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A mathematical model for scheduling of transportation, routing, and cross-docking in the reverse logistics network of the green supply chain

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Abstract

Cross-docking refers to the practices of unloading materials from inbound vehicles and then loading them directly into outbound ones. Removing or minimizing warehousing costs, space requirements, as well as inventory utilization, cross-docking simplifies supply chains and makes them deliver goods to markets in a faster and more efficient manner. Accordingly, a mixed-integer linear programming ($MILP$) model is developed in the present study to schedule transportation routing and cross-docking in a reverse logistics network (RLN). Furthermore, different traffic modes are also considered to reduce fuel consumption, which reduces emissions and pollution. The proposed model is a multi-product, multi-stage, and non-deterministic polynomial-time that is an NP-hard problem. We use the non-dominated sorting genetic algorithm II ($NSGA-II$) to solve the model. A numerical example has been solved to illustrate the efficiency of the method.

Keywords: Cross-Dock Scheduling, Transportation Routing, Inverse Logistics Network, Mathematical Modeling, Green Supply Chain
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1. Introduction

Inventory flow control is among the main concepts raised in supply chain management (SCM). In this sense, cross-docking is regarded as an efficient way to control inventory flow and is of the essence in

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the SCM. As a warehousing strategy, cross-docking also represents an appropriate strategy to reduce inventory once meeting customers' needs. Simplifying the flow between suppliers and producers, the strategy concerned can diminish inventories [11]. Within cross-docking, the materials move directly from an inbound dock to an outbound one, where goods are stored in a dock for short periods of time, typically in less than 12 hours, and are directly sent to customers [4]. The cross-docking strategy primarily puts an end to the inventory performance of a traditional warehouse; however, it still allows the materials to be classified and loaded via an integration process into vehicles [9]. If the vehicles of the pickup fleet fail to reach cross docking simultaneously, the integration process will be delayed after collecting all goods, thus increasing waiting time and inventory level in a crossover manner. A large number of studies on cross-docking have thus far discussed the concept of crossover, its physical design, or its location. About one-third (approximately 1.3 billion tons) of the world's food produced for human consumption is annually lost or wasted. From another perspective, food losses account for about $ 680 billion in industrialized countries and $ 310 billion in developing ones. If only a quarter of the food, currently lost in the world, could be saved, it would be enough to feed 870 million hungry people [14, 26].

It should be noted that the time spent during logistics operations as well as the environmental conditions all through transportation and warehousing can significantly affect the amount of such a waste. To examine this issue and to optimize it in this study, timing vehicles in a cross-dock with several doors along with routing vehicles to minimize the costs of the entire system are taken into account [11]. Vehicles are viewed in such a way, so that inbound vehicles can be used as out bound ones. In other words, in addition to vehicles employed only to exit goods, the inbound vehicles keep those of certain routes and unload the other ones. They then load the goods of the same materials as the already-loaded ones and, as outbound vehicles, exit the cross-dock towards their destinations. After leaving the cross-dock, each vehicle selects the shortest route to a specified destination ifit serves the specified destinations only once, and that returns to the cross-dock after delivering the services to these destinations. The assumption of utilizing inbound vehicles as outbound ones lowers the completion time of all activities as such the inbound vehicles fail to unload certain products to reach their destinations as outbound ones, and this reduces the total work completion time at the cross-dock. With regard to the route to be passed by vehicles, that the model proposed in this study detects whether or not the use of inbound vehicles as outbound ones is cost-effective.

The outline of this paper is as follows. In Section 2, previous studies are reviewed to detect the research gap and to extract parameters and variables affecting cross-dock scheduling and transportation routing in the reverse logistics network (RLN) in order to develop a mathematical programming model. Section 3 encompasses the research method and elaborates on the mathematical modeling. In Section 4, the solution method proposed, which includes presentation of the solution algorithm of the mathematical model, is addressed. In Section 5, the mathematical model presented in Section 3 is analyzed using the algorithm proposed in Section 4. Finally, the study is concluded in Section **??**.

2. Research Background

In this research, cross-dock routing and logistics network redesign are described to review previous studies and to address all the issues raised in the present study.

In this respect, Jansen [16] analyzed logistics networks to examine the effects of a new warehouse on logistics and then developed a model via simulation, efficient routing methods, and planning to utilize a complicated logistics network. He and Li [10] also developed a mixed-integer programming (MIP) model aimed at minimizing routing distance to define a dynamic programming problem (DPP). As well, a nonlinear multi-lane vehicle routing model with heterogeneous vehicles was proposed by Rahmandoust and Soltani (2019) to detect the minimum possible number of cross-docks among the existing sets of discrete locations and to diminish the total cost of opening cross-dock centers and transportation (i.e., distribution and operation costs). Küçükoğlu and Öztürk [19] correspondingly examined the problem of routing and packing vehicles with cross-docking and presented a mixed-integer linear programming ($MILP$) model. Moreover, Liu and Lin [22] reflected on location routing with time window constraints and adopted the fuzzy processing method to express customer satisfaction performance in order to decrease costs, improve customer satisfaction, and promote efficiency by selecting cross-docking centers and modifying routes in an appropriate manner. Similarly, a profitable heterogeneous vehicle routing problem with cross-docking ($PHVRPCD$) was developed by Baniamerian et al. [5] to increase the overall profitability of a cross-docking system. Rahbari et al. [26] also presented a bi-objective $MILP$ model for cross-docking vehicle routing and planning for perishable products with regard to the impact of travel uncertainty. In their study, Nikolopoulou et al. [25] developed a new problem of public vehicle routing with cross-docking using the adaptive memory programming (AMP) method and the tabu search (TS) algorithm to design a set of pickup and delivery routes in order to minimize the distance. In another study, an $MILP$ model, in which order selection and assignment in vehicle routing with cross-docking ($VRPCD$) had been minimized in a cross-docking system, was proposed by Nasiri et al. [24]. Besides, itencompassed total costs including sales, transportation, cross docking, inventory, and early/late delivery penalties. Furthermore, Mancini [23] introduced and formulated hybrid vehicle routing, as an extended version of the vehicle routing problem. In their model, Hiassat et al. [15] similarly added location decision, namely, a strategic decision, to the model proposed by Lee et al. [20], wherein storage and transfer of blood units among hospitals and specific centers had been addressed. Accordingly, a location-inventory-routing model for perishable goods was presented.

In this line, Shuang et al. [28] investigated a reverse logistics production routing model by selecting a control policy for greenhouse gas emission. To this end, they included a reverse supply chain model with reproduction options under different control policies for greenhouse gas emission. Kuşakcı et al. [18] also examined the optimization of an RLN under fuzzy demand with the aim of recycling, preventing rapid depletion of natural resources, and turning generated waste into value in economy. Moreover, Yavari and Graieli (2019) studied the design of a green closed-loop supply chain network for degradable products under uncertain conditions using an $MILP$ model to minimize costs and environmental pollution. In their study, Zhang et al. [32] explored a stochastic reverse production routing model with regard to environmental considerations. The given model was accompanied by reproduction options to reduce greenhouse gas emissions. As well, reverse logistics in automotive services sector was reviewed by Gardas et al. [8] to decrease oil exploration and production using a multi-criteria decision-making ($MCDM$) method. Liao [21] similarly proposed the development of an RLN for product recycling and reproduction as such they designed a general mixed-integer nonlinear programming ($MINLP$) model maximizing total profits by controlling and coordinating product returns for repair, reproduction, recycling, reuse, or incineration/landfill. Additionally, a modelwas presented by Yu and Solvang [31] to provide a set of Pareto solutions between profit and environmental performance to examine the effects of system flexibility on the design of a stable RLN. Rahimi and Ghezavati [27] also proposed a multi-objective multi-period $MILP$ model to develop and plan network profits, to promote social effects, and to reduce environmental impact in an RLN. Furthermore, Trochu et al. [30] assessed the development of an RLN under environmental policy conditions to recycle wood products from manufacturing, reconstruction, and demolition industries. Khodaparasti et al. [17] also proposed a modified allocation model to prevent unintended defects of benchmarks, expressed as a cover model taking account of facility capacity and demand elasticity.

Numerous research studies have been so far conducted on RLNs, examining specific goals and limitations. In these studies, assumptions are less close to the real world and the practical dimensions of the subject matter have been less deliberated due tousing simplified models. As delivery time plays a critical role in an RLN in accordance with goals such as just-in-time (JIT) logistics and given that failure in on-time delivery or delay, for any reason at any stage of the logistics network process, results in loss of market of goods together with financial and environmental complications, the problem raised in this study is solved with regard to goals such as reducing procurement time and costs and promoting customer satisfaction. However, the consumption value of products at the time of delivery is the highest and there is a possibility to collect and recycle products or destroy them. To this end, a mathematical programming model is designed, solved, and analyzed. The inclusion of these goals into the RLN in this study would contribute to achieving the highest levels of efficiency and productivity. From a scientific and theoretical perspective, this study is to combine cross-dock scheduling and transportation routing, less addressed over recent years, even though researchers have thus far much focused on vehicle scheduling in cross-docking.

3. Research Method

When customers are in the order and replenishment cycles provide logistics network decision-makers with information about the amount, type, and time of product delivery. Based on these information and the demand elasticity, the decision-makers can set a plan for inbound and outbound cargoes. To enhance the efficiency of the RLN, the plan should minimize costs and times of cross-dock scheduling and transportation routing and then ensure the timely delivery of products to customers, so that the consumption value of these products is at the highest possible level.

According to this plan, the inbound vehicles coming from the manufacturers are unloaded at the cross-dock unloading gates in accordance with their specified orders and schedules. The unloaded products can be then directly sent to the loading gates for further loading operations, or they can be stored in the middle cross-dock warehouse and wait there until they are merged with other cross-dock orders received. For cross-docking, on the other hand, at loading gates, orders are loaded onto the outbound vehicles in the order and schedule specified by the plan. Moreover, after loading all the orders, the outbound vehicles leave the cross-dock and meet the customers in the planned routing sequence. After delivering the orders and collecting the returned products from the customers, they go back to the returned product collection center located in the cross-dock. As planned, decision-makers will make the following decisions about the inbound vehicles:

- Assigning inbound vehicles to cross-dock unloading gates, wherein the sequence of entry for each inbound vehicle to each specified unloading gate, the entry time of each vehicle to each unloading gate, and the release time of each inbound vehicle and order are determined

Decision makers also make decisions about loading gates and outbound vehicles, as follows:

- Assigning orders to outbound vehicles (i.e., determining how to integrate products for each outbound vehicle)

- Assigning outbound vehicles to cross-dock loading gates, wherein the sequence of each outbound vehicle to load in each specified loading gate, the entry time of each vehicle to each loading gate, and the departure time of each outbound vehicle are determined

- Routing and planning for outbound vehicles in the process of product delivery and collecting returned products from customers

In this study, the routing of vehicles is examined with an emphasis on green practices under the time window constraint to transport goods. Different traffic modes are also considered to obtain the speed of vehicles to detect the optimal number of vehicles and the optimal route for the delivery of retail orders and to reduce fuel consumption, which in turn decreases emissions and pollution. Regarding the last objective, the problem is in the scope of green supply chain, especially green logistics. Upon making these decisions, costs and consumption values of the products delivered to the customers are estimated in accordance with the plan made for cross-dock and transportation scheduling and routing in the RLN. The development of the proposed model depends on the following assumptions:

1. The model includes a cross-dock where the vehicles are loaded at the unloading gates in accordance with the order of the retailers and the sequence specified in the routing plan, and the order of the retailers, i.e., goods to be delivered and returned to the cross-dock.
2. Three eight-hour work shifts and three modes of heavy, semi-heavy, and smooth traffic are ruminated for each mode of average transportation speed (namely, the average speed is determined based on these traffic modes).
3. According to the JIT logistics philosophy, the time window has a time interval, whose non-observance entails late/early penalties.
4. The amount of emissions depends on the amount of fuel consumed by vehicles, as such the heavier and the longer the time of their use, the higher their consumption. Furthermore, traffic enhances the vehicle movement time; hence, fuel consumption and emissions are enhanced. In this regard,given the objectives of green logistics, there are attempts to reduce fuel consumption to prevent emissions.
5. Cross-dock unloading gates have different loading capacities and costs.
6. The model is developed based on a soft time window.
7. It is a multi-product and multi-period problem.

3.1. The Model

In this section, indices, parameters, decision variables, objective functions, as well as model constraints are presented and introduced:

A) Indices and sets

V: Whole set of logistics network nodes

V_s: Set of cross-dock unloading gates ($k \in V_s$)

V_c: Set of retailers ($j \in V_c$)

M : Vehicle set ($m \in M$)

R: Set of traffic modes ($r \in R$)

T: Set of vehicle shifts per day ($t \in T$)

B) Parameters

Ca_m: Capacity of vehicle m

Ic_k: Loading capacity of cross-dock unloading gate

C_{ij}: Distance between nodes i and j

d_j: Demand of retailer j

λ: Cost per mile traveled

CV: Fixed cost of using a vehicle

s_k: Cost of loading operations for each product unit at cross-dock unloading gate K

$\acute{s}_j$: Shipping cost per product unit for retailer j

e_{ijt}: Traffic mode of node i to node j at time interval t

T_{max}: Maximum time allowed using vehicles

U_j: Maximum time of window time of node j at order delivery

L_j: Minimum time of window time of node j at order delivery

LL_j: Lower bound of time window of node j at order delivery

UU_j: Upper bound of time window of node j at order delivery

Er: Cost of early delivery penalty per time unit

Tr: Delay penalty for order delivery per time unit

St_1: Unloading time at retailer per product unit

St_2: Loading time at cross-dock unloading gate per product unit

f_0: Fuel consumption per movement time unit of unloaded vehicle

f_1: Additional fuel consumption per time unit and per load unit when a vehicle is to move

C) Decision variables

X_m: If device m is used, its value is one; otherwise, it is zero.

y_{ijmt}: If vehicle m goes from node i to node j at a time interval t, its value is one; otherwise, it is zero.

$\acute{y}_{ijmr}$: If vehicle m goes from node i to node j under traffic mode r, its value is one; otherwise, it is zero.

Z_{kjm}: If retailer's order is loaded and delivered by vehicle m at the cross-dock unloading gate, its value is one; otherwise, it is zero.

O_i: Auxiliary integer variable in line with movement of vehicle from cross-dock delivery orders to retailers and returning to cross-dock

Fe_j: Early delivery time of order for retailer j

FL_j: Late delivery time of order for retailer j

tt_i: Duration of attendance in node i for order delivery

a_{jm}: Amount of cargo carried by vehicle m when it reaches retailer r

Objective Functions

Objective function 1: It represents the minimization of logistics network costs, which in turn encompasses the cost of travel by vehicles, as well as those of using vehicles, loading operations at cross-dock unloading gates, delivering orders to retailers, together with late/early order delivery penalties.

$$\begin{aligned}\min Z_1 = &\sum_{m\in M}\sum_{t\in T}\sum_{i,j\in V_c\cup V_s, i\neq j} \lambda C_{ij}\ e_{ijt}\ y_{ijmt} + \sum_{m\in M} CV\cdot X_m \\ &+ \sum_{j\in V_c}\sum_{m\in M}\sum_{k\in V_s} S_K\cdot d_j\cdot Z_{kjm} + \sum_{j\in V_c} \acute{S}_j d_j X_m \\ &+ \sum_{j\in V_s\cup V_c} (Er\cdot Fe_j + Tr\cdot FL_j)\end{aligned} \tag{3.1}$$

Objective function 2: It denotes the minimizing vehicle fuel consumption to reach travel logistics objectives to reduce pollution. Moreover, itconsists of two parts: vehicle fuel consumption when carrying cargos in different traffic modes and vehicle fuel consumption when unloaded in different traffic modes.

$$\min Z_2 = \sum_{i,j\in V_c\cup V_s, i\neq j}\sum_{r\in R}\sum_{m\in M}\sum_{t\in T} (f_0 + f_1 a_{jm}) \times \frac{C_{ij}}{V_{ijt}} \acute{y}_{ijmr} \sum_{i\in V_c}\sum_{r\in R}\sum_{m\in M}\sum_{k\in V_s} F_0 \frac{C_{ik}}{V_{ijt}} \acute{y}_{ikmr} \tag{3.2}$$

Constraints

Constraint 3: It indicates that any inbound vehicle entering the location of each retailer must leave the location of the same retailer.

$$\sum_{i\in V} y_{ijmt} = \sum_{i\in V} y_{jimt} \quad \forall m\in M, \forall j\in V_c, t\in T, i\neq j \tag{3.3}$$

Constraint 4: It shows that each retailer' needs must be met.

$$\sum_{m\in M}\sum_{K\in V_s} Z_{kjm} = 1 \quad \forall j\in V_c \tag{3.4}$$

Constraints 5 and 6: They are related to vehicle routing and retailers' demand variables allocated to cross-dock unloading gates and establishment of a relationship among them.

$$\sum_{i\in V_c}\sum_{t\in T} y_{ijmt} \geq Z_{kjm} \quad \forall k\in V_s, \forall j\in V_c, \forall m\in M \tag{3.5}$$

$$\sum_{j\in V_c}\sum_{m\in M} Z_{kjm} \leq M \sum_{m\in M}\sum_{j\in V_c}\sum_{t\in T} y_{kjmt} \quad \forall k\in V_s \tag{3.6}$$

Constraint 7: It determines the loading capacity of each cross-dock unloading gate to meet retailers' demands.

$$\sum_{j\in V_c} d_j\cdot Z_{kj} \leq I\cdot C_k \quad \forall k\in V_s \tag{3.7}$$

Constraint 8: It displays whether any vehicle has been used or not.

$$\sum_{t\in T}\sum_{i,j\in V_c\cup V_s, i\neq j} y_{ijmt} \leq M\cdot x_m \quad \forall m\in M \tag{3.8}$$

Constraint 9: It confines the vehicle load capacity according to its allowed capacity.

$$\sum_{t\in T}\sum_{i,j\in V_c\cup V_s, i\neq j} d_j\cdot y_{ijmt} \leq Ca_m \quad \forall m\in M \tag{3.9}$$

Constraint 10: It exhibits the type of traffic mode traveled by the vehicle between node i and j

$$\sum_{m\in M} y_{ijmt} = \acute{y}_{ijr} \quad \forall i,j\in V_c\cup V_s, i\neq j, \forall t\in T, \forall r=e_{ijt} \tag{3.10}$$

Constraint 11: It estimates the arrival time of each vehicle to each retailer.

$$tt_i = \sum_{r=e_{ijt}}\sum_{t\in T}\sum_{m\in M}\sum_{i\in V_c}\left(tt_i+\frac{C_{ij}}{V_{ijr}}\right) y_{ijmt} \quad \forall j\in V_s \tag{3.11}$$

Constraint 12: It restrains the time window of order delivery to the retailer to the allowed maximum and minimum time.

$$L_j \leq tt_j \leq U_j \quad \forall j\in V_s \tag{3.12}$$

Constraints 13 and 14: They respectively determine the early/late delivery time of the retailers' order.

$$Fe_j \geq LL_j - tt_j \quad \forall j\in V_c \tag{3.13}$$

$$FL_j \geq tt_j - UU_j \quad \forall j\in V_c \tag{3.14}$$

Constraint 15: It calculates the vehicle load at its arrival to the retailer.

$$(a_{im}-d_j-a_{jm})y_{ijmt}=0 \quad \forall i,j\in V_c, \forall m\in M, \forall t\in T \tag{3.15}$$

Constraint 16: It expresses the time limit of using the vehicle.

$$\sum_{j\in V_c} S_{tz}d_j + \sum_{j\in V_c} st_1 d_j + \sum_{k\in V_s}\sum_{i,j\in V_s\cup V_c, i\neq j}\frac{C_{ij}}{V_{ijt}} y_{ijmt} \leq T_{\max} \quad \forall m\in M \tag{3.16}$$

Constraint 17: It ensures that the vehicle is returned to the cross-dock after loading on the cross-dock and delivering the order to retailers.

$$O_i - O_j + My_{ijmt} \leq M-1 \quad \forall i,j\in V_s, m\in M, t\in T \tag{3.17}$$

Constraint 18: It points to the observance of the sequences of values from 1 to T.

$$\sum_{j\in V_c} y_{ijmt} \geq \sum_{j\in V_c} y_{ijm(t+1)} \quad \forall t\in\{1,2,\ldots,T-1\}, m\in M \tag{3.18}$$

Constraint 19: It reflects the type of model variables.

$$\begin{aligned}&X_{mt}, y_{ijmt}, \acute{y}_{ijr}, Z_{kj}\in\{0,1\}; a_{jm}, Fe_j, FL_j, tt_j \geq 0\\ &O_i\in Z^+; \forall i,j\in V_s\cup V_c, \forall m\in M, \forall k\in V_s, \forall r\in R, \forall t\in T\end{aligned} \tag{3.19}$$

4. Solution Method Proposed

"Survival of the fittest" refers to the theory of evolution and inheritance under pinning a genetic algorithm (GA), as a scholastic search algorithm with the following advantages. That is, instead of initiating its search from a specific point, it considers a population of search points as the first population and improves the next generations using genetic operators. In the simplest versions of this algorithm, limited populations of constant-length chromosomes consisting of genes are processed. The two main algorithm operators are crossover and mutation. In this sense, the crossover operator aims to visit different parts of the justified region by integrating the genes of the two chromosomes, and the mutation operator is to divert the search process from local optimums through slightly changing a selected chromosome. The efficiency of the algorithm is associated with the combined utilization of these two operators. In the present study, a developed GA was employed to solve the two-stage random programming problem.

4.1. Non-Dominated Sorting Genetic Algorithm ($NSGA-II$)

The $NSGA-II$ is known as one of the most widely used powerful algorithms for solving multi-objective optimization problems,whose efficiency in solving various problems has been thus far documented. Srinivas and Deb [29] introduced the $NSGA$ optimization method to solve multi-objective optimization problems. Afrouzy et. al. [3] used $NSGA-II$ to design and plan of supply chain networks considering new product development. Also they used A genetic algorithm for supply chain configuration with new product development [2].

The main points to be noted with regard to this optimization method are as follows:

- A solution has a higher score, compared to which no other answers are definitely better. The solutions are also ranked and sorted based on the number of dominating solutions.
- Fitness is assigned to the solutions according to their ranking and non-dominance of other solutions.
- The fitness sharing method is employed for close solutions in order to modify the distribution of solutions in a desirable manner and to distribute the solutions evenly in the search space.

Given the relatively high sensitivity for the performance and the quality of the $NSGA$ solutions to the fitness sharing and other parameters, the second version of the $NSGA$, called $NSGA-II$, was introduced by Deb et al. [7]. In addition to all the functions of $NSGA-II$, it can be respected as a model for formation of many multi-objective optimization algorithms. This algorithm and its unique approach to multi-objective optimization problems have been repeatedly utilized by different individuals to create other novel multi-objective optimization algorithms [1, 6]. Undoubtedly, this algorithm is among the most fundamental members of the multi-objective evolutionary optimization ones as such it is called the second generation of these methods [12]. The main features of this algorithm are as follows:

- Defining crowding distance as an alternative feature to practices such as fitness sharing
- Using binary tournament selection operator
- Saving and archiving unsuccessful solutions obtained in previous steps of algorithm (viz. elitism)

In the $NSGA-II$, a number of solutions are selected from those of each generation via the binary tournament selection method. Within the binary selection method, two solutions are randomly selected from a population and are then compared to select the better one. The selection criteria in the $NSGA-II$ are primarily the ranking of the solutions and secondly their crowding distance; thus, the lower the solution ranking and the greater the crowding distance, the better the solution. Through repeating the binary selection operator on the population of each generation, a set of individuals of the same generation are accordingly selected to take part in mutation and crossover. Mutation operations are further performed on a selected group of individuals, while the crossover ones are implemented on the rest. This would result in a population of offspring and mutants, then merging with the main population. The members of the newly formed population are first ranked in an ascending order. The members of the population with the same rank are also arranged in a descending order with regard to their crowding distance. Now, the members of the population are primarily sorted by ranking and then via crowding distance. Proportionate to the number of the members in the main population, some members are correspondingly selected from the top of the sorted list, and the rest of the population is discarded. The selected members form the next generation, and this cycle is repeated until the termination conditions are met.

Non-dominated solutions obtained from solving the multi-objective optimization problem are often known as the Pareto front. Of note, none of the Pareto Front solutions is superior and each solution can be considered as an optimal decision, depending on the condition.

4.2. $NSGA-II$ Steps

Step 1: Creatinginitial population in this method as usual, based on problem scale and constraints

Step 2: Evaluating generated population with reference to defined objective functions

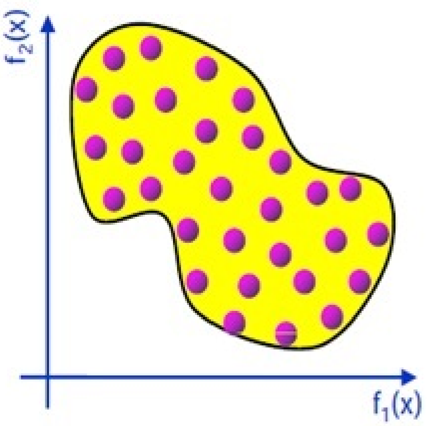


Figure 1: A schematic of the second step

Step 3: Applying a non-dominated sorting method

The members of the population are grouped as such those in the first group are completely non-dominated by the other ones in the existing population. The members in the second group are also dominated in the same way by those of the first group, and this process continues similarly in other groups, so that all the members in each group are assigned a rank in accordance with the group number.

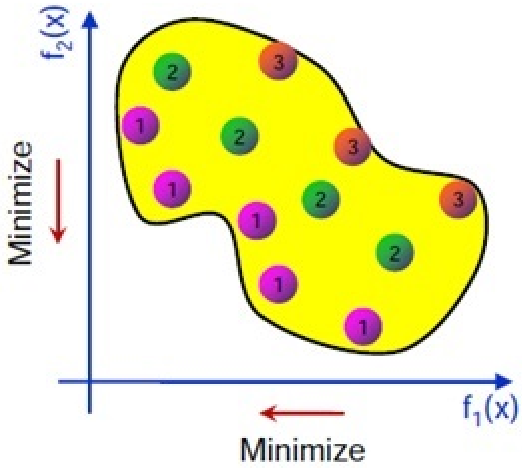


Figure 2: A schematic of the third step

Step 4: Calculating a control parameter called crowding distance

This parameter is calculated for each member in each group, representing the size of the sample with reference to other members of that population. The large value of this parameter leads to divergence and a better range in the population.

$$d_j(k) = \sum_{i=1}^{n} \frac{f_i(k-1) - f_i(k+1)}{f_i^{\max} - f_i^{\min}}$$

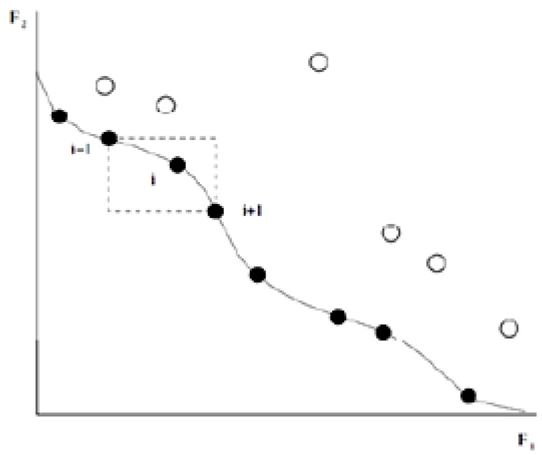


Figure 3: Calculation of a control parameter, i.e., crowding distance [7]

Step 5: Selecting parent population for reproduction

One of the selection mechanisms is based on a binary tournament between two members, randomly selected from the population.

Step 6: Performing crossovers and mutations

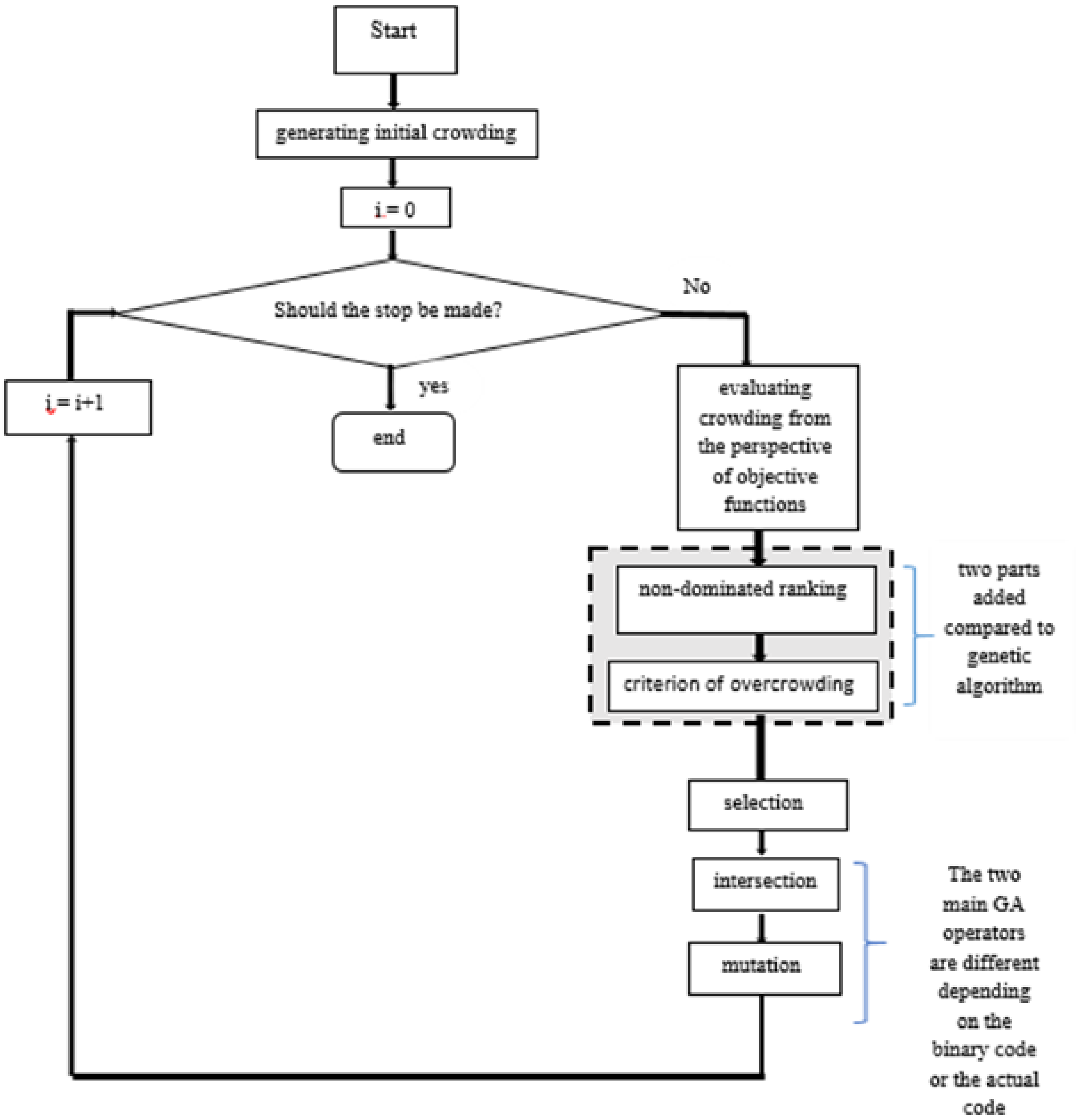


Figure 4: Procedures of $NSGA-II$ [7]

4.3. Modification of parameters

The results of meta-heuristic algorithms depend on the values of their input parameters; for this reason, how the values of the parameters of the proposed algorithm were set are explained. In this regard, the number of times to stop iteration was set to be 20.

4.3.1. Parameter-Setting Methods and Taguchi Method

The design of experiments (DoE) has a wide variety of applications in many systems, as it is an extremely significant tool for process performance and its modification. Parameter-setting methods are as follows:

- Reference to past studies
- Trial-and-error method
- Full experimental method
- Taguchi method
- Solution-level method
- Adaptive neural network and fuzzy neural network
- Use of meta-heuristic algorithms (before or during execution)

In this study, the Taguchi method was implemented. In this sense, Genichi Taguchi has expanded the knowledge of designing experiments. The parameter design method accordingly provides an engineering method to design a product or a process in order to minimize changes and sensitivities to intervening factors. In an efficient parameter design, the first objective is to detect and regulate factors minimizing variations in solution variables.The second objective is to explore controllable and uncontrollable factors.

Taguchi specifically introduced the concept of “loss function”, to combine cost, target, and diversity, from which a measurement criterion is derived, making the specification limits of secondary significance. In addition, he developed the concept of “robustness”. Taguchi also defines quality as the loss imposed on society from the moment the product is shipped. The ultimate objective of this method is to detect an optimal combination of controllable factors. The Taguchi method is under pinned by a strong and solid design. To practice this method, calculations are performed using the Mini tab 16 Statistical Software, selecting DoE option and the Taguchi sub-option; however, the number of factors required to determine the number and the combination of experiment levels as well as the number of levels must be decided (Table 1).

Table 1: Candidate factors and levels in $NSGA-II$

Algorithm parameters	Low	Mid	High
Crowd size	15	30	45
Probability of crossover	0.5	0.7	0.9
Probability of mutation	0.2	0.3	0.4

Regarding the orthogonal arrays, the Taguchi L9 standard is selected as a suitable experimental design to set the proposed parameters. The L9 array is an experimental design with nine experiments. DoE for the proposed algorithm are presented in Table 2.

The proposed meta-heuristic algorithm is conducted for each Taguchi experiment. Figure 5 illustrates the average signal-to-noise ratio (S/N) obtained for each level of algorithm-related factors, and Table 2 presents the optimal levels of input parameters for this algorithm.

Table 2: DoE using L9 orthogonal array for $NSGA-II$

Order of implementation	Algorithm parameters			Solution values
	nPop	Pc	Pm	MID
1	1	1	1	6.9517
2	1	2	2	37,162
3	1	3	3	3.0812
4	2	1	2	9,465
5	2	2	3	5.6565
6	2	3	1	9.5747
7	3	1	3	16.3752
8	3	2	1	14.2128
9	3	3	2	7.9231

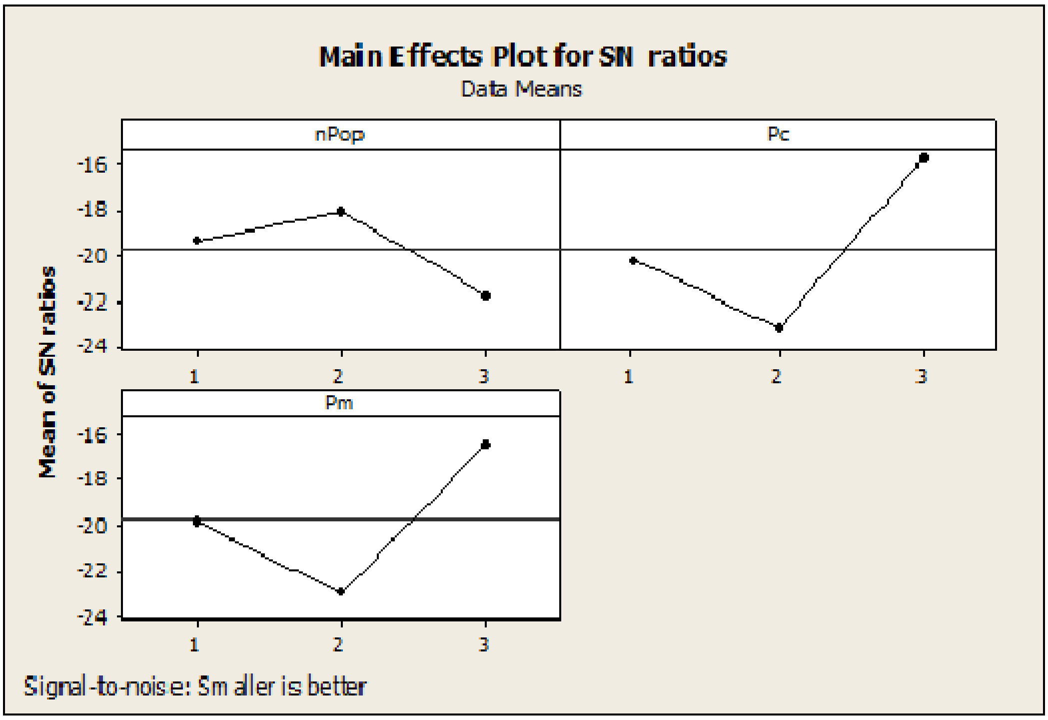


Figure 5: S/N ratio of $NSGA-II$ parameters

The problem of a multi-objective mathematical model for cross-dock scheduling and transportation routing was solved using and RLN, as described in the next section.

5. Solving the Model

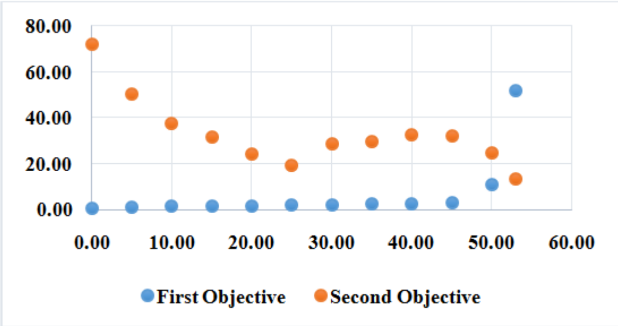
As observed in Section 3, a mathematical programming model was developed to solve the model in an optimal manner through determining the inputs of a series of cross-dock unloading gates, retailers, vehicles, traffic modes, and vehicle shifts per day. In this regard, three problems were designed and implemented in small, medium, and large sizes to solve the mathematical model of the research problem. The number of inbound vehicles for small problems was thus initially set to be one. The maximum value for the number of vehicles in the large-scale solution was set at a maximum of 10. This process also applies to the outbound vehicles. The number of cross-dock unloading and loading gates in small, medium, and large problems was respectively set to be 3, 6, and 10. Finally, the number of products in the process of solving small, medium, and large problems was respectively set to be 5, 10, and 15.

Regarding the complexity of the model in terms of the number of variables, constraints, and data, the model was solved in the space of some sets. To this end, there was an optimization of $NSGA$ in the $MATLAB$ software. Accordingly, as explained in Section 4.5, the parameters of the solution method were modified using the Taguchi method (Section 4.5.1). Furthermore, the input values of the problem were generated as random numbers between 20 and 65 by uniform distribution and then included in the model as inputs. After solving this problem, the output is as follows:

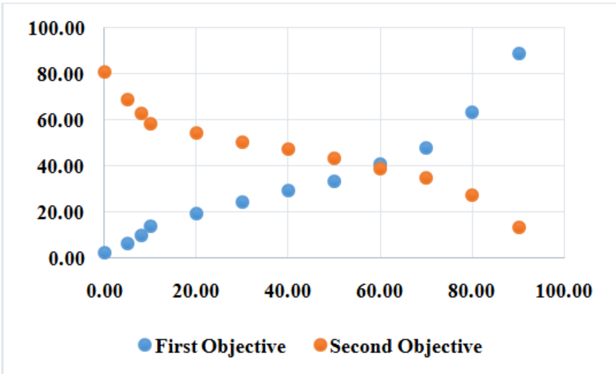
Table 3: Solutions to objective functions for three problems with small, medium, and large sizes

Periods	First objective			Second objective		
	F1-S	F1-M	F1-L	F2-S	F2-M	F2-L
T1	0.59	2.03	14.34	72.18	81.02	93.76
T2	1.25	6.20	33.27	50.30	68.94	84.53
T3	1.41	9.70	40.37	37.80	62.80	81.30
T4	1.53	13.59	47.85	31.55	58.56	77.10
T5	1.70	19.39	52.57	24.14	54.54	71.62
T6	1.96	24.14	56.99	19.39	50.51	67.74
T7	2.14	29.12	63.04	28.66	47.12	62.35
T8	2.42	33.56	67.49	29.87	43.31	55.12
T9	2.65	40.97	71.55	32.88	39.07	44.38
T10	3.24	47.96	75.21	32.00	34.83	38.78
T11	11.21	63.20	78.55	25.00	27.21	33.10
T12	52.11	88.89	89.24	13.59	13.15	16.97

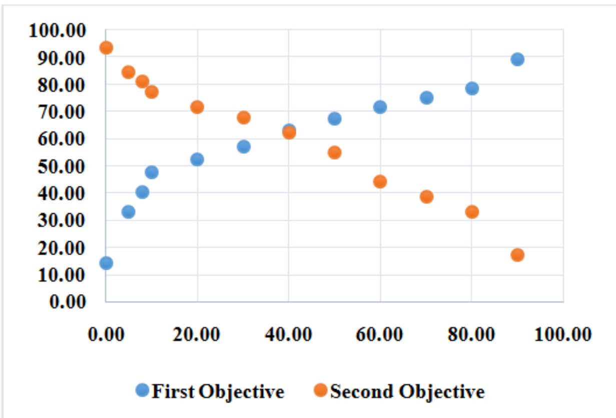
According to Table 3, the data generated to solve the model were considered as the input of the problem. Table 3 presents the results of solving the objective functions with reference to three small, medium, and large sizes of the research problem. As shown in Table 3, the first objective function, representing the minimization of logistics network costs, is given during 12 periods. The first row in Table 3 illustrates the results of the objective functions of the problem in the first period. In this period, the problem is solved in three small, medium, and large sizes, and the results are reported for the first objective function. Such an inconsistency is caused by the difference in the costs imposed on the research problem due to an increase in late/early penalties since the cost of stopping and wasting time and that of maintenance and failure increase as the requested product is delivered earlier than the due date. Regarding the cost of delays, it also includes the cost of customer dissatisfaction. Moreover, as shown in Table 3, the greater the number of the system operation periods (namely, period 6 onwards), the closer the costs of the RLN in medium- and large-size problems. In other words, the delivery time is more balanced and the costs are thus closer to each other when the number of product flows is larger in the network. As observed in Periods 11 and 12, the system costs are closer to each other for any problem size, suggesting an ascending trend in demands and flow of goods among manufacturers, cross-dock, and customers. As a result, the system costs are at their best mode. The right column of Table 3 presents the value of the second objective function in three sizes. As noted in the research model, the second objective function expresses the maximum consumption value of the products delivered to customers. Accordingly, Table 3 shows the consumer value of products to customers.



(a) Small Pareto front



(b) Medium Pareto front

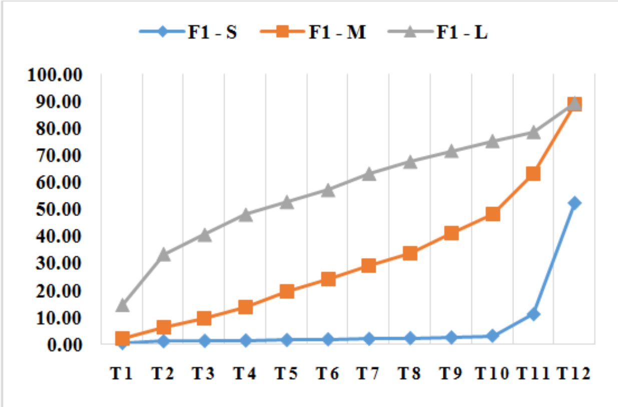


(c) Large Pareto front

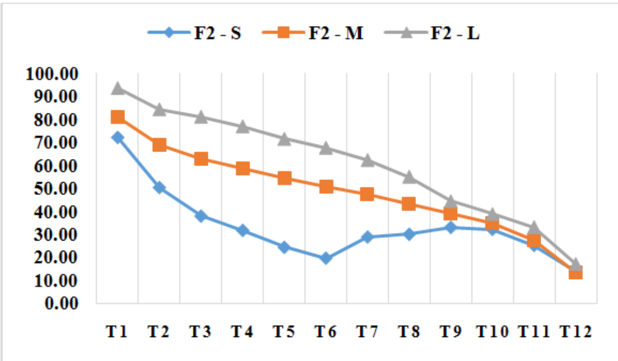
Figure 6: Non-dominated solutions in the first test problem

To analyze the algorithms, different tests with small and large complexities are defined. Accordingly, a total number of 12 tests are generated with regard to benchmarks in the literature. For each test problem, as given in Table 3, the upper and lower bounds of the solutions as well as the optimal solution,in the form of the average of the Pareto fronts, are considered based on the Pareto solutions of the metaheuristics.

To analyze the performance of the algorithms statistically, the interval plots for each assessment



(a) Convergence of the first objective function



(b) Convergence of the second objective function

Figure 7: Convergence of objective functions

metric are provided. In this respect, the data are firstly normalized and then depicted to confirm the robustness of the algorithms. In these plots, as shown in Figures 6 (a) to (c), the lower value provesbetter accuracy and robustness of the algorithms.

6. Conclusion

Transportation and routing decisions are among the main short-term decisions in logistics and SCM. Transportation is not only the most important component contributing to the cost of the final products but also an integral part of any society and one of the key sectors of the economy in each country. Vehicle routing is also considered as one of the most challenging problems in SCM. Moreover, vehicle routing problem as a kind of hybrid optimization problem and integer programming is one of the practical concepts of research on operations. A large number of studies have been thus far conducted on various types of vehicle routing problems via different techniques to solve them. In the present study, the problem of cross-dock scheduling and transportation routing was addressed using the RLN, with the aim of minimizing costs and vehicle fuel consumption in order to achieve the goals of travel logistics and to decrease pollution. Failure to consider these objectives can thus increase the time and the costs associated with logistics operations and reduce the consumption value of products delivered to customers, thereby diminishing customer satisfaction and causing waste of products. In this study, an efficient method using the $NSGAII$ was then demonstrated, resulting in convergent solutions suitable for solving three small, medium, and large problems for the two objective functions of the mathematical model, namely, minimization of cost and vehicle fuel consumption. In this study, uncertainty was not assumed in the input parameters of the problem; therefore, future researchers are suggested to examine the effect of uncertainty on input parameters in designing and solving problems. The proposed model and the findings of this study can be thus employed in all RLNs. Moreover, the mathematical programming model can be generalized to the supply chains of most manufacturing companies.

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