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International Journal of Industrial Engineering Computations

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Part transformation-based spare parts inventory control model for the high-tech industries

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C H R O N I C L E

Article history:
Received March 22 2023
Received in Revised Format July 1 2023
Accepted September 25 2023
Available online September 25 2023

Keywords:
Spare parts
Inventory management
Substitution
Simulation optimization

A B S T R A C T

Timely and cost-effective supply of spare parts is the main purpose of spare parts inventory management and substitution is an effective way to fulfill demand on time. However, direct substitution of spare parts is not suitable for the high-tech industries due to the ever-changing nature of the product structures. Hence, parts should be transformed to be used as substitutes. This paper provides a novel spare parts inventory control model for the high-tech industries. In the proposed model, part transformation-based substitution is considered and the near-optimal values of spare part inventory levels (s, S) that minimize total cost are determined by using a simulated annealing-based simulation optimization approach. Computational analyses are performed for a hypothetical inventory system by considering transformation and no-transformation cases. The results reveal that transformation is very useful for the companies who endure long production lead times and high penalty costs associated with backorders.

1. Introduction

Due to globalization and recent advances in technology, high-tech industries have become an important part of the global economy. Producing innovative and high quality products is a vital issue in those industries, therefore companies put the research and development activities at the core of the company. However, in today's business world, customer satisfaction is the major determinant of business success and leading the technology alone is not enough for competitiveness. In high-tech industries, after sales service is one of the most important factors that influence customer satisfaction and it plays an important role in customer's brand preferences (Shokouhyar et al., 2020; Mo et al., 2020).

After sales service can be defined as any service provided after a customer has purchased a product and it includes warranty service, installation, repair, upgrading, maintenance etc. After sales service becomes the key component of the differentiation and long term success for the companies who manufacture and market complex products. It is obvious that good after sales service contributes to brand loyalty, customer satisfaction, repeat purchases and business growth in the long run. On the other hand, providing high quality after sales service highly depends on the response time to customers and inventory control policies of the spare parts. Therefore, timely and cost effective supply of spare parts is a vital issue in after sales service and it requires an efficient management of spare parts inventories (Boone et al., 2008).

In spare parts inventory management, companies encounter the problem of achieving high service level and low inventory cost simultaneously (Hu et al., 2018). On the other hand, spare parts inventory management is a complex and difficult task due to the large number and variety of parts, erratic demand patterns, risk of stock obsolescence, expensiveness of the parts and demanding nature of customers (Cohen et al., 2006; Murthy et al., 2004; Boylan & Syntetos, 2010). Especially, in high-tech industries products quickly become obsolete and supplying spare parts of these products becomes harder for the companies. Moreover, companies have some strict warranty policies on supplying spare parts and they are under pressure to supply those parts in a short time with desired quality (Gallego et al., 2006).

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ISSN 1923-2934 (Online) - ISSN 1923-2926 (Print)
2024 Growing Science Ltd.
doi: 10.5267/j.ijiec.2023.9.008

Numerous studies have been conducted for determining optimal inventory control policies for spare parts. In most of those studies, researchers considered the (*s*, *S*) inventory model and its variations (i.e. *s*-1, *S*; *s*, nQ) and they aimed to find the re-order (*s*) and the order-up-to (*S*) levels that minimize total cost (Ilgin & Tunali, 2007; Kutanoglu & Mahajan, 2009; Guajardo et al., 2015; Do Rego & de Mesquita, 2015; van Jaarsveld et al., 2015; Khademi & Eksioglu, 2018; Tang et al., 2018; Rodrigues & Yoneyama, 2020; Panagiotidou, 2020) or maximize fill rate (Aronis et al., 2004; Porras & Dekker, 2008; Rodrigues & Yoneyama, 2020). In cost calculation, holding, ordering and shortage costs are commonly considered and mathematical programming techniques (Kutanoglu & Mahajan, 2009; van Jaarsveld et al., 2015; Khademi & Eksioglu, 2018; Tang et al., 2018; Panagiotidou, 2020), heuristic methods (Guajardo et al., 2015; Aronis et al., 2004) and simulation modelling (Ilgin & Tunali, 2007; Do Rego & de Mesquita, 2015; Porras & Dekker, 2008; Rodrigues & Yoneyama, 2020) are used as solution methodologies. The reader may also refer to Do Rego & de Mesquita (2011), Driessen et al. (2015) and Hu et al. (2018) for a detailed review of spare parts inventory management studies.

From another point of view, product substitution is a well-known strategy that is commonly used in inventory management and it is carried out in the form of providing an alternative product when the preferred one is unavailable (Shin et al., 2015; Benkherouf et al., 2017). It provides flexibility to companies in demand fulfillment and also very useful in reducing lost sales and customer dissatisfaction. Product substitution is commonly used in the retail industry where the products are consumed rapidly; pharmaceutical markets and in industries in which products are perishable or tend to be obsolete (Eksler et al., 2019).

In high-tech industries, direct (one-on-one) substitution of products or spare parts is not possible due to short product life cycles. In those industries, substitution is performed only after some transformation operations (Das Roy & Sana, 2022). For instance, mainboards used in computers, cell phones or televisions can be substituted after changing some of the components on the boards or loading appropriate software. In those transformation processes, time requiring changes (i.e. physical, technical) are made on the substitute product and these changes cause an additional cost (i.e. material, labour). One of the challenging points of transformation-based substitution is the number of substitutable products. In two-product substitution problems, there are two grades of products and the lower grade product is usually substituted for the higher grade one. It means there is only one alternative for the substitution and this situation does not require any investigation for the selection of the substitute product. However, when there are more than two substitutable products, the problem becomes more complicated. In this case, substitute product selection rules should be identified in order to manage inventories effectively. Further, time and cost associated with the transformation process cause a trade-off between producing the out of stock products and transforming the on hand ones.

On the other hand, it is obvious that frequent innovations cause overproduction which leads to the waste of natural resources and the growth of e-waste (Nagpal & Chanda, 2022; Pal & Sana, 2022). Today, air pollution, water pollution and climate change are the major environmental problems and adopting green practices has become one of the core responsibilities of the companies (Taleizadeh et al., 2020; Sana, 2020). In this context, transformation-based substitution which helps to reduce inventory waste by using idle inventories is an efficient way to achieve sustainability in high-tech industries. Implementing this approach will prevent obsolete parts from becoming e-waste which is extremely harmful to the environment and will also bring economic benefits to companies.

Considering the aforementioned facts, we propose a novel spare parts inventory control model for the companies in high-tech industries. In the proposed model, part transformation-based substitution is considered in demand fulfillment and near-optimal values of spare part inventory levels (*s*, *S*) are determined by a using simulated annealing (SA) based simulation optimization approach. The objective function is defined as minimization of the total cost which includes holding cost, transformation cost, production cost, and backorder cost. In order to verify the proposed model, a hypothetical inventory system is handled and computational analyses are performed for transformation and no-transformation cases.

The rest of the paper is organized as follows. Related literature is summarized in Section 2. Characteristics of the problem and the proposed spare parts inventory control model are explained in Section 3. Section 4 focuses on the simulation optimization based solution approach that is used to determine the (*s*, *S*) inventory levels. Section 5 is devoted to the computational experiments. Finally, conclusions and future research directions are presented in Section 6.

2. Related Literature

Product substitution has been extensively studied in the operations management literature and numerous studies have been carried out on pricing, inventory management, product assortment planning in this field (Shin et al., 2015). Product substitution can be implemented in three main ways (Tang & Yin, 2007). (i) When the preferred product is not in inventory or on the shelf, the customer demand can be fulfilled by another product that is similar to the preferred one. This is called *inventory-based* substitution. (ii) Customers can sometimes choose a more affordable alternative with similar features to the preferred product even if the product that they preferred is already in inventory. This is called *price-based* substitution. (iii) Customers may choose a more beneficial product from the product assortment of the seller. This is called *assortment-based* substitution.

In this study, we have examined the problem of inventory management involving *inventory-based* substitution and we have investigated the studies closely related to this area in our literature survey. In this regard, we have summarized the investigated papers in Table 1 by considering inventory system and substitution characteristics, performance measures and solution methodologies. The reader may refer to Shin et al. (2015) and Lang (2009) for a detailed review of studies on applying substitution in demand management and also refer to Kök and Fisher (2007), Tan and Karabati (2013) and Shin et al. (2015) for the characteristics of the substitution practices.

As it is presented in Table 1, in most of the studies, substitutable products are limited to two products and inventory decisions are made based on cost minimization or profit maximization. As mentioned earlier, in two-product substitution problems there is only one alternative for the substitution and this makes the problem solving process easier. However, especially in *supplier-driven* substitution problems, the problem becomes more complicated when there are more than two substitutable products. In this case, the seller needs to define some rules for the selection of the substitute product. For instance, Gurnani and Drezner (2000) considered the product grades while making substitution decisions. They assumed that the lower grade (cheaper) products can be substituted for the higher grade ones after transformation processes. Eksler et al. (2019) computed the dependency factor for each pair of products by using association rule mining and made substitution decisions based on the dependencies between the products. On the other hand, Khademi and Eksioglu (2018) chose the substitute spare parts based on the part's reliability. They assumed that the expensiveness of the part is positively correlated with the reliability of the part. In our study, we have performed analyses for the cases in which substitution decisions are made based on the unit transformation time and cost between the spare parts.

From another point of view, substitution cost is evaluated in different ways by the researchers. For instance, Drezner et al. (1995) defined the substitution cost as the price difference between two products. Tan and Karabati (2013), Benkherouf et al. (2017) and Mishra (2017) evaluated the substitution cost as the cost of customer dissatisfaction caused by the inability of the customer to purchase his/her primary choice. Similar to our study, Gurnani and Drezner (2020), Tore et al. (2013) and Durga and Chandrasekaran (2020) handled the substitution cost as the cost of transforming the substitute product to the preferred one. In our study, substitution is performed for the spare parts of a finished product and since the customers do not see or experience the spare parts physically there won’t be any customer dissatisfaction caused by the substitution. In other words, customers only care about the functionality of the main product and customer dissatisfaction will not occur as long as the spare parts make the product in operating condition. For this reason, we defined the substitution cost as the total material and labour cost arise in transforming spare parts into each other.

When we evaluate the studies under concern, we have also observed that production lead time is assumed to be zero in most of the studies. In this case, an important time-based activity in inventory management is ignored and when we consider the real life cases, this assumption makes the problem unrealistic. Therefore, we handled stochastic production lead time in our study. Furthermore, most of the researchers handled the single period (Nagpal & Chanda, 2022; Chen et al., 2015; Parlar, 1985; Pasternack & Drezner, 1991) or multi-period inventory problem with substitution where the demand and lead time are usually deterministic and the inventory review is periodic. They used mathematical programming approaches, calculus or heuristic methods as solution methodology. However, spare parts inventory systems are dynamic systems and involve stochastic factors such as demand arrival and lead time (Ilgin & Tunali, 2007; Rodrigues & Yoneyama, 2020). In this regard, applying simulation modelling techniques in spare parts inventory management studies allows modelling those systems under more realistic conditions.

In the light of the aforementioned facts, it can be concluded that multiple substitutable products, uncertainties associated with demand and lead time, transformation process and associated time and cost make the inventory-based product substitution problems more complicated. Therefore, most of the studies in the literature have dealt with two-product substitution problems, assumed that demand and lead time are deterministic and have not considered transformation time and cost together. To the best of our knowledge, our study appears to be the first to characterize the stochastic spare parts inventory system with multiple parts and transformation-based substitution. We proposed a novel inventory control model for this system and aimed to find the near-optimal values of spare part inventory levels (s, S) that minimize total cost. We used a SA-based simulation optimization approach as solution methodology and performed computational analyses for the transformation and no-transformation cases. Our proposed model differentiates itself from its counterparts by considering multiple substitutable parts, transformation time and cost, stochastic demand and lead time, dynamic substitute part selection and continuous inventory review simultaneously.

Table 1
Characteristics of the studies related to this paper

Reference	Substitutable products	Substitution characteristics	Substitute item selection rule	Demand	Inventory review	Lead time	Objective function	Substitution cost	Substitution time	Decision variable(s)	Solution methodology
McGillivray & Silver (1978)	2	CD, 2W, PT, 1A, D	NA	ST	PR	DT	Min C	NA	NA	S	EOQ
Parlar (1985)	N	CD, 2W, PT, MA, D	excess amount of substitute items and unsatisfied demand of the particular item	ST	PR	NA	Max P	NA	NA	Q	H
Pasternack & Drezner (1991)	2	SD, 2W, FL, 1A, D	NA	ST	PR	NA	Max P	NA	NA	Q	CAL
Drezner et al. (1995)	2	SD, 1W, PT+FL, 1A, D	NA	DT	PR	NA	Min C	√	NA	Q	EOQ
Gurnani & Drezner (2000)	N	SD, 1W, FL, MA, D	product grade	DT	PR	Z	Max P	√	NA	Q, SQ	MP
Xu et al. (2011)	2	SD+CD, 2W, PT+FL, 1A, D	NA	ST	PR	Z	Max R	NA	NA	Q	SDP
Tore et al. (2013)	2	SD, 2W, PT, 1A, T	NA	ST	CT	ST	Min C	√	√	SQ, PQ	MDP
Tan & Karabati (2013)	N	CD, 2W, FL, 1A, D	customers' choice probabilities	ST	PR	Z	Max P	√	NA	S	GA
Zhou & Sun (2013)	2	SD+CD, 1W, PT, 1A, D	NA	ST	PR	Z	Max P	NA	NA	Q	SDP
Salameh et al. (2014)	2	CD, 2W, PT, 1A, D	NA	DT	PR	Z	Min C	NA	NA	Q	CAL
Krommyda et al. (2015)	2	CD, 2W, PT, 1A, D	NA	DT	PR	Z	Max P	NA	NA	Q	CAL
Chen et al. (2015)	2	SD, 1W, FL, 1A, D	NA	ST	PR	NA	Max P	NA	NA	Q	CAL
Benkherouf et al. (2017)	2	SD, 1W, PT+FL, 1A, D	NA	ST	CT	Z	Min C	√	NA	t	MINLP
Mishra (2017)	2	CD, 2W, PT, 1A, D	NA	DT	PR	Z	Min C	√	NA	Q	CP
Khademi & Eksioglu (2018)	N	SD, 2W, FL, MA, D	part reliability	ST	PR	DT	Min C	NA	NA	s, S	SDP
Eksler et al. (2019)	N	SD, 2W, FL, MA, D	product dependencies	DT	PR	DT	Max P	NA	NA	s	EOQ
Mishra & Mishra (2020)	2	CD, 2W, PT, 1A, D	NA	DT	PR	Z	Min C	√	NA	Q	CAL
Durga & Chandrasekaran (2020)	2	CD, 1W, PT, 1A, TS	NA	DT	PR	Z	Min C	√	NA	Q	CAL
van der Walt & Bean (2022)	N	CD, 1W, FL, 1A, D	customers' choice probabilities	ST	PR	Z	Max PSL Min W	NA	NA	Q	MOMIP
Nagpal & Chanda (2022)	2	CD, 1W, FL, 1A, D	NA	ST	PR	Z	Min C	NA	NA	Q	EOQ
This study	N	SD, 1W+2W, FL, MA, T	unit transformation time and cost	ST	CT	ST	Min C	√	√	s, S	SO

Acronyms:
N: multiple, **NA:** not available, **√:** available
SD: supplier-driven, **CD:** customer-driven, **1W:** one-way, **2W:** two-way, **PT:** partial, **FL:** full, **1A:** single-attempt, **MA:** multi-attempt, **D:** direct, **TS:** semi-transformation, **T:** transformation-based
ST: stochastic, **DT:** deterministic, **PR:** periodic, **CT:** continuous, **Z:** zero
C: cost, **P:** profit, **R:** revenue, **PSL:** passenger satisfaction level, **W:** waste, **s:** re-order level, **S:** order up-to level, **Q:** order quantity, **SQ:** substitution quantity, **PQ:** production quantity, **t:** replenishment time
EOQ: economic order quantity, **H:** heuristic, **CAL:** calculus, **MP:** mathematical programming, **SDP:** stochastic dynamic programming, **MDP:** markov decision process, **GA:** genetic algorithm, **MINLP:** mixed integer non-linear programming, **CP:** constraint programming, **SO:** simulation optimization, **MOMIP:** multi-objective mixed integer programming

3. Problem Statement and the Proposed Inventory Control Model

In this study, the spare parts inventory system of a realistic hypothetical company that operates in the high-tech industry is considered. The company makes strong commitments to providing spare parts after the sales and aims to fulfill demand in a cost and time effective way. In the spare parts inventory system under concern, orders are placed by two types of customers (domestic and international customers). The company keeps its average response time to domestic customers below 7 days (168 hr) and the international customers below 20 days (480 hr) to ensure the quality of the after sales service.

Electronic card is a spare part group that has a high demand rate, critical importance for the main product to operate and high tendency of obsolescence. In addition, if those parts cannot be supplied within a certain period of time then the company faces high penalties. Therefore, timely and cost-effective supply of the parts in this group is vital for the company. On the other hand, this spare part group involves several main groups which are configured based on the product versions. The electronic cards in a main group can be transformed into each other according to their technical specifications. Combinations that are generated based on the technical specifications form sub-groups and the transformation is performed between these sub-groups manually by the operator(s) when the inventory level of a sub-group is lower than its demand.

The aim of this study is to determine the near-optimal *s*, *S* inventory levels for each sub-group that minimize total cost. The notation used in the formulations is presented in Table 2 and the problem is mathematically expressed through the equations (1) – (4). Underlying assumptions of the problem are: (i) backorders are allowed with a certain cost; (ii) production capacity is negligible; (iii) storage area is sufficient; (iv) orders cannot be partially delivered; (v) orders cannot be cancelled, (vi) ordering cost is negligible and (vii) transformation processes do not cause any future technical problems.

$$\min \sum_{i=1}^{N} c_i m_i + \sum_{i=1}^{N} \sum_{k=1,k\neq i}^{N} u_i r_{ki} + \sum_{l=1}^{L} \sum_{i=1}^{N} \sum_{j=1}^{o_i} y_{lij} b_i v_{lij} g_{lij} + \sum_{i=1}^{N} f_2 p_i h_i \tag{1}$$

subject to

$$lb_i \le s_i \le ub_i \qquad \forall i \in N \tag{2}$$

$$LB_i \le S_i \le UB_i \qquad \forall i \in N \tag{3}$$

$$s_i, S_i \text{ integer} \qquad \forall i \in N \tag{4}$$

The objective function (1) minimizes the total cost. Constraints (2) ensure that the re-order level of sub-group *i* must take values between predefined lower and upper bounds. Similarly, constraint set (3) ensures that order up-to level of sub-group *i* must take values between predefined lower and upper bounds. Constraints (4) imply that all decision variables must be integers.

Table 2
Notation

Set of indices	
i, k =1,..,N	set of sub-groups
j =1,..,J	set of orders
l =1,..,L	set of customers
Parameters	
N	number of sub-groups
c_i	unit production cost of a part belonging to sub-group *i*
r_{ki}	unit cost of transforming a part from sub-group *k* to sub-group *i*
ut_{ki}	unit time of transforming a part from sub-group *k* to sub-group *i*
f_1	penalty coefficient $0 < f_1 < 1$
b_i	backorder cost per unit time for a part belonging to sub-group *i*
p_i	price of a part belonging to sub-group *i*
v_{lij}	quantity of *j* th order belonging to sub-group *i* placed by customer *l*
f_2	interest rate
R	replication length
lb_i	lower bound for s_i
ub_i	upper bound for s_i
LB_i	lower bound for S_i
UB_i	upper bound for S_i
Decision variables	
s_i	re-order level of sub-group *i*
S_i	order-up-to level of sub-group *i*

Table 2
Notation (Conitinued)

Intermediate variables	
m_i	total production quantity of sub-group i
u_i	total amount of parts transformed from sub-group i to other sub-groups
o_i	total number of completed orders belonging to sub-group i
g_{lij}	tardiness of the j th order belonging to sub-group i placed by customer l
ct_{lij}	completion time of the j th order belonging to sub-group i placed by customer l
dt_{lij}	due-date of the j th order belonging to sub-group i placed by customer l
a_{lij}	arrival time of the j th order belonging to sub-group i placed by customer l
y_{lij}	binary variable $\begin{cases} 0 & \text{if} \quad ct_{lij} < dt_{lij} \\ 1 & \text{otherwise} \end{cases}$
h_i	average inventory level of sub-group i during time period [0, R]
$I_i(t)$	inventory level of sub-group i at time t $\quad t \in R$

In our problem, total cost consists of the total production cost, backorder cost, holding cost and transformation cost as it is expressed by Eq. (1). In this cost formulation, production cost is obtained by multiplying the unit production costs and the total production quantities of the sub-groups. Transformation cost is computed by multiplying the total mumber of parts transformed from one sub-group to another and the corresponding unit transformation costs.

While calculating the backorder cost, in the first step backorder cost per unit item per unit of time is computed for each sub-group by using Eq. (5). In this calculation, the price of the parts belonging to the sub-group and the penalty coefficient for tardiness are taken into account. Afterwards, tardiness is computed for each order by using Eq. (6). The due-date given in this equation is computed by using Eq. (7). Finally, unit backorder cost, tardiness and the order quantity are multiplied for each tardy order. Thus, a penalty is applied to the company by considering both the total monetary value and the tardiness of the order.

$$b_i = p_i f_1 \qquad \forall i \in N \tag{5}$$

$$g_{lij} = ct_{lij} - dt_{lij} \qquad \forall l \in L, \forall i \in N, \forall j \in J \tag{6}$$

$$dt_{lij} = \begin{cases} \text{if} \quad l = 1 & a_{lij} + 168 \text{ hr} \\ \text{otherwise} & a_{lij} + 480 \text{ hr} \end{cases} \qquad \forall l \in L, \forall i \in N, \forall j \in J \tag{7}$$

Holding cost is computed by considering the average inventory levels of the sub-groups, unit prices of the parts and the interest rate. Average inventory level is formulated as a continuous function of time as given by the Eq. (8) and it is computed based on the inventory held during the execution of the system.

$$h_i = \int_0^R I_i(t)\, dt \qquad \forall i \in N \tag{8}$$

In our proposed inventory control model, three main processes namely *transformation*, *inventory replenishment* and *order completion* are run simultaneously as it is depicted in Fig. 1. Variables used in the simulation models are presented in Table 3. In *transformation* process, substitute sub-groups are investigated for the demand that cannot be fulfilled by its own inventory and the transformation operations between the sub-groups are realized. *Inventory replenishment* process is triggered in every inventory movement and the production orders are placed for the sub-groups, if necessary, based on the (s, S) policies. Finally, in *order completion* process, performance measures are computed for each completed order and the overall values of these measures are updated.

Table 3
Temporary variables used in the simulation models

Variable name	**Definition**
M	sufficiently large number (1000)
cn	counter
z	counter
$opor_i$	amount of current production order belonging to sub-group i
por_i	amount of production order to be placed for sub-group i
inv_i	inventory level of sub-group i
req_{lij}	unfulfilled quantity of j th order belonging to sub-group i placed by customer l
$treq_i$	total amount of unfulfilled demand belonging to sub-group i
$orderq$	queue of the orders waiting to be fulfilled
du_{ki}	dummy variable for the unit time of transforming a part from sub-group k to sub-group i

Table 3
Temporary variables used in the simulation models (Continued)

dm_{ki}	dummy variable for the unit cost of transforming a part from sub-group k to sub-group i
mint	minimum unit transformation time
minc	minimum unit transformation cost
tunits	total amount of transformed parts
tpcost	total production cost
trcost	total transformation cost
tbcost	total backorder cost
thcost	total holding cost
tcor	total amount of demand fulfilled
trate	percentage of demand fulfilled by transformation
totalcost	total cost

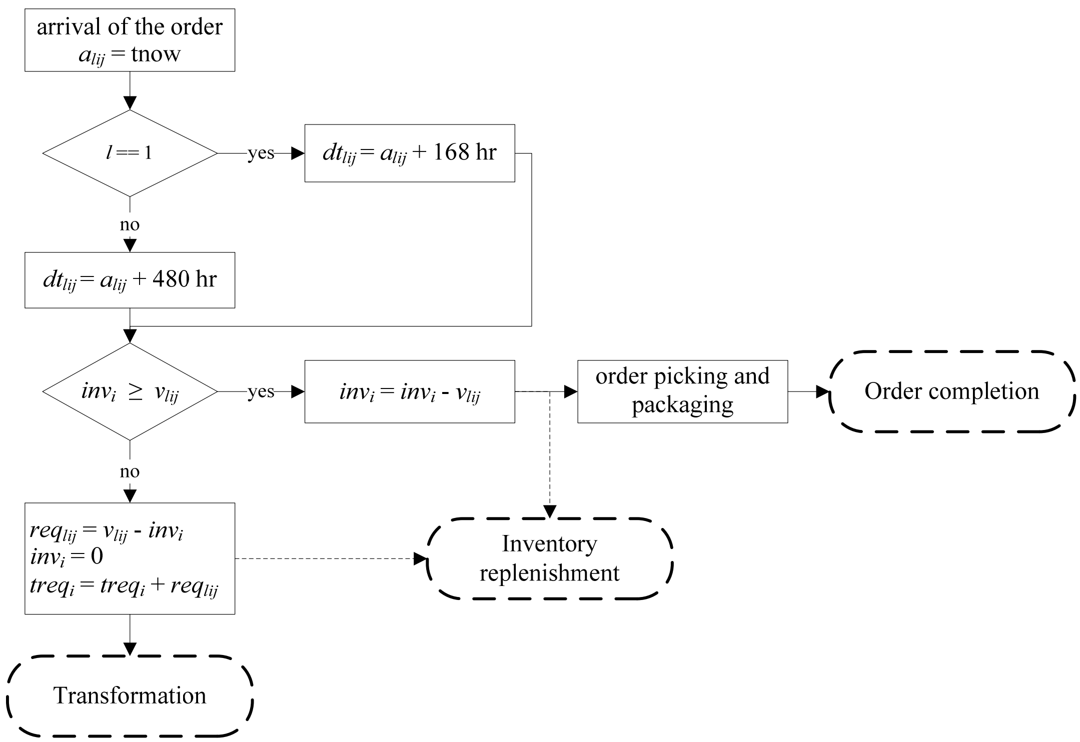


Fig. 1. Flow of the simulation model

In the simulation model of the spare parts inventory system under concern, orders for the sub-groups are placed by two types of customers. Then, the due-date is assigned to each order based on the agreement. In the next step, inventory level of the regarding sub-group is reviewed. If the on hand inventory is sufficient to fulfill the order, then the required amount of inventory is used to fulfill the order, inventory level of the sub-group is updated, order is prepared for shipment and the *order completion* process is triggered respectively.

On the other hand, if the inventory level of the sub-group is not sufficient, then on hand inventory is completely used to fulfill a certain amount of the entire order and the quantity remaining unfulfilled is computed. Then, the *transformation* process is triggered and sub-groups that can be transformed into the ordered sub-group are investigated as it is shown in Fig. 2. In this process, transformation operations are performed based on the earliest due-date rule and the substitute sub-groups are selected based on two types of selection policies:

- Model (I): minimum unit transformation time
- Model (II): minimum unit transformation cost

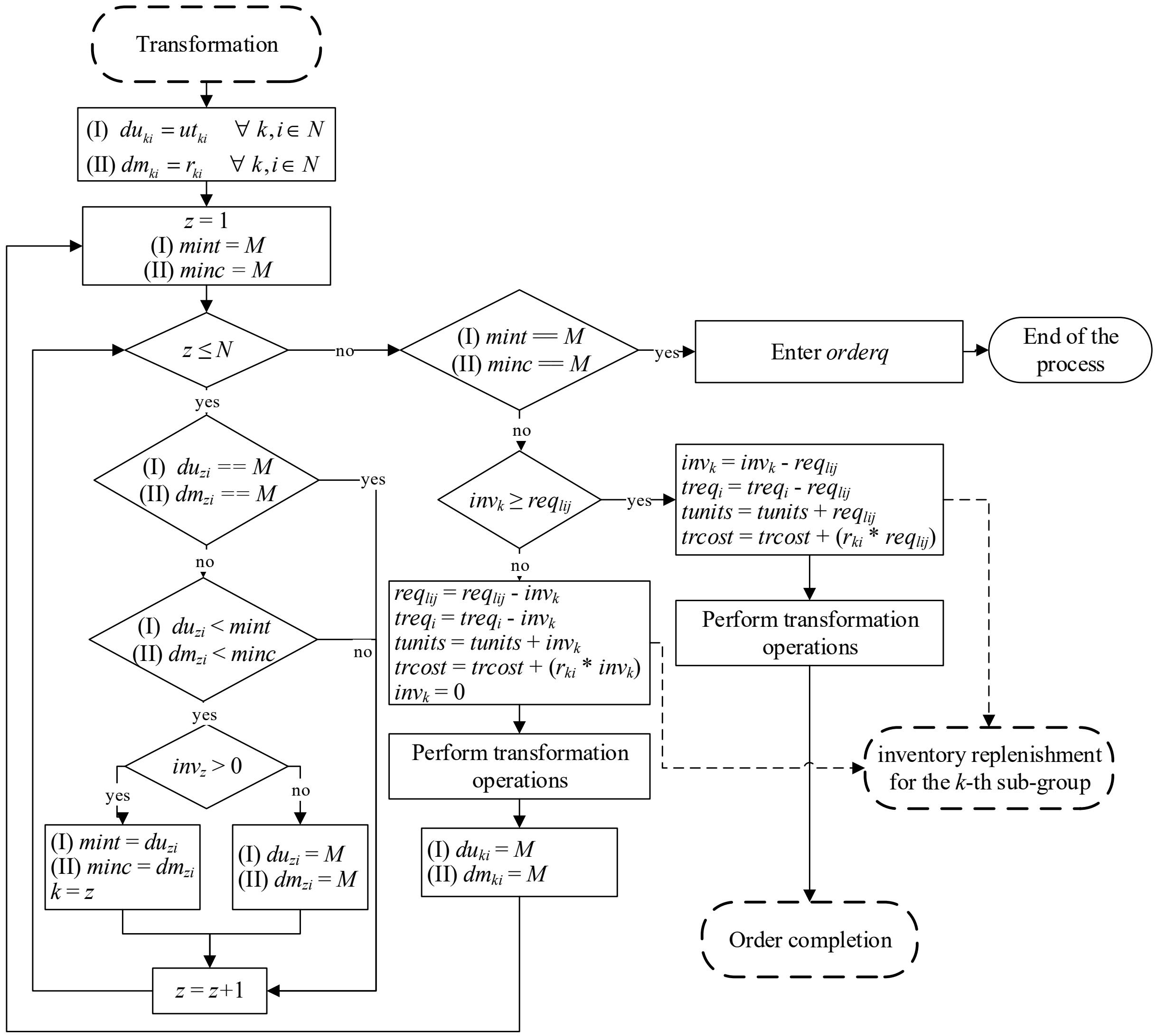


Fig. 2. Flow of the transformation process

After specifying the substitute sub-group, the inventory level of this sub-group is reviewed. If the inventory level is zero, then the model searches for the next sub-group that has the smallest transformation time or cost. On the contrary, if the inventory level is sufficient to fulfill the remaining quantity then the required amount of inventory is used for the transformation, inventory level of the substitute sub-group is updated, transformation cost is computed and the *order completion* process is triggered respectively. Furthermore, if the inventory level of the substitute sub-group is lower than the remaining quantity and different from zero, in this case, on hand inventory is used for the transformation, the remaining quantity of the order is updated and the transformation cost is computed. Afterwards, the next sub-group that has the smallest transformation time or cost is investigated. Transformation is performed recursively until the entire order is fulfilled. However, if there is no other alternative left for the transformation and the order is still not completely fulfilled, the order enters the queue and waits until the produced parts are put on the shelf. During this waiting time, whenever an inventory replenishment has occurred for a particular sub-group, orders waiting in the queue are fulfilled based on the earliest due-date rule and the transformation possibilities for the orders that belong to other sub-groups are investigated again (see Fig. 3).

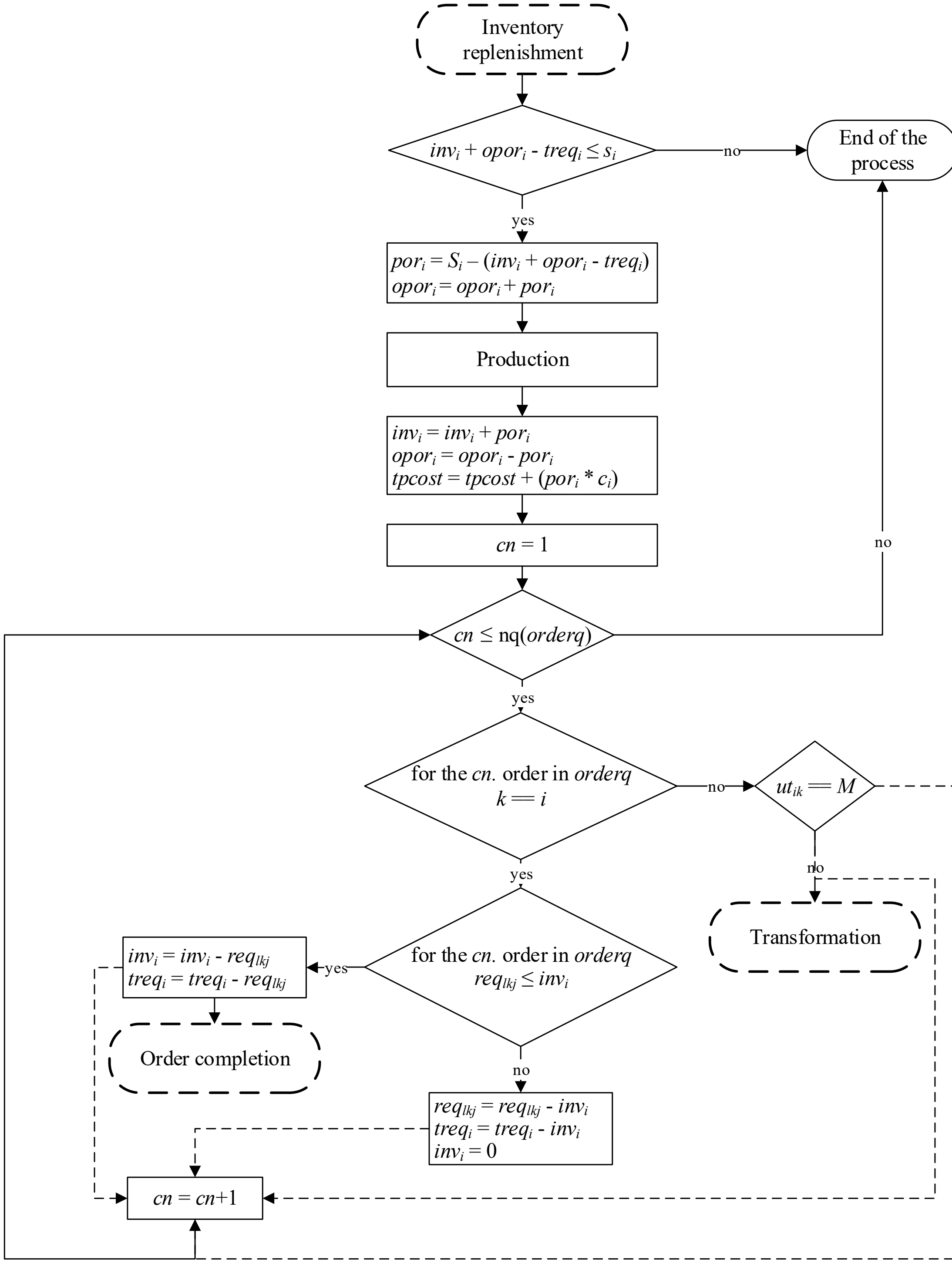


Fig. 3. Flow of the inventory replenishment process

Finally, each completed order enters the *order completion* process as shown in Fig. 4 and the tardiness of the orders are evaluated. Backorder cost is computed for the orders whose completion times are greater than their due-dates. In addition, performance measures such as total amount of demand fulfilled and the total amount of demand fulfilled by transformation are re-evaluated. Moreover, at the end of the replication, total cost is calculated.

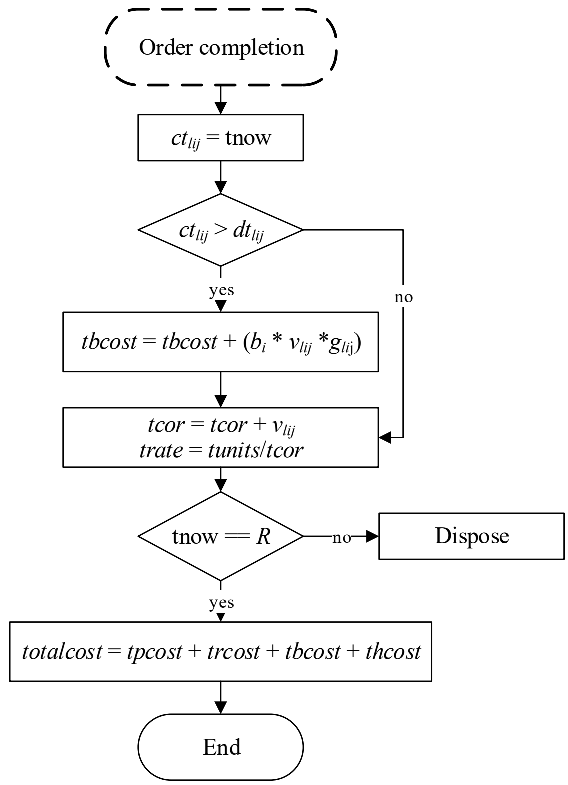


Fig. 4. Flow of the order completion process

4. Methodology

Spare parts inventory control problem under concern involves stochastic issues such as order arrival, order quantity and production lead time and also the transformation process makes the problem more complicated when compared with the classical spare parts inventory control problem. Since our problem is difficult to solve through the analytical approaches, we use simulation modelling due to its ability to model and assess the behavior of complex systems over time.

On the other hand, when the search space of a problem is small, the value of the decision variables that optimize the objective function can be determined by evaluating all combinations of these variables or designing experiments. However, if the problem's search space is large, evaluating all of the combinations of decision variables is almost impossible and the simulation model needs to be integrated with an optimization method in order to obtain near-optimal solutions in a reasonable time (Tekin & Sabuncuoğlu, 2004).

In this concern, we used simulation-optimization in order to find the near-optimal values of the spare part inventory levels (*s*, *S*) that minimize total cost. Discrete-event simulation models of both transformation and no-transformation cases are developed in Arena 14.0 and then these models are integrated with SA coded in Matlab R2021a. In the simulation optimization process, SA generates a candidate inventory policy regarding the inventory levels of sub-groups at each step. Then the simulation model is run for this candidate policy and the output (total cost) obtained from the simulation model is evaluated by the SA. This process continues until the termination criterion is met and finally, near-optimal (*s*, *S*) inventory levels are determined.

4.1 Simulated Annealing Algorithm

SA is a single-solution-based search algorithm that imitates the annealing process of materials. The annealing process involves heating a material to a specific temperature and then cooling it slowly to increase the toughness of the material. SA is a stochastic method and the key feature of this algorithm is that it accepts worse solutions with a probability to escape local optima (Henderson et al., 2003). The main parameters of SA are the initial temperature (T_0), final temperature (T_{min}), cooling rate (α), and number of iterations at each temperature (R).

SA has been widely applied to combinatorial optimization problems and the most common advantages stated are: ease of implementation, less memory requirement, shorter running time and providing reasonably good solutions (Radu & Vintan, 2013). A comprehensive review of SA in optimization problems can be found in the studies of Suman and Kumar (2006) and Siddique and Adeli (2016). The steps of the algorithm can be summarized as follows:

Algorithm 1 Pseudo code of the SA algorithm

1. Set $r = 0$, $T = T_0$
2. Generate a random feasible solution S, compute the objective function value $F(S)$, set best solution $S^* = S$ and $F(S^*) = F(S)$
3. **If** $T > T_{min}$ **then** go to step 4; **else** go to step 8
4. Set $r = r + 1$
5. Generate a random feasible solution S' in the neighborhood of S and compute $F(S')$
6. Let $\Delta = F(S') - F(S)$
6.1. **If** $\Delta \le 0 \rightarrow$ set $S = S'$, $S^* = S'$ and $F(S^*) = F(S')$
6.2. **If** $\Delta > 0 \rightarrow$ generate a random number $x \in [0,1]$
6.2.1. **If** $x \le \exp(-\Delta / T) \rightarrow$ set $S = S'$
7. **If** $r \ge R \rightarrow$ set $T = \alpha^* T$, $r = 0$ and go to step 3; **else** go to step 4
8. Display S^* and $F(S^*)$

4.2 Solution Representation

To represent the solution of our problem, we used an array of length *2m* where *m* is the total number of sub-groups. In this representation, the first *m* elements correspond to re-order levels and the remaining *m* ones correspond to order-up-to levels of the sub-groups.

4.3 Initial Solution Generation and Neighborhood Search

The initial solution is generated randomly by considering the constraints identified in Section 3 by the Eqs (2-4). Then, the neighborhood search is realized as depicted in Fig. 5 by using a temperature level-based step function. This function is used to compute the amount of change to be made on the current solution at *j*th temperature level by considering the value of this function at (*j*-1)th temperature level. With the help of this function, amount of the change decreases as the temperature decreases and the neighbor solutions at lower temperatures are fine-tuned. Value of this function is calculated using Eq. (9) and Eq. (10) where φ is the constant multiplier between (0, 1) and j represents the temperature level which equals 1 for T_0, 2 for (α^* T_0) and so on. For instance, if T_0=1000, T_{min}=1, α=0.95 and *step*(1)=1, then the step function has 135 temperature levels as illustrated in Fig. 6.

$$if \quad rnd(\,) < \lambda$$

$$step(j) = step(j-1) - \exp\left(-\frac{j}{j+1}\right) * \varphi * step(j-1) \tag{9}$$

$$else$$

$$step(j) = step(j-1) + \exp\left(-\frac{j}{j+1}\right) * \varphi * step(j-1) \tag{10}$$

$$end$$

$$solution(i) = solution(i) + (unifrnd(-1,1) * range(i) * step(j)) \tag{11}$$

After computing the value of the step function at *j*th temperature level, the type of change (addition or subtraction) to be made is determined randomly for each element *i* in the solution representation. Then the neighbor solution is generated by using equation (11). In this equation, *range*(*i*) represents the difference between the upper and lower bounds defined for element *i* in the solution representation. For each generated solution boundary constraints are checked and when the value of an element exceeds its predefined lower and upper bounds, it is rounded to its nearest bound as shown in Fig. 5.

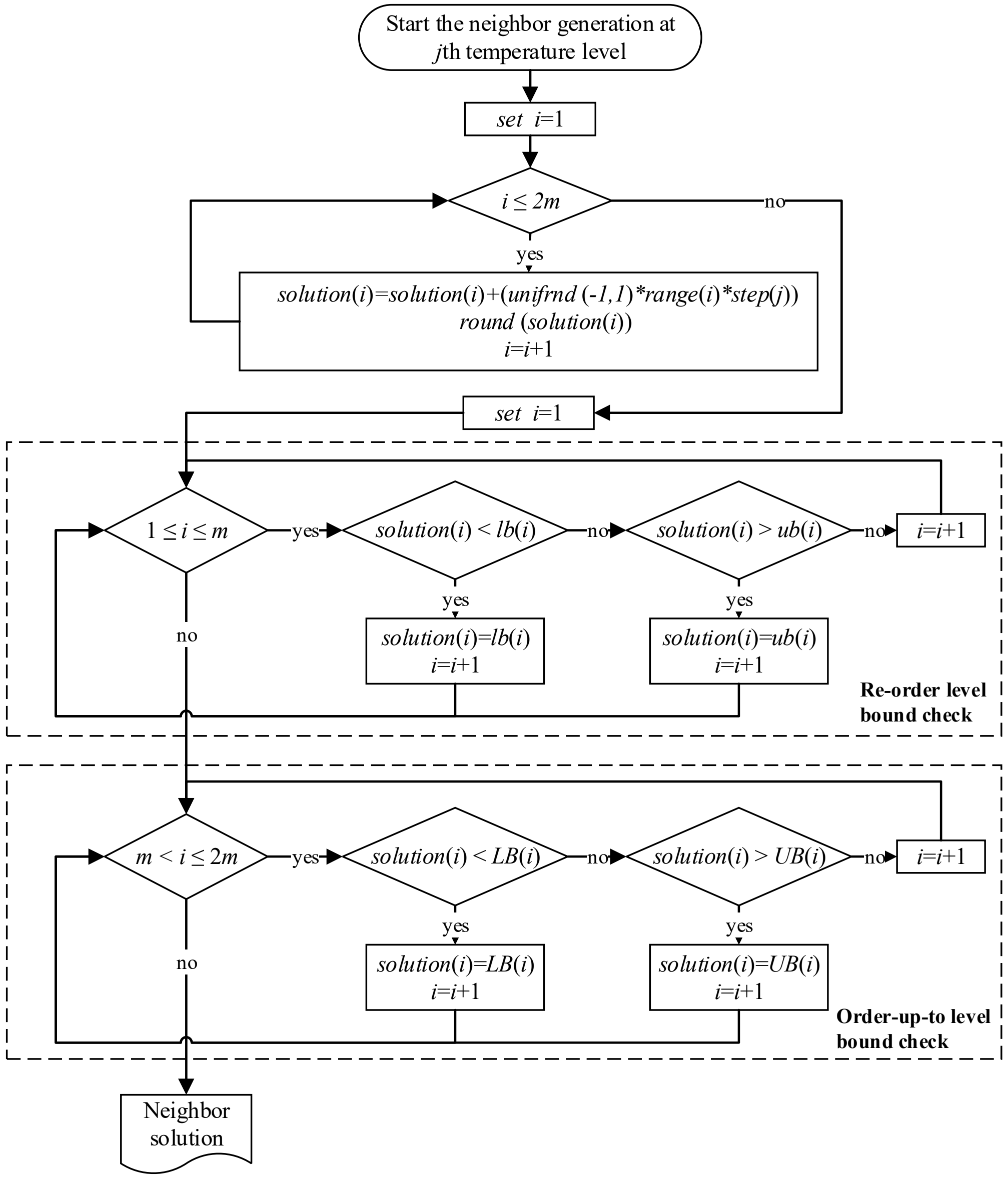


Fig. 5. Neighbor solution generation process

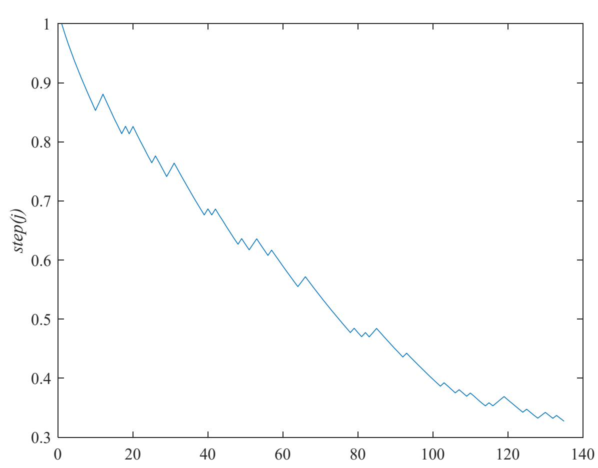


Fig. 6. Value of step function over temperature levels

4.4 Termination

The termination conditions of SA can be reaching a final temperature, reaching a threshold value of the objective function, reaching the maximum number of iterations etc. In our study, SA starts with an initial temperature, and temperature is decreased according to a cooling schedule in each step. Then, the algorithm terminates when the temperature reaches a predetermined final temperature.

5. Computational Analysis

In this section, computational analyses are performed in order to evaluate the efficiency of the proposed inventory control model under different conditions. To this aim, we handled the hypothetical inventory system of an electronic card group and we have focused on the effect of f_l on transformation and no-transformation cases with respect to total cost. As emphasized before, if spare part demands cannot be fulfilled within a certain period of time companies face severe penalties. Therefore, backorder cost is an important issue in spare parts inventory management and the parameters that are used in its calculation should be analyzed.

In the inventory system under concern, the electronic card group consists of four sub-groups and the orders for these sub-groups are placed by two types of customers. Orders arrive from domestic and international customers with equal probabilities (50% for each customer type). Sub-group type of an incoming order can be 1, 2, 3 or 4 with the probability of 25%. Time between the order arrivals is exponentially distributed with a mean of 3 hours. Quantity of an order shows a normal distribution and it varies depending on the customer type and sub-group as it is shown in Table 4. It should be noted here that negative values of order quantity are checked and not allowed in our simulation models.

Table 4
Demand distribution

	i			
l	1	2	3	4
1	norm(8,1)	norm(10,2)	norm(5,1)	norm(7,2)
2	norm(6,1)	norm(6,2)	norm(4,1)	norm(9,1)

Input data that include initial inventory levels, unit production costs and unit prices related to sub-groups can be seen in Table 5. Further, unit transformation times and costs between sub-groups are summarized in Table 6.

Table 5
Input data of sub-groups

i	inv_i^0	c_i ($)	p_i ($)
1	90	30	40
2	50	40	50
3	100	50	60
4	60	35	45

Table 6
Unit transformation time and cost

	ut_{ki} (hr)				r_{ki} ($)			
k	i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=4
1	M	0.500	0.333	0.666	M	10	15	20
2	0.666	M	1.000	M	20	M	25	M
3	M	0.333	M	0.500	M	15	M	25
4	1.166	M	0.666	M	35	M	30	M

Procurement of components constitutes the major part of the production lead time. Therefore, production lead time is evaluated independently from both order quantity and type of the sub-group. The production lead time is 360 hours with 20% probability, 480 hours with 20% probability and 600 hours with 60% probability.

As stated before, our study aims to find near-optimal (s, S) inventory levels for each sub-group that minimize total cost. Three simulation models regarding the transformation and no-transformation cases are developed by using Arena. Model (I) and (II) are the models in which transformations are performed based on the rules specified in Section 3 and the Model (III) represents the case with no-transformation.

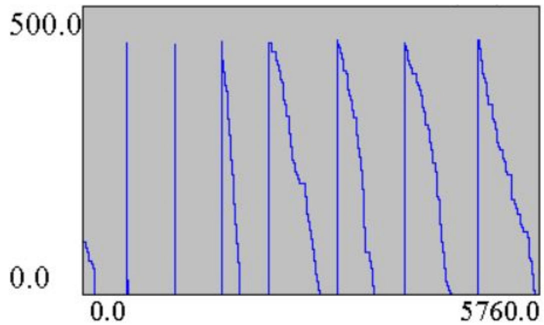
We performed experimental analysis for varying values of f_1 in order to investigate the effect of penalty coefficient on transformation and no-transformation cases with respect to total cost. In our analysis, f_2 is assumed to be 10%. Lower and upper bounds for s and S values are defined for each sub-group as [50, 150] and [151, 500] respectively. In this way, we guarantee that the order up-to level of a sub-group must be greater than its re-order level. Simulation models run 10 replications for 8 months (5760 hr) and the simulation optimization is run three times for each value of f_1. In addition, T_0, α, R, T_{min} and $step(1)$ are determined as 10000, 0.99, 10, 1 and 1 respectively. In neighborhood search, we chose φ as 0.04 and λ as 0.8, since higher values of φ cause dramatic changes between two consecutive values of the step function.

After the optimization process, near-optimal s_i and S_i values are obtained as presented in Table 7 and an example Arena output of the sub-groups' inventory replenishment processes is illustrated in Fig. 7. When we interpret the results given in Table 7, we can conclude that sub-groups 1 and 4 have higher production volumes than sub-groups 2 and 3 in Model (I). As sub-group 1 is the most transformable one among the other sub-groups, parts belonging to this sub-group are used to fulfill both their own demand and the demand of other sub-groups. Therefore, there is a high need for producing the parts belonging to this sub-group. On the other hand, since transforming parts from other sub-groups to sub-group 4 requires longer time, the model prefers to produce parts from sub-group 4 in higher volumes to avoid transformation. From another point of view, sub-group 3 has more transformation alternatives and transforming parts from other sub-groups to sub-group 2 requires less time. Therefore, the model mostly prefers to fulfill demand of these sub-groups through transformation and this situation causes the parts belonging to these sub-groups to be produced in lower volumes.

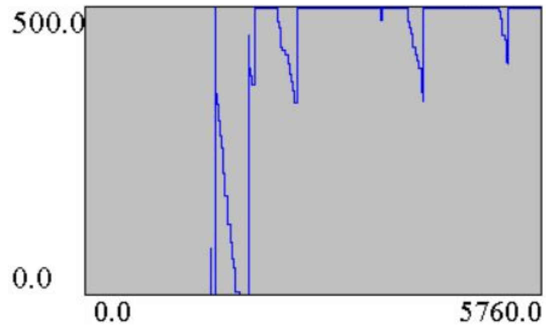
Table 7
Near-optimal inventory levels of sub-groups under different f_1

f_1		Model (I)		Model (II)		Model (III)	
	i	S_i	s_i	S_i	s_i	S_i	s_i
0.1	1	500	150	500	150	500	150
	2	151	150	151	150	500	50
	3	435	90	151	150	500	123
	4	500	67	319	150	151	150
0.3	1	486	150	500	150	459	150
	2	500	150	151	150	500	150
	3	151	82	500	88	151	150
	4	468	88	500	150	224	150
0.5	1	500	68	500	150	500	150
	2	490	50	151	150	500	150
	3	216	150	475	88	500	145
	4	442	150	500	150	151	150
0.7	1	500	73	500	150	500	150
	2	166	150	151	150	500	131
	3	500	137	481	88	469	143
	4	337	54	500	89	154	150
0.9	1	487	137	500	150	238	150
	2	151	150	151	144	500	137
	3	500	90	500	90	500	150
	4	416	78	388	150	151	150

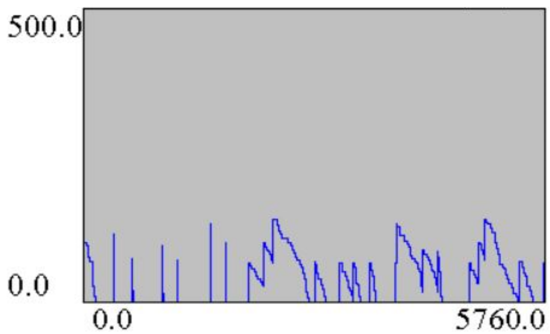
When the s_i and S_i values obtained for Model (II) are evaluated, it can be concluded that sub-group 3 has higher and sub-group 2 has lower production volume. Since the cost of transforming parts into sub-group 2 is relatively low, the model prefers to fulfill demand for this sub-group through transformation rather than producing parts of this sub-group in higher volumes. On the other hand, although the number of sub-groups that can be transformed into sub-group 3 is higher, producing parts belonging to this sub-group in higher volumes is more advantageous due to the higher unit transformation costs. In addition, the results corresponding to the near-optimal s_i and S_i values are summarized in Table 8 and Fig. 8. As shown in Table 8, transformation gives superior results than the no-transformation case in terms of total cost for all values of f_1. On the other hand, Model (II) that makes the transformation decisions based on the minimum unit transformation cost provides better results than Model (I) for lower values of f_1 with respect to total cost. However, Model (I) becomes more advantageous for the higher values of f_1 because any increase in tardiness will lead to higher backorder cost. When we examine the change in total cost over varying values of f_1, we can observe that, at lower values of f_1, for instance 0.1, the difference between the Model (I) and Model (III) is about 11% and the difference between Model (II) and Model (III) is 14%. When f_1 is 0.9, the difference between Model (I) and Model (III) reaches 84% and the difference between Model (II) and Model (III) is obtained as 65%. As an interpretation of these results, we can conclude that transformation provides much better results in case the penalty cost associated with backorders is higher.



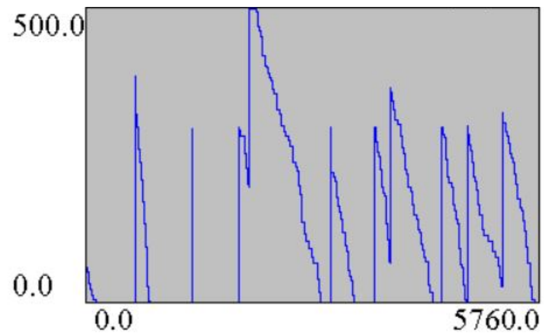
a) inventory replenishment of sub-group 1



b) inventory replenishment of sub-group 2



c) inventory replenishment of sub-group 3



d) inventory replenishment of sub-group 4

Fig. 7. Inventory replenishment of sub-groups (Model (I), f_l=0.5)

Table 8
Results of near-optimal inventory levels for different values of f_l

		Model (I)	Model (II)	Model (III)
f_l = 0.1	*tcor*	13192	13296	13140
	tunits	4768.5	3040.9	0
	trate	0.36	0.23	0
	trcost	98160	60602	0
	tpcost	500870	494760	536870
	tbcost	72960	104690	208920
	thcost	1840.3	1686.2	5366.4
	totalcost	673830.3	661738.2	751156.4
f_l = 0.3	*tcor*	13068	13344	13116
	tunits	4422.6	4185.5	0
	trate	0.34	0.31	0
	trcost	89138.5	85929	0
	tpcost	491600	507310	535550
	tbcost	343060	281570	651440
	thcost	2105.7	2236.7	5311.3
	totalcost	925904.2	877045.7	1192301
f_l = 0.5	*tcor*	13065	13224	13328
	tunits	4638.1	4071.4	0
	trate	0.36	0.31	0
	trcost	95527.5	82819	0
	tpcost	502680	505570	548390
	tbcost	516790	477760	1122500
	thcost	2161.9	2258.4	5713.1
	totalcost	1117159	1068407	1676603

Table 8
Results of near-optimal inventory levels for different values of f_l

		Model (I)	Model (II)	Model (III)
$f_l = 0.7$	*tcor*	13119	13291	13139
	tunits	5247.8	4534.4	0
	trate	0.4	0.34	0
	trcost	109362	92306	0
	tpcost	509890	506790	538820
	tbcost	750100	675380	1454500
	thcost	1682.8	2043.4	5500.5
	totalcost	1371035	1276519	1998821
$f_l = 0.9$	*tcor*	13224	13356	13166
	tunits	4725.2	4359.3	0
	trate	0.36	0.33	0
	trcost	95311.5	84616.5	0
	tpcost	506310	505642	539090
	tbcost	712560	883452	1883400
	thcost	1943.6	2103.8	5705.4
	totalcost	1316125	1475814	2428195

Further, as it is illustrated in Fig. 8, Model (I) and Model (II) are very effective in decreasing both backorder cost and holding cost. By the help of transformation, companies can meet the demand of an out of stock part by transforming other parts already in inventory instead of waiting long production lead times. In this way, companies can rapidly meet demand and the cost associated with the backorders decreases. In addition, transformation increases the inventory turn-over rate by using on hand inventory to meet both primary demand and the demand of the other parts. Thus, parts do not wait idle in stock until a demand for their own sub-group is received. On the other hand, when we evaluate the results with respect to the production cost, it is clearly seen that the production costs are lower in both Model (I) and Model (II). The main reason is that, in case of transformation, the model prefers meeting demand by transforming other parts rather than producing in high volumes and storing them. In this way, both production and holding costs are decreased.

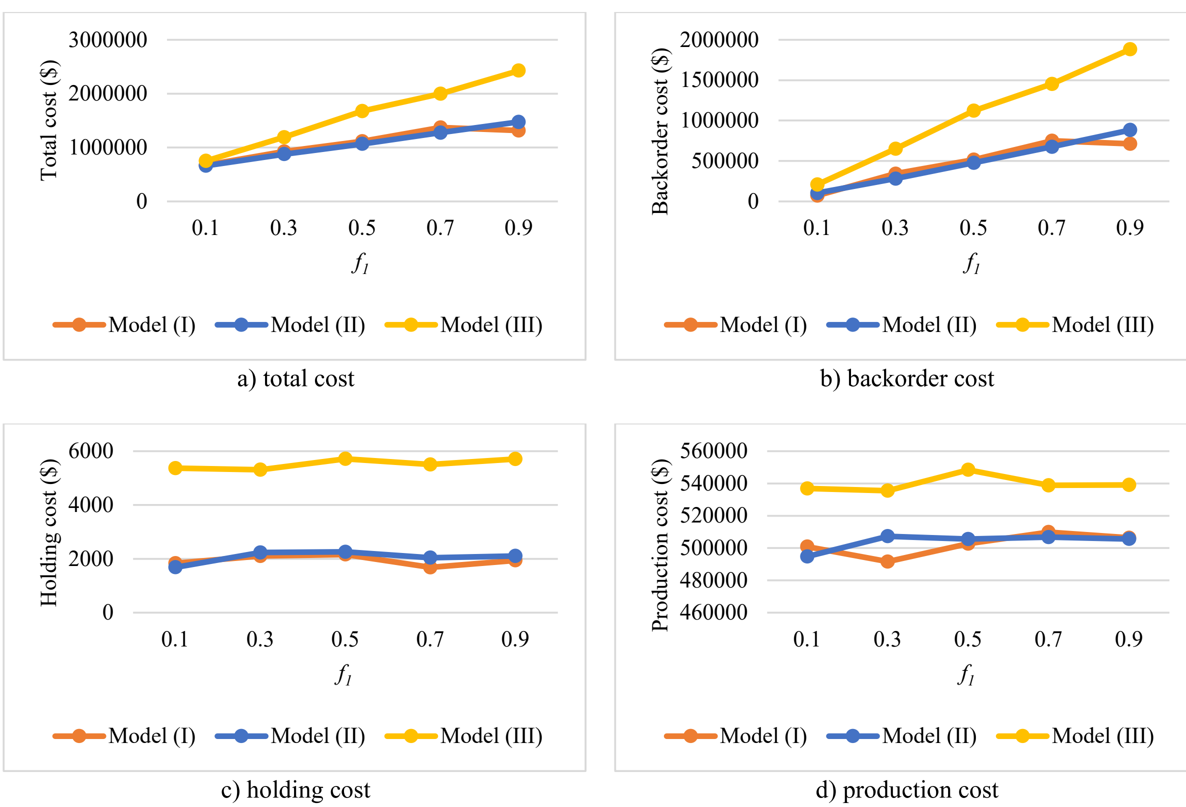


Fig. 8. Change of cost components over f_l

When we examine the results in terms of transformation, in our hypothetical inventory system, the transformation rate varies between 20% and 40% in Models (I) and (II). In addition, as presented in Table 9, both Model (I) and Model (II) parts from sub-groups 3 and 4 are the less preferred parts for the transformation operations. The reason for this situation can be explained by the unit transformation times and costs given in Table 6. In Table 6, we can clearly see that transforming a part belonging to sub-group 4 into another type of part takes a longer time than other sub-groups. Further, the cost of transforming a part from sub-groups 3 and 4 into other sub-groups is much higher in comparison with other sub-groups.

Table 9
Total amount of parts used in transformation

	$i = 1$		$i = 2$		$i = 3$		$i = 4$		total	
f_l	Model (I)	Model (II)	Model (I)	Model (II)	Model (I)	Model (II)	Model (I)	Model (II)	Model (I)	Model (II)
0.1	1036.3	785.4	1439.6	952.5	1097.1	690.7	1195.5	612.3	4768.5	3040.9
0.3	1424.7	1161.9	1020.7	1423.6	1358	683.2	619.2	916.8	4422.6	4185.5
0.5	1579.2	1169.9	1212.8	1388.4	1085.2	671.4	760.9	841.7	4638.1	4071.4
0.7	1196.3	1238.3	1299.6	1436.6	945.1	694	1806.8	1165.5	5247.8	4534.4
0.9	859.2	980.5	1574.6	1572.8	950	657.4	1341.4	1148.6	4725.2	4359.3

6. Conclusions and Future Research Directions

In today's markets, creating value for customers and increasing loyalty are vital for companies for their survival. Hence, after sales service management is becoming increasingly important for many industries. With a successful after sales service management, companies can achieve strategic goals such as customer loyalty, high service levels, revenue maximization, cost minimization etc.

As discussed earlier, after sales service performance highly depends on the management efficiency of spare parts inventories. Providing necessary spare parts timely and in a cost effective way will improve the service performance of the company. Part transformation, which can be considered as a special case of substitution, allows companies to rapidly meet demand and it gives the opportunity of reducing holding, backorder and production costs. However, the cost and time associated with the transformation process and the inventory sharing capability of this process differentiates it from the classical product substitution practices and more advanced methods are needed to find effective inventory control policies.

In this concern, a spare parts inventory control model that uses the transformation-based substitution in demand fulfillment is proposed in this study. It is aimed to find the near-optimal values of spare part inventory levels (s, S) that minimize total cost. To this aim, a SA based simulation optimization approach is used and the computational analyses are performed on a hypothetical inventory system.

In our computational analysis, transformation and no-transformation cases are compared for varying values of penalty coefficient. When we evaluate the obtained results, we can conclude that the transformation is an efficient way to meet demand rapidly and it is more beneficial for the companies who endure long production lead times and high penalty costs associated with backorders. In addition, for higher values of the tardiness penalty, selecting substitute items based on unit transformation time rather than cost yields better results.

These results provide some valuable insights for managers. First, using the proposed model, inventory managers can decide under what conditions they will use transformation-based substitution and how they should select the substitute part. Second, the proposed approach contributes to sustainable manufacturing which is an important issue for the environment. As we know, high-tech products have short product life cycles and spare parts of obsolete products are rapidly becoming e-waste. E-waste is a growing problem in the world and it poses serious threats to the environment. Our proposed model supports sustainable manufacturing and reduces e-waste by using idle inventories.

On the other hand, the proposed model has some limitations. First, our model assumes that all transformed parts meet the quality requirements. However, transformation operations can sometimes cause quality problems. Including a quality control process in the simulation model for the transformed parts may overcome this limitation. Second, the intermittent and lumpy nature of spare parts demand is ignored in our model. Our model considers the maturity phase of the product life cycle in which spare parts demands are stable. However, spare parts demands are not stable at the initial phase or end-of-life phase. In future, using different probability distributions across product life cycle phases may extend the proposed model. In addition, investigation of the effect of different sequencing rules used to prioritize the orders waiting for transformation and different criteria used to select the substitute sub-group for transformation can be very interesting future research topics.

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