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Bi-objectives Approach for a Multi-period Two Echelons Perishable Product Inventory-routing Problem with Production and Lateral Transshipment

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ABSTRACT

In this study, a two echelons supply chain system in which a supplier is producing perishable product and distribute it to multiple customers is considered. By allowing lateral transshipment mechanism, it is also possible to deliver products to some customers in some periods in bulk, then customers using their own vehicle to tranship goods between each other seeking further reduction in the overall cost. The aim here is minimizing the production, inventory carrying cost, and distribution as the first objective, and transshipment cost as the second objective, which is contrary objectives, without facing any shortage anywhere in the chain during the planning horizon. This problem is formulated as a bi-objectives mixed integer programming (BOMIP), and then a proper Pareto front as a set of multiple decision alternatives is provided using NSGAII and NRGA approach. Novelty of this research is providing a bi-objectives mathematical modeling of perishable product inventory routing with production and transshipment (BO-P-PIRPT) that help the decision maker to choose the best mixture of routing and transshipment.

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NOMENCLATURE

Sets & indexes	Description
n	the numbers of retailers
O	the supplier's node; $O = \{0\}$
V'	set of nodes including retailers; $V' = \{1,\dots,n\}$
V	set of nodes including supplier and retailers; $V = V' \cup O = \{0,1,\dots,n\}$
p	the length of the planning horizon
T	$T = \{1,\dots,p\}$
t	index of each time period ; $t \in T$
i,j	index of each node; $i,j \in V$
A	set of arcs; $A = \{(i,j): ij \in V, i \neq j\}$
Parameters	
C_i	maximum capacity of retailer i
e_{ij}	routing cost from vertex i to j, $(i,j) \in A$
a_{ij}	unit cost associated with transshipping products from i to j
d_i^t	demand rate at retailer i in period t
Q	vehicle capacity
h_0	unit inventory holding costs at supplier
h_i	unit inventory holding costs at retailer i
τ_{max}	maximum shelf life of product
ψ	set of time period before the product get spoiled; ψ={1,…,τ_max}
f^t	unit production cost in period t
Variables	
X_{ij}^t	if and only if customer j immediately follows customer i on the route of the supplier's vehicle in period t is equal to 1; otherwise equal to 0
W_{ij}^t	the amount of product delivered directly from i∈V to j∈V^' in period t ∈T using the outsourced carriers
Y^t	the amount of products manufactured by supplier at the time t ∈T
I_i^0	inventory level at the vertex i∈V at the beginning of the planning horizon
I_i^t	inventory level at the vertex i∈V at the end of period t∈T
q_i^t	the quantity of product delivered from the supplier to retailer i in time period t
v_i^t	continuous variables to enforce sub-tour elimination

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1. INTRODUCTION

Some supply chains systems allow flexible approaches like transshipment in which, the goods can be shared between supplier and retailers so that out of plan, the goods can be directly sends to some retailers when unforeseen demands variations occur [1]. The transshipment in the inventory routing (IRPT) was firstly introduced in reference [2]. Additionally, perishable products in which the products are of short life cycle such as food, medical products, blood, and in IRP (PIRP) is a less paid attention issue in the literature. Here, the term “perishable” is used for referring to a category of products that have fixed lifetime and after that time it cannot be used and must be discarded [3]. A clear known fact in the coordination of decisions related to inventories and delivering is that the inventory carrying and production decision are contrary to routing and transshipment decisions so that increase in one would lead to increase in another and vice versa. A few researchers [4] try not to conceal inherent contradiction in the IRP objectives and make their way through multi-objective modeling approaches. There are some advantages over introducing the PIRP as a multi-objective optimization problem [5]. One of them is allowing DM to analysis the problem easier by offering a range of solutions which can show trade-offs between inventory and transporting decisions. That is why the P-PIRPT is modeled as a bi-objective mixed integer programming (MIP).

Here, a two echelons supply chain with one supplier and multiple customers is considered (Figure 1). In some periods some customers may be served only by supplier vehicle to fulfill their demand while in some other periods, this is done only through transshipment.

Complexity of P-PIRPT which stemming from embedded VRP and perishability and transshipment option, make us take the metaheuristic based solution approach.

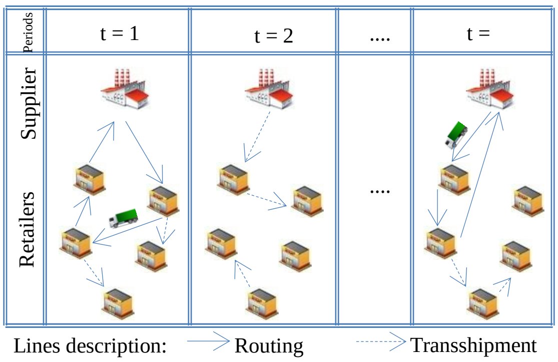

Figure 1. The two echelons supply chain network for a multi-period PIRP with transshipment

So, the non-dominate sorting genetic algorithm II (NSGAII) and non-dominated ranked genetic algorithm (NRGA) aiming for providing a set of solutions for P-PIRPT are used. Then, using some common performance evaluation metrics, some comparison analysis to find better-performed algorithm is brought. To check the validity of Pareto solution sets, a single objective genetic algorithm (GA) to solve each of the objectives separately is provided. Novelty of this research is providing a bi-objectives mathematical modeling for perishable product inventory routing with production and transshipment (BO-P-PIRPT) and an enhanced NSGAII and NRGA as solution approach.

2. LITERATURE REVIEW

Here, focus is to uncovered papers and latest work done about PIRP from the year 2012 which were not reviewed in surveys. Andersson et al. [6], Coelho et al. [7], SETAK and Daneshfar [8] have studied vendor managed inventory (VMI) policy for deteriorating items and provides an EOQ model for a two-level supply chain. Sahraeian and Zabihi [9] studied truck scheduling in a cross-dock problem with multiple perishable products and provide solution using two-level approach for solving their a mixed integer nonlinear programming (MINLP) mathematical modeling. Jain et al. [10] investigate an economic production quantity (EPQ) model for perishable items. Shaabani and Kamalabadi [11] also studied multi-period PIRP with single perishable product that a fleet of homogeneous vehicles should distribute goods between multiple customers. They provide a column generation-based heuristic algorithm to obtain a good solution for their problem. Al Shamsi et al. [12] considered the age for the only product in their three echelons supply chain problem and using B&B solution method they found that Mirzaei and Seifi [13] represent a mixed integer non-linear programming for PRIP in which the end customers’ demand depends on the age of the inventory. The solution approach devised using a hybrid of Simulate Annealing and Tabu Search meta-heuristics linearize after linearizing the model. Shaabani and Kamalabadi [11] studied a multi-period multi-product multi-retailer P-PRIP that products have a fixed lifetime. They introduced a population-based simulated annealing (PBSA) algorithm, which they showed it has some superiority over the simulated annealing (SA), and genetic algorithms (GA). Devapriya et al. [14] present two heuristics using GA to find approximate solution for the large size P-PIRP problem and reported their comparison using some test problems.

The multi-objective formulation approach for IRP is not a widely common approach in literature. Rahimi et al. [15] proposed a bi-objective mathematical model for multi-products with different shelf life PRIP and considering social issues. Huber et al. [16] have proposed a simulation based multi-objective IRP which solve it using a bi-level solution approach. Niakan and Rahimi [17] propose a fuzzy multi-objective Healthcare Inventory Routing Problem (HIRP) that distributes medicinal drug to healthcare centers. As a solution method and considering the uncertainties embedded in the problem, they use a fuzzy possibility programming method. Rahimi et al. [18] looked a closer look to IRP for the perishable products. Their proposed multi-objective models, in one hand, tries to minimize the costs and in the other hand do not want to lose their customers satisfaction by delayed deliveries to them as the second objective.

3. MATHEMATICAL MODELING

The bi-objective perishable production inventory routing problem with transshipment (BO-P-PIRPT) is defined on a graph $\mathrm{G} = (\mathrm{V}, \mathrm{A})$ with a node set V including a supplier (node 0) and a number of retailers, and an arc set.

Assumptions:

- A single capacitated vehicle is able to perform one route at the beginning of each time period
- Maximum level (ML) policy for inventories is considered
- The retailers have limited storage capacity
- Transshipment from supplier to customers and from any customer to another customer is allowed using third-party logistics (3-PL) providers
- A single perishable product with fixed life time is considered
- The deliveries from the supplier to the retailers are always of new or freshly processed product and also LIFO inventory management is considered
- The production is not capacitated and its cost is only related to the volume
- The last three assumptions are new in our study comparing to reference [2], due to considering perishability in our study.

Mathematical model of BO-P-PIRPT:

$$Z_1 = \min \sum_{t\in T} f^t Y^t + \sum_{t\in T} h_0 I_0^t + \sum_{i\in v'} \sum_{t\in T} h_i I_i^t + \sum_{i\in v} \sum_{j\in v} \sum_{t\in T} e_{ij} \chi_{ij}^t \tag{1-a}$$

$$Z_2 = \min \sum_{i\in v} \sum_{j\in v'} \sum_{t\in T} a_{ij} e_{ij} w_{ij}^t \tag{1-b}$$

s.t.

$$I_0^t = I_0^{t-1} + Y^t - \sum_{i\in v'} q_i^t - \sum_{i\in v'} W_{0i}^t \;, t \in T \tag{2}$$

$$I_0^t \geq 0 \;, \; t \in T \tag{3}$$

$$I_i^t = I_i^{t-1} + q_i^t - d_i^t + \sum_{j\in v'} W_{ij}^t - \sum_{j\in v} W_{ji}^t \;, \; i \in v', t \in T \tag{4}$$

$$I_i^t \geq 0, \; i \in v', t \in T \tag{5}$$

$$I_i^t \leq C_i \;, \; i \in v', t \in T \tag{6}$$

$$\sum_{i\in v} I_i^t \leq \sum_{i\in v'} \sum_{s\in\psi} d_i^{t+s-1} \quad , t \in T \tag{7}$$

$$q_i^t \leq C_i - I_i^{t-1}, \quad i \in v', t \in T \tag{8}$$

$$q_i^t \leq C_i \sum_{j\in v} X_{ij}^t \;, \; i \in v', t \in T \tag{9}$$

$$\sum_{i\in v'} q_i^t \leq Q \;, \; t \in T \tag{10}$$

$$\sum_{i\in v} X_{ij}^t = \sum_{i\in v} X_{ji}^t \;, \; j \in v, t \in T \tag{11}$$

$$\sum_{i\in v} X_{i0}^t \leq 1 \;, t \in T \tag{12}$$

$$v_i^t - v_j^t + Q X_{ij}^t \leq Q - q_j^t \;, i,j \in v', t \in T \tag{13}$$

$$q_i^t \leq v_i^t \leq Q \;, i \in v', t \in T \tag{14}$$

$$q_i^t \geq 0 \;, i \in v', \; j \in v \;, \; t \in T \tag{15}$$

$$v_i^t \geq 0 \;, i \in v', \; t \in T \tag{16}$$

$$Y^t \geq 0 \;\;, t \in T \tag{17}$$

$$W_{ij}^t \geq 0 \;, \; i \in v, j \in v' \;, i \neq j \;, t \in T \tag{18}$$

$$X_{ij}^t = \{0,1\} \;, \; i,j \in v \;, i \neq j \;, t \in T \tag{19}$$

The first objective function (1-a) include fore parts: (i) production cost (ii) inventory holding cost at supplier (iii) inventory holding cost at retailers and (iv) distribution (routing) cost of the supplier's vehicle, and the second objective function (1-b) is minimizing the transshipment cost. Constraints (2) - (6) relate to the inventory decisions. Constraints (7) relate to the perishability of products and limit the aggregate inventory level of the whole supply chain (for all customer plus supplier), up to the sum of proceeding demand of all customers during the lifetime of perishable product. The difference between our defined set of constraints in reference [11] is proposing a summation over all inventories and demand for all customers because here the transshipment is allowed. It is worth mentioning that these constraints work just like the constraints (6) and in different numerical instances, one of these constraints may get nonbinding. Constraints (8)–(9) relate to the quantity delivered by supplier's vehicle based on the ML policy. Constraint (10) guarantees that the vehicle capacity is respected. Constraints (11)–(14) are concerned with routing of the supplier‘s vehicle. In particular, constraints (11) ensure flow conservation for vehicle at each node in each period. Constraints (12) mean that there is only one vehicle. Constraints (13) and (14) are concerned with subtour elimination. Constraints (15)–(19) ensure the integrality and non-negativity of decision variables.

4. SOLUTION METHOD

One of the high-performance and widely used multi-objective metaheuristic, which provides high quality solution to the complex problems, is Non-dominant Sorting Genetic Algorithm (NSGAII) that first introduced by Deb et al. [19]. Here, a Non-dominated Ranking Genetic Algorithm (NRGA) is also applied which its process is alike NSGAII algorithm with the exception of their selecting process and will be discussed latter in sections.

Begin
Input:
– P: the number of periods in planning horizon
– I: the numbers of customers
– $Npop$: the number of population
For $n = 1$ to $Npop$
For $t = 1$ to P
Routing construction:
– Determining number of customers to be serviced (delivery periods): generate a random integer number $R1$ from interval $[0 , I]$
– Determining customers to be serviced and assigning routing priorities to them: randomly assign $R1$ integer numbers from interval $[1 , R1]$ to the $R1$ randomly selected customers then assign zero to remaining $I - R1$ customers.
End For
Let $K^i = \{RT^{i1}, \dots, RT^{it} | RT^{i1} > 0\}$ which shows the delivery periods for each customer i
For $i = 1$ to I
Repairing the shortages:
–If $\{K^i(1) - 1\} \neq \emptyset$ (which $K^i(1) - 1$ is the periods before the first planned delivery), and $\sum_{t=1}^{K^i(1)-1} d_i^t > 0$ assign priority of $R1 + 1$ to the first member of $\{K^i(1) - 1 | d_i^t > 0\}$
End if
Delivery determining:
For $r = 1$ to $R1$
– Calculate $\mu = \sum_{i=1}^{K^i(r)} d_i^t$ as the cumulative unsatisfied demand up to delivery point $K^i(r)$
– Calculate $\beta = \sum_{i=K^i(r)+1}^{K^i(r+1)} d_i^t$ as the cumulative unsatisfied demand to delivery point $K^i(r + 1)$
– Generate a random real number $R2$ from interval $[0 , 1]$
– Calculate $\omega = \mu + \beta * R2$ and let $Y^{it} = \omega$ where t is related to $K^i(r)$
– If R2 > 0, update the unfilled demand between two delivery point $[K^i(r) + 1, K^i(r + 1)]$ based on ω value and substitute it with the original demand
– End if
End For
End For
For $t = 1$ to P
For $i = 1$ to I
Randomly decide if $DL^{it} = Y^{it}$ or $TR^{ijt} = Y^{it}$ that j randomly selected from {1,..., I, $I+1$} where $I+1$ is the index of manufacturer
End For
End For
End For
Finish.

Figure 4. Pseudo code of construction heuristic (CH)

4. 1. Solution Chromosome

To display each solution chromosome of a multi-period P-PRIPT, an array with structure of $(N+N+N*N)*P$ elements (genes) is propose which N is total number of customers and P is total number of periods (Figure 2).

Additionally, i and j related to index of each customer and t is index of each period in the planning horizon. The first part of chromosome, Dl^{it}, shows amount of commodities at any period t that supplier deliver to each customer i. The value RT^{it} shows the routing priorities for any customer i at any period t. The transshipment quantities TR^{ijt} are presented in the third part of solution chromosome. A sample solution chromosome with 3 customers (N=3) and 2 periods (P=2) is shown in Figure 3. In this study, determining the values of RT^{it} and Dl^{it}, is done with a randomized based construction heuristic which is presented in the following sections.

4. 2. Construction Heuristic (CH)

For achieving better results, the pure random initialization process is blended with heuristics like “partial delivery” and a repairing infeasible mechanism. The basic idea of patrial delivery heuristic is sending a part of the future demand of each customer in current period, which provides more random solutions in term of transportation. Our approach here, is based on Abdelmaguid and Dessouky [20]. Before representing detailed construction process, using an example, the delivery periods for the customer i by matrix $\mathrm{K^i}$ is introduced which is the set of the periods that vehicle should met customer i based on the routing part of chromosome. So, $\mathrm{K^i} = [\mathrm{k_1}, \mathrm{k_2}, \dots, \mathrm{k_j}]$ where $\mathrm{k_{j \in T}} = t$ if $RT^{it} \neq 0$. For example considering sample solution chromosome of Figure 3 for customer i=2 we have $\mathrm{K^2} = [1,2]$. The pseudo code of construction procedure is presented in Figure 4.

4. 3. Violated Constraints

For handling the violated constraints, some smart penalty approach is used, which consider some different distance metrics from the feasible region [21].

$$\left[\overbrace{\begin{matrix} Dl^{11} & \cdots & Dl^{i1} \\ \vdots & \ddots & \vdots \\ Dl^{1t} & \cdots & Dl^{it} \end{matrix}}^{deliveries} \middle| \overbrace{\begin{matrix} RT^{11} & \cdots & RT^{i1} \\ \vdots & \ddots & \vdots \\ RT^{1t} & \cdots & RT^{it} \end{matrix}}^{routing\ priorities} \middle| \overbrace{\begin{matrix} TR^{111} & \cdots & TR^{i11} & TR^{121} & \cdots & TR^{i21} & TR^{1j1} & \cdots & TR^{ij1} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ TR^{11t} & \cdots & TR^{i1t} & TR^{12t} & \cdots & TR^{i2t} & TR^{1jt} & \cdots & TR^{ijt} \end{matrix}}^{transshipment} \right]$$

Figure 2. The proposed solution chromosome

$$\left[\overbrace{\begin{matrix} 0 & 25 & 5 \\ 0 & 4 & 15 \end{matrix}}^{deliveries} \middle| \overbrace{\begin{matrix} 0 & 1 & 2 \\ 0 & 2 & 1 \end{matrix}}^{routing\ priorities} \middle| \overbrace{\begin{matrix} 0 & 9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{matrix}}^{transshipment} \right]$$

Figure 3. Sample solution chromosome

To be more specific, the following sample problem (20) with q inequalities constraints and |N|-q equalities constraints where $\vec{x}$ is the vector of solutions ($\vec{x} = x_1, x_1, \dots, x_s$) and there are k conflicting objective functions, is considered.

$$\begin{aligned}
&Optimize\ f(\vec{x}) = f_1(\vec{x}), f_2(\vec{x}), \dots, f_k(\vec{x}) \\
&\text{s.t.} \\
&g_j(\vec{x}) \le b_j\,, \qquad j = 1, \dots, q \\
&h_j(\vec{x}) = l_j\,, \qquad j = q+1, \dots, N
\end{aligned} \tag{20}$$

The following penalty functions are used.

$$F(\vec{x}) = \begin{cases} f(\vec{x}) & \vec{x} \in feasible\ region \\ f(\vec{x}) + M\sum_{i=1}^{|N|} d_i & \vec{x} \notin feasible\ region \end{cases} \tag{21}$$

Where

$$d_i = \begin{cases} \max\{0, g_j(\vec{x}) - b_j\}\,, & for\ \ j = 1, \dots, q \\ |h_j(\vec{x}) - l_j|\,, & for\ \ j = q+1, \dots, N \end{cases}$$

The notation (21) shows how the distance based penalty strategy adds some extra value of $M\sum_{i=1}^{|N|} d_i$ to the objective functions $f(\vec{x})$.

4. 4. Crossover and Mutation The crossover operator applied here is based on Abdelmaguid and Dessouky [20] and Moin et al. [21] that use a mask crossover operator as a random binary matrix 1*N (where N is the number of customers). In Figure 5, an example with 3 customers and 2 periods is brought. The digit 1 and 0, states that the first child inherits the property from the parent 1, and inherit property from the parent 2, respectively. For the second child the reverse operation is performed.

As the transportation in this research is done in each period independent of the other periods, so considering a process which try to integrate deliveries that take place in different periods during the planning horizon with respect to other restrictions, may lead to reduced transportations. The main idea of devising a mutation process in this study is based on this consolidation idea, which is presented in Figure 6 with the following notation.

q_i^t = the amount of delivered products to customer i in period t;
RQ^t = the unused vehicle capacity in the period t;
RU_i^t = the unused capacity of the customer's warehouses i in period t;
ED_i^t = set of deliveries that can be fully transferred from customer i in period greater than t to period t considering the vehicle and warehouses capacities.

Some other mutation mechanisms which consider trade-off between the transshipments and deliveries can be seen in the following.

- Randomly substitute delivery by transshipment for one customer in one period
- Randomly substitute transshipment by delivery for one customer in one period
- Substitute delivery by transshipment for *n* best customers
- Substitute transshipment by delivery for *n* best customers

In this study, the combination of these four operators plus the integrating transportations operator, which are selected randomly each time the mutation is run, is used for mutation.

4. 5. Improvement For improving the objective function of individuals, which are resulting from different stages of algorithm, it is possible to apply some neighboring search techniques that are vastly used in classical VRP. These techniques help the vehicle to take the shortest route in serving the customers. Among different methods used for this reason 2-opt, 3-opt, remove and insertion, reverse all, and partial reverse for the routing section of the solution chromosome is applied.

4. 6. Proposed Hybrid-NSGAII and Hybrid-NRGA Here to increase algorithm's effectiveness, NSGAII is hybridized procedures discussed in the previous sections (Figure 7).

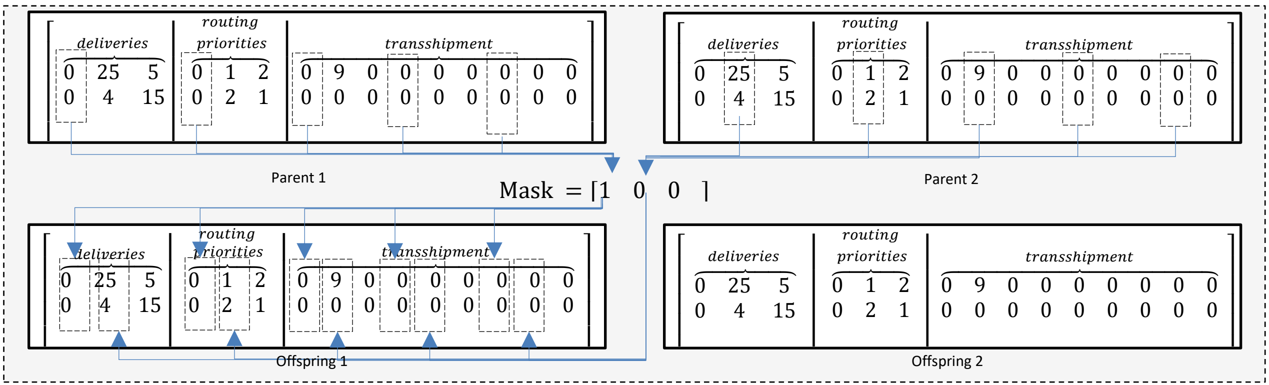

Figure 5. An example of how a Mask crossover works

Begin
Input:

- N : the numbers of retailers
- $Nmute$: the number of population that will go under mutation
- P : the number of periods in planning horizon

For j =1 to $Nmute$
For i = 1 to N
For t =1 to P
Calculate q_i^t ;
Calculate RQ^t;
Calculate $ED_i^t = \{q_i^s \mid s \in (t+1, \dots, P)\,,\ q_i^s \leq RQ^t,\ q_i^s \leq RU_i^t\}$
If $ED_i^t \neq \emptyset$,
Calculate $\mu = min\{RQ^t\,,\ RU_i^t\}$
Calculate $A = \{q_i^s \in ED_i^t \mid \sum q_i^s \leq \mu\,)\}$
Select $B \in A$ so that the cardinality of $|B|$ is maximized (meaning that select B with the maximum number of elements that transferring them to the same customer i from successive periods of t will not violate both the customer's warehouse capacity and vehicle's capacity constraints of period t)
End If
If $B \neq \emptyset$, add the values of $q_i^s \in B$ to q_i^s, then for the transferred q_i^s, set its related routing priority in the routing part of chromosome to zero
End If
End For
End For
End For
Finish.

Figure 6. Mutation operator pseudo code

Begin
Input:

- Np: number of population
- It: number of iteration
- Pc: probability of crossover
- Pm: probability of mutation

Generate population P(1) with size Np using proposed CH procedure
Improve P(1) using our proposed neighboring search operators
Non-dominated sort P(1)
Generate offspring population Q(1) form P(1) applying binary tournament selection, crossover, and mutation
While j ≤ It do
R(j) = P(j) ∪ Q(j)
Non-dominated sort R(j)
Select P(j + 1) from the first Np number of chromosomes selected from R(j)
Generate Q(j + 1) from P(j + 1), applying binary tournament selection, crossover, and mutation
Improve Q(j + 1) using our proposed neighboring search operators
j= j + 1
End while
Finish.

Figure 7. Proposed Hybrid-NSGAII procedure

Another algorithm which is used here is NRGA, which developed firstly by Al Jadaan et al. [22] and is a successor of NSGAII. The only difference between them is their selection strategy. In NSGAII, selection process is based on tournament selection while NRGA use a ranked based roulette wheel in selection of frontier between existing frontiers $(F_1, F_2, \dots, F_n)$, also in selection of one solution from the existing solutions on the selected frontier. The probability of selecting ith front, F_i, when exist N fronts and $Rank_{F_i}$ is calculated based on non-dominance rank, is as Equation (22).

$$P_{F_i} = \frac{2*Rank_{F_i}}{N(N+1)} \tag{22}$$

Similar procedure is applied for probability calculation of selecting solution j when there are M solutions in a selected F_i then $Rank_{sol_j}$is calculated based on crowding distance ranking. This can be seen in Equation (23).

$$P_{sol_j} = \frac{2*Rank_{sol_j}}{M(M+1)} \tag{23}$$

As the values $Rank_{F_i}$ and $Rank_{sol_j}$ are higher, it means that the possibility of the selection would be higher.

5. RESULTS

NSGAII and NRGA with MATLAB-2014a and run it on a PC, Intel Core2Duo, CPU 2.93 GH, windows 7 – 32 bit, and 3.2 GB RAM is implemented. To test the performance of algorithms, the benchmark examples for IRP produced by Archetti et al. [23] with some minor changes in order to consider production and perishable product (Table 1) is used. Using the parameters from Table 2, instances in three groups with general coding of "P-PIRPT-p-τ_{max}-Nn" is categorized that "P-PIRPT" is related to the problem, the first number after that shows the number of periods, the second number shows the shelf time of product, and N indicates that the number coming after is total number of customers.

5. 1. Tagouchi Method For Parameter Setting

Since metaheuristic are sensitive to their input parameters, using Tagouchi method is tried to adjust them. In the Table 2, one can see the possible range of parameters for probability of crossover (Pc), probability of mutation (Pm), population size (Npop), and iteration (Itr). Using MINITAB17 and selecting Tagouchi design of experiments, then selecting plan L9 where signal to noise is selected as small is better. The results of experiment are shown in Figure 8. The best parameters also are summarized in Table 3.

TABLE 1. Test problems data structure

Index	Value	Description
H	3,6	Planning horizon
$\tau_{\max}$	2 when H=3 and 2,3 when H=6	Shelf life time
n	5K that k= 1,2, … , 10 when H=3 and k= 1,2, …, 6 when H=6	Number of retailers
d_i	~Uniform(10,100)	Demand of each customer i per period
$\mathrm{C_i}$	If $\tau_{\max} = 3$, $d_i * g_i$ $that$ $g_i \sim Uniform(2,3)$ and otherwise infinite	Maximum warehouse capacity of customer i
$\mathrm{I_i^0}$	$C_i - d_i$	Customer i initial inventory level
$\mathrm{I_0^0}$	0	Supplier initial inventory level
$\mathrm{h_i}$	[0. 1, 0. 5]	Inventory holding cost by customer i
$\mathrm{h_0}$	0. 3	Inventory holding cost by supplier
Q	$1.5 * \sum_{i \in n} d_i^t$	Vehicle capacity
$(\mathrm{x_i}, \mathrm{y_j})$	~Uniform(0, 100)	Nodes' locations
$\mathrm{C_{ij}}$	$\lfloor \sqrt{(\mathrm{x_i} - \mathrm{x_j})^2 + (\mathrm{y_i} - \mathrm{y_j})^2} \rfloor$	Transportation cost
f^t	2	Unit production cost in period t

* Sign ⌊ ⌋ means the largest integer less than or equal to the value inside

TABLE 1. Factors, parameter range, and levels

Factor	Parameter range	Level (value)		
		1 (low)	2 (middle)	3 (high)
Pc	0.7-0.9	0.7	0.8	0.9
Pm	0.1-0.25	0.1	0.2	0.25
Npop	100-300	100	200	300
Itr	100-300	100	200	300

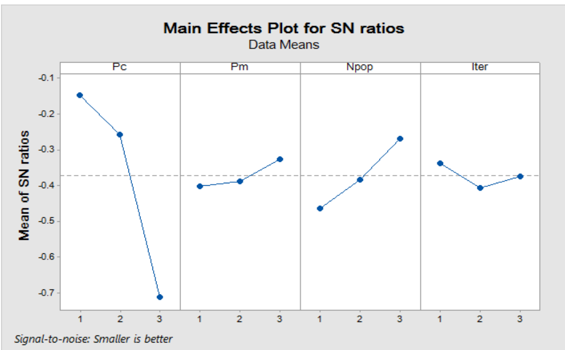

Figure 8. Taguchi S/N ratio plot

TABLE 3. Tuned values of factors

Factor	value
Pc	0.7
Pm	0.25
Npop	300
Itr	200

5. 2. Experiments

Figure 9 depicts solution represented by NSGAII for the instance "P-PIRPT-3-2-N50". It simply shows that the objective functions are in conflict. For checking the validity of implementing NSGAII and NRGA algorithms, a GA for solving single objective function of problem is introduced by linearization of two objective functions into one objective function with the same parameter setting for NSGAII and NRGA.

Using the tuned factors, every instance is run five times and the average results are reported in Table 4 and Figure 10. In the GA column, (Z1+Z2)* is the optimum value found by single objective function GA and Z1* is the values related to first objective. In the columns heading NSGAII and NRGA, "Best Z1" is the best value found for Z1, disregarding its related Z2, and "Best Z2" is the best value found for Z1, disregarding its related Z1.

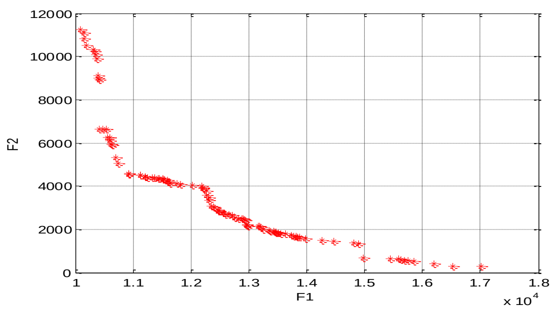

Figure 9. Relationship between objective functions for instance "P-PIRPT-3-2-N50".

TABLE 4. The objective function values and test the validity of them

Instance				GA		NSGAII			NRGA		
code	N	T	Pt	Z1*	(Z1+Z2)*	Best Z1	Best Z2	Best (Z1 + Z2)	Best Z1	Best Z2	Best (Z1 + Z2)
P-PIRPT-3-2-N5	5	3	2	557.17	864.21	556.49	0.00	864.82	565.446	0	880.518
P-PIRPT-3-2-N10	10	3	2	2151.00	3560.85	2128.14	0.00	3543.08	2140.856	15.652	3671.26
P-PIRPT-3-2-N15	15	3	2	2758.05	4580.97	2793.92	0.00	4355.62	2779.178	66.124	4658.826
P-PIRPT-3-2-N20	20	3	2	3507.36	6097.89	3513.58	6.69	5378.28	3559.004	84.264	5971.064
P-PIRPT-3-2-N25	25	3	2	4093.20	7408.62	4141.52	0.66	6558.30	4150.91	214.634	7447.304
P-PIRPT-3-2-N30	30	3	2	5819.81	10630.81	5951.02	16.90	9404.54	5946.612	587.054	10132.68
P-PIRPT-3-2-N35	35	3	2	5556.57	9730.07	5570.44	119.31	9238.48	5837.54	795.916	9845.372
P-PIRPT-3-2-N40	40	3	2	6523.21	13688.57	6635.00	524.23	11085.75	6925.46	995.57	12183.29
P-PIRPT-3-2-N45	45	3	2	7550.25	13688.57	7979.95	271.82	12746.07	7894.674	780.89	13376.99
P-PIRPT-3-2-N50	50	3	2	8371.74	15951.30	9988.10	390.23	14441.78	9540.958	1397.326	15239.78
P-PIRPT-6-2-N5	5	6	2	3005.53	5962.08	3007.40	121.75	5742.80	3006.55	438.26	5920.13
P-PIRPT-6-2-N10	10	6	2	5337.30	11412.42	5345.29	1714.61	11498.68	5343.58	1653.05	11571.69
P-PIRPT-6-2-N15	15	6	2	8285.26	16466.04	8312.52	3287.85	16416.20	8326.95	3403.86	16765.36
P-PIRPT-6-2-N20	20	6	2	10040.68	20467.79	12143.05	5368.71	21665.05	11118.69	5081.88	21699.20
P-PIRPT-6-2-N25	25	6	2	10383.30	22436.11	11620.83	5649.16	23495.01	10772.53	6391.51	24070.42
P-PIRPT-6-2-N30	30	6	2	16214.97	33300.87	20260.53	9553.02	34647.89	19945.73	11103.69	36608.02
P-PIRPT-6-3-N5	5	6	3	3008.83	5048.97	3012.34	0.00	4904.82	3009.98	267.52	5660.47
P-PIRPT-6-3-N10	10	6	3	5339.05	9575.44	5356.80	13.62	9332.93	5351.12	1279.02	11018.45
P-PIRPT-6-3-N15	15	6	3	8304.56	13865.04	8325.16	148.59	13206.09	8301.41	2352.67	15521.71
P-PIRPT-6-3-N20	20	6	3	10070.68	17532.49	10303.42	320.39	17075.21	10682.29	3928.08	20848.23
P-PIRPT-6-3-N25	25	6	3	10405.96	22436.108	10852.63	1113.34	19278.77	11075.10	4418.04	22072.18
P-PIRPT-6-3-N30	30	6	3	16239.12	33300.87	18686.85	1820.07	28588.87	17566.60	6766.60	32746.52

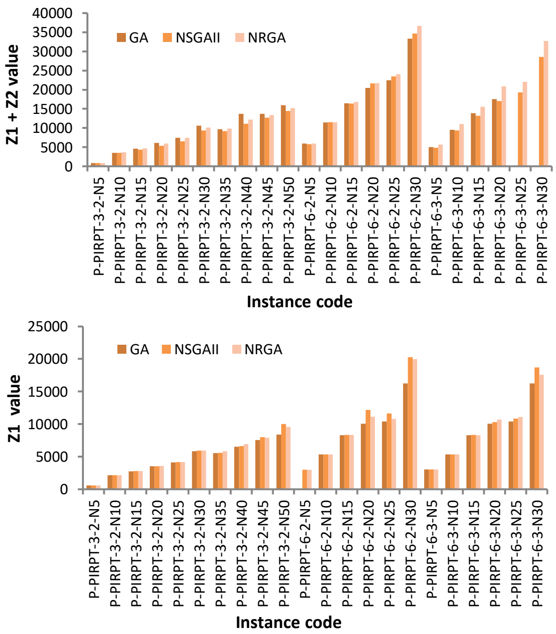

Figure 10. Validity check for NRGA and NSGAII results using single objective GA

"Best (Z1 + Z2)" column is solution found with minimum summation of both Z1 + Z2. The minor difference between these values shows that NSGAII and NRGA algorithms have been successful in finding a good rang of solution. To do the performance analysis of both algorithms, different metrics is used to compare the result of running each instance. The metrics [24] here includes MID (mean ideal distance) which calculate the closeness between Pareto solution and ideal point (0, 0). DM criterion, which is abbreviation of diversification matrix, gives an indication of the diversity of solutions obtained. NPS which indicates the number of Pareto solutions is calculated by counting the number of non-dominated. Spacing indicates the consistency of distance between solutions in a Pareto front. For calculating these metrics, each of all instances is run five times and the average results of these experiments are summarized in Table 5. The larger the better of each criterion is indicating by (↑). It can be seen that NSGAII outperform with 15, 12, 21, 13 out of 22 test problems in NPS, Spacing, MID, and DM performance measures, respectively.

TABLE 5. Metric's results

Instances' name	NSGAII				NRGA			
	NPS ↑	Spacing ↓	MID ↓	DM ↑	NPS ↑	Spacing ↓	MID ↓	DM ↑
P-PIRPT-3-2-N5	**41**	**1.04**	**1116.89**	**196.69**	29	1.16	1092.09	169.52
P-PIRPT-3-2-N10	**44**	**1.24**	**3395.12**	**350.10**	32	1.46	3507.76	317.15
P-PIRPT-3-2-N15	**73**	1.78	**4119.21**	**470.57**	51	**0.99**	4316.30	441.76
P-PIRPT-3-2-N20	**81**	**1.25**	**5674.52**	**645.54**	56	1.48	6069.82	584.24
P-PIRPT-3-2-N25	**85**	**0.95**	**6121.06**	616.46	74	1.58	6669.44	**623.31**
P-PIRPT-3-2-N30	**104**	**1.01**	**9545.43**	**963.84**	83	1.11	10570.78	907.41
P-PIRPT-3-2-N35	**121**	**0.94**	**8884.34**	**957.79**	72	1.16	9051.87	729.84
P-PIRPT-3-2-N40	**134**	**1.02**	**11221.55**	**1155.43**	92	1.03	11444.61	936.14
P-PIRPT-3-2-N45	116	1.19	**11827.38**	1080.91	**119**	**1.07**	12674.47	**1117.59**
P-PIRPT-3-2-N50	73	1.36	**13838.80**	907.96	**90**	**1.34**	14132.86	**1041.18**
P-PIRPT-6-2-N5	**83**	**1.11**	**4903.17**	549.06	72	1.99	5089.58	**551.14**
P-PIRPT-6-2-N10	78	1.28	9851.91	770.88	**82**	**0.96**	**9758.43**	**773.15**
P-PIRPT-6-2-N15	**99**	1.54	**13289.68**	**909.42**	95	**0.90**	13598.73	902.88
P-PIRPT-6-2-N20	72	1.14	**17441.66**	813.57	**97**	**0.91**	17778.74	**1025.03**
P-PIRPT-6-2-N25	96	**0.88**	**18338.79**	994.83	**111**	0.92	18520.92	**1065.60**
P-PIRPT-6-2-N30	**75**	**1.14**	**27501.69**	**981.79**	69	1.15	28729.06	961.19
P-PIRPT-6-3-N5	**74**	**2.13**	**4362.92**	486.89	71	2.22	4856.84	**526.94**
P-PIRPT-6-3-N10	**96**	1.65	**8538.30**	**850.49**	77	**1.20**	9526.82	773.78
P-PIRPT-6-3-N15	96	1.30	**11920.34**	**941.41**	**99**	**0.89**	12920.37	922.93
P-PIRPT-6-3-N20	**113**	**0.93**	**16742.83**	**1343.14**	99	0.95	17640.72	1118.30
P-PIRPT-6-3-N25	**105**	0.92	**16605.12**	**1155.61**	89	**0.88**	18258.08	1019.17
P-PIRPT-6-3-N30	84	1.11	**25807.77**	1250.56	**94**	**0.76**	28380.26	**1383.56**

For schematic comparison of Pareto front resulting from NSGAII and NRGA and studying the effects of changes in time horizon and shelf time in different instance, the objective function values are brought for six instances when number of customers are 30, time horizon is 3 and 6 and shelf time is 2 and 3 in Figure 11. Generally, from the picture it is evident that in all of these instances NSGAII outperform NRGA in terms of objective function values. It also can be seen that as the number of periods in the planning horizon increase the total objective function will grow. Considering the instances with t=6, when the shelf time, decrease from τ_{max}=3 to $\tau_{max} = 2$, both objective function values increase dramatically. This proves that when the products are highly perishable, the cost of supply chain system is higher than the time when the products are not as perishable as that. It is also interesting to note that Z2 as the lateral transshipment cost can be omitted as an optional distribution mode in our instances although this will results in higher cost of managing the supply chain.

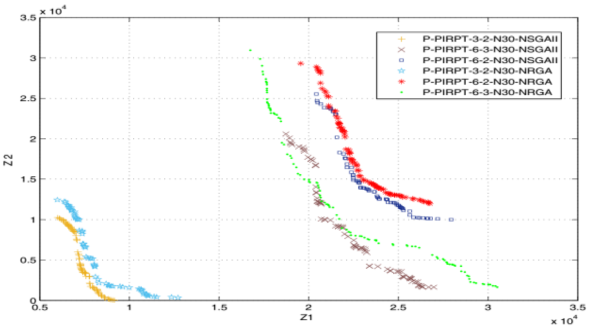

Figure 11. Comparison of Pareto fronts obtaining from NSGAII and NRGA for instances with 30 customers

6. CONCLUSION

Here, the problem of production inventory-routing problem with lateral transshipment (P-PIRPT) is studied and mathematical modeling as bi-objectives mixed integer programming (BO-MIP) is provided and is solved using NSGAII and NRGA algorithms. The problem runs through some generated instances and using performance metrics, some comparisons for both algorithms is provided. It has been observed that lateral transshipment as one of the objective functions is in conflict with inventory handling and conventional transportation as the other objective function. Also, in our problem as the shelf time of products increases the overall cost of supply chain decrease and vice versa. For following up this study, we propose considering some uncertainties in some parameters of problem like demand, and study the situation the supply chain can face some perishability in products with its related cost.

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Bi-objectives Approach for a Multi-period Two Echelons Perishable Product Inventory-routing Problem with Production and Lateral Transshipment

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چکیده

در این مطالعه، یک زنجیره تامین دو سطحی که در آن یک عرضه کننده محصولات فاسد شدنی تولید می نماید و آن را بین مشتریان متعدد توزیع می نماید مد نظر است. با مجاز بودن جابجایی جانبی، امکان حمل کالا بطور انبوه به بخشی از مشتریان توسط خودروی حمل عرضه کننده و سپس خود مشتریان کالا را بین یکدیگر با خودروهای خود در مقادیر کوچکتر توزیع نمایند، فراهم می گردد، بطوریکه کل هزینه های زنجیره کاهش یابد. هدف در اینجا کاهش هزینه های تولید، نگهداری موجودی و هزینه های توزیع به عنوان تابع هدف اول و هزینه های جابجایی جانبی به عنوان هدف دوم است بطوریکه هیچ کمبودی برای هیچ کدام از اعضای زنجیره در هیچ دوره ای رخ ندهد. این مسئله بصورت یک برنامه ریزی عدد صحیح مختلط دو هدفه مدلسازی شده (BOMIP) و توسط الگوریتم های NSGAII و NRGA یک جبهه پارتو مناسب به عنوان مجموعه جواب های قابل قبول ارایه شده است. نوآوری مقاله تهیه یک مدل دو هدفه برای مسئله مسیریابی موجودی برای تولید کالای فاسد شدنی با مجاز بودن جابجایی جانبی (BO-P-PIRPT) می باشد که به انتخاب بهترین ترکیب مسیریابی و جابجایی جانبی کمک می کند.

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