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Research Article

A New Multi-Objective Mathematical Model for A Citrus Supply Chain Network Design: Metaheuristic Algorithms

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Abstract

Nowadays, the citrus supply chain has been motivated by both industrial practitioners and researchers due to several real-world applications. This study considers a four-echelon citrus supply chain, consisting of gardeners, distribution centers, citrus storage, and fruit market. A Mixed Integer Non-Linear Programming (MINLP) model is formulated, which seeks to minimize the total cost and maximize the profit of the Citrus supply chain network. Due to the complexity of the model when considering large-scale samples, two well-known meta-heuristic algorithms such as Ant Colony Optimization (ACO) and Simulated Annealing (SA) algorithms have been utilized. Additionally, a new multi-objective ACO algorithm based on a set of non-dominated solutions form the Pareto frontier developed to solve the mathematical model. An extensive comparison based on different measurements analyzed to find a performance solution for the developed problem in the three sizes (small, medium, and large-scale). Finally, the various outcomes of numerical experiments indicate that the MOACO algorithm is more reliable than other algorithms.

***Keywords*:** Citrus supply chain network; MINLP model; Metaheuristic algorithms.

1. Introduction

In today's world, one of the bases of human problems is the supply of food. The food security and the importance of quality are the main goals for governments to focus on the characteristics of supply chain network design in this regard. Meanwhile, the production of agricultural products has been given particular attention (Reardon& Zilberman, 2018). In general, the "*food supply chain*" includes the steps that start with the production of primary raw materials in agricultural fields and livestock units, and then includes the stages of loading, transportation, processing, and production in production lines, packaging and warehousing, and distribution (Sahebjamnia et al., 2020). Food products after these steps, finally, it reaches the consumer. in the "food supply chain", since the "production and processing", "distribution" and "sale" of a connected network create the necessary coordination between " production and processing "," distribution "and "Sales" requires integrated and precise management methods in order to meet the needs of the market, the product should be in health with fit quality and in keeping with the standards required by the consumer. The food supply chain industry can be divided into three categories: "production and processing," "distribution," and "selling" (Eslamipoor et al., 2015).

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One of the main parts of the food supply chain refers to the citrus supply chain. In the definition of the citrus supply chain, it describes the activities of production to distribution that bring agricultural and horticultural products from farms in the fields. One of the key factors in the Citrus supply chain is to increase the quality and security of foods and other variables related to weather conditions.

Commonly, the Citrus supply chain distribution problem is one of the important fields in manufacturing systems for both researchers and industrial practitioners to achieve a robust network considering all aspects of real-world applications. Finally, the existing relevant works focusing on fruit and food supply chains have been analyzed carefully to achieve the literature gaps.

In order to design the fruit and food supply chain network have been studied and overviewed repeatedly like Rong et al. developed an optimization method for managing fresh food quality throughout the supply chain. Also, they proposed a mixed-integer linear programming (MILP) model utilized production and distribution planning (Rong et al., 2011). Etemadnia et al. (2015) developed a fruit and vegetable supply chain network with bimodal transportation options and a new optimal wholesale facility location problem within the fruit and vegetable supply chain network with bimodal transportation options. Also, they developed a mixed-integer linear programming (MILP) in fruit and vegetables supply chain network and a heuristic solution regional food access optimal hub locations. In addition, there is always a trade-off between transportation costs and fixed costs of building hub capacity in the problem. Nadal-Rigo and Pla (2015) developed an integer linear programming model for planning daily transport of fruit from warehouses to processing plants is presented, aiming to minimize transport costs. Therefore, they proposed a novel Operational optimization for reducing daily truck trips, aiming to supply fruit from warehouses to processing plants. Mousavi et al. (2015) proposed a location-allocation-inventory problem in a two-echelon supply chain network. Also, this problem is formulated as a mixed integer-binary nonlinear programming (MIBNP) in the network. Lamsal et al. (2016) presented a new use of a technique borrowed from the piecewise linearization. Also, they developed an integer programming model for planning the movement of the crop from farm to processing plant. This paper mainly focused on sugar cane, sugar beets, and vegetable crops. The model has been solved using a two-phase solution method with decomposition. Hyland et al. (2016) considered analytical models of rail transportation service in the grain supply chain. Also, they developed three mathematical models of grain transportation for the determination of time, aggregate cost, and rail network capacity. Soto-Sliva et al. (2016) proposed a novel fresh fruit supply chain to the operational research models. Also, they review many of the literature applied to the fresh fruit supply chain. They identified some of the main challenges of fresh fruit supply chain problem such as long supply lead time, the disparity in supply and demand. Zhang et al. (2017) proposed a location model for distribution centers for fulfilling electronic orders of fresh foods under uncertain demand. Also, the objective model to optimize the location model in discrete demand probabilistic scenarios. Musavi and Bozorgi-Amiri (2017) designed a perishable food supply chain network with a new multi-objective and multi-period sustainable hub location-scheduling problem. This model is formulated as mixed-integer linear programming, in which the proposed model aims to optimize the total transportation costs, freshness, and quality of foods at the time of delivery and the total carbon emissions of the vehicles to fulfill the sustainability. the desire of the environment. Bortolini et al. (2018) designed a novel bi-objective mixed-integer linear programming model of fresh food supply chain networks with reusable and disposable packaging containers. They focus on fresh fruit and vegetable distribution forward and reverse supply chain that the aims of the model to minimize cost and environmental impact. Sembiring et al. (2018) developed a mixed-integer linear programming model for Crude Palm Oil supply chain planning. Also, they used a neighborhood search method to solve this model in supply chain integrated problem. Banaeian et al. (2018) developed a green supplier selection using fuzzy group decision making approaches with a case study from the agri-food industry. This study knowledge area by comparing the application of three popular multiple criteria supplier selection approaches in a fuzzy environment. Sellitto et al. (2018) analyzed the role of critical success factors in the Short Food Supply Chain Network (SFSCN). Therefore, they presented a small farmers' cross-cultural analysis- two Italian and two Brazilian milk and dairy producers. The objectives of this study include shortened their Food Supply Chain Network (FSCN) to get closer to the consumers and to deliver products with high quality and traceability, increase profits, the reduction of distances, and the elimination of intermediaries, solely, may increase production earnings in the SFSCN. Watiz et al. (2018) considered a decision support system for efficient last-mile distribution of fresh fruits and vegetables as part of E-Grocery operations. The proposed delivery days, fees, time windows, and discounts in the distribution system. Therein, to model shelf life and schedule deliveries, food quality models and vehicle routing procedures are further integrated within the system. Sahebjamnia et al. (2020) developed a novel multi-objective integer non-linear programming (INLP) model for designing a citrus three-echelon supply chain network. Also. The proposed model objectives to minimize network costs including waste cost, transportation cost, and inventory holding cost, and to maximize the network's profits. Mogale et al. (2018) developed a new integrated multiple fitness, multiple models, and multiple period mathematical model for the location-allocation problem with dwell time for optimization of food grain supply chain network. This model is formulated as a mixed-integer non-linear programming (MINLP) for food grain supply chain.

Nunez et al. (2014) considered a multi-objective model predictive control for dynamic pickup and delivery problems. Also, they proposed two relevant dimensions, user and operator costs in a dynamic objective function. In addition, they used a genetic algorithm (GA) to solve due to mathematical model complexity. Maiyar et al. (2015) developed an effective cost minimization model for four-stage food grain shipments. In this study, only the first stage has been formulated as a bi-level nodal capacity network flow problem with a linear model in the first storage and a mixed-integer non-linear programming model in the second stage considering minimization of transportation costs. They used two variants of particle swarm optimization algorithms to solve the model. Masson et al. (2016) proposed a simple two-stage solution method to solve the annual dairy transportation problem (ADTP), so, they designed the routes that collect milk from farms and deliver it to processing plants. Therefore, they used a two-stage approach according to an adaptive large neighborhood search (ALNS).

Kuo and Nugroho (2017) developed a fuzzy multi-objective vehicle routing problem for perishable products with time windows and time-dependent travel time. This aim model to minimize total cost and balancing the load in each vehicle.

To solved using fuzzy multi-objective gradient evolution (GE) algorithm in the proposed model. Also, they used the original GE algorithm is modified into a discrete GE algorithm to solve the multi-objective problem and compared with the genetic algorithm (GA). Mogale et al. (2017) proposed a multi-period inventory transportation model for planning of food grain supply chain. This model is formulated as a mixed-integer non-linear programming model (MINLP). Therefore, the objective function is minimizing the overall cost. In addition, an efficient and useful meta-heuristic is developed to solve this model, which on the basis of the strategy of sorting elite ants and pheromone trail updating called Improved Max-Min Ant System (IMMAS). The solutions obtained through IMMAS is validated by implementing the Max-Min Ant System (MMAS). Mogale et al. (2018) designed a two-echelon food supply chain network of public distribution systems with multi-period and multi-model bulk wheat transportation and storage problems. Also, they developed a mixed-integer non-linear programming model (MINLP) after studying the Indian wheat supply chain scenario. The objective of this model is included to minimize the total cost of the food grain. In addition, to addressed this complex model of the food grain supply chain, they have developed the new several of Chemical Reaction Optimization (CRO) algorithm and Tabu Search and named it a hybrid CROTS algorithm. Mogale et al. (2017) proposed an MINLP model to support the movement and storage decision of the Indian food grain supply chain. Also, they aim a model to minimize the total cost in the supply chain network. As well as, they addressed the new three-echelon food grain distribution problem. Therefore, they proposed a Hybrid Particle-Chemical Reaction Optimization (HP-CRO) algorithm to solve the model. Fathollahi Fard and Hajiaghaei-Keshteli (2018) developed a novel three-echelon programming model for location-allocation design. And, they are proposed a novel nested method, three-level metaheuristic. Also, they have introduced Water Wave Optimization and Keshtel algorithms firstly in the literature.

To tackle the current challenges in the Citrus supply chain, the department of agriculture Jahad (DAJ) is moving towards the modernized Citrus supply chain network of Citrus handling, transportation, and storage. In this modernized system, Citrus is transported in box form using the truck as well as specially designed Nissans s and stored in Citrus storage. Suitable planning and coordination among all the entities of the Citrus supply chain network can reduce transportation as well as inventory and waste costs. Similarly, the determination of each type of capacitated vehicle used for shipment among various entities is also the crucial aspect of the Citrus supply chain problem because the sufficient availability of capacitated vehicles helps for the quick transfer of Citrus from producing cities to consuming cities. This paper considers the four-echelon of Citrus supply chain network, including the supplier (gardeners), distribution centers, Citrus storages, and fruit markets. An MINLP model is formulated of the Citrus supply chain network. The solution of the model will be helpful to Citrus corporation for taking the timely intra-city as well as inter-city movement and storage-related decisions. This paper developed the work carried out by the Mogale et al. and differs in the following aspects. Here, 1. Four-echelon Citrus supply chain network is considered where Citrus can be shipped from a supplier to distribution centers, Citrus storages, or fruit markets 2. Inventory holding, waste and operational costs considered at distribution centers and Citrus storages, 3. Included the new vehicle, waste capacity related constraints, 4. Various problem instances of the formulated MINLP model are solved using the recently developed MOACO algorithm and obtained results compared with the ACO and SA results. 5. In addition, the convergence behavior and movement along with the storage activities of a few selected instances are analyzed in detail.

Generally, the main similarities and findings of the aforementioned researches can explain as follows.

There are only a few studied that utilized an MINLP model for developing a food and fruit supply chain problem (Maiyar et al. (2015), Masson et al. (2016), Mogale et al. (2018)), which is similar to this paper on mathematical modeling and solving methods. The similarity of this paper with these papers Maiyar et al. (2015), Masson et al. (2016), Mogale et al. (2018) are in the mathematical model formulated as MINLP, and the solution method is also used meta-heuristic algorithms method. This paper uses a metaheuristic method to solve a Mixed Integer Non-Linear Programming (MINLP) model in a food and fruit supply chain with a multi-objective, multi-echelon, and multi-period in the supply chain network problem.

There is a difference between this paper and other reviewed papers in the literature. Firstly, this paper considered the product of oranges, which is perishable. Therefore, we considered the waste cost in this paper, but not in other papers, and also in comparison with the papers (Abarqhouei et al.,2012; Khalifehzadeh, Fakhrzad, 2019; Sembiring et al., 2018) that are single-objective and the costs reduce in the network, but in this paper, in addition to minimizing the costs of in the network, it is considered a profit, which at different periods of time, the price of oranges will increase, so we will profit at the levels available on the network, which is considered as the second objective function in the mathematical model this paper.

The continuation of this paper is as follows. Section 2 the detailed delineation of considered problem is provided. Section 3 The mathematical model with notations, objective function and constraints are illustrated. Section 4 discusses the solution approach employed for solving the mathematical model. Section 5 depicts the results and analysis of computational experiments. Finally, in section 6 Conclusion and future work of the study is given.

2. Problem Background

In this paper, the Citrus supply chain problem is considered with the objectives to minimize the total costs and to maximize the profit Citrus supply chain. There are several entities like gardeners, department of agriculture Jahad (DAJ), Citrus of sorting and packing units, Roadways, rural cooperatives, etc. presents Citrus supply chain network which makes it complex compared with other fruit supply chain problems. The unsuitable coordination and planning between these entities lead to an increase in Citrus losses and other costs. Gardeners take their Citrus to nearby distribution centers using various capacitated vehicles such as tractors, small trucks, and Nissan, etc. for selling to Citrus corporation and DAJs. This harvest and procurement would take place in one season, i.e. eight-month planning horizon (from November to April). In this paper, we have considered various villages within one cluster and named it as the supplier, also quantity available at any supplier is the sum of all the villages quantity considered in that cluster. The Citrus from distribution centers is transported to Citrus storage. The stores are normally utilized for sorting and packing Orange only, thus we considered an Orange supply chain. DAJ has advertised that the Citrus stores will also work as distribution centers during the marketing season. Therefore, gardeners can sell their products to either distribution centers or Citrus stores depending on their requirements. Then, based on deficit states demand and their offtakes in the prior period, DAJ distributes the Citrus to different deficit states. Citrus from Citrus storage is transported to fruit markets. Intra-state movement of Citrus is mostly carried out by the road. The overall scenario of these four is explained in pictorial form in Fig. 1.

The Citrus movement in all four echelons is mainly affected by various constraints about each echelon. Main constraints include the Citrus quantity available at each supplier, the capacity of distribution centers and Citrus stores, the demand of fruit markets, timely availability of various capacitated vehicles (trucks and Nissan) at each echelon, fixed as well as the variable cost of vehicles, operational, waste, and buffer stock maintenance. This problem objects to find out the useful, effective, and efficient storage and movement fruit of Citrus supply chain, which minimizes the transportation, handling inventory, waste, and storage costs. The next section presents the MINLP formulation of the considered problem.

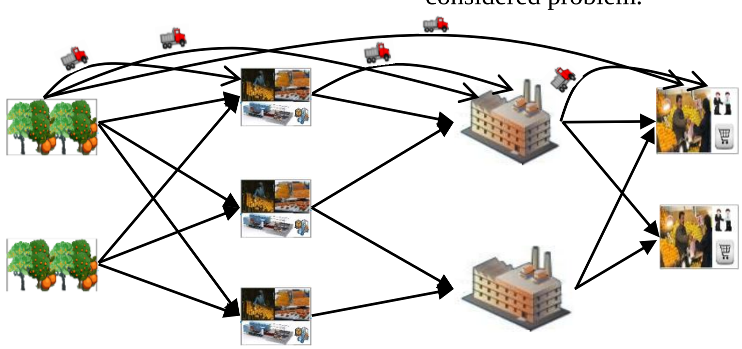

Fig. 1. Structure of the Citrus supply chain considered in this paper

3. Mathematical Model Formulation

Different assumptions considered and notations utilized while developing the model are described below:

3.1. Assumptions

(1) Every supplier represents the cluster of villages.
(2) The procurement quantity, the capacity of distribution centers, Citrus storage and demand of fruit markets are well known and deterministic.
(3) The truck and Nissan types along with their availability are limited at respective stages.
(4) The amount of Citrus procured is adequate to fulfill the demand of each fruit markets.
(5) The fruit markets demand must be satisfied during the particular time period.
(6) The model is developed for a single product and multi-objective.

3.2. Notations

The following notations have been utilized to formulate the model.

Sets/indices

S	Sets of supplier indexed by $s \in S$
D	Sets of distribution center indexed by $d \in D$
B	Sets of Citrus storage indexed by $b \in B$
C	Sets of fruit markets indexed by $c \in C$

M	Sets of trucks among supplier, base Citrus stores, and procurement center indexed by $m \in M$
N	Sets of trucks among base Citrus stores and procurement center indexed by $n \in N$
O	Sets of Nissans among base Citrus stores and fruit markets indexed by $o \in O$
T	Sets of time period indexed by $t \in T$
Parameters	
fc_{sd}^{m}	Fixed cost for trucks of type m used on arc *(s, d)*
fc_{sb}^{m}	Fixed cost for trucks of type m used on arc *(s, b)*
fc_{sc}^{m}	Fixed cost for trucks of type m used on arc *(s, c)*
fc_{db}^{n}	Fixed cost for trucks of type n used on arc *(d, b)*
fc_{bc}^{o}	Fixed cost for Nissans of type o used on arc *(b, c)*
vc_{δ}	variable cost of Citrus transportation by road (unit cost/km i.e. per Metric Tonne (MT) per km)
λ_{sd}^{t}	Sales price for supplier *s* to distribution center *d* in period *t*
ϑ_{db}^{t}	Sales price for distribution center *d* Citrus storage *b* to in period *t*
ψ_{bc}^{t}	Sales price for Citrus storage *b* to fruit markets *c* in period *t*
ihc_{d}	Inventory holding cost per MT quantity of Citrus per time at distribution center *d*
ihc_{b}	Inventory holding cost per MT quantity of Citrus per time at Citrus storage *b*
oc_{d}	Operational cost per MT quantity of Citrus at distribution center *d*
oc_{b}	Operational cost per MT quantity of Citrus at Citrus storage *b*
wc_{d}	Waste cost per MT quantity of Citrus at distribution center *d*
wc_{b}	Waste cost per MT quantity of Citrus at Citrus storage *b*
μc_{b}	Storage cost per MT quantity of Citrus at Citrus storage *b*
$Snum_{s}^{mt}$	Number of m types of trucks available at supplier *s* in time period *t*
$Pnum_{d}^{nt}$	Number of n types of trucks available at distribution center *d* in time period *t*
$Bnum_{b}^{ot}$	Number of o types of Nissans available at base Citrus storage *b* in time period *t*
σ_{m}	Capacity of m types of truck available at the supplier
e_{n}	Capacity of n types of truck available at distribution centers
q_{o}	Capacity of o types of rakes available at Citrus storages
D_{c}^{t}	Demand of fruit markets *c* during time period *t*
D_{d}^{t}	Demand of distribution centers *d* during time period *t*
$dist_{sd}$	Distance from supplier *s* to distribution center *d*

$dist_{sb}$	Distance from supplier *s* to Citrus storage *b*
$dist_{sc}$	Distance from supplier *s* to fruit markets *c*
$dist_{db}$	Distance from distribution center *d* to Citrus storage *b*
$dist_{bc}$	Distance from Citrus storage *b* to fruit markets *c*
G_s^t	Citrus quantity available at supplier *s* in period *t*
$Pcap_d$	Inventory holding capacity of distribution center *d*
$Bcap_b$	Inventory holding capacity of Citrus storage *b*
$pcaps_d$	Storage capacity of distribution center *d*
$bcaps_b$	Storage capacity of Citrus storage *b*

Decision variables

Binary variables

X_{sd}^t	1 if supplier s is allocated to distribution center *d* in period t 0 otherwise
Y_{db}^t	1 if distribution center *d* is allocated to Citrus storage b in period t 0 otherwise
V_{sb}^t	1 if supplier s is allocated to Citrus storage b in period t 0 otherwise
Z_{bc}^t	1 if Citrus storage b is allocated to fruit markets *c* in period t 0 otherwise
L_{sc}^t	1 if supplier *s* is allocated to fruit markets *c* in period t 0 otherwise

Continuous variables

m_{sd}^t	Quantity of Citrus transported from supplier *s* to distribution center *d* during time period *t*
h_{db}^t	Quantity of Citrus transported from distribution center *d* to Citrus storage *b* in time period *t*
g_{sb}^t	Quantity of Citrus transported directly from supplier *s* to Citrus storage *b* in time period *t*
w_{bc}^t	Quantity of Citrus transported from to Citrus storage *b* to fruit market *c* in time period *t*
r_{sc}^t	Quantity of Citrus transported from to supplier *s* to fruit markets *c* in time period *t*
α_d^t	Quantity of Citrus at distribution center *d* in time period *t*
β_b^t	Quantity of Citrus at Citrus storage *b* in time period *t*
A_d^t	Amount of waste Citrus at distribution center *d* in time period *t*
B_b^t	Amount of waste Citrus at Citrus storage *b* in time period *t*
η_b^t	Amount of storage Citrus at Citrus storage *b* in time period *t*

Integer variables	
n_{sd}^{mt}	number of m types of trucks used on arc *(s, d)* in time period *t*
v_{db}^{nt}	number of n types of trucks used on arc *(d, b)* in time period *t*
u_{sb}^{mt}	number of m types of trucks used on arc *(s, b)* during time period *t*
j_{sc}^{mt}	number of m types of trucks used on arc *(s, c)* during time period *t*
r_{bc}^{ot}	number of *o* types of Nissans used on arc *(b, c)* in time period *t*

3.3. Objective function

This paper objective to assess the time-dependent movement and storage plan of Citrus supply chain of four-echelon beginning from gardeners (supplier), distribution centers, Citrus storage and fruit markets, so that total cost of Citrus supply chain is minimized and the distribution center, Citrus storage, and fruit market profits is maximized.

Minimize total cost = Transportation cost + Operational cost + Inventory holding cost + Waste cost+ storage cost

Components of objectives

Transportation cost =

$$\sum_{s=1}^{S}\sum_{d=1}^{D}\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\left(fc_{sd}^{m}.n_{sd}^{mt}\right)+\left(dist_{sd}.vc_{\delta}.m_{sd}^{t}\right)\right]\times X_{sd}^{t}+\sum_{s=1}^{S}\sum_{b=1}^{B}\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\left(fc_{sb}^{m}.u_{sb}^{m}\right)+\left(dist_{sb}.vc_{\delta}.g_{sb}^{t}\right)\times V_{sb}^{t}\right]$$

$$\sum_{s=1}^{S}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\left(fc_{sc}^{m}.j_{sc}^{mt}\right)+\left(dist_{sc}.vc_{\delta}.r_{sc}^{t}\right)\right]\times L_{sc}^{t}$$

$$+\sum_{d=1}^{D}\sum_{b=1}^{B}\sum_{n=1}^{N}\sum_{t=1}^{T}\left[\left(fc_{db}^{n}.v_{db}^{nt}\right)+\left(dist_{db}.vc_{\delta}.h_{db}^{t}\right)\right]\times Y_{db}^{t}+\sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{o=1}^{O}\sum_{t=1}^{T}\left[\left(fc_{bc}^{o}.r_{bc}^{ot}\right)+\left(dist_{bc}.vc_{\delta}.w_{bc}^{t}\right)\right]\times Z_{bc}^{t}$$

Operation cost =

$$\sum_{t=1}^{T}\left[\sum_{s=1}^{S}\sum_{d=1}^{D}m_{sp}^{t}+\sum_{d=1}^{D}\sum_{b=1}^{B}h_{db}^{t}\right].oc_{d}+\sum_{t=1}^{T}\left[\sum_{s=1}^{S}\sum_{b=1}^{B}g_{sb}^{t}+\sum_{d=1}^{D}\sum_{b=1}^{B}h_{db}^{t}+\sum_{b=1}^{B}\sum_{c=1}^{C}w_{bc}^{t}+\right].oc_{b}$$

Inventory holding cost =

$$\sum_{d=1}^{D}\sum_{t=1}^{T}\alpha_{d}^{t}.ihc_{d}+\sum_{b=1}^{B}\sum_{t=1}^{T}\beta_{b}^{t}.ihc_{b}$$

Waste cost =

$$\sum_{d=1}^{D}\sum_{t=1}^{T}\left(wc_{d}.A_{d}^{t}\right)\times\alpha_{d}^{t}+\sum_{b=1}^{B}\sum_{t=1}^{T}\left(wc_{b}.B_{b}^{t}\right)\times\beta_{b}^{t}$$

Storage cost =

$$\sum_{b=1}^{B}\sum_{t=1}^{T}\left(\mu c_{b}.\mu_{b}^{t}\right)\times bcaps_{b}$$

Maximize profit Citrus supply chain = sale prices – total costs = distribution centers Profit + Citrus storage profit + Fruit markets profit

Distribution centers Profit =

$$\left(\begin{array}{l}\sum_{s=1}^{S}\sum_{d=1}^{D}\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\left(\lambda_{sd}^{t}\times Snum_{s}^{mt}\right)\right]-\left(\sum_{s=1}^{S}\sum_{d=1}^{D}\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\left(fc_{sd}^{m}.n_{sd}^{mt}\right)+\left(dist_{sd}.vc_{\delta}.m_{sd}^{t}\right)\right]\times X_{sd}^{t}\right)\\ -\left(\sum_{t=1}^{T}\left[\sum_{s=1}^{S}\sum_{d=1}^{D}m_{sd}^{t}+\sum_{d=1}^{D}\sum_{b=1}^{B}h_{db}^{t}\right].oc_{d}\right)-\left(\sum_{p=1}^{D}\sum_{t=1}^{T}\alpha_{d}^{t}.ihc_{d}\right)-\left(\sum_{d=1}^{D}\sum_{t=1}^{T}\left(wc_{d}.A_{d}^{t}\right)\times\alpha_{d}^{t}\right)\end{array}\right)$$

Citrus storage profit =

$$+\left(\begin{array}{l}\sum_{d=1}^{D}\sum_{b=1}^{B}\sum_{n=1}^{N}\sum_{t=1}^{T}\left[\left(\vartheta_{db}^{t}\times Pnum_{d}^{nt}\right)\right]-\left(\sum_{d=1}^{D}\sum_{b=1}^{B}\sum_{n=1}^{N}\sum_{t=1}^{T}\left[\left(fc_{db}^{n}.v_{db}^{nt}\right)+\left(dist_{db}.vc_{\delta}.h_{db}^{t}\right)\right]\times Y_{db}^{t}\right)-\\ \sum_{t=1}^{T}\left[\sum_{s=1}^{S}\sum_{b=1}^{B}g_{sb}^{t}+\sum_{d=1}^{D}\sum_{b=1}^{B}h_{db}^{t}+\sum_{b=1}^{B}\sum_{c=1}^{C}w_{bc}^{t}+\right].oc_{b}-\left(\sum_{b=1}^{B}\sum_{t=1}^{T}\beta_{b}^{t}.ihc_{b}\right)-\left(\sum_{b=1}^{B}\sum_{t=1}^{T}\left(\mu c_{b}.\mu_{b}^{t}\right)\times bcaps_{b}\right)\end{array}\right)$$

Fruit markets profit =

$$+\left(\sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{o=1}^{O}\sum_{t=1}^{T}\left[\left(\psi_{bc}^{t}\times Bnum_{b}^{ot}\right)\right]-\left(\sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{o=1}^{O}\sum_{t=1}^{T}\left[\left(fc_{bc}^{o}.r_{bc}^{ot}\right)+\left(dist_{bc}.vc_{\delta}.w_{bc}^{t}\right)\right]\times Z_{bc}^{t}\right)\right)$$

s.t.

$$\sum_{d=1}^{D}\sum_{b=1}^{B}\sum_{c=1}^{C}\left(m_{sd}^{t}.X_{sd}^{t}+g_{sd}^{t}.V_{sd}^{t}+r_{sc}^{t}.L_{sc}^{t}\right)\leq G_{s}^{t}\qquad\forall s,t\tag{1}$$

$$\sum_{b=1}^{B}\left(h_{db}^{t}.Y_{db}^{t}\right)\leq\alpha_{d}^{t}\qquad\forall d,t\tag{2}$$

$$\sum_{c=1}^{c}\left(w_{bc}^{t}.Z_{bc}^{t}\right)\leq\beta_{b}^{t}\qquad\forall b,t\tag{3}$$

$$\alpha_{d}^{t=1}=0\qquad\forall d,t\tag{4}$$

$$\beta_{b}^{t=1}=0\qquad\forall b,t\tag{5}$$

$$A_{d}^{t=1}=0\qquad\forall d,t\tag{6}$$

$$B_{b}^{t=1}=0\qquad\forall b,t\tag{7}$$

$$\alpha_{d}^{t-1}+\sum_{s=1}^{S}\left(m_{sd}^{t}.X_{sd}^{t}\right)\leq Pcap_{d}\qquad\forall d,t\tag{8}$$

$$\beta_{b}^{t-1}+\sum_{s=1}^{S}\sum_{p=1}^{P}\left(g_{sb}^{t}.V_{sb}^{t}+h_{pb}^{t}.Y_{pb}^{t}\right)\leq Bcap_{p}\qquad\forall b,t\tag{9}$$

$$A_{d}^{t-1}+\sum_{s=1}^{S}\left(m_{sd}^{t}.X_{sd}^{t}\right)\leq pcaps_{d}\qquad\forall d,t\tag{10}$$

$$B_{b}^{t-1}+\sum_{s=1}^{S}\sum_{d=1}^{D}\left(g_{sb}^{t}.V_{sb}^{t}+h_{db}^{t}.Y_{db}^{t}\right)\leq bcaps_{d}\qquad\forall b,t\tag{11}$$

$$\sum_{b=1}^{B}\left(w_{bc}^{t}.Z_{bc}^{t}\right)=D_{c}^{t}\qquad\forall c,t\tag{12}$$

$$\sum_{d=1}^{D}\left(h_{db}^{t}.Y_{pb}^{t}\right)=D_{d}^{t} \qquad \forall d,t \tag{13}$$

$$\alpha_{d}^{t-1}+\sum_{s=1}^{S}\left(m_{sd}^{t}.X_{sd}^{t}\right)-\sum_{b=1}^{B}\left(h_{db}^{t}.Y_{db}^{t}\right)=\alpha_{d}^{t} \qquad \forall d,t \tag{14}$$

$$\beta_{b}^{t-1}+\sum_{s=1}^{S}\sum_{d=1}^{D}\left(g_{sb}^{t}.V_{sd}^{t}+h_{db}^{t}.Y_{db}^{t}\right)-\sum_{c=1}^{C}\left(w_{bc}^{t}.Z_{bc}^{t}\right)=\beta_{b}^{t} \qquad \forall b,t \tag{15}$$

$$\sum_{d=1}^{D}m_{sd}^{t}.X_{sd}^{t}\leq\sum_{d=1}^{D}\sum_{m=1}^{M}\left(n_{sd}^{mt}.\sigma_{m}\right) \qquad \forall s,t \tag{16}$$

$$\sum_{b=1}^{B}g_{sb}^{t}.V_{sb}^{t}\leq\sum_{b=1}^{B}\sum_{m=1}^{M}\left(u_{sb}^{mt}.\sigma_{m}\right) \qquad \forall s,t \tag{17}$$

$$\sum_{c=1}^{C}r_{sc}^{t}.L_{sc}^{t}\leq\sum_{c=1}^{C}\sum_{m=1}^{M}\left(j_{sc}^{mt}.\sigma_{m}\right) \qquad \forall s,t \tag{18}$$

$$\sum_{b=1}^{B}h_{db}^{t}.Y_{db}^{t}\leq\sum_{b=1}^{B}\sum_{n=1}^{N}\left(v_{db}^{nt}.e_{n}\right) \qquad \forall d,t \tag{19}$$

$$\sum_{c=1}^{C}w_{bc}^{t}.Z_{bc}^{t}\leq\sum_{c=1}^{C}\sum_{o=1}^{O}\left(r_{bc}^{ot}.q_{o}\right) \qquad \forall b,t \tag{20}$$

$$\sum_{d=1}^{D}\sum_{b=1}^{B}\sum_{c=1}^{C}\left(n_{sd}^{mt}+u_{sd}^{mt}+j_{sc}^{mt}\right)\leq Snum_{s}^{mt} \qquad \forall s,m,t \tag{21}$$

$$\sum_{b=1}^{B}v_{db}^{nt}\leq Pnum_{d}^{nt} \qquad \forall d,n,t \tag{22}$$

$$\sum_{c=1}^{C}r_{bc}^{ot}\leq Bnum_{b}^{ot} \qquad \forall b,o,t \tag{23}$$

$$X_{sd}^{t},Y_{db}^{t},V_{sb}^{t},Z_{bc}^{t},L_{sc}^{t}=\{0,1\} \qquad \forall s,d,b,c,t \tag{24}$$

$$m_{sd}^{t},h_{db}^{t},g_{sb}^{t},w_{bc}^{t},r_{sc}^{t},A_{d}^{t},B_{b}^{t},\alpha_{d}^{t},\beta_{b}^{t}\geq 0 \qquad \forall s,d,b,c,t \tag{25}$$

$$n_{sd}^{mt},v_{db}^{nt},u_{sb}^{mt},r_{bc}^{ot},j_{sc}^{t}\in Z \qquad \forall s,d,b,c,m,n,o,t \tag{26}$$

The objective function (1) of the model is to minimize the total cost which includes transportation cost, operational cost, waste cost, storage cost, and inventory holding cost. In the transportation cost, first, the second, and the third term gives shipment costs containing fixed and variable costs from suppliers to distribution centers, to Citrus storage, and fruit market, respectively. The direct transportation cost includes fixed and variable costs from distribution centers to Citrus storages is represented by the third term. The last term provides the inter-state Citrus movement cost including fixed as well as variable costs from Citrus storages to fruit markets. There are two terms in operational cost, in which first and second term indicates the operational cost at distribution centers and Citrus storages, respectively. The inventory holding costs at distribution centers and Citrus storages are included in the inventory holding cost component of the objective function. There are two terms in waste cost, in which the first and second term indicates the waste cost at distribution centers and Citrus storages, respectively. The storage costs at Citrus storage are included in the storage cost component of the objective function. The objective function (2) of the model is to maximize the distribution center, Citrus storage, and fruit market profits. These profits achieve through the sale of

Citrus to the distribution center, Citrus storage, and fruit market. the first part is the sale price of Citrus from supplier to distribution center minus the set of costs including transportation cost from the supplier to the distribution center, operation, inventory holding, and waste costs of the distribution center. the second part is the sale price of Citrus from distribution center to Citrus storage minus the set of costs including transportation cost from distribution center to Citrus storage, operation, inventory holding, and waste costs of Citrus storage. The third part is the sale price of Citrus from Citrus storage to the fruit market minus the costs of transportation cost from Citrus storage to the fruit market.

Constraint (1) shows the Citrus quantity transferred from a supplier to distribution centers, Citrus storages, and fruit markets, to maximum Citrus quantity available at the supplier during each period. Constraint (2) restricts the Citrus quantity transferred from distribution centers to the Citrus stores, to maximum available inventory at a given procurement center in a given period. Similarly, Constraint (3) restricts the supply constraint of the Citrus storages. The primary inventory at the beginning period in each distribution center and Citrus storages is zero and represented by constraints (4) and (5), respectively. The initial waste at the beginning period in each distribution center and Citrus stores is zero and represented by constraints (6) and (7), respectively. Constraints (8) and (9) show that inventory at the distribution center and Citrus storage does not exceed the inventory holding capacity of the distribution center and Citrus storage, respectively. Constraints (10) and (11) show that waste at the distribution center and Citrus storage does not exceed the storage capacity of the distribution center and Citrus store, respectively. Constraint (12) depicts that the total Citrus quantity transferred from Citrus storage must be equal to the demand for that particular fruit market during period. Constraint (13) depicts that total Citrus quantity transferred from distribution centers must be equal to the demand of that particular Citrus storage during period □. The inventory flow balance equations of the distribution center and Citrus storage are described by constraints (14) and (15), respectively. Constraints (16), (17), and (18) make sure that maximum Citrus quantity transported from supplier to distribution center, supplier to Citrus storage, and supplier to fruit markets must be less than or equal to the maximum capacity of all trucks being utilized in that period on the same path, respectively. Similarly, Constraints (19) and (20) explains the truck and Nissan capacity constraints from the distribution center to Citrus storage and Citrus storage to the fruit market, respectively. Constraint (21) illustrates that the number of trucks used on the route (s, p), (s, b), and (s, c) must be less than or equal to the maximum trucks available at the supplier s in each period. In the same way, Constraint (22) limits the number of trucks employed on the route (p, b), to maximum trucks available at the distribution center during a given period. Also, several Nissans utilized on the route (b, c) must be less than or equal to the maximum Nissans available at the Citrus storage in each period and same represented by the Constraint (23). Constraints (24)– (26) portrays the binary, continuous, and integer variables respectively utilized in the model.

4. Solution Approach

The current four stage Citrus supply chain problem. Therefore, due to the more complex, challenging, and NP-hard problem in medium and large sizes used meta-heuristic algorithms to solve. Therefore, solving is time-consuming with using exact methods. In this study, we compare the model to problems with different sizes of metaheuristic algorithms. This section is devoted to introducing ACO, SA, MOACO algorithms.

To implement the metaheuristics, a plan should be designed to encode the problem (Goodarzian et al., 2020). Regarding this goal, a two-stage technique named Random-Key (RK) is utilized (Goodarzian et al., 2020; Fathollahi-Fard., 2020; Billal and Hossain, 2020) . This technique converts an unfeasible solution to a feasible one by a set of procedures in two phases (Fakhrzad et al., 2018; Fakhrzad and Goodarzian, 2019; Goodarzian and Hosseini-Nasab, 2019; Fakhrzad et al., 2019; Goodarzian et al., 2020; Fathollahi-Fard., 2020). To the best of our knowledge, this study firstly uses this technique in the literature for the presented model developed. To encode the solution representation, a numerical example is revealed as follows. Consider that there are five suppliers (S) with three types of vehicles (M, N, and O) and six fruit markets and Citrus storages (B and C) and three distribution centers (D). First of all, the type of used vehicle for each supplier should be specified. In this regard, an array by a length of S is generated by a uniform distribution (0, MNO). After that, the type of vehicle assigns to each supplier should be clarified. Accordingly, a set of procedures has been addressed by Fig. 2. As can be seen, the second type of vehicle is utilized for nurses s_1, s_2 and s_4. Also, the first and third type of vehicles are used for suppliers s_3 and s_5, respectively.

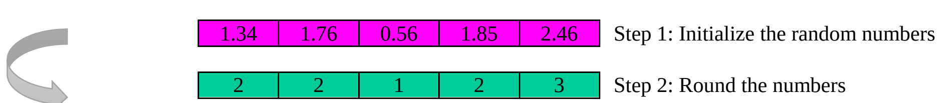

Fig. 2. The utilized technique to assign a type of vehicle for suppliers

4.1. Ant colony optimization algorithm

The ACO was first introduced by Marco Dorigo (1992) in his Ph.D. thesis. Also, the first algorithm was aiming to search for an optimal path in a graph, on the basis of the behavior of ants seeking a path among their colony and a source of food. The original idea has since diversified to solve a wider class of numerical problems, and as a result, various problems have emerged, drawing on various aspects of the behavior of ants. From a broader perspective, ACO performs a model-based search and shares some similarities with estimation of distribution algorithms (Xu et al., 2018). Ant colony optimization (ACO) is a population-based metaheuristic that can be utilized to find approximate solutions to difficult optimization problems. In ACO, a set of software agents called artificial ants search for good solutions to a given optimization problem. To apply ACO, the optimization problem is transformed into the problem of finding the best path on a weighted graph. The artificial ants (hereafter ants) incrementally build solutions by moving on the graph. The solution construction process is stochastic and is biased by a pheromone model, that is, a set of parameters associated with graph components (either nodes or edges) whose values are modified at runtime by the ants (Gupta and Saini, 2018). Therefore, the following pseudocode presents the simulated annealing heuristic in Fig. 3.

```
Initial pheromone τ_ij ;
Repeat for all ants i : construct solution (i);
        for all ants i : global pheromone update (i);
        for all ant's edges: evaporate pheromone;
                    (τ_{i-j} = (1-ρ).τ_{i-j})
Construct solution (i):
Initial ant;
While not yet a solution:
        Expand the solution bye one edge probabilistically according to the pheromone;
(τ_{ρi-j} / Σ ρi-j.τ_{ρi-j});
Global_pheromone_update (i):
For all edges in the solution:
      Increase the pheromone according to the quality;
            (Δτ_{i-j} = 1/length of the path stored)
        End
        End
End while
End
```

Fig. 3. Pseudocode of ACO algorithm

Recently, various papers have presented ACO algorithms for multi-objective problems. Also, we present a public ACO framework for multi-objective problems.

In the multi-objective optimization problem, a set of non-dominated solutions form the Pareto frontier. Also, to solve the multi-objective problems, we proposed the algorithm shown in Fig. 4. In the initial step: Ants are generated each beginning with a set X, the objective weights P_k is determined randomly for each ant. In the construction step of the MOACO algorithm, each ant tries to construct a feasible set X by using a pseudo-random proportional rule. Next, a set has been constructed, its feasibility and efficiency is determined. Pheromone updating is performed by using the best solution X_k of the current iteration for each objective k (Song and Chen, 2018).

```
Random initialization of the pheromone value Do
 For each iteration
        For each ant
        Create the set X of the ant;
Label: Determine the objective weight P_k for each objective k randomly;
           For each project k Select a project;
           Add it to X ;
           End
If set X is feasible and efficiencies store set X and remove dominated ones;
   If not go to Label
   End if
   For each project k determine the best solution and update pheromone;
End
     End
          End
End
```

Fig. 4. pseudocode of MOACO algorithm

4.2. Simulated annealing algorithm

Simulated annealing (SA) is a probabilistic technique for approximating the global optimum of a given function. It was first proposed as an optimization technique by Kirkpatrick and Cerny (1984). Now, we are going to explain the overall algorithm as follows:

The state of some physical systems, and the function $E(s)$ to be minimized, is analogous to the internal energy of the system in that state. The goal is to bring the system, from an arbitrary *initial state*, to a state with the minimum possible energy (Wei et al., 2018).

The probability of making the transition from the current state s to a candidate new state s' is specified by an acceptance probability function $P(e, e', T)$, that depends on the energies $e = E(s)$ and $e' = E(s')$ of the two states, and on a global time-varying parameter T called the temperature. States with a smaller energy are better than those with a greater energy. The probability function P must be positive even when e' is greater than e. This feature barricades the approach from becoming stuck at a local minimum that is worse than the global one.

When T tends to zero, the probability $P(e, e', T)$ must tend to zero if $e' > e$ and to a positive value otherwise. For sufficiently small values of T, the system will then increasingly favor moves that go "downhill" (i.e., to lower energy values), and avoid those that go "uphill." With $T = 0$ the procedure reduces to the greedy algorithm, which makes only the downhill transitions.

In the original description of simulated annealing, the probability $P(e, e', T)$ was equal to 1 when $e' < e$—i.e., the procedure always moved downhill when it found a way to do so, irrespective of the temperature. Many descriptions and implementations of simulated annealing still take this condition as part of the approaches definition. But, this condition is not essential for the method to work.

The P function is usually chosen so that the probability of accepting a move decreases when the difference $e' - e$ increases—that is, small uphill moves are more likely than large ones. But, this requirement is not strictly necessary, provided that the above requirements are met (Liu et al., 2018).

Given these properties, the temperature T plays a crucial role in controlling the evolution of the state s of the system with regard to its sensitivity to the variations of system energies. To be precise, for a large T, the evolution of s is sensitive to coarser energy variations, while it is sensitive to finer energy variations when T is small (Liu et al., 2018).

Therefore, to solve an optimization problem, the algorithm SA first starts with a prior response, and then moves to neighboring solutions in a repeating loop. If the neighbor's answer is better than the current one, the algorithm puts it as the current answer; otherwise, the algorithm accepts that answer with the probability $\exp\left(-\frac{\Delta E}{T}\right)$ as the current answer). In this case, ΔE is the difference among the objective function of the current answer and the neighboring response, and T is a parameter called temperature. At each temperature, various repetitions are performed, and then the temperature is slowly reduced. In the prior steps, the temperature is set very high, which is more likely to accept worse solutions. Therefore, with a gradual decrease in temperature, in the final steps, there will be less chance of accepting worse solutions, and so the algorithm converges to a good solution. Also, the following pseudocode presents the simulated annealing heuristic in Fig. 5. It begins from a state s_0 and continues until a maximum of k_{max} steps have been taken. In the process, the call neighbor (s) should generate a randomly chosen neighbor of a given state s; the call random(0, 1) should pick and return a value in the range [0,1], uniformly at random. The annealing schedule is defined by the call temperature (r), which should yield the temperature to use, given the fraction r of the time budget that has been expended so far (Liu et al., 2018).

```
Let s = s_0
For k = 0 through k_max (exclusive):
    T ← temperature (k/ k_max)
    Pick a random neighbor, s_new ← neighbor(s)
    If P(E(s), E(s_new), T) ≥ random (0, 1):
s ← s_new
Output: the final state s
End
  End
```

Fig. 5. Pseudocode of SA algorithm

5. Parameters Setting

To the best of our knowledge and according to the novelty of the presented model, no existing study has treated a similar model in the literature. Therefore, the benchmarks existing in the literature are not available for the model, and an approach is needed to design the test problems. To show the complexity of the model, we need to design problems in different sizes. Nine test problems including three classifications i.e. small, medium, and large sizes are presented with ten runs including random data based on a uniform distribution. Here, we will set parameters of the metaheuristic algorithms as well as the parameters of the problem model. To evaluate the efficiency of the proposed algorithms, we compare the model to several problems of different sizes. Table 1 shows the parameters of the model. Each problem instance is characterized by the number of suppliers (S), number of distribution centers (D), number of Citrus storage (B), number of fruit markets (C), and number of time periods (T). The detailed delineation of all the nine problem instances along is mentioned in Table 2. In addition, all the problem instances are classified into three groups according to the total number of decision variables of the problem instances.

Table 1
Data ranges of parameters used in the model.

Parameters	Range of values
Fixed cost of three different types of trucks utilized on arc *(s, d)*	300, 250, 200
Fixed cost of three different types of trucks utilized on arc *(s, b)*	300, 250, 200
Fixed cost of three different types of trucks utilized on arc *(s, c)*	300, 250, 200
Fixed cost of three different types of trucks utilized on arc *(d, b)*	200, 300, 400
Fixed cost of three different types of Nissans utilized on arc *(b, c)*	900, 700, 500
variable cost of road transportation	20
Sales price for supplier to distribution center	500
Sales price for distribution center to Citrus storage	1000
Sales price for Citrus storage to fruit markets	1500
Inventory holding cost at distribution center	200
Inventory holding cost at Citrus storage	150
Operational cost at distribution center	90
Operational cost at Citrus storage	60
Waste cost at distribution center	80
Waste cost at Citrus storage	50
Storage cost at Citrus storage	100
Number of m_1 types of trucks available at supplier	400-900
Number of m_2 types of trucks available at supplier	500-1000
Number of m_3 types of trucks available at supplier	600-1100
Number of n_1 types of trucks available at distribution center	500-900
Number of n_2 types of trucks available at distribution center	600-1000
Number of n_3 types of trucks available at distribution center	700-1100
Number of o_1 types of Nissans available at Citrus storage	5-14
Number of o_2 types of Nissans available at Citrus storage	7-17
Number of o_2 types of Nissans available at Citrus storage	8-19
Capacity of m types of trucks $(m = 1, 2, 3)$	20, 15, 10
Capacity of n types of trucks $(n = 1, 2, 3)$	30, 25, 20
Capacity of o types of rakes $(k = 1, 2, 3)$	3500, 3000, 2500
Demand of fruit markets	2000-3500
Demand of distribution centers	1500-3000
Distance from supplier to distribution center	5-45
Distance from supplier to Citrus storage	15-60
Distance from supplier to fruit markets	25-90
Distance from distribution center to Citrus storage	40-120
Distance from Citrus storage to fruit markets	450-950
Citrus quantity available at supplier	150000-50000
Inventory holding capacity of distribution center	20000-60000
Inventory holding capacity of Citrus storage	40000-700000
Storage capacity of distribution center	50000-800000
Storage capacity of Citrus storage	60000-900000

Table 2
Dimensions of problem instances and sizes

Problem Instance size	Problem instance (S-P-B-C-T)	Supplier	Distribution center	Citrus storage	Fruit Market	Time period
Small size	Instance1(3-2-3-2-3)	3	2	3	2	3
	Instance2(4-5-3-4-3)	4	5	3	4	3
	Instance3(7-8-6-5-3)	7	8	6	5	3
Medium size	Instance4(11-9-7-8-2)	11	9	7	8	2
	Instance5(14-10-9-8-2)	14	10	9	8	2
	Instance6(17-13-11-10-2)	17	13	11	10	2
Large size	Instance7(20-16-13-11-3)	20	16	13	11	3
	Instance8(23-18-11-17-3)	23	18	11	17	3
	Instance9(26-19-16-20-3)	26	19	16	20	3

5.1. Experimental results

In this section, the MOACO, ACO, and SA algorithms are coded in MATLAB R2017 and the Intel Core i5, 2.50 GHz processor with 6 GB RAM. In order to evaluate the performance of the proposed algorithms, the responses obtained from these three algorithms are investigated in three different sizes. Also, the optimal response values, the best response in three different sizes, the average, and their standard deviation of total cost are reported in Table 3.

As it is seen, in nine solved problems, with the help of the ACO algorithm, four of the problems have been able to achieve the optimal response. Moreover, expected 2 state of problem size, standard deviations increase as the problem size increases. It is also clear that the standard deviation of Problem 1 in the small size is zero. In this sense, in all algorithmic performances, they have reached the optimal response. This can be because of the small size of the problem.

The SA algorithm has responded to the optimal response in four problems where the ACO algorithm has achieved the optimal response, with the difference that in 3 cases the standard deviation is zero. This means that in three categories of these problems, exactly each run is optimized for the response. While in ACO algorithm, only in problem 1 all the repetitions have reached the optimal response. Therefore, can demonstrate the power of the SA algorithm to ACO in solving these cases.

The MOACO algorithm has also been able to achieve optimal resolution in four problems, but only in 2 categories of these problems, which is optimized for each run.

Table 3
The total cost comparison between MOACO, ACO, SA

Instance	ACO				
	Optimum	Best	Avg.	SD	Time (s)
(3-2-3-2-3)	2252.13	2252.13	2252.13	0	34.65
(4-5-3-4-3)	2865.52	2865.52	3024.125	84.74	97.33
(7-8-6-5-3)	3791.81	4174.10	3982.95	167.43	107.66
(11-9-7-8-2)	6320.53	6320.53	6435.91	65.77	194.33
(14-10-9-8-2)	6773.30	6773.30	6871.99	95.45	274.07
(17-13-11-10-2)	8582.53	8810.24	8696.38	177.04	597.54
(20-16-13-11-3)	46940.71	49240.21	48090.46	855.33	770.45
(23-18-11-17-3)	58250.48	62830.78	60540.63	1104.76	958.65
(26-19-16-20-3)	87511.81	92510.56	90011.18	1997.85	1634.55
	SA				
(3-2-3-2-3)	2059.71	2059.71	2103.61	0	31.43
(4-5-3-4-3)	2687.43	2687.43	2824.37	80.54	88.42
(7-8-6-5-3)	3540.55	3984.61	3762.58	154.70	99.01
(11-9-7-8-2)	5949.32	5949.32	6053.71	0	167.01
(14-10-9-8-2)	6454.34	6454.34	6667.82	0	230.32
(17-13-11-10-2)	8231.62	8416.31	8323.96	154.32	487.33
(20-16-13-11-3)	37542.70	41354.30	39448.35	733.09	691.04
(23-18-11-17-3)	54367.02	60918.06	57642.54	988.12	883.22
(26-19-16-20-3)	85866.61	90821.70	88344.15	1522.26	1403.98
	MOACO				
(3-2-3-2-3)	1982.04	1982.04	1987.92	0	29.43
(4-5-3-4-3)	2486.23	2486.23	2633.77	75.12	67.22
(7-8-6-5-3)	3276.41	3721.91	3499.16	132.07	78.33
(11-9-7-8-2)	5731.31	5731.31	5793.09	0	141.32
(14-10-9-8-2)	6251.46	6251.46	6421.48	58.44	184.93
(17-13-11-10-2)	7956.53	8118.25	8037.39	112.67	365.07
(20-16-13-11-3)	34346.21	39719.21	37032.71	652.43	541.42
(23-18-11-17-3)	52721.40	58541.30	55631.35	766.54	766.41
(26-19-16-20-3)	81838.18	89591.30	85714.74	1322.98	1230.54

These algorithms were also evaluated in terms of runtime. As you can see from the table above, the minimum solving time according to the parameters used is related to the MOACO algorithm, so that for problems with higher sizes, for example, the problem size 9 of these times effect can be easily seen. Therefore, the ACO algorithm needs more time than SA over 0.859 times, and despite the fact that the best response from SA is better than ACO every time it runs. But overall, average and more standard deviation more than this algorithm. So, we want to measure the average, the standard deviation and time required, the SA algorithm can be better for higher sizes than ACO. Fig. 6 shows the time to solve different problems with the algorithms. In these figures, it is clear that the time of the ACO and SA algorithms performs very similarly. The figure of the MOACO indicates that in the small size, there is almost a routine, but with increasing size, the time of resolution greatly increases.

The best solution is summarized in 5 different replication algorithms in Fig. 7. In this figure, it is clear that the first six problems, which have smaller sizes, all the algorithms have been able to achieve the optimal response.

Interestingly, each time it repeats, the best answer to issues 3, 5, 6, 7.8 and 9 has not reached the optimum value in any of the algorithms, while in problems 1 and 2 all the algorithms can achieve the optimal response. Moreover, it is clear from the chart below that the ACO with the structure for it is intended compared to other algorithms, it shows a weaker performance. In contrast, MOACO and SA has been placed in better priority in terms of the best responses received, respectively.

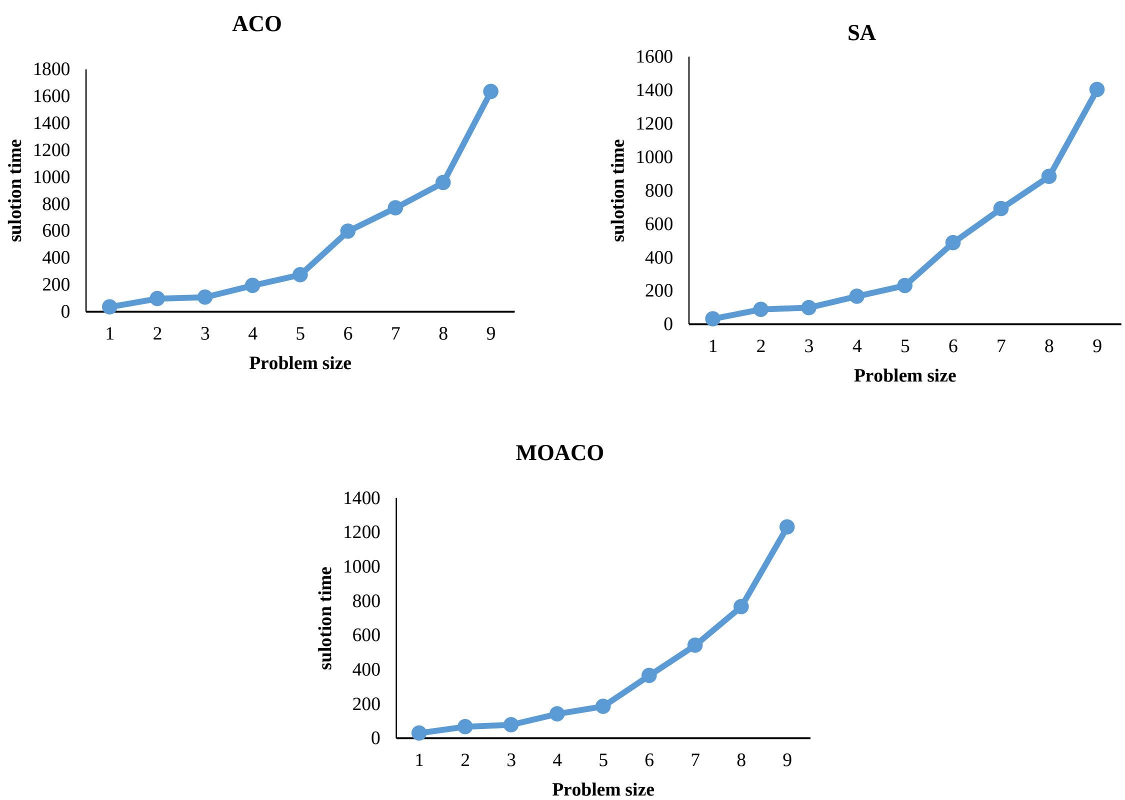

Fig. 6. Time comparison of algorithms according to the sizes of the problem

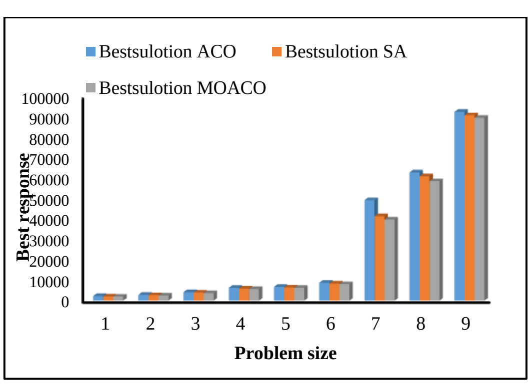

Fig. 7. Compare between the best responses

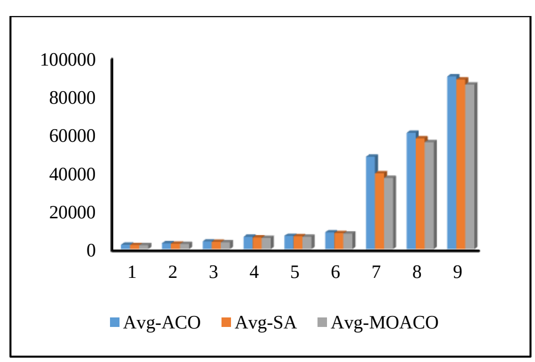

Fig. 8. Compare between the average of the obtained responses

Therefore, if we want to compare the average of the answers obtained from the algorithms, it will be clear that the ACO algorithm has a higher average than other algorithms. Also, it is clear that the MOACO algorithm has been better than the other meta-heuristic algorithms Fig. 8.

6. Conclusions and Future Work

In this work, a new mathematical model for the citrus supply chain network along with two objectives including minimization of the transportation, inventory holding, waste, storage, and operational cost of Citrus and maximization of the distribution center, Citrus storage, and fruit market profits of the model is designed. The proposed MINLP model incorporates multi-period, multi-level, and multi-objective. Regarding the literature review, a comprehensive survey on the classifications of previous works in food and fruit supply chain was provided. Then, a number of recent metaheuristic algorithms were used in this research. Due to the complexity of the problem and NP-hard, a new metaheuristic algorithm named MOACO that combines ACO and SA algorithms have been used to solve the Citrus supply chain problem. To validate the proposed algorithm, 9 test problems are generated in three sizes (small, medium, and large), and the performance and reliability of the MOACO algorithm was evaluated in comparison with ACO and GA algorithms. The results were showed that the ACO algorithm has a high computational (CPU) time than other algorithms, but MOACO has a low CPU time and better solutions than other algorithms. Additionally, the MOACO algorithm was one of the best algorithms that could be used to solve the presented model, because both the best solutions and the average of the solutions were in a better position than the other proposed algorithms. Then, the SA algorithm has less CPU time than the other ACO algorithm.

The present model can be extended by considering a stochastic or probability demand and procurement. Multi-modal transportation can be used instead of intermodal transportation for transporting products. In future research, a multi-objective optimization model can be made by adding the transportation time minimization objective into the current model. Also, interested scholars can use the presented mathematical model for other similar domains, such as the vegetable supply chain networks.

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