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# Fresh Produce Supply Chain Network Design and Management Using Swarm Intelligence: A Case Study of Egypt

Sherif Fahmy[1*], Yomna Gaber[2], Areej Zaki[2], Mohamed Gaafar[1]

[1]*The American University in Cairo (Egypt)*
[2]*Cairo University (Egypt)*

[*]*Corresponding author: fahmy.sherif@aucegypt.edu*
*y.hossam@fci-cu.edu.eg, areej.m.zaki@fci-cu.edu.eg, m_gaafar@aucegypt.edu*

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***Abstract:***

***Purpose:*** The objective of this work is to fulfil a strategic requirement in Egypt's agriculture industry by establishing a fresh produce supply chain network (SCN) that manages the collection, processing, packaging, and distribution of products.

***Design/methodology/approach:*** A cost minimization dynamic facility location-allocation (FLA) problem is modeled and solved using a hybrid binary particle swarm optimization (BPSO) algorithm, to strategically locate a network of food aggregation hubs across the country for the collection, consolidation, and distribution of products. The hub FLA decision is then complemented with optimal fleet sizing, transportation scheduling, and routing decisions, by solving the split-delivery vehicle routing problem (SDVRP) using a hybrid ant-colony optimization (ACO) algorithm, considering positioning loading constraints, and shelf-lives of products.

***Findings:*** Two national fresh produce SCN configurations were obtained; one that minimizes the total cost of the network, and the other minimizes the number of aggregation hubs. Results showed a strong correlation between the locations and capacities of the hubs, and the locations of supply points and densely populated demand areas. The hybrid ACO algorithm was further utilized to optimize the fleet sizing, routing and scheduling decisions for one of the obtained hubs.

***Practical implications:*** Establishment of the SCN can reduce the proportion of wasted product during transit, and improve the quality of the delivered products. In addition, accounting for product spoilage has a significant effect on network design, and collection and distribution decisions.

***Social implications:*** Establishment of the SCN will improve the exposure of small farmers to wider markets, and hence their return and standard of living, and potentially reduce the prices for the final customer.

***Originality/value:*** This study is the first attempt to establish an efficient fresh produce supply chain network in Egypt. In addition, the proposed solution approach considered a multitude of problem characteristics, simultaneously for the first time.

***Keywords:*** supply chain network design, aggregation hubs, split-delivery vehicle routing, particle swarm optimization, ant colony optimization

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## 1. Introduction

With a population that currently exceeds 105 million people, potential loss of cultivated lands due to climate change, and scarcity of water, Egypt is a country in a critical need for efficient management and preservation of its water, and hence its food resources. Nonetheless, and despite the national and international efforts aiming to overcome these serious risks, there still lacks an efficient, sustainable supply chain network (SCN) that can collect, preserve, and nationally distribute Egypt's fresh produce wealth efficiently.

A major problem in Egypt's fresh produce industry, is the deficiency of the SCN that transports crops from small and mid-sized farms to the end customer. Consequences include a considerable percentage of wasted products (almost 30% of production), low return for the farmers, and high prices for the end customer. Indeed, complementing agricultural activities with support services and linking small farmers with markets by developing marketing systems and channels is a major goal in Egypt's 2030 vision for agricultural development (Arab Republic of Egypt, 2009)

A fresh produce aggregation hub is a facility that manages the collection, marketing, and distribution of products, for small and mid-sized farming businesses. Over the past decade, many of such hubs have been established in the US and other parts of the World, not only providing support and marketing activities for small farmers, but with almost 31% of hub owners reporting annual profits in excess of $1 million (Fischer, Hamm, Pirog, Fisk, Farbman & Kiraly, 2013). Yet, most are facing challenges in capacity determination, warehousing, and transportation activities. In transportation networks in general, establishing transshipment hubs leads to much cost savings due to the flow concentration and consolidation they create (Horner & O'kelly, 2001). Adding the values of collection, distribution, and marketing, makes establishing such hubs an even more economically attractive opportunity.

In the SC context, the hub establishment problem is typically a facility location-allocation (FLA) problem, which aims to find the best location for a transshipment facility in a SCN, along with the amount of product flow to allocate to (Melo, Nickel & Saldanha-da-Gama, 2009). Managing the incoming and outgoing flows from such a hub requires solving a vehicle routing problem (VRP), with the hub acting as a central depot. The perishable and delicate nature of the products in the current case, increases the complexity of solving such a problem. Essentially, lengthy transportation routes and improper handling and loading of products, can accelerate the potential spoilage, and hence increase the amount of wasted products (Priyadarshi, Routroy & Garg, 2020).

In lieu with the above, the current work aims to fulfill a strategic requirement in Egypt's agriculture industry by establishing an efficient SCN for the national collection and distribution of fresh produce. The approach starts following the footsteps of Ge, Goetz, Canning and Perez (2018) in the US, by strategically locating and allocating flow to a network of aggregation hubs across the country. This is accomplished by solving a cost minimization dynamic FLA problem for multiple perishable products, considering the different cultivation seasons. With each hub acting as a transshipment node in the SCN, the second phase of the approach is to complement the hub FLA decision with optimal fleet sizing, transportation schedules and routing decisions. This is achieved by solving the split-delivery VRP (SDVRP) for collection and distribution of products, considering loading constraints, and using a heterogeneous fleet of vehicles. Due to the complexity of both problems, a hybrid binary particle swam optimization (BPSO) algorithm is utilized for solving the dynamic FLA problem, while a hybrid ant-colony optimization-local search (ACO-LS) algorithm is used for the SDVRP, both considering the aforementioned problem characteristics.

The rest of the paper is hence organized as follows. In Section 2, the literature on fresh produce aggregation hubs and on integrating vehicle routing with the FLA decision is reviewed. In Section 3, the dynamic FLA and the

SDVRP problems are described and formulated, and the hybrid BPSO and ACO-LS solution algorithms are presented. In Section 4, data that pertains to the Egyptian fresh produce industry is presented and the dynamic FLA problem is solved to obtain two national SCN configurations. In addition, the hybrid ACO-LS solution is illustrated for a selected hub. In Section 5, the work is concluded with some insights regarding the outcomes, limitations of the work, and future research directions.

## 2. Literature Review

Designing a SCN that incorporates transshipment facilities, requires determining the locations of the facilities, and simultaneously allocating flow to them (Akkerman, Farahani & Grunow, 2010). In SCN design (SCND), the facility location problem is a strategic planning decision, and being an NP-hard problem, has been proven to be very difficult to solve to optimality (Owen & Daskin, 1998). The FLA problem further complements the location decision with supply and demand flow allocations, to minimize the total distribution costs throughout the network. Due to their interdependency, combining the FLA strategic decision with the tactical vehicle routing and scheduling decisions, results in significant improvements in the overall SCN design, especially when dealing with perishable products (Musavi & Bozorgi-Amiri, 2017).

### 2.1. Fresh Produce Aggregation Hubs

In recent years, perishability of products in the FLA context has gained some attention in literature due to its effect on the SCN design and operations, with focus on fresh produce products in a considerable number of these studies (Lucas & Chhajed, 2004). In a review conducted in He, Huang, Li, Shi and Wu (2018), many aspects of the management of food supply chains were discussed. The SCN design task was defined as an effort to simultaneously optimize the position of aggregation hubs, and the flow from upstream farmers and producers to downstream merchants and customers. It was highlighted that product quality degradation has a significant impact on the network design and reliability, and that new problem models need to be developed to solve more realistic situations using existing or new approaches.

The work in Etemadnia, Goetz, Canning and Sadegh (2015) studied optimal locations of aggregation hubs of fresh foods in the US, that minimize land and air transportation costs. The authors formulated a mixed integer linear programming (MILP) model to solve the problem to optimality using GAMS/CPLEX in order to minimize the total transportation cost. In Orjuela-Castro, Sanabria-Coronado and Peralta-Lozano (2017), another MILP was proposed to model the problem of establishing collection and processing centers (hubs) in a multi-echelon, multi-product, fresh fruits distribution network in Bogota, Colombia, and was solved to optimality using GAMS. In de Keizer, Akkerman, Grunow, Bloemhof, Haijema and van der Vorst (2017), the effect of quality degradation on the design decisions of a fresh produce SCN of heterogeneous products was studied using a MILP model of the problem. Results showed that if services provided in the aggregation hubs affect the shelf-lives of products, product spoilage rates should be considered in the problem. In Ge et al. (2018), a comprehensive study was conducted to determine the optimal locations of aggregation hubs of fresh produce products across the US, taking into consideration the economies of scale and different hub capacities. Findings revealed that economies of scale effects have a big influence on how hub locations decisions are made, and emphasized the importance of the inclusion of aggregation hubs in the collection and distribution network. This work was extended in Ge, Goetz, Cleary, Yi and Gómez (2022) to encompass empirical models that improved the reliability of the facility location solution towards a wide range of social economic and demographic factors.

In Maiyar and Thakkar (2019a), a multi-objective mixed integer nonlinear model was proposed to find optimal aggregation hub locations in the grain supply network in India, in order to minimize the total SCN cost and greenhouse gases (GHG) emissions. Given the computational complexity of the problem, a multi-objective particle swarm optimization (PSO) algorithm with differential evolution was utilized. The authors extended their work in Maiyar and Thakkar (2019b) by considering a multi-period model and a hub and spoke system to connect source nodes to destination nodes. A robust optimization model was proposed in Kambli and McGarvey (2021) to help Missouri and Illinois farmers transport their products from their farms to a central hub in St. Louis. The objective was to minimize the total distance travelled by farmers to deliver their products by establishing a network of regional hubs, where farmers can drop off their products to relatively closer destinations. This FLA problem was solved using GAMS/CPLEX and the analysis showed that the hub capacity plays an important role in the optimal assignment. The work in Mejía, Granados-Rivera, Jarrín, Castellanos, Mayorquín and Molano (2021) addressed the problem of fresh food supply in Colombia's rural communities by locating the best subset of hubs between farmers and customers to minimize transportation costs. Taking into consideration the regional characteristics, the model accounted for delivery to hubs or directly to the customers.

### 2.2. Integrating Location and Routing Decisions

The integration of tactical and operational decisions, like vehicles routing and scheduling and inventory, with the strategic location/allocation decision in SCNs, has been the focus of a growing number of studies in the past two decades. A survey on location-routing problems (LRPs) was conducted in Nagy and Salhi (2007) and another in Prodhon and Prins (2014), where the interdependency between facility (hub) location and vehicle routing problems was highlighted, and the different variants of the LRP were discussed. In Veenstra, Jan, Coelho and Zhu (2018), a branch-and-bound algorithm and a hybrid variable neighborhood search (VNS) algorithm were proposed to solve the LRP for a pharmaceutical distribution network. The network consisted of a single source that distributes its products using two sets of distribution vehicles.

As for perishable products, in Govindan, Jafarian, Khodaverdi and Devika (2014), a multi-objective model was proposed for a two-echelon LPR with time windows, to determine the locations of a number of distribution facilities. The authors proposed a hybrid multi-objective PSO with adapted multi-objective VNS to solve the problem and recommended consideration of more realistic problem characteristics like cross-docking. In Musavi and Bozorgi-Amiri (2017), a non-sorting genetic algorithm II (NSGA-II) was employed to solve the hub location problem, considering vehicles scheduling in a two-echelons network, to minimize the transportation costs and carbon emissions, and maximize product quality. In Hiassat, Diabat and Rahwan (2017), the location decision was integrated with the inventory-routing decisions to determine the locations of a number of warehouses, routes to serve customers, and inventory levels for a single manufacturer with a single perishable product, using a GA to solve the problem. In Turan, Minner and Hartl (2017), inventory and routing decisions were considered for the distribution of multiple perishable products with uncertain demand from one source, where some of the destination nodes were considered as transshipment nodes to redistribute the products and balance inventories across the different retailers. In Rafie-Majd, Pasandideh and Naderi (2018), the LRP was modelled and solved for multiple perishable products with uncertain demand sent from a single source. The model considered vehicles with different capacities, order-splitting, that each customer (destination) can be assigned to one distribution center only, and that deterioration of products only occurs at the customer level. In Partovi, Seifbarghy and Esmaeili (2023), a bi-level programming approach was used to model the LRP for a two-echelon SCN of perishable products. The authors obtained solutions for the problem using a revised fuzzy programming method to account for uncertainty in demand, highlighting the importance of integrating the strategic location decision with the tactical and operational inventory and routing decisions.

### 2.3. Split-Delivery and Loading Constraints

In traditional VRP, it has been assumed that the demand of each customer can be fulfilled by one vehicle. Relaxing this constraint and allowing split-delivery (SDVRP) leads to reductions in transportation costs, and allows the demand of a single customer to exceed the capacity of the available vehicles (Dror & Trudeau, 1989). In Archetti and Speranza (2012), a survey was conducted on the SDVRP and its variants, and the different approaches utilized to solve this family of problems up to the year 2012. These approaches included exact methods (Archetti, Bianchessi & Speranza, 2014; Dror, Laporte & Trudeau, 1994), heuristics (Dror & Trudeau, 1990), and meta-heuristics (Aleman & Hill, 2010; Tang, Ma, Guan & Yan, 2013; Tavakkoli-Moghaddam, Safaei, Kah & Rabbani, 2007).

In recent years, hybrid algorithms have been proposed for new variants of the problem. Examples include a hybrid ACO with GA and LS (Rajappa, Wilck & Bell, 2016), tabu search (TS) with batch combination (Qiu, Fu, Eglese & Tang, 2018), large neighborhood search (LNS) and random variable neighborhood descent (VND) (Haddad, Martinelli, Vidal, Martins, Ochi, Souza et al., 2018), PSO with LS heuristics (Shi, Zhang, Wang & Fang, 2018), and GA with fuzzy simulation (Mehlawat, Gupta, Khaitan & Pedrycz, 2020). In Shahabi-Shahmiri, Asian, Tavakkoli-Moghaddam, Mousavi and Rajabzadeh (2021), a hybrid Epsilon constraint method was utilized to solve the problem while considering heterogeneous vehicles (regular and refrigerated), cross-docking, and perishable products in a multi-criteria decision making problem.

The handling of multiple perishable and delicate fresh produce products should account for relative positioning constraints in the transportation vehicles. Yet, loading constraints have not been considered much in the VRP literature, and even less often in the perishable products context. The work in Gendreau, Iori, Laporte and Martello (2006) introduced and solved the three-dimensional loading capacitated VRP using a TS algorithm. In Ceschia, Schaerf and Stützle (2013), the combined loading-routing problem was considered while accounting for split-delivery opportunities. In Bortfeldt and Yi (2020), forced and optional splitting were considered in the loading-routing problem, and a hybrid GA with LS was utilized to solve the problem. In Guo, Zhang and Boulaksil (2021), incompatibility loading constraints were considered for the SDVRP, and the problem was solved using a hybrid Clarke-Wright savings algorithm with LS, and a sweep algorithm with SA and adaptive LNS.

### 2.4. Summary and Motivation

Distribution of fresh produce products constitute a major component of national SCNs and of the logistics industry in general. Due to their perishable and delicate nature, planning the handling and distribution of such products should consider their quality and freshness, as well as typical distribution criteria like cost and delivery speed. In developing countries like Egypt, such planning efforts have to further ensure effective market access for the main sources of these products, which are small and medium-sized farms.

In recent years, an increasing number of studies have considered the SCND problem for fresh produce and the utilization of aggregation hubs, and have proposed solution approaches for the problem. In addition, a growing number of algorithms have been proposed for solving the VRP considering perishable products, including fresh produce, while accounting for a wide range of problem characteristics. Yet, very few studies have complemented the FLA strategic decision for locating and allocating flow to fresh produce hubs, with the tactical distribution decision, or considered loading constraints when planning the collection and distribution routes. In addition, most approaches that focused on the SCND problem for fresh produce have relied on exact methods to solve the problem. While such methods can efficiently solve small and potentially mid-sized instances of the problem, solving the problem on a national scale considering a multitude of realistic constraints, along with the dynamic nature of the problem, requires more robust approaches. Furthermore, to the best of the authors' knowledge, considering the dynamic nature of the problem, the perishability of the products, the effect of packaging and processing functions in the transshipment hubs on the shelf lives of products, and the economies of scale when determining the capacities of the selected hubs, have not been simultaneously considered in previous problem models.

In lieu with the above, the current work aims to establish an efficient SCN for the national collection and distribution of fresh produce products in Egypt, by strategically locating and allocating flow to a number of aggregation hubs, to act as transshipment points between farms and markets across the country. These hubs will act as the focal points for collection and distribution, while providing processing and packaging services to preserve the quality of the products. This will be achieved by modeling and solving a novel dynamic FLA problem considering different harvesting seasons, perishability of products, economies of scale, processing functions and their effect on shelf-lives, among other problem characteristics. Due to the size and characteristics of the considered problem, a hybrid BSPO algorithm is employed to obtain solutions for the problem. In the second phase, the strategic hub location and allocation decision is complemented with the tactical distribution decision, by solving the SDVRP for the established aggregation hubs using a hybrid ACO-LS algorithm. For each hub, the solution will provide the fleet size of heterogeneous vehicles and the collection and distribution routes and schedules, while accounting for the different perishability rates of the products based on the vehicle type, and the positioning-loading constrains.

## 3. The Two Phases Solution Approach

Traditionally, the hub location problem has been approached with FLA models, with the objective of minimizing the total transportation cost in the network (Alumur & Kara, 2008). The FLA problem at hand considers the distribution of a supply of multiple perishable products at $n$ source nodes (farms) that changes from one harvesting season to another, to satisfy the demand at $m$ destination nodes (markets), by creating an intermediate echelon of aggregation hubs for the collection, processing, and distribution of the products. The solution to this problem requires the determination of the number, locations and capacities of the hubs to be established, and the allocation of flow to/from the hubs for each product in each harvesting season. The second phase of designing and managing the intended national SCN, entails solving the split-delivery VRP (SDVRP) for each aggregation hub to determine the size of the required collection and distribution fleet, and the routes and schedules of the individual trucks. Because of the perishable nature of the products, the SDVRP solution should account for the heterogeneity of the pickup/delivery (P/D) trucks, the different perishability rates, and positioning loading constraints of the products when constructing the collection and distribution routes.

### 3.1. The SCN Design Problem

To capture the above hub FLA problem description, the proposed model considers that each source $i$ has a supply $a_{iph}$ of product $p$ in season $h$, and each destination $j$ has and a demand $b_{jph}$. The cost per unit $c_{ph}$ of each product $p$ depends on the harvesting season $h$, and each product $p$ has a spoilage rate per unit distance $s^b_p$ that can be reduced to $s^a_p$ after processing and packaging in the aggregation hub. The capacity $G_l$ of a hub with level $l$ is determined based on the maximum amount of flow allocated to this hub in any given season, and its fixed cost $C^F_l$ is based on this capacity. To account for the economies of scale, the processing cost per unit $e_{pk}$ of a product $p$ in hub $k$ depends on its capacity level. In addition to the above, the following assumptions govern the model:

- supply and demand of all nodes are deterministic and known
- all $n$ source node locations are candidates for hub establishment
- distances between all nodes are known
- direct flow between supply and demand nodes is not allowed
- direct flow between hubs is not allowed
- product pre-processing spoilage rates are higher than post-processing ones
- a source can send flow to any hub that lies within a maximum distance $D$ from the source, to minimize the pre-processing spoilage of the product
- flow can be sent from any hub to any destination node, with no distance restriction
- to maintain freshness of products, inventory carrying is not allowed at the hubs; hubs act as cross-docks

#### 3.1.1. The Dynamic FLA Model

In lieu with the above description, and in addition to the above notation, the FLA problem at hand can be formulated as follows:

Indices:

| | |
|---|---|
| $h$ | harvesting season |
| $i, j, k$ | node |
| $l$ | capacity level |
| $p$ | product type |

Parameters:

| | |
|---|---|
| $ct_p$ | transportation cost per unit distance per unit of product $p$ |
| $d_{ik}$ | distance between nodes $i$ and $k$ |
| $e_{pl}$ | processing cost per unit of product $p$ in a hub with capacity level $l$ |
| $D$ | set of destination nodes |
| $K$ | set of candidate hub nodes |
| $L$ | number of different capacity levels |

$M$ maximum number of required hubs

$N$ set of source nodes

Decision Variables:

$x_{ikph}$ allocated flow of product $p$ from node $i$ to node $k$ in season $h$

$y_{kl}$ 1 if node $k$ is selected for a hub with capacity level $l$; 0 otherwise

$z_{ik}$ 1 if flow is allocated between source $i$ and hub $k$; 0 otherwise

$$Min.\ Z = \sum_{k\in K}\sum_{l} C_l^F . y_{kl} + \sum_{h}\sum_{i\in N}\sum_{k\in K}\sum_{p}\left(1 - s_p^b \cdot d_{ik}\right)e_{pk}.x_{ikph} + \sum_{h}\sum_{p}\Big[\sum_{i\in N}\sum_{k\in K}(c_{ph}.s_p^b + ct_p)d_{ik}.x_{ikph} + \sum_{k\in K}\sum_{j\in F}(c_{ph}.s_p^a + ct_p)d_{kj}.x_{kjph}\Big] \tag{1}$$

$$\sum_{k\in K} x_{ikph} \leq a_{iph} \quad \forall i \in N; \forall p, h \tag{2}$$

$$\sum_{i\in N}\sum_{p}\left(1 - s_p^b \cdot d_{ik}\right) x_{ikph} \leq \sum_{l} G_l y_{kl} \qquad \forall k \in K;\ \forall h \tag{3}$$

$$\sum_{l} y_{kl} \leq 1 \qquad \forall k \in K \tag{4}$$

$$e_{pk} = \sum_{l} e_{pl}.y_{kl} \quad \forall k \in K; \forall p \tag{5}$$

$$\sum_{k\in K}\sum_{l} y_{kl} \leq M \tag{6}$$

$$\sum_{j\in F} x_{kjph} = \sum_{i\in N}\left(1 - s_p^b \cdot d_{ik}\right) x_{ikph} \quad \forall k \in K; \forall p, h \tag{7}$$

$$\sum_{k\in K}\left(1 - s_p^a \cdot d_{kj}\right) x_{kjph} = b_{jph} \quad \forall j \in D; \forall p, h \tag{8}$$

$$\sum_{p} x_{ikph} \leq z_{ik}\sum_{p} a_{iph} \quad \forall i \in N;\ \forall k \in K;\ \forall h \tag{9}$$

$$z_{ik}.d_{ik} \leq D \quad \forall i \in N;\ \forall k \in K \tag{10}$$

In the above model, the objective function (1) minimizes the total cost of the SCN including the fixed cost for establishing the hubs, processing costs of products accounting for economies of scale, and transportation and product spoilage costs. Constraint set (2) restricts the total amount of a product sent from any source in any season to its available supply of this product in that season. Constraint set (3) determines the capacity level of a hub based on the maximum quantity of unspoiled product flow received in any given season. Constraint set (4) restricts each hub to one capacity level. Constraint set (5) accounts for economies of scale in determining the processing costs of products in the hubs, based on their capacities. Constraint (6) is an *optional* limit on the number of required hubs in the network. Constraint set (7) limits the quantity of product sent from each hub in each season to the unspoiled quantity received by that hub from all source nodes. Constraint set (8) ensures the satisfaction of demand of each product in each season at each destination node, while accounting for the post-processing reduced spoilage rates during transportation. Finally, Constraint sets (9) and (10) restrict the hubs that can receive flow from any source to those within a distance $D$ from the source node, to reduce the spoilage that occurs before processing and packaging.

The proposed model accounts for the availability of the fresh produce products and the variation in their costs throughout the harvesting seasons. In addition, it considers different transportation costs for the different products, and accounts for the reduction in shelf-life with different rates that reflect the benefits of processing and packaging functions that take place within a close proximity of the source farm. Furthermore, the model determines the fixed capacity of a hub based on the expected flow of products in the different seasons, which in turn controls the processing costs of the products that pass through such hub. The modeling of such benefit from economies of scale lead to the non-linearity of the model, which contributed to the complexity of obtaining exact solutions for large problem instances, and to the need for an approximate solution approach.

### 3.1.2. The Hybrid BPSO Algorithm

The proposed solution approach is a hybrid of two algorithms, each devised to tackle one of the two decisions; location and flow allocation. Due to its mathematical complexity, along with the determination of the number of facilities, a binary particle swarm optimization (BPSO) algorithm is utilized to address the facility location decision. As for the flow allocation decision, and in hybridization with the BPSO, the problem can be reduced to a typical transportation problem with transhipment nodes, for which optimum solutions can be obtained in polynomial time. Yet, such solution has to be obtained for each season, and to account for the product spoilage that occurs during transportation. This hybridization of BPSO with the transportation algorithm was proposed in an earlier study to address the static FLA problem (Fahmy, Zaki & Gaber, 2023), where it outperformed simulated annealing (SA) in terms of solution consistency and quality, and was able to obtain optimum solutions for most test problems. In the current study, this hybrid algorithm is extended to account for the dynamic nature of the addressed problem resulting from seasonality, economies of scale, and the effect of processing functions on the shelf-lives of products.

PSO is a population-based evolutionary computation technique devised to search large solution spaces (Eberhart & Kennedy, 1995). Since its induction, it has been extensively used for solving a multitude of optimization problems, including the FLA problem (Kambli & McGarvey, 2021; Maiyar & Thakkar, 2019a). The essence of PSO is based on the behavior of swarms as they collectively move and converge to desired destinations. In PSO, candidate solutions to the problem are represented using a population of particles that form a swarm.

The algorithm starts with randomly initialized particles, whose movement (search direction) is henceforth governed by three factors; i) cognitive behavior, or personal best ($P_{best}$), which is the location with the best solution value ($P_{sol}$) visited by the individual particle, ii) social behavior, or global best ($G_{best}$), which is the location with the best solution value ($G_{sol}$) attained by any particle in the swarm, and iii) inertia, or current search direction ($v_{pos}$) of the particle. The algorithm then proceeds by updating the search direction ($v_{new}$) and current position ($C_{pos}$) of each particle in each iteration using Equations (11) and (12), respectively, by factoring in the cognitive and social effects, and the inertia (Rezaee-Jordehi & Jasni, 2013):

$$v_{new} = w.v_{pos} + c_1.R_1(P_{best} - C_{pos}) + c_2.R_2(G_{best} - C_{pos}) \tag{11}$$

$$C_{pos} = C_{pos} + v_{new} \tag{12}$$

where,

$c_1$ is the cognitive acceleration coefficient,
$c_2$ is the social acceleration coefficient,
$w$ is the inertia weight,

and $R_1$ and $R_2$ are random numbers generated to increase the randomness in the exploration (social effect) and exploitation (cognitive effect) of the search direction of a particle.

As mentioned earlier, the objective of using PSO in the current approach is to tackle the selection decision of the number and locations of the hubs. Such selections can be conveniently attained using ones and zeros, leading to a binary format for each particle in the swarm, and hence to a binary PSO (BPSO) search algorithm. Each particle is hence presented as a binary vector of length $n$ of ones and zeros, indicating whether (1) or not (0) a hub is established at a node $k$. BPSO then uses the same PSO procedure, with the exception of using a sigmoid function $S(v_{new})$ to normalize the velocity of a particle between 0 and 1 for each position of the particle (Kennedy & Eberhart, 1997).

Each particle in the swarm provides a candidate solution for the hub location problem. The complementing step becomes that of finding the best flow allocation and the associated capacities of the hubs. This problem can be modelled as a transshipment problem, which can then be reduced to a transportation problem, by replacing each transshipment node with a source and a destination. Given the perishability of the products, the modified algorithm is devised to account for the spoilage rates of the products when solving the transportation problem, to determine the actual flow reaching the hubs, and eventually ensure the satisfaction of demand at each destination node.

For each season $h$, the algorithm proceeds by constructing a transportation tableau for each product $p$. To account for product spoilage and allow a hub to receive and distribute any quantities of products, the source and destination nodes representing each candidate hub $k$ are assigned supply and demand set as $max(HS_i, HD_j)$, where:

$$HS_i = \sum_{i \in N} a_{iph}(1 - s_p^b \cdot d_{ik}) \tag{13}$$

$$HD_j = \sum_{j \in F} b_{jph}(1 + s_p^a \cdot d_{kj}) \tag{14}$$

Flow allocations from source nodes directly to destination nodes, or to a distant hub node (distance more than $D$), or from any hub to another, are all penalized as the problem model stipulates. After setting the tableau, the minimum cost method is used to obtain the initial solution. To account for spoilage, when a flow allocation $x_{ikph}$ is made from a source $i$ to a hub $k$, the demand of hub $k$ is reduced by $x_{ikph}(1 - s_p^b \cdot d_{ik})$ only. Similarly, an allocation $x_{kjph}$ reduces the supply of hub $k$ by $x_{kjph}(1 + s_p^a \cdot d_{kj})$, to ensure that the demand of a node $j$ is satisfied with unspoiled product. The classical Modified Distribution Method (MODI) is then used to improve the initial solution. In each iteration of the MODI, the selection of the leaving variable is firstly based on the original allocation before accounting for spoilage, and the perishability rates are then applied to update the affected allocations.

Since in each season the transportation problem is solved for each product $p$ individually, all flow allocations for all products are eventually combined to determine the capacities of the hubs in each season. An improvement step is finally conducted to reallocate flow portions to hubs with underutilized capacities, if this would lead to any reduction in the total cost. The capacity of each hub $k$ is set as the maximum required capacity of the hub throughout all seasons, and the fixed cost and processing cost of each product $e_{pk}$ are determined accordingly. The total cost of each solution provided by each particle ($C_{sol}$) in the swarm is calculated using Equation (1). The steps of the overall hybrid BPSO algorithm are illustrated in Figure 1.

By definition, each of the aggregation hubs will centrally manage the collection of products from neighboring farms and the distribution to whole markets and major retailers in the different governorates. Accordingly, all the pickup/delivery (P/D) activities will start and end at the hub. To maintain the freshness and preserve the shelf-lives of the products, from a routing perspective the transition between collection and distribution should be a cross-docking operation with limited time assigned for processing and packaging products, with no inventory carried. The aggregation hub will hence act as a central depot for product processing and packaging, and cross-docking of the trucks.

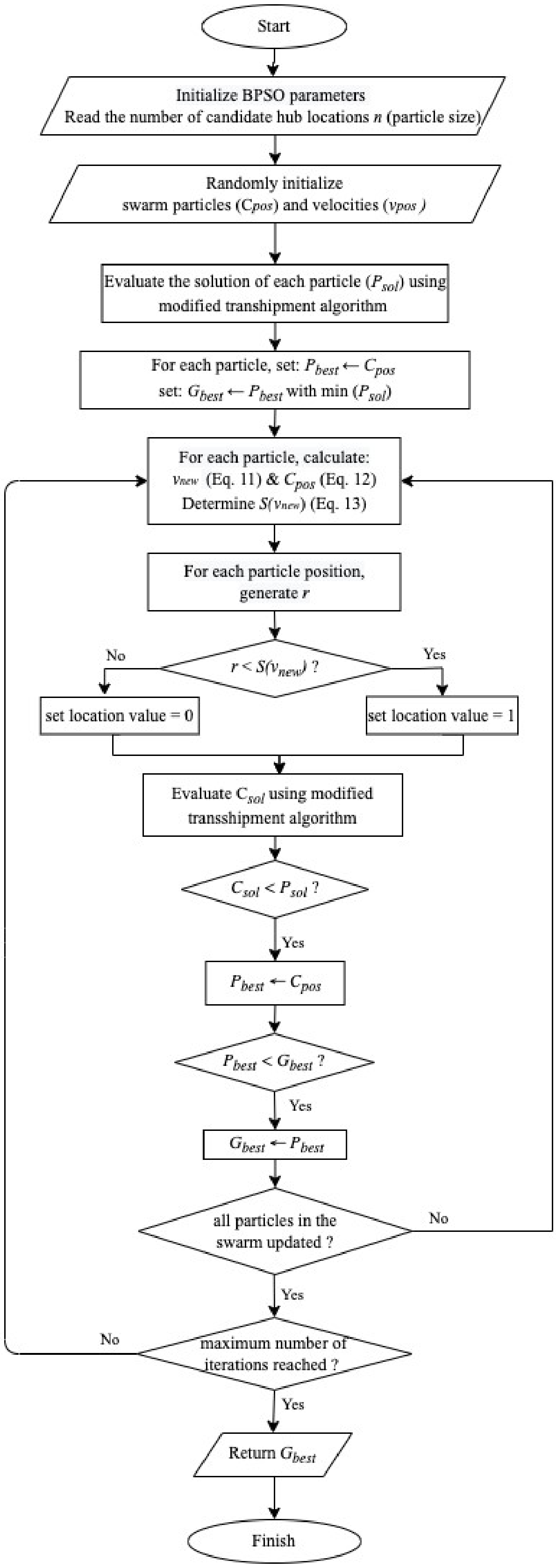


Figure 1. The overall hybrid BPSO algorithm

### 3.2. The SDVRP for Collection and Distribution

To accomodate the nature of the product being transported in a manner that minimizes the transportation cost while preserving freshness, two types of trucks are utilized; regular (non-refrigerated) and refrigerated. To reduce the transportation costs and size of the fleet, the P/D tasks of the trucks at the supply, demand, and hub locations, are coordinated and timely scheduled, while allowing for some recess time for the truck (driver) after completing each tour. Furthermore, damage to frail products is minimized during transit by accounting for relative positioning loading constraints in the trucks while developing the routes and P/D schedules. Finally, order splitting is utilized in pickups and deliveries to minimize the transportation costs.

In addition to the above, the following assumptions are made in the SDVRP model:

- Demand and supply of each product type at each node, and capacity of trucks are defined in terms of weight.
- The spoilage rate per unit time of transit of each product type depends on the type of truck handling the load.
- Product types are assumed to have lower spoilage rates in the distribution routes (post-processing and packaging) than those in the collection routes.
- A P/D node can be visited by the same truck multiple times in different tours.
- In a pickup tour, a truck leaves the hub empty and does not perform any deliveries, and vice versa.
- Based on its frailty, each product type is assigned to one of three virtual loading levels in a truck.

#### 3.2.1. The SDVRP Model

Given a transportation network of any hub (depot) consisting of $n$ P/D nodes, the SDVRP can be formulated as follows:

Indices:

$i, j$ node index

$l$ loading level index

$p$ product type index

$r$ truck tour index

$v$ truck index

Parameters:

$a_{ip}$ supply/demand of product $p$ in pickup/delivery node $i$

$c_p$ cost per unit weight of product $p$

$D$ set of delivery nodes

$FC_v$ fixed cost of truck $v$

$h$ handling time per unit weight of product

$I$ set of depot inbound pickup & delivery nodes = $\{n+3, n+4\}$

$l_p$ allowed truck level of product $p$

$M_R$ maximum number of tours for any truck

$N$ set of pickup nodes

$O$ set of depot outbound pickup & delivery nodes = $\{n+1, n+2\}$

$P$ set of all product types

$P_l$ set of products that require level $l$ of a truck

$P_R$ set of products needing refrigeration; $P_R$  $P$

$Q_v$ capacity of truck $v$

$rt$ recess time of truck in depot

R set of truck levels = {1, 2, 3}

$s^a_{pv}$ spoilage rate of product $p$ in truck $v$ per unit time in distribution tours

$s^b_{pv}$ spoilage rate of product $p$ in truck $v$ per unit time in collection tours

$S$ shift of truck (driver)

$t_{ij}$ travel time between nodes $i$ and $j$

$T_v$ set of tours of truck $v$ = $\{1,\ldots, M_R\}$

$U$ set of all P/D nodes = $\{1,\ldots, n\}$

$vc_v$ variable cost of truck $v$ per unit travel and product handling time

$V$ set of all trucks = $\{1,\ldots, m\}$

$V_G$ set of regular trucks; $V_G$ $V$

$W$ set of all nodes = $\{1,\ldots, n+4\}$

Decision Variables:

$o_{ivr}$ arrival time of truck v at node $i$ in tour $r$

$q_{pivlr}$ quantity of product $p$ loaded/unloaded at node $i$ in level $l$ in tour $r$ of truck $v$

$u_{pivr}$ handling time of product $p$ at node $i$ in tour $r$ of truck $v$

$w_{ivlr}$ load of layer $l$ in truck $v$ when entering node $i$ in tour $r$

$x_{ijvr}$ 1 if truck $v$ travels from node $i$ to node $j$ in tour $r$; 0 otherwise

$y_{vr}$ 1 if tour $r$ of truck $v$ is a collection tour; 0 if a distribution tour

$z_v$ 1 if truck $v$ is selected for service; 0 otherwise

$$Min\ Z = \sum_{v} FC_v z_v + \sum_{p}\sum_{v}\sum_{r\in T_v}[(vc_v + c_p s^b_{pv}).(\sum_{i\in\{N\cup n+3\}} u_{pivr} + \sum_{i\in N}\sum_{j\in\{N\cup n+3\}} t_{ij}x_{ijvr}) + (vc_v + c_p s^a_{pv}).(\sum_{i\in\{D\cup n+2\}} u_{pivr} + \sum_{i\in\{D\cup n+2\}}\sum_{j\in D} t_{ij}x_{ijvr})] \tag{15}$$

$$\sum_{v}\sum_{r\in T_v}\sum_{i\in W} x_{ijvr} \geq 1 \quad \forall\, j \in U \tag{16}$$

$$\sum_{j\epsilon W} x_{ijvr} - \sum_{j\epsilon W} x_{jivr} = 0 \quad \forall\, i \in N; \forall v \in V; r \in T_v \tag{17}$$

$$\sum_{v}\sum_{i\in\{D,n+2\}}\sum_{j\in\{N,n+3\}}\sum_{r\in T_v} x_{ijvr} = 0 \tag{18}$$

$$\sum_{v}\sum_{i\in\{N,n+1\}}\sum_{j\in\{D,n+4\}}\sum_{r\in T_v} x_{ijvr} = 0 \tag{19}$$

$$\sum_{i\in O}\sum_{j\in U}\sum_{r\in T_v} x_{ijvr} \leq M_R z_v \quad \forall\, v \in V \tag{20}$$

$$\sum_{j\in N} x_{n+1,j,v,r} \leq y_{vr} \qquad \forall\, v \in V; r \in T_v \tag{21}$$

$$\sum_{j\in D} x_{n+2,j,v,r} \leq (1 - y_{vr}) \qquad \forall\, v \in V; r \in T_v \tag{22}$$

$$Q_v \sum_{j\in N} x_{n+1,j,v,r} - \sum_{j\in N} \sum_{l} \sum_{p\in P_l} q_{pjvlr} \geq 0 \qquad \forall v \in V; r \in T_v \tag{23}$$

$$Q_v \sum_{j\in D} x_{n+2,j,v,r} - \sum_{j\in D} \sum_{l} \sum_{p\in P_l} q_{pjvlr} \geq 0 \qquad \forall v \in V; r \in T_v \tag{24}$$

$$\sum_{j\in N} x_{n+1,j,v,r} - \sum_{j\in N} x_{j,n+3,v,r} = 0 \qquad \forall\, v \in V; \forall r \in T_v \tag{25}$$

$$\sum_{j\in D} x_{n+2,j,v,r} - \sum_{j\in D} x_{j,n+4,v,r} = 0 \qquad \forall\, v \in V; \forall r \in T_v \tag{26}$$

$$\sum_{l} \sum_{p\in P_l} q_{pjvlr} \leq \sum_{p} a_{jp} \sum_{i\in V} x_{ijvr} \qquad \forall\, j \in U; v \in V; r \in T_v \tag{27}$$

$$\sum_{v} \sum_{r\in T_v} q_{pivl_pr} = a_{ip} \qquad \forall\, i \in U; p \in P \tag{28}$$

$$q_{pivl_pr} = \sum_{j\in U} q_{pjvl_pr} \qquad \forall\, i \in \{n+2, n+3\}; \forall\, v \in V; r \in T_v\,; p \in P \tag{29}$$

$$\sum_{p} \sum_{v} \sum_{l} \sum_{r\in T_v} q_{pivlr} = 0 \qquad \forall\, i \in \{n+1, n+4\} \tag{30}$$

$$\sum_{i\in U} \sum_{p} q_{pivl_pr} \leq Q_k \qquad \forall\, v \in V; r \in T_v \tag{31}$$

$$\sum_{i\in U} \sum_{r\in T_v} q_{pivl_pr} = 0 \qquad \forall\, p \in P_R; v \in V_G \tag{32}$$

$$w_{jvlr} + Q_v\left(1 - x_{n+2,j,v,r}\right) \geq \sum_{p\in P_l} q_{p,n+2,v,l,r} \qquad \forall j \in D; v \in V; r \in T_v; l \in R \tag{33}$$

$$w_{ivlr} - w_{jvlr} + Q_v\left(1 - x_{ijvr}\right) \geq \sum_{p\in P_l} q_{pivlr} \quad \forall i,j \in D; v \in V; r \in T_v; l \in R \tag{34}$$

$$w_{jvlr} - w_{ivlr} + Q_k\left(1 - x_{ijvr}\right) \geq \sum_{p\in P_l} q_{pivlr} \quad \forall i,j \in N; v \in V; r \in T_v; l \in R \tag{35}$$

$$u_{pivr} = hq_{pivl_pr} + 2h \sum_{l<l_p} w_{ivlr} \quad \forall i \in U; v \in V; r \in T_v; p \in P \tag{36}$$

$$u_{pivr} = hq_{pivl_pr} \quad \forall i \in \{I, O\}; v \in V; r \in T_v; p \in P \tag{37}$$

$$o_{jvr} - o_{ivr} + S(1 - x_{ijvr}) \geq \sum_p u_{pivr} + t_{ij} \quad \forall i,j \in W; v \in V; r \in T_v \tag{38}$$

$$o_{i,v,r+1} - o_{jvr} \geq \sum_p (u_{p,i,v,r+1} + u_{pvjr} + rt) \quad \forall i \in O; j \in I; v \in V; r \in T_v \tag{39}$$

$$o_{jvr} - o_{ivr'} \leq S \quad \forall v \in V; r \in T_v; r' \leq r;\ j \in I; i \in O \tag{40}$$

The objective function (15) minimizes the total cost, including the fixed cost (number) of trucks, and transportation and product spoilage costs during collection and distribution tours. Constraint sets (16 & 17) are basic vehicle routing constraints, while constraint sets (18 & 19) separate collection and distribution tours. Constraint set (20) determines if a truck *v* is utilized. Constraint sets (21 & 22) determines the type of tour *r* made by truck *v*; collection or distribution. Constraint sets (23 to 26) ensure that all tours originate and end at the depot. Constraint sets (27 & 28) ensure that all supply is picked up and all demand is delivered in all P/D nodes. Constraint sets (29 to 31) determine the quantity of each product type loaded/unloaded at the depot in any tour and ensure that the capacity of the truck is not exceeded. Constraint set (32) prevents regular trucks from handling products that require refrigeration. Constraint sets (33 to 35) update the load at each level of a truck when entering a node in collection and distribution tours. Constraint sets (36 & 37) determine the product handling time at any node, while accounting for unloading and reloading the products at the upper levels (if any) of the truck. Constraint sets (38 & 39) determine the arrival time at each node in each tour of a truck, and prevent sub-tours. Constraint set (40) finally ensures that a truck must complete all its assigned tours within the given time window (shift).

The above model not only solves the VRP, but it also develops a schedule for each truck for any number of tours within its shift, while allowing order splitting to maximize the capacity utilization of the trucks and minimize transportation costs. The model further ensures that collection and distribution routes are developed while accounting for the spoilage of products and the product handling time (cost) at the nodes.

### 3.2.2. The ACO Routing and Scheduling Algorithm

Ant-colony optimization (ACO) algorithms (Dorigo, Maniezzo & Colorni, 1996; Dorigo & Stützle, 2010; Dorigo, 1992) have been extensively used to solve routing problems in previous literature. In this context, individual ants represent vehicles trying to find the best routes, by resembling the search for food process, in which ants dispose pheromones to mark the potential paths that start at their colony and end at the source of food. Out of the potential alternative paths explored by each ant, and using pheromones deposition, alternative paths are gradually eliminated in each iteration until the best path is found.

In the current study, a hybrid ACO-LS is utilized to solve the problem with the objective of minimizing the total cost of operating and routing a heterogeneous (regular and refrigerated) fleet of trucks for both collection and distribution, while maintaining the quality of products by minimizing the spoilage cost. Variants of ACO have often been combined with other local search (LS) heuristics to improve the routes already constructed by the ACO. The hybrid ACO-LS makes use of intra- and inter-route LS techniques while solving the problem (Fahmy & Gaafar, 2023).

To capture the characteristics of the current problem, loading constraints are imposed by dividing the truck capacity into three virtual levels and assigning products to these levels based on their frailty. The time required to load/unload products in the lower levels of a truck is further accounted for when developing the collection and distribution routes and schedules. The steps of the algorithm in each iteration can hence be outlined as follows:

- **Step 1 - initial solution:** beginning at the depot, each ant constructs a path by selecting one node at a time using the ant colony system (ACS) pseudo-random-proportional rule (Dorigo & Gambardella, 1997), until the capacity of the truck is reached, all orders have been fulfilled, or the shift of the truck is about to end.
- **Step 2 – selection bias:** to prevent splitting the orders of distant nodes, they are given a preferable bias when constructing the routes in the initial few iterations. The LS techniques can then rearrange the routes and place such distant nodes in their best positions.
- **Step 3 – exploration vs. exploitation:** an ant can either exploit its current path or explore new paths, by generating a random number and comparing it to the set relative importance of exploitation versus exploration.
- **Step 4 – pheromone trail:** pheromone trails are updated locally and globally in each iteration using a 2-pheromone-trail system to differentiate between regular and refrigerated trucks. Local updates modify the quantity of pheromone, as an ant travels each arc, using the pheromone evaporation rate. Global updates are conducted once all the ants complete their paths, while adding extra pheromone to the current best global solution.
- **Step 5 – improvement:** LS techniques are utilized to improve the constructed routes using intra- and inter-route improvement algorithms. For intra-route improvements, the *2-opt* algorithm is utilized for re-arranging the nodes of a route to minimize the distance (time) travelled by the truck. As for inter-route improvements, first, the *2-opt** algorithm is utilized to create new potentially improved routes by exchanging the paths emanating from two nodes in two different routes of trucks of the same type. A relocate operator is finally applied to randomly select and relocate nodes to alternative routes of other trucks.

## 4. Egyptian Fresh Produce Network

With just about 4% of Egypt's land area suitable for agriculture, the agricultural sector constitutes almost one eighth of the country's GDP and employs around one quarter of the population. Three quarters of the agricultural land are dedicated for field crops, leaving just one quarter of the land to fresh produce, along with livestock products and other specialty crops (Britannica, 2023). In addition, small farms that do not necessarily follow proper standards in cultivation, harvesting, and distribution, are the main source for fresh produce products. As mentioned earlier, this leads to almost 30% waste of the fresh produce production, mainly in transit, low return for the farmers, and high prices for the end customer, which calls for establishing an efficient SCN for the collection and distribution of these products.

### 4.1. Data Collection and Preparation

To model the problem on hand using the description outlined and formulated in Section 3, the configuration of source and demand nodes across Egypt had to first be identified. Administratively, Egypt is divided into 27 governorates, each in turn is divided into either centers (*marakez*) in rural areas or sectors (*aksam*) in urban areas. The rural centers, are further sub-divided into villages, where farming takes place. Because of the difficulty of keeping accurate supply data on the local farm and villages level, the Egyptian Ministry of Agriculture and Land Reclamation (MALR) keeps track of fresh produce production on the centers level only. As of the year 2016, 188 rural centers were reporting agricultural activities, for which data is being tracked by MALR. Accordingly, in this study, the 188 centers will represent the supply nodes of the SCN and the candidate locations for the hubs. As for the demand nodes, and since no national data is reported for fresh produce consumption, and since population census is mainly tracked on the governorate level, the 27 governorates will be utilized to represent the demand nodes, for which the demand for each product type will be assumed to be proportional to each governorate's population (CAPMAS, 2022). The Euclidian distances in kilometers between the rural centers, and those between centers and geographical centers of governorates are obtained from the Egyptian General Survey Authority (EGSA).

Reports on the fresh produce production (supply) quantities of the rural centers are prepared by MALR every 5 to 7 years. The most recent report, which is used in the current study, was prepared in the period between 2016 and 2018. Out of all the product types reported, 14 types of vegetables and fruits were selected for the current study. The selected product types represented the majority of fresh produce products in terms of quantities, while avoiding field crops and other strategic crops (like sugarcane), for which industrial supply chains are already well established, and also avoiding exotic and pricey products that do not necessarily represent the average Egyptian household consumption.

There are three harvesting seasons in Egypt. The main ones are summer and winter seasons, and there is also the *Nile* season, which takes place during the Fall period. For the 14 selected product types, 12 of these product types are harvested in the summer season, 11 types in the winter season, and 7 in the Nile season, totaling more than 22.8 million (metric) tons of products throughout the three harvesting seasons. Along with the production data, for each product type, industry partners were consulted to obtain figures for the cost of product/ton, processing and packaging cost/ton depending on facility size and labor component, transportation cost/km/ton depending on vehicle type (regular or refrigerated), and the shelf-life in hours before processing and packaging. To transform the shelf-lives into the required spoilage rates per km before processing, an average vehicle velocity of 60 km/hr was assumed. The spoilage rate after processing and packaging is assumed to be 50% less.

Furthermore, based on a market survey, the cost of establishing a generic fresh produce processing and packaging facility with a daily output of 50 tons was found to be around EGP 2 million (approximately USD $66,000). This cost figure accounted for the construction of the facility, panels, conveyors, tables, and a refrigeration unit. Assuming 90 days per harvesting season, this cost figure is translated into a hub establishment unit cost per ton per season, which will be used to proportionally estimate the hub establishment cost for any hub size (capacity level).

### 4.2. Solving the SCN Design Problem

To solve the problem on hand, which includes 215 nodes (188 sources and 27 destinations), using the hybrid BPSO algorithm, the swarm size is set to 150 particles and the number of iterations to 100. Accordingly, to initialize the algorithm, a swarm of 150 particles is randomly generated, each with 188 binary values indicating whether a hub in the corresponding location (rural center) is established (1) or not (0). The algorithm then proceeds as described in Figure 1. The allowed distance $D$ between a supply node and a hub receiving its product is set at 200 km for all products in all seasons. For practicality reasons, a ceiling of 1 million tons per season is used as a limit for the capacity of any established hub. Using the market figures, this translates into a processing and packaging facility with an area of roughly 9,000 square meters, with a total establishment cost of about EGP 440 million (USD $14.4 million). In each iteration of the algorithm, the hubs configuration with the minimum total cost attained by each particle ($P_{best}$), along with that attained by the whole swarm ($G_{best}$) are used to update the configuration of each particle using Equations (11) and (12).

Two solutions are retained for the given problem from the final swarm. The first solution (A) is $G_{best}$ that resulted in the minimum total cost, which is the main objective of the model. The second solution (B) resulted in a slightly higher cost but had the minimum number of hubs, as shown in Table 1. The distribution of the hubs across the country along with their ranges of capacities for solutions A and B are shown on supply and demand heat maps of Egypt in Figures 2 and 3, respectively. It should be noted that the supply distribution shown in Figure 2 is based on the governorate level, and is obtained by adding the supply of the 14 product types from all rural centers in a governorate. In Figure 3, the demand of each governorate is obtained by proportionally distributing the total annual supply according to the populations of the governorates.

| Solution | Total cost | Number of hubs |
|---|---|---|
| A | EGP 14,031 millions | 41 |
| B | EGP 14,529 millions | 32 |

Table 1. Best solutions

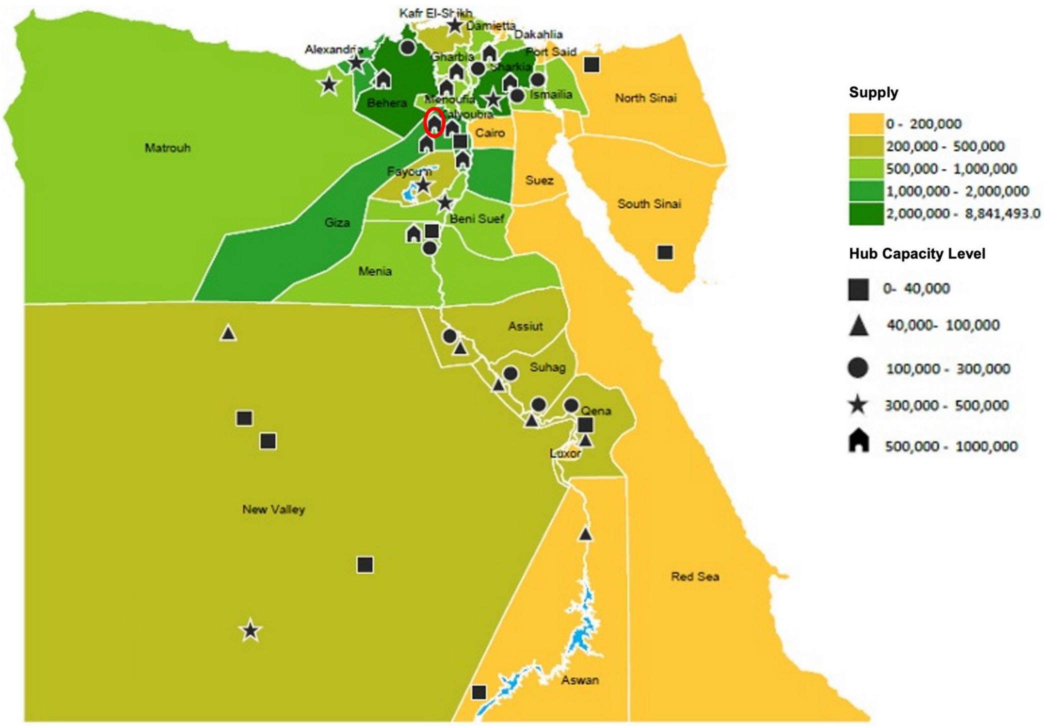


Figure 2. Solution A - 41 hubs

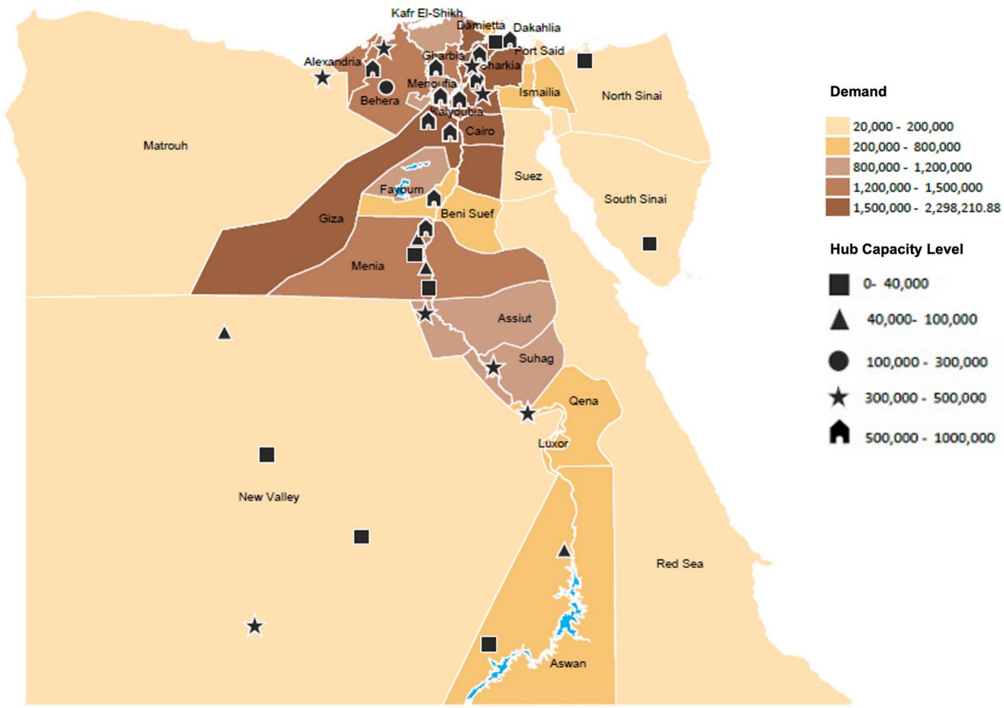


Figure 3. Solution B - 32 hubs

As can be seen from Figures 2 and 3, multiple aggregation hubs can be located in one governorate, but each rural center is limited to host a maximum of one hub. The results have also shown that a few hubs were not utilized during the Nile harvesting season because of the relatively low supply during that period of the year. On the other hand, the winter season featured the highest utilization of the hubs in both solutions, with an average hub inflow of 274,500 tons and 351,500 tons in solutions A and B, respectively.

### 4.3. Solving the SDVRP for Ossim Hub

To illustrate the use of the ACO-LS algorithm, its application on one of the hubs is explained in this section. The hub selected for that purpose is the one located in Ossim center, which is circled in Figure 2. Ossim center is located in the north-west of Giza governorate, and in both solutions A and B, it was selected as one of the largest hubs in the network, due to its abundant supply of diverse products, and its proximity to other supply centers and to high demand destinations as well.

#### 4.3.1. Products Transportation Data and Assumptions

In solution A, Ossim hub is allocated a capacity of 786,800 tons of products, which represents its maximum required capacity in the winter season. During this season, the hub is planned to receive 8 different product types from 21 centers (including Ossim) located in 6 different governorates, and distribute these products on 9 different governorates, including Giza, as shown in Figure 4. More than 55% of the total supply of the hub is received from just 2 of the 21 supply centers (supply nodes 15 and 20), with more than 80% of the total supply emanating from centers within a vicinity of 25 kms. Out of the 9 demand governorates, Cairo (demand node 6), which is the most populated governorate in Egypt and lies within a vicinity of only 5 kms, is planned to receive 60.8% of the products flowing through the hub, while Giza (demand node 4), the second most populated and host governorate, is planned to receive 24.6%.

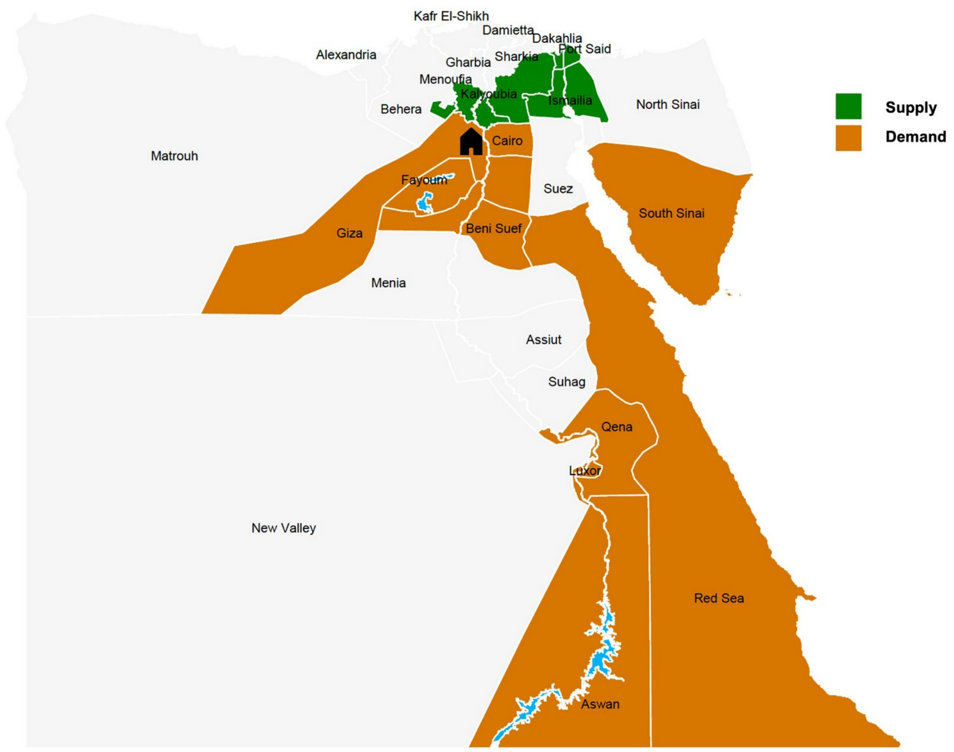


Figure 4. Supply and demand governorates of Ossim hub

Table 2 shows the different product types, along with their loading levels in the trucks (1 is the top-most level), total supply of each product type in tons, product costs (EGP per ton), transportation costs per ton per km, and spoilage percentages per min (of transit). The differences between product types in the transportation costs are mainly due to the volume occupied per unit weight of each product type. The spoilage percentages are calculated based on the shelf-life of each product. Post-processing (in distribution tours) spoilage rates are assumed to be 50% less, and refrigerated spoilage rates are assumed to be 70% of their regular counterparts. As for the trucks, 3.5 (3 for refrigerated) tons capacity trucks are the standard in the Egyptian market for hauling fresh produce, and are used in the model, with an average travel velocity of 60 kms/hr, and an unloaded running cost of EGP 3.2 per km.

| Index | Product | Loading level | Total supply | Product cost | Transp. cost | | Spoilage % |
|---|---|---|---|---|---|---|---|
| | | | | | reg. | ref. | |
| P1 | Tomatoes | 1 | 132,408 | 1425 | 1.68 | 2.19 | 0.0096 |
| P2 | Strawberry | | 29,031 | 5500 | 3.22 | 3.74 | 0.0232 |
| P3 | Cucumber | 2 | 3,587 | 3000 | 1.43 | 1.49 | 0.0097 |
| P4 | Eggplant | | 11,928 | 2375 | 1.43 | 1.49 | 0.0097 |
| P5 | Oranges | | 259,506 | 4000 | 1.43 | 1.49 | 0.0116 |
| P6 | Potatoes | 3 | 81,862 | 1700 | 0.95 | 1.07 | 0.0005 |
| P7 | Onions | | 248,880 | 3750 | 0.78 | 0.91 | 0.0005 |
| P8 | Carrots | | 19,606 | 2000 | 0.95 | 1.07 | 0.0041 |

Table 2. Products data

To determine the number of required trucks and solve the routing problem, it is assumed that the supply of each product type is uniformly distributed throughout the harvesting season, which takes on average 90 days. Hence, total supply data is divided by 90 to solve the problem and create the truck routing schedules on a daily basis. This results in around 8,740 tons of products to be collected and distributed every day through the selected hub. The following assumptions are further used to solve the problem:

- The daily shift of each truck is 16 hrs long, during which it can conduct any number of collection and/or distribution tours.
- Loading/unloading time is 5 mins/ton in both truck types, which can increase to account for accessing the lower levels of a truck.
- A recess time of 30 mins is scheduled after completing a tour of a truck.

#### 4.3.2. The Resulting Collection and Distribution Plan

Applying the hybrid ACO-LS algorithm on the above problem data resulted in a best solution with a total daily cost of EGP 2,918,100 (excluding the fixed cost of the trucks), allocated between collection and distribution tours as shown, along with other plan results, in Table 3 (all costs in EGP). This plan required a total of 797 trucks (606 regular and 191 refrigerated), where 263 of these trucks were used for both collection and distribution. All trucks started and ended their tours at the hub.

| | Collection | Distribution | Total |
|---|---|---|---|
| Quantity (tons/day) | 8742.3 | 8704.2 | 17446.5 |
| Transportation cost | 652,850 | 1,435,300 | 2,088,150 |
| Spoilage cost | 515,550 | 324,400 | 839,950 |
| Daily plan cost | 1,168,400 | 1,759,700 | 2,928,100 |
| Spoilage percentage (cost-based) | 0.91% | 0.58% | 1.50% |
| Number of tours | 2,585 | 2,583 | 5,168 |
| Distance travelled (km) | 122,450 | 375,970 | 498,420 |
| Cost incurred per kg of products | 0.13 | 0.20 | 0.33 |

Table 3. Collection and distribution plan and costs

Because of the large quantities of products (in supply or demand) compared to the capacities of the trucks, 2,562 tours of the 2,585 collection tours and 2,576 tours of the 2,583 distribution tours, were single-node tours. The details and quantities of products collected and distributed in these single-node tours are shown in Tables 4 and 5, respectively. The routes of the remaining 23 collection and 7 distribution tours are shown in Figures 5 and 6, respectively, using the actual longitude and latitude coordinates of the nodes. It should be noted that Ossim hub is node 1 in the collection and distribution tours. Ossim center is also represented as supply node 10 in the collection tours. It should also be noted that multi-node collection routes 5 and 6, 7 and 8, and 17 and 18, visited the same supply nodes in the same order, but for different product mixes.

| Supply node | Truck type | No. of tours | Products | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 |
| 2 | reg. | 5 | 0 | 0 | 0 | 17.5 | 0 | 0 | 0 | 0 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | reg. | 223 | 0 | 0 | 0 | 0.2 | 403.5 | 376.7 | 0 | 0 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | reg. | 2 | 0 | 0 | 0 | 7 | 0 | 0 | 0 | 0 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | reg. | 20 | 0 | 0 | 0 | 0.2 | 23.1 | 1.5 | 29.3 | 15.9 |
| | ref. | 12 | 33.1 | 2.9 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | reg. | 2 | 0 | 0 | 0 | 7 | 0 | 0 | 0 | 0 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | reg. | 196 | 0 | 0 | 0 | 0.5 | 105.5 | 231.2 | 348 | 0.9 |
| | ref. | 1 | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | reg. | 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 73.5 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | reg. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | ref. | 93 | 279 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 13 | reg. | 33 | 0 | 0 | 0 | 0 | 0 | 54.7 | 55.3 | 5.6 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14 | reg. | 88 | 0 | 0 | 0 | 2.2 | 147.5 | 11.9 | 140 | 6.3 |
| | ref. | 104 | 22 | 290 | 0 | 0 | 0 | 0 | 0 | 0 |
| 15 | reg. | 650 | 0 | 0 | 0 | 0.2 | 1995 | 13.6 | 263 | 2.7 |
| | ref. | 2 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16 | reg. | 194 | 0 | 0 | 0 | 0 | 60.4 | 18.6 | 569 | 31.1 |
| | ref. | 5 | 0 | 15 | 0 | 0 | 0 | 0 | 0 | 0 |
| 17 | reg. | 39 | 0 | 0 | 0 | 0 | 0 | 40.3 | 21.1 | 75.1 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 19 | reg. | 50 | 0 | 0 | 0 | 0.2 | 0 | 121.7 | 51.3 | 0 |
| | ref. | 31 | 93 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | reg. | 447 | 0 | 0 | 40 | 83.3 | 133.3 | 24.8 | 1283 | 0 |
| | ref. | 344 | 1032 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 4. Single-node collection tours

In lieu with the supply and demand percentages mentioned in Section 4.3.1, it can be noticed from Table 4 that more than 55% of the single-node collection tours were dedicated to supply nodes 15 and 20. As for the distribution tours, from Table 5, it can be noticed that more than 62% of the single-node tours were destined for node 6 (Cairo governorate), and more than 24% for node 4 (Giza). As mentioned earlier, single-node tours constituted almost all the collection and distribution routes of the plan, while the multi-node routes, shown in Figures 5 and 6, were just utilized to transport the limited product quantities that remained, especially to/from distant nodes.

| Demand node | Truck type | No. of tours | Products | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 |
| 2 | reg. | 103 | 0 | 0 | 6.6 | 9.2 | 338.7 | 0 | 0 | 6.1 |
| | ref. | 18 | 0 | 51.2 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | reg. | 28 | 0 | 0 | 1.5 | 0 | 96.5 | 0 | 0 | 0 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | reg. | 562 | 0 | 0 | 0 | 0 | 0 | 0 | 1967 | 0 |
| | ref. | 61 | 0 | 0 | 3.8 | 0 | 0 | 0 | 118 | 61.3 |
| 5 | reg. | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | reg. | 1020 | 0 | 0 | 19.3 | 123.1 | 1799 | 907.6 | 653.5 | 67.7 |
| | ref. | 580 | 1471 | 268.1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | reg. | 91 | 0 | 0 | 0 | 0 | 307.3 | 0 | 0 | 10.3 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | reg. | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | reg. | 16 | 0 | 0 | 0 | 0 | 27.9 | 0 | 25.3 | 0.7 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | reg. | 85 | 0 | 0 | 7.9 | 0 | 272.9 | 0 | 0 | 16.7 |
| | ref. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 5. Single-node distribution tours

To maximize the utilization of trucks, the solution not only determined the best routes for the trucks, but it also developed a utilization schedule for each truck that accounted for all its collection and/or distribution tours, the loading/unloading time considering the loading level of each product type at each P/D location and at the hub, and the 30 mins recess time at the hub after the completion of each tour. An excerpt of such schedules for the routes of the trucks utilized in the multi-node distribution tours displayed in Figure 6, is shown in Table 6, including the quantities of products being delivered. The shown schedules represent just a small portion of the day for each of the utilized trucks, where each is assumed to operate a 16 hrs-shift from 08:00 to 24:00. The rest of the shift is assigned to single-node or other multi-node collection or distribution tours.

### 4.4. Analysis and Discussion

For the SCN design problem, two solutions were obtained for managing the annual flow of about 23 million tons of 14 different product types through a network of strategically located aggregation hubs. These transshipment hubs shall be responsible for the collection, processing, packaging, consolidation, and distribution of the products. Solution A featured 41 hubs, and resulted in the minimum total network cost. Solution B on the other hand resulted in a slightly higher total cost, but was associated with the minimum number (32) of hubs. Yet, from both solutions, it can be deduced that the locations and capacities of the established hubs can be associated with the supply emanating from the host rural center and other neighboring centers, and the proximity to densely populated governorates (high demand locations). That is why the majority of hubs, especially large capacity ones, are located in the Nile Valley and the Delta region, owing to the abundance of agricultural lands as well as the high population density in these areas. While the importance of locating the hubs in close proximity to the source farms has been highlighted in terms of reducing the spoilage of products, such proximity can further improve the welfare of small farmers in terms of the easier and wider market access, and the more fair prices it would provide for them.

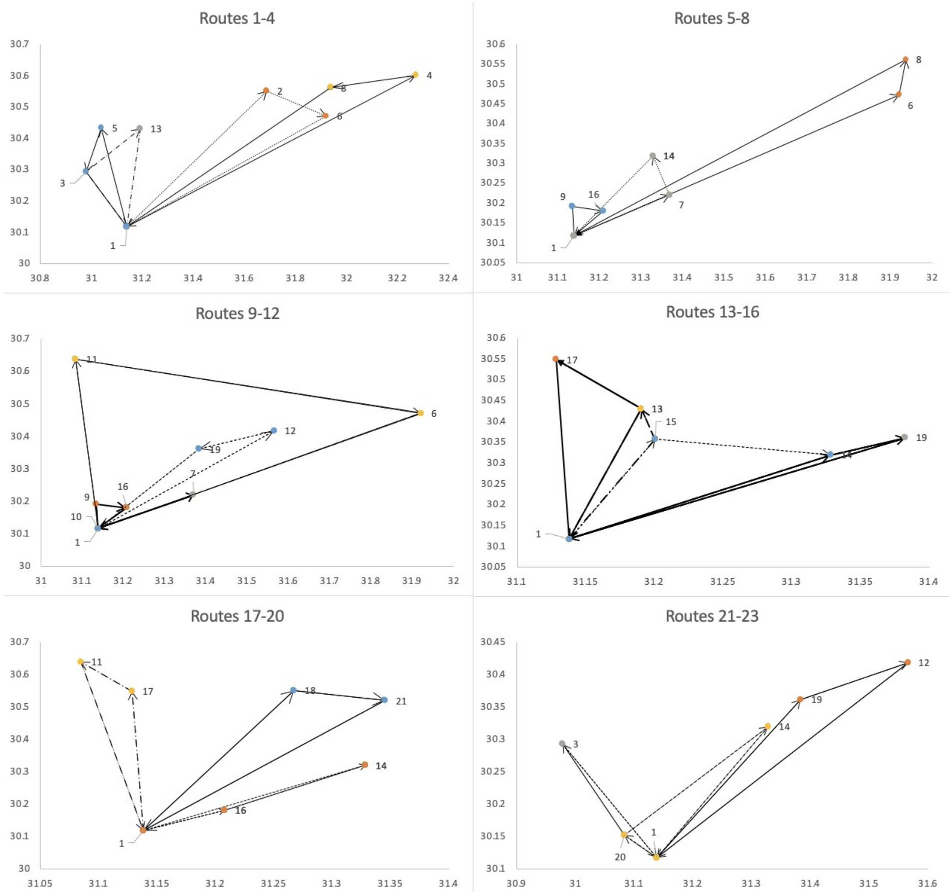


Figure 5. Multi-node collection routes

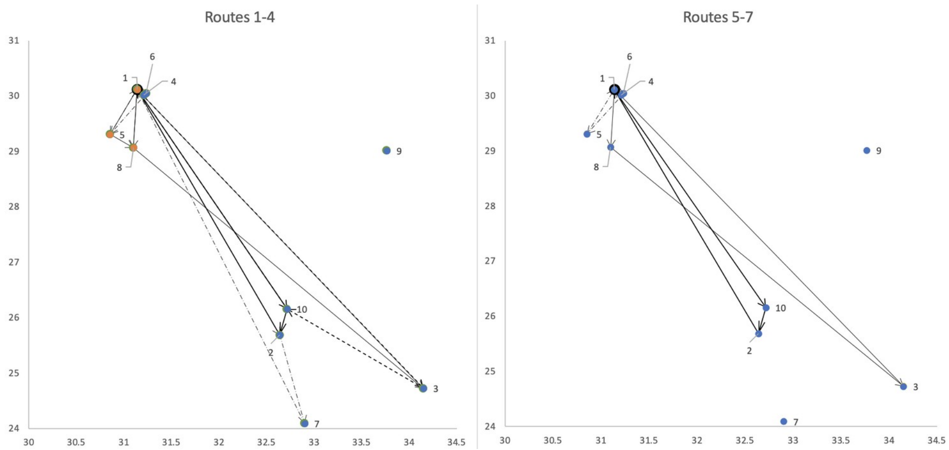


Figure 6. Multi-node distribution routes

| Routes | Schedule | | | | | Products | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 |
| 1 | Nodes | 1 | 2 | 7 | 1 | 0 | 0 | 0 | 0 | 3.5 | 0 | 0 | 0 |
| | Quantity | 0 | 0.65 | 2.85 | 0 | | | | | | | | |
| | Time | 8:17 | 8:56 | 9:13 | 9:23 | | | | | | | | |
| 2 | Nodes | 1 | 3 | 10 | 1 | 0 | 0 | 0 | 0 | 2.0 | 0 | 0 | 1.5 |
| | Quantity | 0 | 2.03 | 1.47 | 0 | | | | | | | | |
| | Time | 12:02 | 12:32 | 12:43 | 12:49 | | | | | | | | |
| 3 | Nodes | 1 | 4 | 6 | 1 | 0 | 0 | 0 | 0 | 0 | 1.9 | 1.6 | 0 |
| | Quantity | 0 | 1.57 | 1.93 | 0 | | | | | | | | |
| | Time | 9:22 | 9:30 | 9:40 | 9:40 | | | | | | | | |
| 4 | Nodes | 1 | 5 | 8 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3.5 |
| | Quantity | 0 | 2.73 | 0.77 | 0 | | | | | | | | |
| | Time | 13:54 | 14:17 | 14:21 | 14:23 | | | | | | | | |
| 5 | Nodes | 1 | 6 | 5 | 1 | 0 | 0 | 0 | 0 | 1.7 | 0 | 0 | 1.8 |
| | Quantity | 0 | 1.74 | 1.76 | 0 | | | | | | | | |
| | Time | 11:32 | 11:59 | 12:09 | 12:10 | | | | | | | | |
| 6 | Nodes | 1 | 8 | 3 | 1 | 0 | 0 | 0.4 | 0 | 0 | 0 | 0 | 3.1 |
| | Quantity | 0 | 0.57 | 2.93 | 0 | | | | | | | | |
| | Time | 9:25 | 9:59 | 10:20 | 10:25 | | | | | | | | |
| 7 | Nodes | 1 | 10 | 2 | 1 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 | 2.7 |
| | Quantity | 0 | 0.81 | 2.69 | 0 | | | | | | | | |
| | Time | 10:53 | 11:30 | 11:45 | 11:52 | | | | | | | | |

Table 6. Schedules of multi-node distribution routes

On the other hand, lightly-populated border governorates, which also offer low fresh produce supply, mostly featured smaller capacity hubs for the collection of the limited supply. Nevertheless, and due to the maximum distance restriction between supply centers and hubs, exceptions can occur. This can be noticed in the large capacity hub located in the New Valley governorate (south-west) in both solutions, because of the large areas of unpopulated lands that have been cultivated in recent years in reclamation projects that made use of water aquifer systems and endorheic lakes.

In addition, and to benefit from the economies of scale, 25-35% of the hubs in both solutions had a capacity of more than 500,000 tons, with 2 and 4 hubs reaching the maximum capacity of 1 million tons in solutions A and B, respectively. This proportion of large hubs could have further increased if the 200 km distance limit between a supply node and a collection hub was relaxed. This however would have consequently increased the amount of pre-processing wasted product.

To manage the collection and distribution operations at each of the established hubs, as an illustration, the hybrid ACO-LS algorithm was utilized to solve the SDVRP for one of the main hubs featured in both solutions A and B; Ossim hub. This solution required 797 trucks to daily collect and distribute about 8,800 tons of eight different product types from 21 source nodes to eight demand locations. 16 hours-shift schedules were built for each truck, where almost all routes were single-node routes due to the limited capacity of the trucks compared to the quantities being transported.

From the results shown in Table 3, it can be noticed that the collection tours had a lower transportation cost (travelled distance) than the distribution ones, which can be attributed to the proximity of the supply areas to the hub when compared to the demand locations, as shown in Figure 4. Yet, the spoilage cost in these shorter collection pre-processing tours was higher than in the distribution tours due to the higher spoilage rates of products in the collection tours. In addition, the product spoilage cost during transit in general accounted for more than 28% of the total logisitcal plan cost, which emphasizes the importance of considering spoilage costs whenever planning for the transportation of such perishable products. This significant spoilage cost could have even been higher if positioning loading constraints were not considered in the problem model and solution.

The above results indicate that, unlike other types of consolidation hubs, which are usually located at central positions between supply and demand nodes, fresh produce aggregation hubs should be located closer to the supply nodes to reduce the spoilage of products. While poor logistical planning typically results in higher product costs in most industries, for fresh produce products and other similar perishables, poor logistical planning results in the loss of the product itself, whose production further relies on very limited resources.

The use of fresh produce aggregation hubs is becoming common practice and has proven success in North America. The adoption of such practice is yet to become a reality in less developed regions of the World, where most of the supply comes from small farms that do not necessarily follow international standards in cultivation and harvesting, let alone distribution. In developing countries like Egypt, there is a huge need for establishing sustainable SCNs for a diversity of industries. With a shortage in fresh and irrigation water supply, and agricultural land that recently increased to only 4% of the total land area, the country cannot afford to lose 30% or more of its fresh produce production due to poor or lack of proper logistics planning. The work proposed in this study is thus intended to complement the current efforts of the Egyptian government in increasing the agricultural land via reclamation projects, and availing more irrigation water using treatment processes, by reducing the amount of waste in fresh produce and efficiently control its flow through the country.

## 5. Conclusions

The work proposed in this study is perhaps the first attempt to establish an efficient fresh produce supply chain network (SCN) in Egypt. The objective of the current effort is hence to manage, control and regulate the flow of fresh produce from the source farms to the markets in a way that reduces the proportion of wasted product during transit, preserves freshness, and potentially increases the exposure of small farms to wider markets, hence increasing the return to farmers and possibly reducing the prices to the final customer.

To reach this goal, this study proposed a two-phase approach to establish and manage a SCN that connects the source farms scattered in all rural areas of Egypt to the end markets, through aggregation hubs strategically located across the country. The first phase entailed solving a dynamic facility location-allocation (FLA) problem to determine the best locations and flow allocations to/from, and capacities of the aggregation hubs through the different harvesting seasons. The problem was formulated as a dynamic FLA model that considered the three harvesting seasons in Egypt, and accounted for the perishability of products during transit and economies of scale, with the objective of minimizing the total cost of establishing the hubs, transportation, processing of products, and spoilage (before and after processing). Because of the hardness of the problem, a hybrid binary particle swarm optimization (BPSO) algorithm was developed to solve the problem. Two solutions were retained for the problem; the one with the minimum total cost, and that with the minimum number of established hubs. Analysis of the solutions emphasized the strong correlation between the geographical locations and capacities of the established hubs, and the proximity to supply points and densely populated demand areas.

The objective of the second phase was to determine the size and type (regular or refrigerated) of the required transportation fleet, along with the best operational schedules and routes of each truck. For that purpose, and based on the flow allocations determined in the first phase, and with each hub acting as a central cross-docking depot, the split-delivery vehicle routing problem (SDVRP) problem was modelled and solved using a hybrid ant colony optimization – local search (ACO-LS) algorithm. The solution accounted for spoilage rates of products that differed in the collection and distribution tours, and further depended on the type of truck utilized (regular or refrigerated). In addition, positioning loading constraints were imposed during loading and unloading of products and accounted for while constructing the best routes and operational schedules of each truck. While such a solution needs to be obtained for each hub, the problem was solved for one selected hub only during one harvesting season as an illustration. The solution revealed the significance of accounting for spoilage of products when solving the routing problem, as the spoilage cost amounted to more than 28% of the total operational cost.

Limitations of the current work included the dependency on available data, which in some cases dated back to 2016. If adopted and applied in reality on the national level, more recent data should be utilized upon availability, to reflect the most updated needs in the intended SCN. In addition, the supply of fresh produce relies on uncertain factors like weather and market conditions, availability of irrigation water and other cultivation resources. Accordingly, assuming a deterministic and steady supply of fresh produce is another limitation in the developed models, and stochastic models that address such uncertainties should be considered in future works that tackle the current problem.

The current work can be further extended by studying the economic effects of establishing such a SCN on the farm owners and the market prices of the products. In addition, the economic viability of establishing the hubs, along with its operational resources, should be studied to investigate the investment potential of the private sector in this arena. The sustainability of the SCN is another aspect of the problem that could be studied in upcoming works. The effect of establishing and operating such a national SCN on the environment, like the resulting carbon emissions, should be evaluated and compared to the current practice. In addition, and due to the mentioned uncertainty in product supply, maximizing the responsiveness and resilience of such a SCN should be addressed.

## Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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