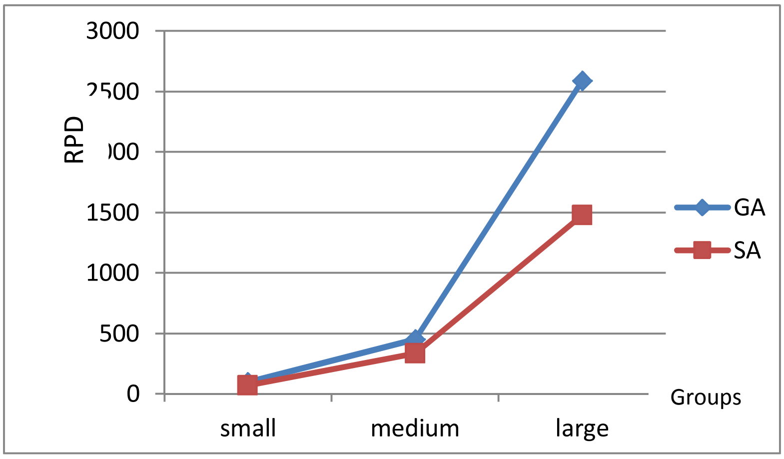


Fig 6. The average *RPD* for *GA* and *SA* in small-to-large problems.

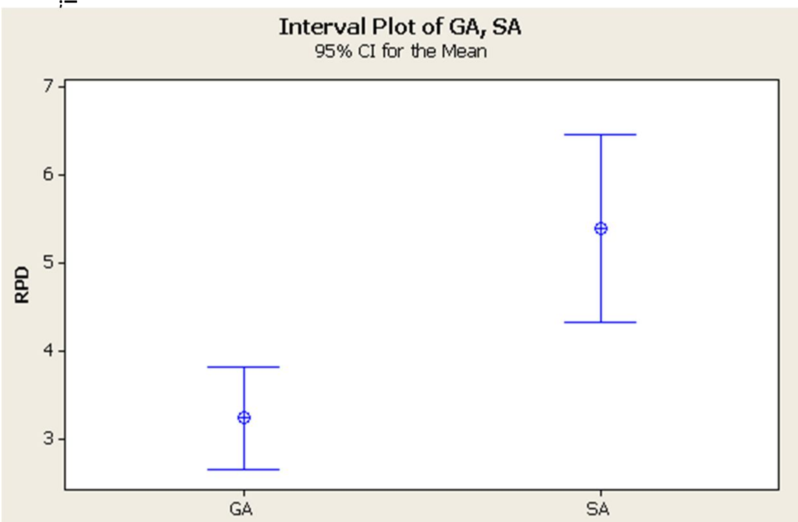


Fig 7. The average computation times for *GA* and *SA* in small-to-large problems.

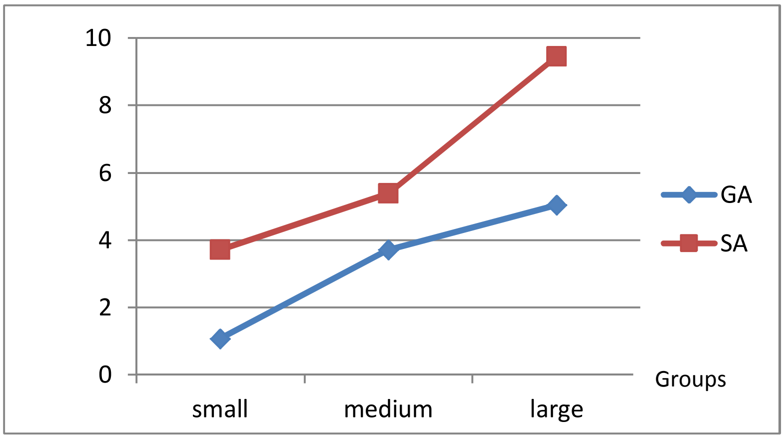


Fig. 8. Means plot and *LSD* interval for the algorithms.

Based on the obtained results presented in Figure 8, the *SA* and the *GA* algorithms are statistically different which means *t* test rejects the null hypothesis of equality the *SA* and the *GA* at a 95% significance level. Hence, the difference between means is significant and it can be seen that the average of the *GA* is statistically smaller than the *SA*.

On the other hand, Figure 6 also demonstrates this fact that in the small to large sizes, the average *RPD* of the *GA* is significantly smaller than the *SA*. Although the computation time of *SA* is smaller than the *GA*, the *GA* has better performance in the three groups. Thus from the obtained results, the proposed *GA* is recommended for the problem.

6. Conclusions and Future Research

This paper deals with a multi-objective problem of integrated production/distribution and inventory planning in which there are a set of plants with parallel production lines that produce perishable products with fixed life time during a planning horizon. Also, there are *m* vehicles to deliver the products from plants to distribution centers at the end of each week. Furthermore, an inventory system is integrated with this production/distribution planning in which for each distribution center, net inventory, shortage, *FIFO* system and spoilage of items are calculated. This investigation aims to minimize setup costs between products, holding costs, shortage costs, spoilage costs, transportation costs and production costs. A mixed integer non-linear programming model (*MINLP*) is proposed for the considered problem. Regarding the complexity of the problem, a genetic algorithm (*GA*) and a simulated annealing (*SA*) algorithm are proposed to solve the model for the real size applications. According to the obtained results, the proposed *GA* outperforms the *SA* in terms of deviation from optimal solution although the computation time of the *SA* is smaller than the *GA*.
Further research could focus on extension the problem to probabilistic or fuzzy environments.

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