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Innovative Applications of O.R.

Formulation and solution technique for agricultural waste collection and transport network design

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ABSTRACT

Agricultural waste management in developing countries has become a challenging issue for rural planners due to the lack of an efficient planning tool. In the countries, farmers burnt agricultural waste at fields after each harvesting season to solve the issue. As a result, it has caused air and water pollution in the rural areas of the countries. In this paper, we present a mixed-integer nonlinear programming model for agricultural waste collection and transport network design that aims to stop burning waste and use the waste to produce bio-organic fertilizer. The model supports rural planners to optimally locate waste storages, and to determine the optimal set of routes for a fleet of vehicles to collect and transport the waste from the storages to the bio-organic fertilizer production facility. In the novel location-assignment-routing problem, the overall objective is to minimize total cost of locating storages, collecting waste from fields and planning vehicle routes. A solution technique is developed to linearise the mixed-integer nonlinear programming model into a model in linear form. In addition, a parallel water flow algorithm is developed to solve efficiently the large-sized instances. The efficiency of the proposed model and algorithm is validated and evaluated on the real case study in Trieu Phong district, Quang Tri province, Vietnam, as well as a set of randomly generated large-sized instances. The results show that our solution approach outperforms the general optimisation solver and tabu search algorithm. Our algorithm can find the optimal or near-optimal solutions for the large-sized instances within a reasonable time.

1. Introduction

In developing countries, agricultural sectors have rapidly developed to become major contributions to the growth of national economy. Accompanying the development, however, agricultural waste management has posed a challenge for rural planners due to the lack of an efficient planning tool. In 2019, for example, Vietnam' s agricultural export revenue achieved US$15.25 billion (Minstry of Agriculture & Rural Development of Vietnam, 2019). The consequence of the achievement is that the country needs to deal with the huge amount of agricultural waste, approximately 76 million tons including 45.22 million tons of rice straw, 8.73 million tons of rice husk, 4.04 million tons of sugarcane bagasse, 6.33 million tons of maize by-products, 1 million tons of coffee shell and 10 million tons of vegetable by-products (Pham, Ngo, & Dao, 2019). Burning the agricultural waste at fields after each harvesting season is the present solution at the country (see Fig. 1). This solution has increasingly caused air and water pollution in rural areas of the country. Hence, there is an urgent need of innovative solution approaches for dealing with the challenge.

Bio-organic fertilizer production from agricultural waste (Pham et al., 2019) is studied and considered as a potential solution to stop the countries' waste burning and create organic products towards United Nation's Sustainable Development Goals (SDGs) (United Nations, 2022) such as SDG9 - Industry, Innovation and Infrastructure, SDG12 - Responsible Consumption and Production and SDG13 - Climate Action. The organic agriculture approach has become a trend worldwide and is developing rapidly in the world to support the developing countries in a sustainable agricultural waste management. Besides that technology development for bio-organic fertilizer production, agricultural waste collection and transport network design from fields to the production facility is also an important problem to ensure the success of the organic agriculture approach. The efficient waste collection and transport network can provide fully the input materials of the bio-organic

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Fig. 1. The current solution for agricultural waste at developing countries. *Source:* https://moitruong.net.vn (left), https://btnmt.1cdn.vn (top right), https://kinhtedothi.vn (bottom right).

fertilizer production and avoid any production disruption risk due to material shortage.

In this paper, we propose a proof-of-concept planning model for rural planners to design an efficient agricultural waste collection and transport network. The model can determine the optimal storage locations for collecting agricultural waste from fields (i.e., since rural road network is not convenient for trucks to collect waste, farmers directly transport waste from fields to storages by farm vehicles) and seek the optimal set of routes for a fleet of vehicles to collect and transport the waste from the storages to the facility. This is an extension of the well-known location-routing problems (LRPs) (Mara, Kuo, & Asih, 2021). Unlike the LRPs in which only facility location and vehicle routing are studied, agricultural waste collection and transport network design investigates storage location, vehicle routing from the storages to the facility, and assignment of storages to fields for waste collection. This problem is referred to as the location-assignment-routing problem (LARP). The objective of the LARP is to minimize total cost of locating waste storages, collecting waste from fields to storages, and routing vehicles for transporting waste from storages to the facility. A mixed-integer nonlinear programming model (MINLP) for this problem is formulated. The MINLP is linearised so that it can be solved using a general purpose solver. A parallel water flow algorithm (PWFA) is developed to solve the large-sized instances within a reasonable computation time. The linearised model and algorithm are validated and evaluated in the case study of agricultural waste collection and transport network design at Trieu Phong district, Quang Tri province, Vietnam. In addition, a set of large-sized instances is randomly generated to evaluate the performance of PWFA, and to make a comparison between our algorithm and tabu search algorithm.

The remaining of this paper is organized as follows. A literature review of LRPs is presented in Section 2. Sections 3 and 4 describe the mathematical programming models and the PWFA, respectively. Section 5 is the case study and the experimental results of solving the case study and the large-sized instances by the model and algorithms. Finally, Section 6 provides the conclusion and future works.

2. Literature review

In logistics, facility location and vehicle routing are known as two of the most important optimisation problems. These problems are often studied separately. A study of interdependence between two optimisation problems was started in 1989 (Salhi & Rand, 1989). Since then, the continuous research of the integrated approach of these problems is done, known as LRP. A literature review of the LRP and its variants over the past few years has been done and reported in Mara et al. (2021). This study draws the state-of-the-art of LRP research and its applications.

The authors studied two main characteristics of LRPs such as:

- *Problem scenario:* data, planning period, objective, generalised customer, prize collecting, load splitting, backhaul, inventory decision, time window structure, vehicle usage, and open trip;
- *Physical characteristics:* echelon, location of facilities, routing, product or service, vehicle homogeneity, capacity consideration, inter-facility transport, and intra-route facilities.

The characteristics are related to strategic, tactical and operational decisions in the LRPs, for example, problem scenario (i.e., strategic and tactical decisions) and physical characteristics (i.e., strategic and operational decisions). Based on the different characteristics, various modelling and solution approaches have been developed to adopt with the specific problems.

The study pointed out that the knowledge gap between academic and practitioners in LRP has been gradually eliminated when the application of LRP model in real-life case studies has increased. Application areas of LRP case studies consist of agriculture, airline, automotive logistics, city logistics, defence and military, e-commerce, electric vehicles, emergency and disaster management, food distribution, healthcare logistics, oil and energy, postal delivery, railroad, telecommunication, underground logistics system, unmanned aerial vehicles, and waste management. The following literature review concentrates in three main streams: applications of LRP for waste management or agriculture, and related location-inventory-routing problem (LIRP).

2.1. Application of LRP for waste management

In municipal solid waste management, a mixed-integer programming model of the LRP is formulated to locate the facilities (e.g., transfer stations, treatment, recycling and disposal centers) from the site candidates and determine the routes and amounts of shipments among the selected facility locations to minimize the total cost of transportation and facility establishment (Hossein, Samsung, & Mojtaba, 2015). A simulated annealing algorithm is adapted to solve efficiently the large-sized instances for the integrated municipal solid waste LRP (Asefi, Lim, & Maghrebi, 2017). A hybridisation of variable neighbourhood search and simulated annealing for exploring the feasible solution space and overcoming the traps of local optimums is developed to improve the algorithm's performance (Asefi, Lim, Maghrebi, & Shahparvari, 2019).

In obnoxious waste management (i.e., wastes generated by dry cleaners, auto repair shops, exterminators, chemical manufacturers, and oil refineries), a multi-objective LRP model is developed to minimise the treatment and disposal facility undesirability, different related costs, and the risk associated with transportation of untreated materials (Nasrin, Mohsen, Masoumeh, Maryam, & Zanjirani, 2016). A memetic algorithm that uses a tabu search in the local search phase is developed to solve the multi-objective optimisation problem.

In hazardous waste management (i.e., medical and industrial wastes) in which energy recovery from waste and polluter pays principle are considered, a profit-oriented mixed-integer programming model is proposed to determine the locations and numbers of recycling, incineration, sterilization, interim storage and disposal centers, and plan the vehicle routes for transferring various types of hazardous waste and waste residues among these centers from the perspective of environmental protection (Aydemir-Karadag, 2018). Ghezavati & Morakabatchian (2015) developed a multi-objective location-routing model for solving a real case study of Petrochemical Special Economic Zone in Khuzestan, Iran. This model can determine the optimal locations of suitable treatment, recycling and disposal centers, and the optimal routes for transporting of different types of industrial wastes between the centers. Two objective functions are to minimize total costs of transportation and establishment of the centers and total transportation and site risks. In addition, they consider fuzzy customer satisfaction level for the waste collection system. Hu, Li, Zhang, Shang, & Zhang (2019) investigated the constraint of traffic restrictions in inter-city roads for hazardous material logistics, and proposed an adaptive weight genetic algorithm for solving the problem in which multiple paths between every possible origin-destination pair are allowed. A real-world case study was constructed to demonstrate the efficacy of the proposed model and solution method.

In used oil management, Zhao & Verter (2015) presented a bi-objective LRP model to minimize the total environmental risk and the total cost. They applied a modified weighted goal programming approach to deal with this problem. The model is applied in Chongqing of Southwest China. Renan, Koc, & Bektas (2016) studied a multi-period LRP for the collection of Olive Oil Mill Wastewater to the treatment facilities by using a fleet of vehicles. This study aims to reduce potential contamination impact on environment due to disposal of wastewater into soil or rivers. They proposed an adaptive large neighbourhood search metaheuristic for solving this problem, and constructed a case study to evaluate the algorithm.

Another application of LRP in waste management can be encountered in glass recycling (Rahim & Sepil, 2014) in which a combination of maximal covering location problem and selective traveling salesman problem is studied to determine the location of bottle banks and the route of a collecting vehicle visiting a number of customers and the bottle banks. A nested heuristic procedure was proposed to solve the problem. Sheriff, Nachiappan, & Min (2014) studied a plastic recycling industry in Southern India to cope with the problem of picking up recyclable plastic bottles using private collecting agents, transferring those bottles to the initial collection points, and then transshipping and consolidating them at the centralized return centers for final shipments to the processing centers where these bottles were treated for recycling. The main contribution of this study includes the simultaneous consideration of location, allocation, and routing decisions. In addition, it first considers incentive payments, the quality level of products, and multiple types of products. Sakti, Yu, & Sopha (2018) applied the LRP to the design of a waste supply chain network in the Special Region of Yogyakarta, Indonesia. The model studied two types of fleets to determine depot locations, waste-based power plant locations, service allocations, and associated routes.

In addition, integration of inventory into LRP in waste management is considered in some research works. For example, Lerhlaly, Lebbar, Allaoui, Ouazar, & Afifi (2016) studied the optimisation of operating costs, risks and routing's CO_2 emissions in Hazmat supply chain. The study aims to determine the location of capacitated depots, the allocation of customers to depots, the quantities from these depots to customers per period, and the vehicle routes. An exact bi-objective model is developed for solving the small-and-medium-sized problem. The model is tested on a case study to demonstrate its industrial practicality. Zhalechian, Tavakkoli-Moghaddam, Zahiri, & Mohammadi (2016) studied environmental impacts of CO_2 emissions, fuel consumption, wasted energy, and social impacts of created job opportunities and economic development on a closed-loop location-routing-inventory supply chain network design under mixed uncertainty. A stochastic-possibilistic programming approach was applied to cope with the uncertainty and a hybrid meta-heuristic algorithm was developed to solve the problem efficiently. The applicability of model and algorithm was demonstrated in a real case study. Yuchi, He, Yang, & Wang (2016) introduced a new location-inventory-routing problem in forward and reverse logistic network design. The problem considers simultaneously decisions of distribution centers location, their inventory policies, and vehicle routes in serving customers such that minimisation of the total costs of manufacturing and remanufacturing goods, building distribution centers, shipping, distributing, ordering and storage costs of goods. A nonlinear integer programming model was developed to formulate the problem. A new tabu search algorithm was proposed to solve the problem. Zhao & Ke (2017) studied impact of inventory risks on location and routing decisions in explosive waste management. An optimization model was developed to simultaneously minimize total cost and risk. The model locates the collection centers, manages the inventory level for each center, determines the number of vehicles to be purchased, finding the optimal routes for transporting explosive wastes from generation nodes to collection centers, and from collection centers to recycling centers. A case study in Nanchuan of Southwest China was used to test and evaluate the performance of this model.

2.2. Application of LRP in agriculture

There are some recent applications of LRP in agriculture. For example, Chen, Qiu, & Hu (2018) investigated the LRP with full truckloads for low-carbon supply chain network design. A bi-objective optimisation model is developed to determine the number and locations of facilities and optimise the flows among different types of nodes and truck routes such that total cost and environmental effects are simultaneously minimised. A multi-objective hybrid approach based on the combination of genetic algorithm and tabu search, is proposed to solve this problem. They applied the model for the regional timber supply network design in Jiangle county, Fujian province, China. Akararungruangkul & Kaewman (2018) investigated the special case of the LRP in which fuel consumption depends on the distance of travel and the condition of the road. They customised the model for the rubber field industry in Nakorn Panom province, Thailand.

2.3. Other LIRP applications

Considering simultaneously three decision variables (location, inventory and routing) has also been studied and applied in a range of fields. Ambrosino & Grazia Scutella (2005) was known as the first researchers that combined three decision variables of warehouse location, inventory management and route planning into distribution network design problem. Two kinds of mathematical programming formulations were proposed for the integrated network design, together with a proof of their correctness. Ahmadi-Javid & Seddighi (2012) built a ternary-integration MINLP model for the LIRP in a multi-source supply chain and developed a three-phase heuristic algorithm for solving efficiently the large-sized instances. Guerrero, Prodhon, Velasco, & Amaya (2013) introduced a 5-index mixed-integer linear programming (MILP) model for the LIRP over a discrete time planning horizon, and proposed a hybrid method, embedding an exact approach within a heuristic scheme, to solve the problem. Zhang, Qi, Miao, & Liu (2014) formulated a 4-index MILP model to address long-term replenishment strategies, in which a smart representation of inventory cost is used to reduce computational complexity. In addition, the authors proposed a hybrid metaheuristic algorithm consisting of initialization, intensification and post-optimization to solve the large-sized instances. Ghorbani & Akbari Jokar (2016) investigated a multi-product multi-source LIRP with backlogging policy for the split-souring of products, and developed a hybrid heuristic algorithm based on the simulated annealing and imperialist competitive algorithm to solve the problem. Hiassat, Diabat, & Rahwan (2017) developed a 3-index MILP model for the multi-period LIRP with perishable products, and applied a genetic algorithm with a novel chromosome representation for finding good solutions within a reasonable computational time. Zheng, Yin, & Zhang (2019) studied the integrated LIRP model with the limited number of customers in a route and restrictions on service radius, reformulated it as a 4-index mixed-integer convex program with nonlinear objective function, and developed an exact algorithm based on Generalized Benders Decomposition method for solving the reformulated model. Wu, Zhou, Lin, Xie, & Jin (2021) built a multi-period multi-echelon LIRP model with time windows and fuel consumption in which the replenishment is considered and the stock-out situation is allowed. The authors proposed a two-stage hybrid metaheuristic algorithm for solving the problem, in which a customized genetic algorithm is used in the first stage, and a gradient descent algorithm is applied in the second stage for the inventory decision improvement in reducing the total cost.

Recently, Shang, Zhang, Jia, & Almanaseer (2022) studied the LIRP model for a healthcare supply system with multiple products, multiple periods and multi-type delivery. In the model, some potential warehouses are selected as vendor managed inventory (VMI) warehouse locations, and products are delivered to VMI warehouses by bulk delivery to hospitals through direct shipping. The authors proposed a deterministic MILP model for the integrated LIRP, and a robust optimisation model (which is transformed into a tractable linear equivalent formulation) for solving the problem under uncertain demand. In addition, a new robust optimisation model was developed to consider the effect of COVID-19 pandemic on the demand and delivery time.

For environmental context, Ji, Ji, Ji, & Liu (2022) studied the sustainable combined location-inventory-routing problem (CLIRP) for a garment chain enterprise, in which the objective function is to minimise logistics costs and emission simultaneously. The authors proposed a two-stage solution method where a heuristic algorithm finds the initial solution, and a hybrid heuristic algorithm between tabu search and simulated annealing is applied to search for the global near-optimal solution. Lv & Sun (2022) developed a multi-objective mixed-integer programming (MIP) model for the CLIRP in auto parts supply logistics to minimise the total system cost and carbon emissions while concerning multi-period production demand. A robust optimisation model is proposed to deal with the problem under uncertain demand. Nasiri, Mousavi, & Nosrati-Abarghooee (2023) studied a green LIRP with simultaneous pickup and delivery under disruption risks. The model is to minimise lost demands, and the network's total costs are considered budget constraints. A scenario-based approach is applied to deal with the demand uncertainty and risks caused by the centers' capacity disruptions.

Wang & Nie (2023) introduced a path-based LIRP model for a dynamic last-mile emergency supply distribution plan, including a local distribution center, points of distribution, and demand points. In the model, both cost and equity are considered into the objective function to ensure that distribution of emergency supplies is cost-efficient and fair. The model outperforms different comparison models as applying for a case study of the flooded Red Hook neighborhood in New York City during Hurricane Sandy.

Table 1 provides a summary of these recent works for LRP in waste management and agriculture, as well as related LIRP under a classification of real-world application, single/multi-objective function, type of decision variable, and solution method. We observe four types of decision variables in the LRP such as location, routing, assignment and inventory. Unlike the allocation of customers to depots/facilities via vehicle routes that is included in routing decisions, allocation (i.e., assignment) decisions which we consider in this paper are similar to the assignment of customers to facilities in a facility location problem (Tran, Scaparra, & OHánley, 2017). From the literature review, therefore, Sheriff et al. (2014) is the most relevant work to our studying LARP. However, their model specialises for the optimisation problem in the plastic recycling industry, and is challenge to extend for dealing with other areas. The main difference between the LARP and the problem of Sheriff et al. (2014) is that Sheriff et al. (2014) studied the problem of picking up recyclable plastic bottles, transferring the bottles to the initial collection points (ICPs), and then transshipping and consolidating them at the centralized return centres (CRCs) for final shipments to the recycling centres. This problem thus combines the LRP with the balanced allocation problem in the closed-loop supply chain network. In other words, the authors consider simultaneously location decisions of ICPs and CRCs for allocation of pick-up points to ICPs, as well as allocation of ICPs to CRCs, and routing decisions at ICPs and CRCs level. Again, the allocation decisions are to find optimal vehicle routes to collect and transport plastic bottles to ICPs, CRCs and the recycling centres.

It can be seen that the LRP application for agricultural waste management has not been investigated fully. Hence, this paper aims to enhance the LRP application for agricultural waste collection and transport network design in efficient waste management. The main contributions of this paper include:

Table 1
A summary of various LRP applications in agriculture and/or waste management.

Reference	Application	Objective	Decision* L	R	A	I	Solution method
Rahim & Sepil (2014)	Glass recycling	Single	x	x			Nested heuristic algorithm
Sheriff et al. (2014)	Plastic recycling	Single	x	x	x		MILP
Hossein et al. (2015)	Municipal solid waste	Single	x	x			MIP
Ghezavati & Morakabatchian (2015)	Hazardous waste	Multiple	x	x			Fuzzy service level constraint programming
Zhao & Verter (2015)	Used oil	Multiple	x	x			Modified weighted goal programming
Nasrin et al. (2016)	Obnoxious waste	Multiple	x	x			Combination of memetic algorithm and tabu search
Lerhlaly et al. (2016)	Drinking water distribution	Multiple	x	x		x	Exact bi-objective model
Renan et al. (2016)	Olive oil mill wastewater	Single	x	x			Adaptive large neighbourhood search meta-heuristic
Zhalechian et al. (2016)	Closed-loop supply chain	Multiple	x	x		x	Stochastic-possibilistic programming, meta-heuristic
Asefi et al. (2017)	Municipal solid waste	Single	x	x			Simulated annealing
Zhao & Ke (2017)	Explosive waste	Multiple	x	x		x	TOPSIS method
Aydemir-Karadag (2018)	Hazardous waste	Single	x	x			Profit-oriented mixed-integer programming
Sakti et al. (2018)	Waste supply chain	Single	x	x			Mathematical model and greedy algorithm
Asefi et al. (2019)	Municipal solid waste	Single	x	x			Variable neighbourhood search, simulated annealing
Hu et al. (2019)	Hazardous material logistic	Single	x	x			Adaptive weight genetic algorithm
Yuchi, Wang, He, & Chen (2021)	Forward and reverse logistic	Single	x	x		x	Tabu search
Akararungruangkul & Kaewman (2018)	Rubber field	Single	x	x			Modified differential evolution algorithm
Chen et al. (2018)	Timber supply chain	Multiple	x	x			Multi-objective hybrid approach
Shang et al. (2022)	Healthcare supply system	Single	x	x		x	MILP, robust optimisation
Ji et al. (2022)	Garment chain enterprise	Single	x	x		x	Tabu search and simulated annealing
Lv & Sun (2022)	Auto parts supply logistic	Multiple	x	x		x	Robust optimisation
Nasiri et al. (2023)	Green logistic	Single	x	x		x	Scenario-based approach
Wang & Nie (2023)	Emergency supply distribution	Single	x	x		x	MILP
This paper	Agricultural waste	Single	x	x	x		MINLP, linearise model, PWFA

*Note that L = Location, R = Routing, A = Assignment, and I = Inventory.

- Formulating a MINLP for the LARP in agricultural waste management.
- Applying a linearisation technique to transform the MINLP into a linear form that can be solved by any optimisation solver.
- Developing a PWFA for efficiently solving the large-sized instances of LARP.
- Applying the model and algorithm for solving a real case study in Trieu Phong district, Quang Tri province, Vietnam.

3. Agricultural waste collection and transport network design

In this section, we describe the LARP for agricultural waste collection and transport network design. Notations for modelling the problem in mathematical form are presented. A MINLP is formulated to solve the problem, and its linearised form is provided.

3.1. Location-assignment-routing problem

Fig. 2 is an example of the LARP for agricultural waste collection and transport network design. There is only one production facility (and this facility is already located), but many temporary waste storages considered in the LARP. In the problem, a set of temporary waste storages are located to collect and store agricultural waste from the fields. Each field is assigned to only one storage. The assignment depends on the distance between field and storage, the demand of field, and the capacity of storage. The phase of location and assignment in the LARP is similar as the capacitated facility location problem (CFLP) (Tran et al., 2017) in which minimisation of total location-assignment cost is concerned. While seeking the optimal set of storage locations for the minimisation of total cost, we simultaneously consider minimisation of total vehicle routing cost to collect agricultural waste from the storages to the facility. Total cost consists of fixed cost of using vehicle and transport cost. Assume that the fleet of vehicles have the same capacity. We need to determine the optimal number of vehicles used to transport the waste to the facility. In the LARP, the phase of collecting waste from storages to the facility is similar as the capacitated vehicle routing problem (CVRP) (Toth & Vigo, 2002).

The CFLP and CVRP are studied and widely applied for real-world. However, the integration of these two problems for agricultural waste collection and transport network design has not been investigated. We can solve separately sequentially each optimisation problem to find a solution for the LARP. It is likely not the global optimal solution. In the paper, we thus propose an integrated formulation for both optimisation problems to solve the LARP. Next, we present mathematical notations that are used to formulate the LARP. The forms of MINLP and MILP are described in the next subsections.

3.2. Mathematical notations

Table 2 presents the mathematical notations in the formulations of LARP. The notations include sets and indexes, parameters, and decision variables that are used in the MINLP and MILP.

With the mathematical notations, the location-assignment-routing problem can be described as follow. To collect all the agricultural waste from fields, a number of storages are opened from the set of site candidates J (where m is the number of sites) to serve a set of agricultural waste fields I (where n is the number of the fields). For each field i, d_i represents amount of waste to be collected. A fixed cost to open storage j is f_j,and its capacity is q_j. To transport the waste from storages to the facility **0**, a set of vehicles are routed to collect the waste. Given k is a number of vehicles, and Q is the capacity of a vehicle. Distance between node i and node j (or node u and node v) is denoted by c_{ij} (or c_{uv}) where node represents a storage or the facility (J_0 is a set of storages and the facility). Decision variables X_j,Y_{ij} and Z_{uv} represent open/close storage location, assignment between field and storage, and route between nodes. Auxiliary variables T_u and T_v are used for sub-tour elimination constraint in the routing problem. They can be known as the load in a truck when this truck arrives at nodes u and v, respectively.

3.3. Mixed-integer nonlinear programming model

A mathematical programming model is formulated to solve the LARP for determining optimal storage locations, assignments of

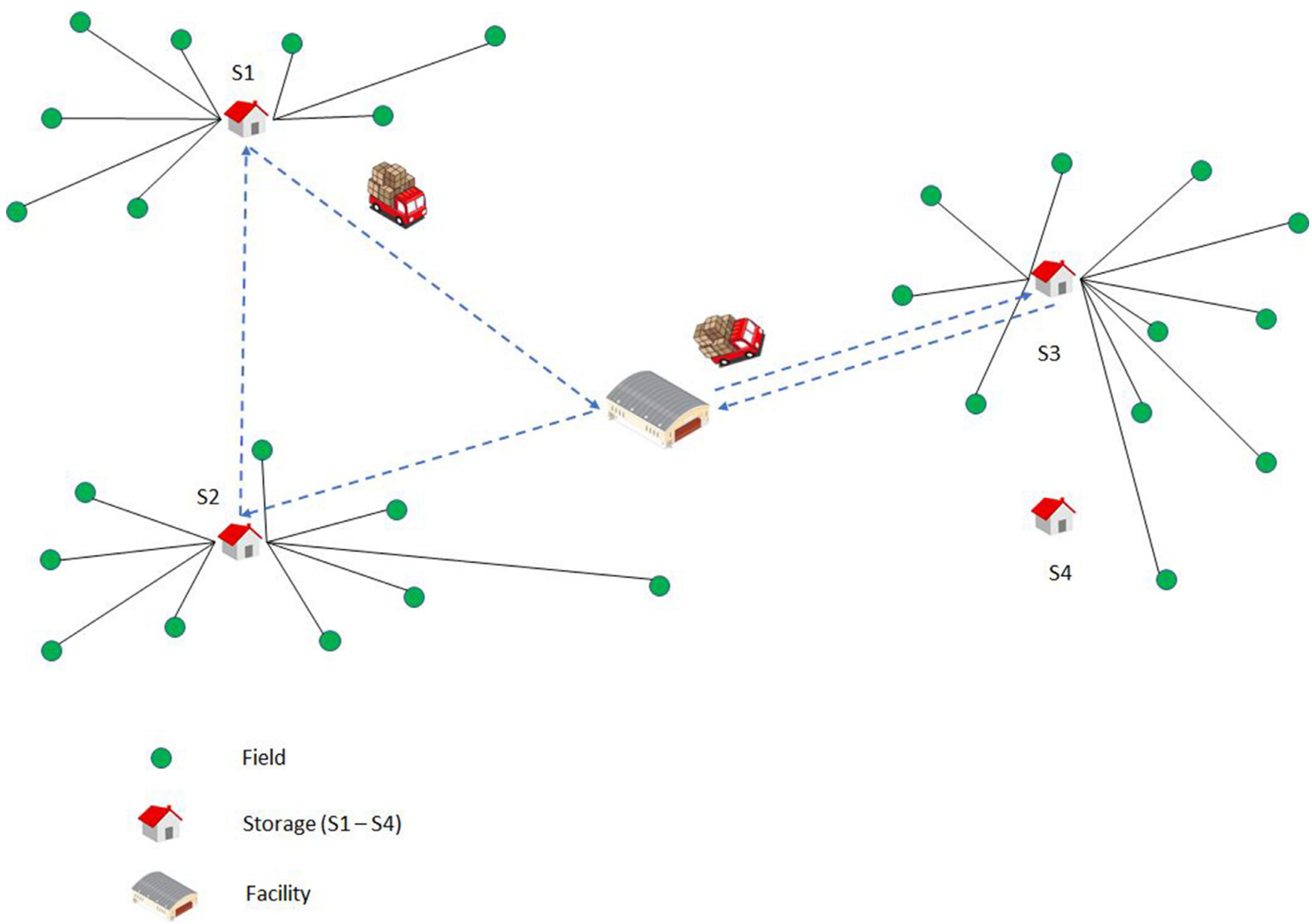

Fig. 2. An example of LARP.

Table 2
The list of notations.

Notation	Description
Sets and indexes:	
I	Set of agricultural waste fields (indexed by i)
J	Set of storages (indexed by j)
$\mathbf{0}$	Index of the facility that produces bio-organic fertilizer from waste
$J_\mathbf{0}$	Set of storages and the facility, i.e., $J_\mathbf{0} = J \cup \{\mathbf{0}\}$ (indexed by u, v)
Parameters:	
n	Number of agricultural waste fields
m	Number of storages
f_j	Fixed cost to open storage j
c_{ij}, c_{uv}	Distance between node i and node j, distance between node u and node v
d_i	Amount of agricultural waste to be collected at field i
q_j	Capacity of storage j
k	Number of vehicles
Q	Capacity of vehicle
Decision variables:	
$X_j = \begin{cases} 1 & \text{if a storage is located at site } j \\ 0 & \text{otherwise} \end{cases}$	
$Y_{ij} = \begin{cases} 1 & \text{if field } i \text{ is served by storage } j \\ 0 & \text{otherwise} \end{cases}$	
$Z_{uv} = \begin{cases} 1 & \text{if a vehicle travels from node } u \text{ to node } v \\ 0 & \text{otherwise} \end{cases}$	
T_u, T_v	Auxiliary variables for sub-tour elimination constraint

field and storage, and vehicle routes for collecting and transporting agricultural waste from storages to the facility.

[LARP-NP]:

$$\min \sum_{j\in J} f_j X_j + \sum_{i\in I}\sum_{j\in J} c_{ij} d_i Y_{ij} + \sum_{u\in J_\mathbf{0}} \sum_{v\in J_\mathbf{0}:v\neq u} c_{uv} Z_{uv} \tag{1}$$

$$\text{s.t.: } \textstyle\sum_{j\in J} Y_{ij} = 1, \ \forall i \in I, \tag{2}$$

$$\sum_{i\in I} d_i Y_{ij} \le q_j X_j, \ \ j \in J, \tag{3}$$

$$\sum_{u\in J} Z_{u\mathbf{0}} = k, \tag{4}$$

$$\sum_{v\in J} Z_{\mathbf{0}v} = k, \tag{5}$$

$$\sum_{u\in J_\mathbf{0}:u\neq v} X_u Z_{uv} = X_v, \ \ \forall v \in J, \tag{6}$$

$$\sum_{v\in J_\mathbf{0}:v\neq u} X_v Z_{uv} = X_u, \ \ \forall u \in J, \tag{7}$$

$$T_u - T_v + Q Z_{uv} \le Q - \frac{1}{k}\sum_{i\in I} d_i Y_{iv}, \ \ \forall u, v \in J : u \neq v, \tag{8}$$

$$\frac{1}{k}\sum_{i\in I} d_i Y_{iu} \le T_u \le Q, \ \ \forall u \in J, \tag{9}$$

$$X_j \in \{0, 1\}, \ \ \forall j \in J, \tag{10}$$

$$Y_{ij} \ge 0, \ \ \forall i \in I, j \in J, \tag{11}$$

$$Z_{uv} \in \{0, 1\}, \ \ \forall u, v \in J_\mathbf{0} : u \neq v, \tag{12}$$

$$T_u \ge 0, \ \ \forall u \in J. \tag{13}$$

In this model, the objective function (1) aims to minimise total cost that includes cost of storage location ($\sum_{j\in J} f_j X_j$), cost for collecting waste from fields to storages ($\sum_{i\in I}\sum_{j\in J} c_{ij} d_i Y_{ij}$), and cost for transporting waste from storages to the facility ($\sum_{u\in J_\mathbf{0}}\sum_{v\in J_\mathbf{0}:v\neq u} c_{uv} Z_{uv}$). Since the transportation cost for collecting and transporting waste is proportional to the travelling distance, and the fuel unit cost is dynamic, the model directly uses the travelling distance in the objective function. Constraints (2) ensure that each field is served by one storage. Constraints (3) ensure that fields are assigned to only opening storages and total demand at fields is less than the capacity of storage that they are assigned. Constraints (4) and (5) ensure that the number of vehicles k travel out and back the same facility. Constraints (6) and (7) are the updated conservative constraints that aim to allow one and only one vehicle traveling in and out the opening storage. Constraints (8) and (9) are to avoid the sub-contours of vehicles and ensure that the amount of collected waste are not greater than the capacity of vehicle. Constraints (10)–(13) are binary and non-negative decision variables.

There exist nonlinear terms in constraints (6) and (7). Therefore, this is a MINLP model that cannot be easily solved by general optimisation solvers (e.g., CPLEX). We need to apply a linearisation technique to transform the MINLP model into a linear form for solving it by the solvers.

3.4. Mixed-integer linear programming model

To linearise the nonlinear terms in the MINLP, we applied a well-known linearisation technique for product variables. Let $W_{uv} = X_u Z_{uv}$ and $W'_{uv} = X_v Z_{uv}, \forall u, v \in J_\mathbf{0} : u \neq v$, then constraints (6) and (7) can respectively be written as

$$\begin{aligned} &\sum_{u\in J_\mathbf{0}:u\neq v} W_{uv} = X_v, \ \ \forall v \in J, \\ &W_{uv} \le X_u, \ \ \forall u, v \in J_\mathbf{0} : u \neq v, \\ &W_{uv} \le Z_{uv}, \ \ \forall u, v \in J_\mathbf{0} : u \neq v, \\ &W_{uv} \ge X_u + Z_{uv} - 1, \ \ \forall u, v \in J_\mathbf{0} : u \neq v, \end{aligned} \tag{14}$$

$$\begin{aligned} &\sum_{v\in J_\mathbf{0}:v\neq u} W'_{uv} = X_u, \ \ \forall u \in J, \\ &W'_{uv} \le X_v, \ \ \forall u, v \in J_\mathbf{0} : u \neq v, \\ &W'_{uv} \le Z_{uv}, \ \ \forall u, v \in J_\mathbf{0} : u \neq v, \\ &W'_{uv} \ge X_v + Z_{uv} - 1, \ \ \forall u, v \in J_\mathbf{0} : u \neq v. \end{aligned} \tag{15}$$

Constraints (14) and (15) are linear. The LARP in a linear form can then be presented by

[LARP-LP]:

$$\min \sum_{j\in J} f_j X_j + \sum_{i\in I}\sum_{j\in J} c_{ij} d_i Y_{ij} + \sum_{u\in J_\mathbf{0}} \sum_{v\in J_\mathbf{0}:v\neq u} c_{uv} Z_{uv} \tag{16}$$

$$\text{s.t.: } \textstyle\sum_{j\in J} Y_{ij} = 1, \ \forall i \in I, \tag{17}$$

$$\sum_{i\in I} d_i Y_{ij} \le q_j X_j, \ \ j \in J, \tag{18}$$

$$\sum_{u\in J} Z_{u\mathbf{0}} = k, \tag{19}$$

$$\sum_{v\in J} Z_{\mathbf{0}v} = k, \tag{20}$$

$$T_u - T_v + Q Z_{uv} \le Q - \frac{1}{k}\sum_{i\in I} d_i Y_{iv}, \ \ \forall u, v \in J : u \neq v, \tag{21}$$

$$\frac{1}{k}\sum_{i\in I} d_i Y_{iu} \le T_u \le Q, \ \ \forall u \in J, \tag{22}$$

$$\sum_{u\in J_\mathbf{0}:u\neq v} W_{uv} = X_v, \ \ \forall v \in J, \tag{23}$$

$$W_{uv} \le X_u, \ \ \forall u, v \in J_\mathbf{0} : u \neq v, \tag{24}$$

$$W_{uv} \le Z_{uv}, \ \ \forall u, v \in J_\mathbf{0} : u \neq v, \tag{25}$$

$$W_{uv} \ge X_u + Z_{uv} - 1, \ \ \forall u, v \in J_\mathbf{0} : u \neq v, \tag{26}$$

$$\sum_{v\in J_\mathbf{0}:v\neq u} W'_{uv} = X_u, \ \ \forall u \in J, \tag{27}$$

$$W'_{uv} \le X_v, \ \ \forall u, v \in J_\mathbf{0} : u \neq v, \tag{28}$$

$$W'_{uv} \le Z_{uv}, \ \ \forall u, v \in J_\mathbf{0} : u \neq v, \tag{29}$$

$$W'_{uv} \ge X_v + Z_{uv} - 1, \ \ \forall u, v \in J_\mathbf{0} : u \neq v. \tag{30}$$

$$X_j \in \{0, 1\}, \ \ \forall j \in J, \tag{31}$$

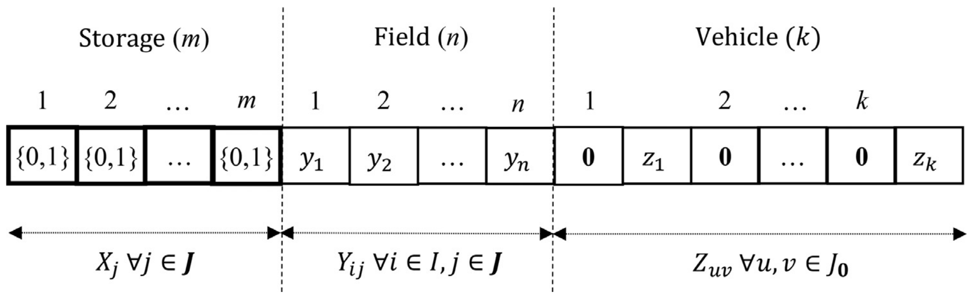

Fig. 3. A solution representation for the LARP.

$$Y_{ij} \geq 0, \ \forall i \in I, j \in J, \tag{32}$$

$$Z_{uv} \in \{0, 1\}, \ \forall u, v \in J_\mathbf{0} : u \neq v, \tag{33}$$

$$T_u \geq 0, \ \forall u \in J, \tag{34}$$

$$W_{uv}, W'_{uv} \in \{0, 1\}, \ \forall u, v \in J_\mathbf{0} : u \neq v. \tag{35}$$

This is a MILP that can solve by any optimisation solver (e.g., CPLEX). The complexity of this model is $O(m^2 + nm)$, particularly including $3m^2 + m$ binary variables, $m(n+1)$ continuous variables, and $7m^2 + 4m + n + 2$ constraints.

4. Parallel water flow algorithm

In this section, we present how to adapt the water flow algorithm (Ng & Tran, 2019; Tran & Ng, 2011; 2013) for solving the LARP. The important components of this algorithm such as terminology, solution representation, neighborhood structure, operational mechanism are described in next sub-sections.

4.1. Definition of terminology in the algorithm

In the algorithm, a cloud represents an iteration. *MaxCloud* is the maximum number of iterations in which the algorithm stops as reaching it. A drop of water (*DOW*) is defined as an agent and represented by a solution. An eroded position is a local/global optimal solution found by *DOW* and satisfying a certain erosion condition. Erosion condition is defined as a set of criteria to determine promising solutions for applying erosion process. An un-eroded direction is a solution generated by a neighbourhood structure and not applied the local search yet. Erosion process is a heuristic algorithm that helps *DOW* overcome the local optimal solution to achieve a better solution.

4.2. Solution representation

A solution of LARP is represented by three lists, i.e., storages, fields and vehicle routes. The list of storages consists of m binary values $X_j \ \forall j \in J$ where $X_j = 1$ if storage j is located. The list of fields includes n integer values within a range of 1 and m. The list of vehicle routes contains k sequences of storages that the fleet of vehicles travel to collect waste. Fig. 3 illustrates a solution representation for the LARP where $y_i = \{j | Y_{ij} = 1 \ \forall j \in J\}, \ i = 1, 2, \ldots, n$ and $z_t = \{Z_{uv} = 1 \ \forall u, v \in J_0\} \ t = 1, 2, \ldots, k$ for the list of fields and the list of vehicle routes, respectively. It can be seen that the assignment between fields and storages, and the vehicle routes are dependent on the storage locations. In other words, they are dependent decision variables. Hence, the solution representation can be reduced into the list of storages. Neighborhood structures, exploration and exploitation procedures are designed on the binary sequence of the storage locations.

4.3. Neighborhood structures

In the PWFA, two neighbourhood structures (namely, 1-opt and swap) are used to generate the set of neighbouring solutions for finding the improved solutions. The 1-opt neighbourhood structure is to change the status (open/close) of a storage, while the swap neighbourhood structure is to exchange the status (open/close) between two storages. The neighbourhood structures are sequentially applied to generate the set of candidates for solution improvement. Figures 4 and 5 illustrate these two neighbourhood structures on an example of 4 storages, 8 fields and 2 vehicles.

In the current solution of this example (see Fig. 4a), storages are located at sites 1, 2 and 3. Fields 2, 5 and 8 are assigned to storage 1; fields 1, 4 and 6 are assigned to storage 2; and fields 3 and 7 are assigned to storage 3. There are two vehicle routes, e.g., route #1: the facility, storage 1, then storage 3, back the facility, and route #2: the facility, storage 2 and back the facility. In Fig. 4b, if the 1-opt neighborhood structure is applied for storage 1, the storage is changed its status from open ($X_1 = 1$) to close ($X_1 = 0$). Since storage 1 is close, fields 2, 5 and 8 are required to reassign to other opening storages (e.g., storage 2 or 3). In addition, storage 1 is removed from vehicle route #1. Figure 4c–e illustrates the neighbouring solutions as the result of applying the 1-opt neighbourhood structure for storage 2–4, respectively.

When applying the swap neighbourhood structure for the current solution at storages 1 and 4 (note that the neighbourhood structure is only effective for swapping between opening storages and closing storages), a neighbouring solution can be achieved as shown in Fig. 5b. Fields 2, 5 and 8 are reassigned to new opening storage 4 since storage 1 is close. Storage 4 also replaces the location of storage 1 in vehicle route #1, i.e., vehicle #1 travels from the facility to storage 4, then storage 3 and back the facility. Figures 5c-d illustrates the neighbouring solutions as the result of applying the swap neighbourhood structure for the pairs of storages (2, 4) and (3, 4), respectively.

Note that only feasible solutions (that satisfy all the constraints of the LARP) generated by these neighbourhood structures are considered to be improved solutions. Hence, when applying a neighbourhood structure to generate a neighbouring solution, all the constraints of the LARP are checked for the solution to ensure that no constraint is violated.

4.4. Memory lists

To support the search for the global optimal solution in the PWFA, we use three memory lists, namely the best positions list (P0-list), the un-eroded positions list (UE-list), and the eroded positions list (E-list). The P0-list is used to save the positions of drops of water(*DOW*s) with the best-known objective value. The UE-list is used to record the local optimal positions which have not been eroded due to the erosion condition not being satisfied. The E-list is used to save the eroded local optimal positions. The E-list plays a

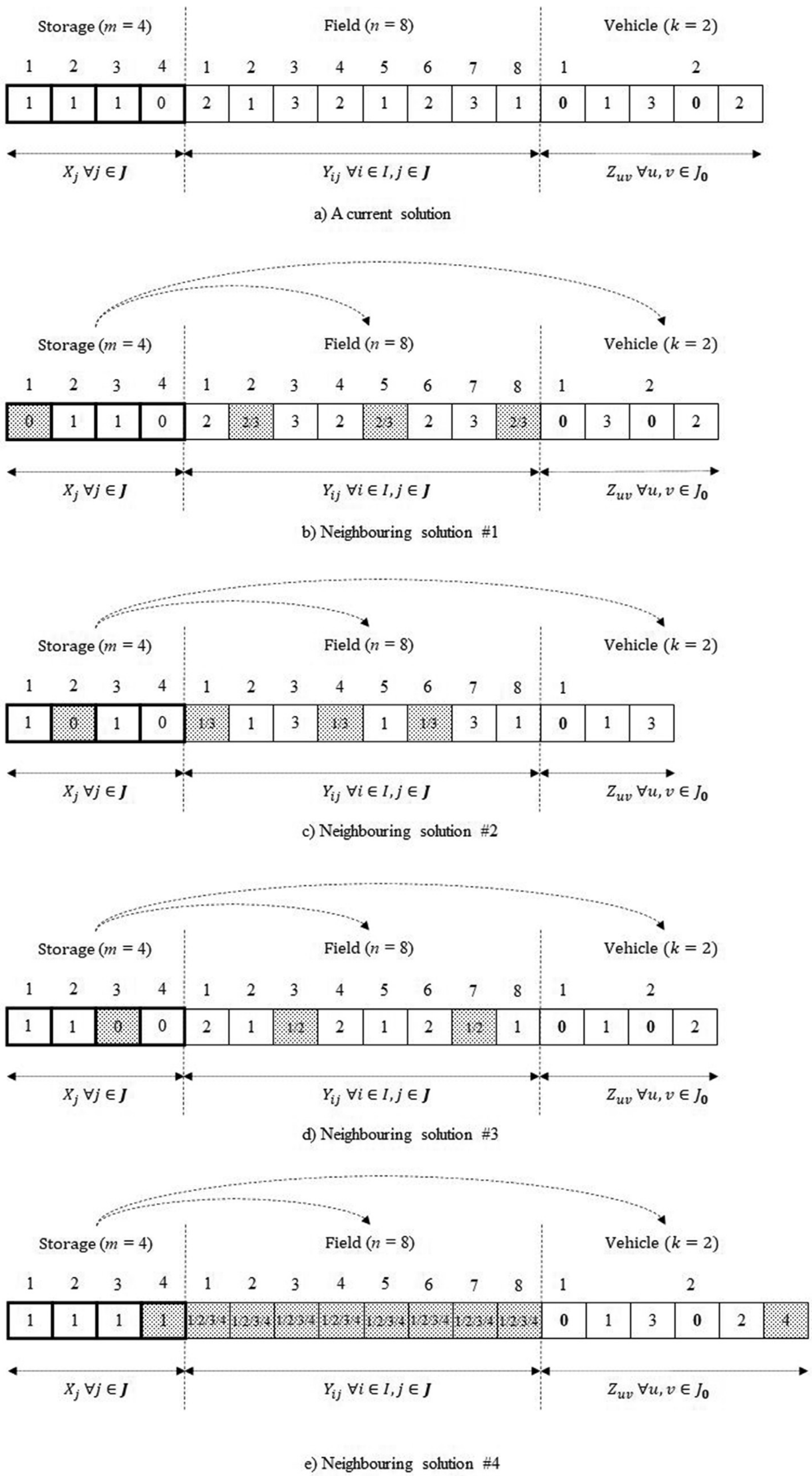

Fig. 4. An example of the 1-opt neighbourhood structure.

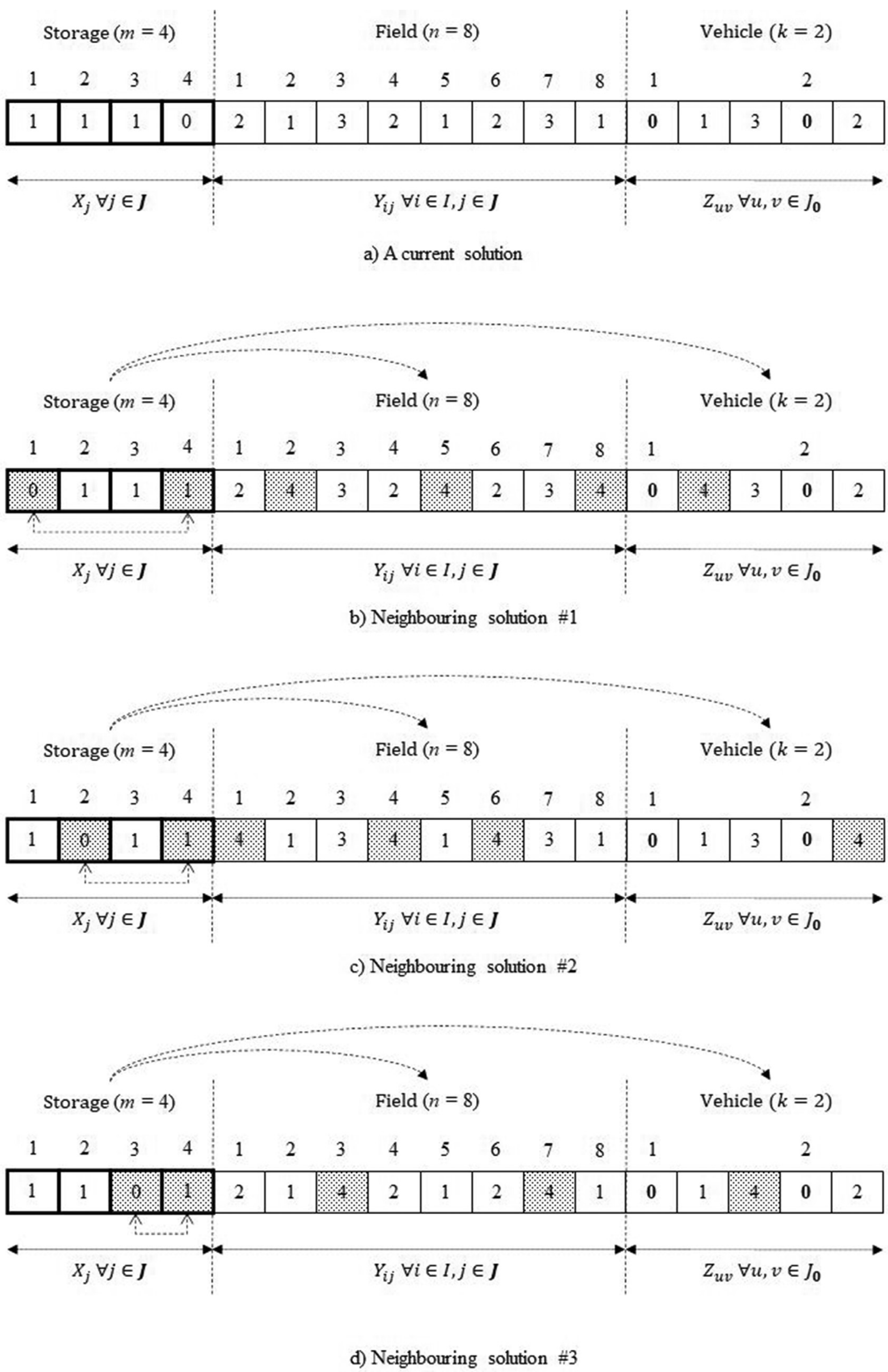

Fig. 5. An example of the swap neighbourhood structure.

critical role in preventing the next clouds from regenerating *DOW*s to the eroded positions that helps improve the computation time of the algorithm. Both the UE-list and the E-list are updated after performing the erosion process. The UE-list and the P0-list are also updated each time a *DOW* seeks a new local optimal position.

4.5. Operational mechanism

Water flow algorithm, introduced by Tran & Ng (2011) for solving flexible flow shop scheduling problem and then applied for other combinatorial optimisation problems (Ng & Tran, 2019; Tran & Ng, 2013), mimics the hydrological cycle in meteorology and the erosion phenomenon in nature to design the algorithm's operational mechanism. The simulation of phenomena aims to seek a balance between solution exploration and exploitation capabilities. There are two main phases in the algorithm: exploration phase and exploitation phase. A general procedure of the algorithm is described as follow. At the exploration phase, a cloud representing an iteration randomly generates a set of *DOW*s onto some positions on the ground, which represent solutions of the optimisation problem. Due to the gravity force of the Earth represented by a heuristic algorithm, the *DOW*s automatically move to local optimal positions. They are held at these positions until the erosion condition is satisfied before performing the erosion process. At the exploitation phase, depending on the amount of precipitation, the falling force of precipitation and soil hardness at the local optimal positions, the erosion process then helps the *DOW*s overcome the local optimal positions to find better or global ones. The procedure terminates as reaching the maximum number of iterations, the maximum amount of computational time, or the best solution found is not improved after some iterations.

This algorithm has been applied to solve successfully several combinatorial optimisation problems (Tran, 2011). Its performance is very competitive (even outperformed) compared with some natural-inspired algorithms for permutation flow shop scheduling problem, flexible flow shop scheduling problem, multi-objective flexible flow shop scheduling problem, quadratic assignment problem and vehicle routing problem. Therefore, we selected this algorithm to solve the LARP. Based on the structure of a specific optimisation problem, the algorithm is adapted on solution representation and neighborhood structures to solve efficiently the problem. In particular, we adapted the algorithm proposed by Ng & Tran (2019) to solve the LARP in which parallel computing strategy is developed for improving local search and erosion processes. A flowchart of the PWFA for the LARP is shown in Fig. 6.

Exploration phase: A number of *DOW*s (*MaxPop*) are generated randomly for each cloud to explore the solution space of LARP. The positions of *DOW*s are not in E-list to explore new solution regions. A number of *DOW*s are equally divided into h groups to perform the parallel local search procedure for finding the local optimal positions. These positions are updated in UE-list to be considered for the erosion process in the exploitation phase.

Exploitation phase: The erosion process aims to overcome the local optimal positions to find better solutions. A parallel computing strategy is applied for the erosion process. It means that if a local optimal position in UE-list satisfies the erosion condition (i.e, the number of *DOW*s at the position increases to the threshold *MinEro*), a number of un-eroded directions at the position are simultaneously searched to seek an improved solution. In the erosion process, a topological parameter representing the geographical shape of the surface is defined by the difference of total cost between the local optimal position and its neighbouring position. The aim of computing the topological parameter is to support the erosion process in choosing the most direction to perform erosion. In nature, the smallest topological parameter is chosen to be the first erosion direction. If the erosion process for the erosion direction is not able to find a better solution after *MaxUIE* steps, searching an improved solution for that direction stops and we say that the direction is blocked. This is then followed by a backtracking procedure in which the search from the former local optimal position is restarted using another erosion direction with the next smallest topological parameter. If all the directions are blocked, we say that the local optimal position is fully blocked and we move it into E-list so that it is not be considered for the erosion process in next clouds. On the other hand, if the erosion process is able to find a better solution than the eroding local optimal position, that erosion direction is chosen to erode the local optimal position permanently. The new local optimal position is updated into the UE-list to continue with performing the erosion process. The erosion process terminates if an improved solution is found or all un-eroded directions are considered.

Local search: A flowchart of the local search procedure in the exploration phase and the erosion process in the exploitation phase is shown in Fig. 7. In particular, the sequence of 1-opt and swap neighbourhood structures is performed to find an improved solution. The first and the best improvement strategies are applied for the 1-opt and swap neighbouring structures, respectively. In addition, we applied a parallel computing strategy for seeking an improved solution by the local search procedure by dividing the neighbouring solution space into h regions and assigning to h computer cores for searching simultaneously the improved solution. The procedure terminates if all neighbouring solutions are considered and no improved solution is found.

Termination: The PWFA stops if the maximum number of iterations (*MaxCloud*) is reached or the best solution found is not improved after *MaxI* iterations. Then, the best solution from P0-list is reported.

5. Numerical experiments

In this section, we investigate an efficacy of solving the LARP for agricultural waste collection and transport network design by the proposed model and algorithm. We evaluate the efficacy on a case study in Trieu Phong district, Quang Tri province, Vietnam. In addition, a set of randomly generated large-sized instances based on the case study is used to evaluate the performance of PWFA. The algorithms were implemented in Visual Studio C++ and the mathematical model was solved by the IBM ILOG CPLEX version 12.9 callable library. The experiments were run on the Microsoft Windows 7 Enterprise PC with an Intel Core i3-6100 Processor 2.30 GHz and 8 GB of RAM.

5.1. A case study

Quang Tri is Vietnam's pioneer province in the development of bio-organic fertilizer production network from agricultural waste. Agricultural waste management models play a critical role to enhance the efficiency of bio-organic fertilizer production network. The models ensure that agricultural waste from fields are collected and transported economically to the production facilities. Therefore, Quang Tri's planners study solutions to seek efficient management models. The case study is constructed at Trieu Phong, one of Quang Tri's emerging districts in the implementation of agricultural waste management models.

In the case study, we consider three site candidates for locating an bio-organic fertilizer production facility and six storages to collect agricultural waste from 110 collection points (i.e., fields). A fleet of 10-tone trucks are used to serve the collection of agricultural waste from storages to the facilities. Since the rural road network is not convenient for routing trucks to collect agricultural waste from fields, agricultural waste is directly transported

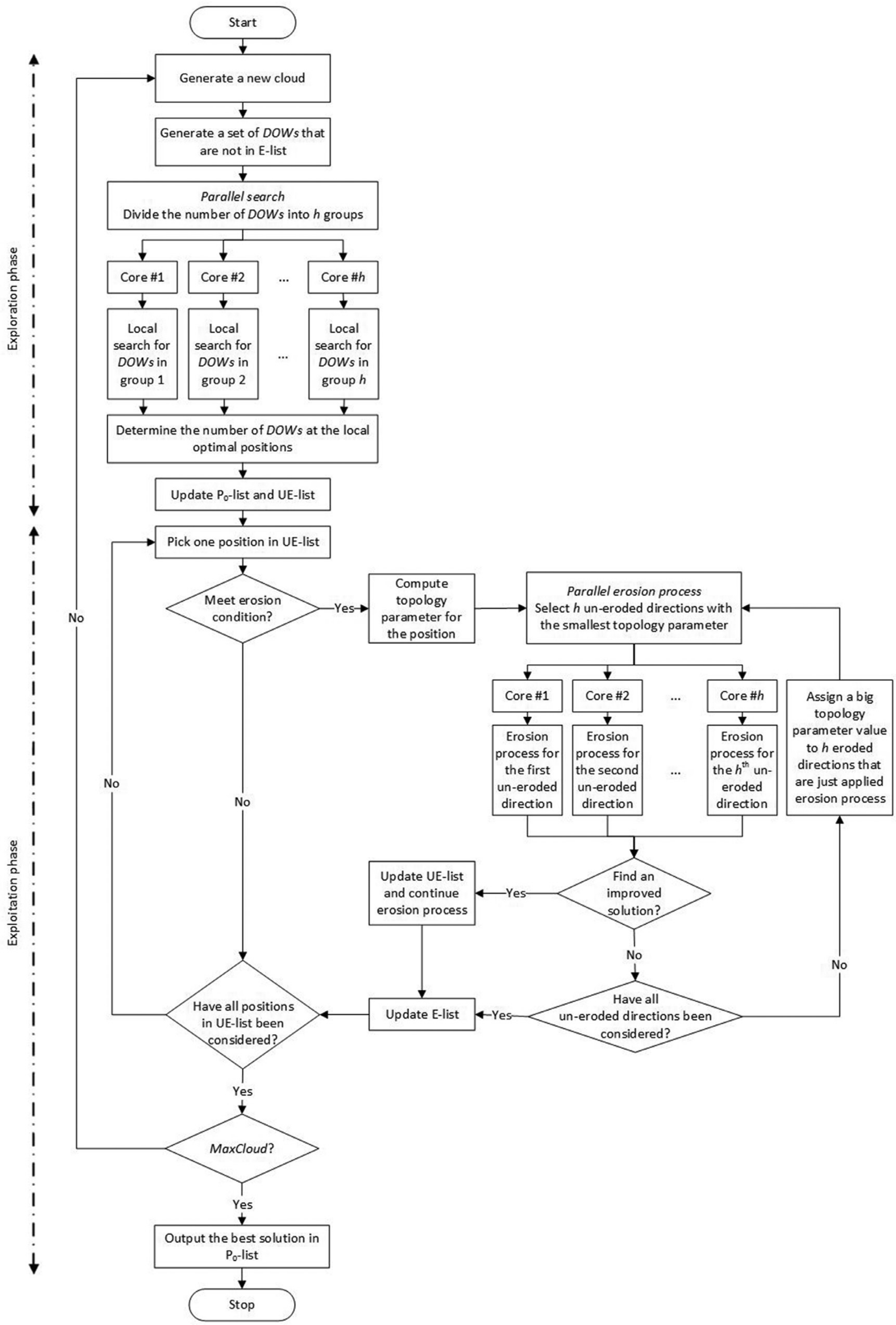

Fig. 6. A flowchart of the PWFA for the LARP.

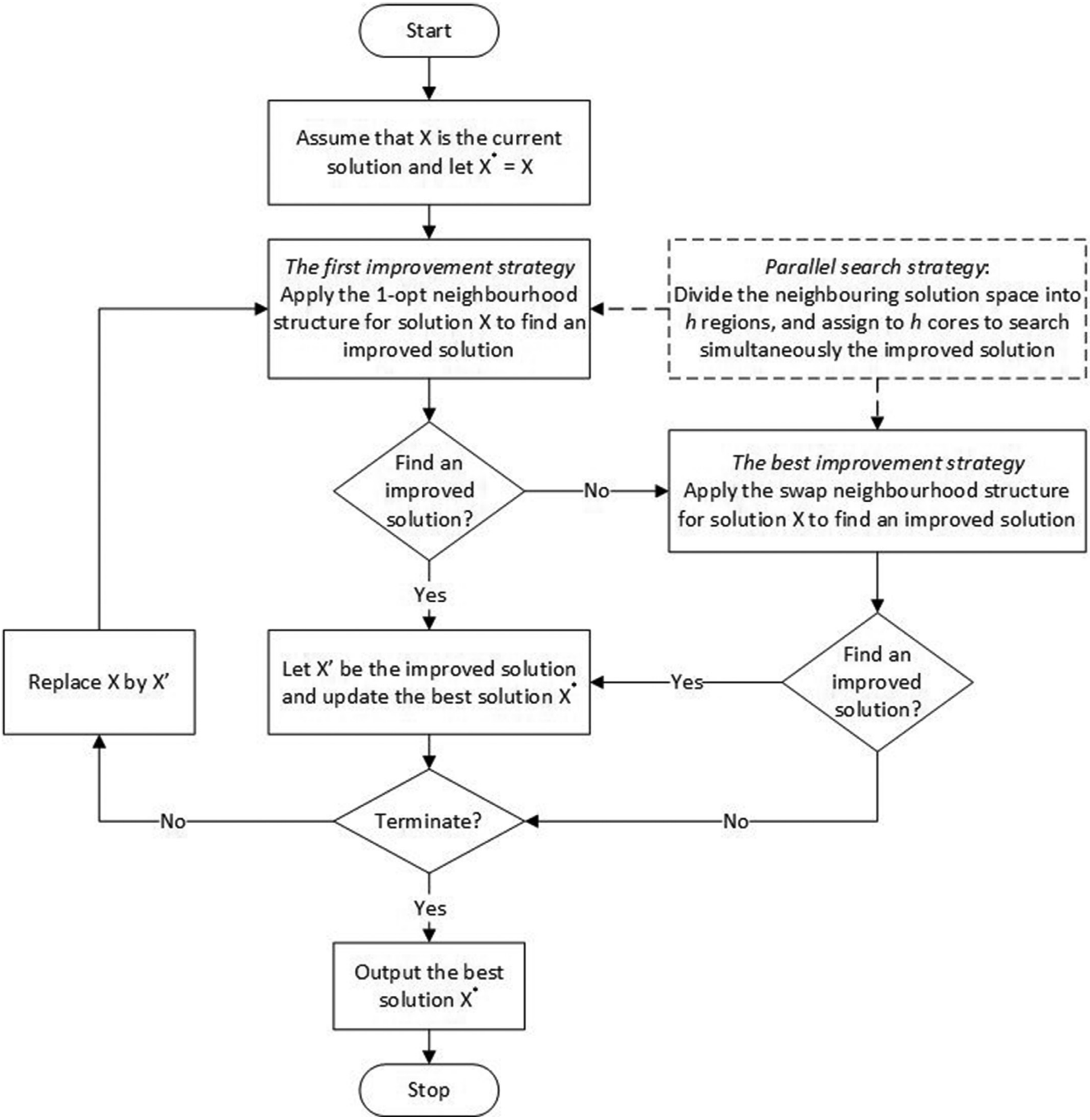

Fig. 7. A flowchart of the local search procedure in the PWFA.

by farmers (with self-designed farm vehicles) from fields to storages. Distance matrices between fields and storages, and between storages and facilities are computed based on real road network. A survey of agricultural waste amount at fields and operational costs is done at 110 households in Trieu Phong. Sine many fields are located closely, the travel distance from fields to storages are the same. In other words, three is not a significant difference of travel distance from some fields to storages. We grouped 110 fields into seven clusters based on their geographical locations. Other data (e.g., fixed cost for opening storage, storage capacity, etc.) are collected from the interviews of experts and planners. Tables 3–6 are the data of facilities, storages and clusters in the case study.

Table 3
Amount of agricultural waste at clusters.

Cluster	C1	C2	C3	C4	C5	C6	C7
Demand (tonnes)	3	4	3	4	3	4	3

Figure 8 illustrates locations for three site candidates of facilities (green squares), six storages (amber triangles) and seven clusters of fields (yellow circles). It can be seen that potential locations of facilities and storages are out of residential areas due to environmental issues.

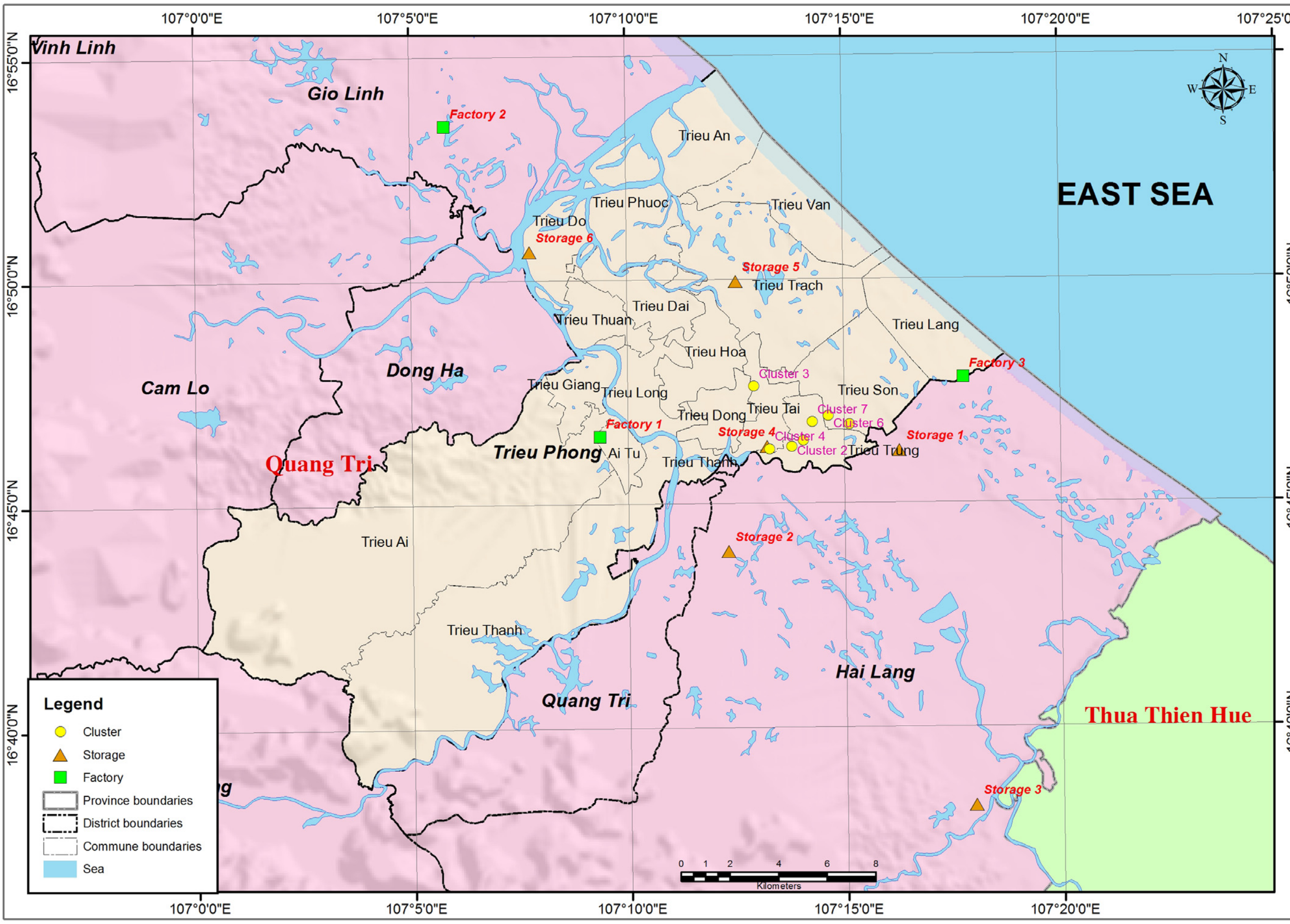

Fig. 8. A map of the potential locations of facilities, storages and fields in the case study.

Table 4
Cost and capacity of storages.

Storage	S1	S2	S3	S4	S5	S6
Cost (millions VND)	100	100	100	100	100	100
Capacity (tonnes)	8	8	8	6	6	6

Table 5
Distance (kilometer) matrix of clusters and storages.

	S1	S2	S3	S4	S5	S6
C1	3.8	5.7	16.8	1.5	5.7	13.0
C2	4.4	5.0	16.6	9.2	6.0	12.8
C3	6.2	6.9	19.5	2.5	3.4	10.3
C4	5.2	4.5	17.0	0.3	6.0	12.5
C5	2.6	7.0	17.0	3.0	5.7	13.9
C6	2.0	7.5	16.7	3.7	6.2	14.5
C7	3.5	6.2	17.0	7.0	5.4	13.2

Table 6
Distance (kilometer) matrix of facilities and storages.

	Facility			Storage					
	F1	F2	F3	S1	S2	S3	S4	S5	S6
F1	–	–	–	13.0	7.5	21.0	7.0	8.5	8.5
F2	–	–	–	23.0	22.0	35.0	18.6	14.5	6.0
F3	–	–	–	4.0	12.0	15.0	8.5	11.0	17.5
S1	13.0	23.0	4.0	–	8.0	19.0	5.0	9.5	16.5
S2	7.5	22.0	12.0	8.0	–	17.0	4.5	9.0	14.5
S3	21.0	35.0	15.0	19.0	17.0	–	21.0	28.0	33.5
S4	7.0	18.6	8.5	5.0	4.5	21.0	–	5.0	15.0
S5	8.5	14.5	11.0	9.5	9.0	28.0	5.0	–	10.0
S6	8.5	6.0	17.5	16.5	14.5	33.5	15.0	10.0	–

5.2. Results and discussions

After clustering the number of households based on their geographical locations, the case study can be solved by the MILP model (implemented in CPLEX) since the size of problem is significantly reduced. Three scenarios for solving the case study are investigated:

- Scenario #1: the facility is located at site 1 (F1).
- Scenario #2: the facility is located at site 2 (F2).
- Scenario #3: the facility is located at site 3 (F3).

The results of solving the case study under three scenarios are shown in Table 7. From the table, it can be seen that the best solution is on scenario #3. In this solution, storages S1, S2, S4 and S5 are opened. Clusters C6 and C7 are assigned into storage S1 (its filling rate: 87.5%), clusters C2 and C4 are assigned into storage S2 (its filling rate: 100%), clusters C1 and C5 are assigned into storage S4 (its filling rate: 100%), and cluster C3 is assigned into storage S5 (its filling rate: 50%). The filling rates are the same for three scenarios. No cluster is assigned to storages S3 and S6. In other words, storages S3 and S6 are not opened. In this scenario, three trucks are used to collect agricultural waste from storages with the following routes: route R1 (F1-S1-F1), route R2 (F1-S4-S2-F1) and route R3 (F1-S5-F1). The corresponding transportation cost is 55.00 millions VND which is the lowest transportation cost among there

Table 7
Results for solving the case study (unit: millions VND).

Sce.	Total cost	L_c	A_c	T_c	Assignment						Route		
					S1	S2	S3	S4	S5	S6	R1	R2	R3
1	537.2	400	80.2	57.0	C6, C7	C2, C4	–	C1, C5	C3	–	S1, S4	S2	S5
2	599.4	400	80.2	119.2	C6, C7	C2, C4	–	C1, C5	C3	–	S1, S2	S4	S5
3	535.2	400	80.2	55.0	C6, C7	C2, C4	–	C1, C5	C3	–	S1	S4, S2	S5

Where Sce. = scenario, L_c = Location cost, A_c = Assignment cost, T_c = Transportation cost.

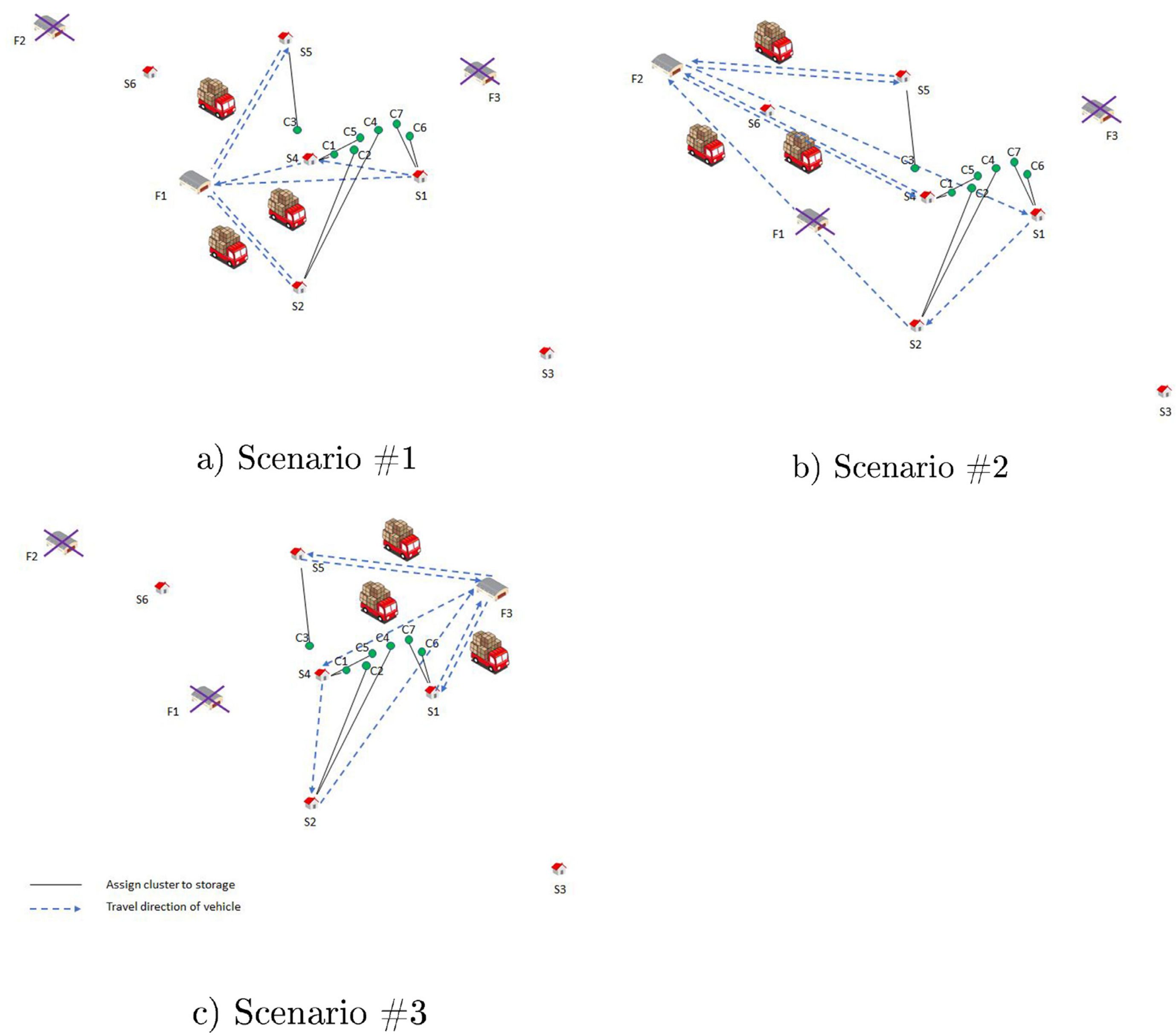

Fig. 9. Illustration of the optimal solutions for three scenarios in the case study.

scenarios. The other costs (i.e., location cost and assignment cost) are the same for three scenarios. For the best scenario, total cost is 535.20 millions VND. Figure 9 illustrates the optimal solutions for all these scenarios.

We also solved the case study without clustering 110 fields. Table A.1 in Appendix A shows the location (coordinates), demand (tonnes) and cluster for each field (households). Note that only data of amount of agricultural waste that are demanded to collect at fields are changed. Hence, the input data in Table 3 needs to be updated. The distance matrix of fields and storages are still based on Table 5 in which the fields belonging to the same cluster have the same travel distance. The optimal results of solving the case study (without clustering) for three scenarios by CPLEX are presented in Table 8. It can be seen that these results are the same as the one by solving the case study (with clustering). Fields belonging to the same cluster are assigned into the same storage. For three scenarios, only storages S1, S2, S4 and S5 are opened to minimise total cost. Among costs, location cost contributes signifi-

Table 8
Results for solving the case study without clustering 110 fields (unit: millions VND).

Sce.	Total cost	L_c	A_c	T_c	Assignment						Route		
					S1	S2	S3	S4	S5	S6	R1	R2	R3
1	537.2	400	80.2	57.0	H96–H110	H16–H25, H56–H75	–	H1–H15, H76–H95	H26–H55	–	S1, S4	S2	S5
2	599.4	400	80.2	119.2	H96–H110	H16–H25, H56–H75	–	H1–H15, H76–H95	H26–H55	–	S1, S2	S4	S5
3	535.2	400	80.2	55.0	H96–H110	H16–H25, H56–H75	–	H1–H15, H76–H95	H26–H55	–	S1	S4, S2	S5

Where Sce. = scenario, L_c = Location cost, A_c = Assignment cost, T_c = Transportation cost.

Table 9
Comparison results of CPLEX, PWFA and tabu search for the large-sized LARP..

n	m	#instances	CPLEX		Tabu search		PWFA		
			$\overline{\triangle}$	Time (s)	$\overline{\triangle}$	Time (s)	$\overline{\triangle}$	Time (s)	
								1 core	8 cores
100	10	5	0.00	580	0.00	175	0.00	120	32
	20	5	1.41	2015	0.05	1328	0.05	1015	249
	50	5	5.13	7250	1.42	4513	1.03	3630	934
	100	5	9.05	13,651	4.25	5247	4.16	4520	1265
	200	5	13.24	17,505	8.80	9042	6.78	7285	2131
500	10	5	6.52	6927	2.38	2046	2.36	1574	386
	20	5	8.78	12,046	5.04	5022	4.75	3556	912
	50	5	15.94	18,000	6.25	7245	5.80	6012	1583
	100	5	31.55	18,000	9.13	9128	8.25	7318	2065
	200	5	70.37	18,000	17.46	12,305	14.86	10,615	2950
1000	10	5	10.36	13,089	4.26	3325	4.10	2630	648
	20	5	14.07	18,000	7.18	6012	6.22	4078	1119
	50	5	29.45	18,000	10.82	10,027	8.68	7591	2007
	100	5	62.18	18,000	13.07	12,984	12.34	10,524	2518
	200	5	95.40	18,000	24.48	15,618	19.45	14,025	3627
	Average		24.90	13,271	7.64	6934	6.59	5633	1495

cantly to total cost. Hence, the storage location decisions are very important. The average filling rate is 84.375%. However, in the case study making final decision to locate the facility is based on transportation cost. It can be seen that transportation cost for scenario #3 is the minimum cost as compared with the other scenarios. The computational time for solving the case study (without clustering) is 168 seconds, which demonstrates the capability of solving medium-sized instances by CPLEX.

5.3. Performance of the PWFA

Based on the case study, a set of large-sized instances is randomly generated to evaluate the performance of the PWFA for solving large-scale LARP. In the instances, the number of clusters ranges from 100, 500 to 1000, and the number of storages ranges from 10, 20, 50, 100 to 200. Demand of clusters is a uniform distribution [1–10]. Capacity of storages is 1000, and cost of storage is an uniform distribution [50–200]. There is only one production facility considered. Location of the facility, storages and clusters are randomly generated in a grid of [1000, 1000]. Distance matrix between the facility and storages, as well as the storages and clusters are then computed. The number of vehicles is 5 with their capacity Q =2000. For each size of problem, we generated 5 instances.

Table 9 shows the results of solving the large-sized instances by CPLEX, PWFA and tabu search algorithm. We choose tabu search algorithm to make a comparison with our algorithm since it solved successfully the LRPs (see Table 1) and can use the PWFA's neighbourhood structures for a fair comparison. We adapted tabu search algorithm (Tran & Nguyen, 2019) with the neighbourhood structures (described in Section 4.3) for solving LARP. We computed the percentage deviation (denoted $\triangle$) between the objective value found by a given algorithm (denoted Obj) and the optimal value (denoted Opt) or the lower bound (denoted LB) found by CPLEX. In the table, $\overline{\triangle}$ is defined as the average percentage deviation for all instances of a particular problem size, and #instances is the number of instances at each problem size. Computation time is given in CPU seconds.

$$\triangle = \begin{cases} \dfrac{(\text{Obj}-\text{Opt})}{\text{Opt}} \times 100 & \text{if a known optimal solution exists,} \\ \dfrac{(\text{Obj}-\text{LB})}{\text{LB}} \times 100 & \text{otherwise.} \end{cases} \tag{36}$$

For solving the instances by CPLEX, a time limit is set to 5 hours (or 18,000 seconds). For the parallel computation in the PWFA, we used 8 computer cores. From the preliminary experiments, we chosen to set the best parameters of PWFA as follows: $MaxPop = 10$, $MaxCloud = 20$, $MaxUIE = 5$, $MinEro = 2$ and $MaxI = 4$. For the best parameters of tabu search algorithm, the maximum number of iterations, the time limit, and the length of tabu list are 100, 18,000 seconds and 5, respectively. In addition, the algorithm terminates if there is no improvement on the best solution found during 10 iterations. For the comparison of PWFA and tabu search algorithm, only one computer core was used. It can be seen that PWFA outperforms CPLEX and tabu search algorithm for all tested instances in terms of solution quality and computation time. Specifically, the average percentage deviation of PWFA (6.59%) versus CPLEX (24.90%) and tabu search (7.64%), and the average computation time of PWFA (5633 seconds for running with 1 CPU core, and 1495 seconds for running with 8 CPU cores) versus CPLEX (13,271 seconds) and tabu search (6934 seconds for running with 1 CPU core). The results show the capability of PWFA for efficiently solving the large-sized instances.

Using the number of CPU cores reduced the computation time of PWFA. For example, PWFA (with 8 cores) decreased about 4 times of computation time than the algorithm (with only 1 CPU core). Hence, our algorithm design with parallel computing strategy can get benefit from the strong development of new computer generations where the number of CPU cores increases significantly.

6. Conclusion and future works

In this paper, an efficient agricultural waste management model is proposed to stop burning the amount of waste at fields after each harvesting season in developing countries, and to use the waste to produce bio-organic fertilizer. This model is towards three SDGs of United Nations, including SDG9 - Industry, Innovation and Infrastructure, SDG12 - Responsible consumption and production, and SDG13 - Climate Action. In this model, an MINLP is formulated to support planners to seek the optimal solutions for the agricultural waste collection and transport network design. In particular, the MINLP aims to minimise total cost of the assignment of fields and storages, and the waste collection and transportation from storages to the facility. A MILP model is constructed to support solving the MINLP problem by any optimization solver. In addition, a PWFA is adopted to solve the large-sized instances within a reasonable computation time. The efficiency of the proposal model and algorithm is tested and evaluated on the real case study at Trieu Phong district, Quang Tri province, Vietnam where bio-organic fertilizer production from agricultural waste is considered a high-priority task and a critical strategy towards sustainable agriculture. In addition, numerical experiments carried out on the set of randomly generated instances are performed to demonstrate the performance of the proposed PWFA for solving the large-sized problem. The experimental results show that PWFA outperforms tabu search algorithm in terms of both solution quality and computational time. The results of PWFA for LARP is considered to be benchmarking for researchers who are interested in the development of other meta-heuristic algorithms for this problem.

The mathematical model does not consider decisions of waste treatment facility location. However, this model can determine the optimal locations for LARP with a small number of facility sites (see the results of case study). If the number of facility sites increases significantly, we need to extend the mathematical model. Other future works consist of an extension of this model for determining the optimal number of vehicles used, solving the problem with various types of waste in which their aging time are different, or studying the impact of flooding on facility, storage locations and road network. Furthermore, an integration of bio-organic fertilizer and by-product supply chain into agricultural waste management could be an interesting topic.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Location and demand of 110 fields in the case study

Cluster	Household	Location (coordinates)	Demand (tonnes)
C1	H1	16.7766468,107.2367790	0.16
C1	H2	16.7766468,107.2367790	0.37
C1	H3	16.7766468,107.2367790	0.27
C1	H4	16.7750183,107.2365547	0.21
C1	H5	16.7750183,107.2365547	0.16
C1	H6	16.7750123,107.2365547	0.27
C1	H7	16.7750183,107.2365547	0.19
C1	H8	16.7750183,107.2365547	0.16
C1	H9	16.7769710,107.2352649	0.27
C1	H10	16.7769710,107.2352649	0.16
C1	H11	16.7769710,107.2352649	0.13
C1	H12	16.7769710,107.2352649	0.11
C1	H13	16.7766468,107.2367790	0.16
C1	H14	16.7766468,107.2367790	0.21
C1	H15	16.7766468,107.2367790	0.19
C2	H16	16.7748340,107.2390898	0.42
C2	H17	16.7772143,107.2410297	0.57
C2	H18	16.7739121,107.2282147	0.28
C2	H19	16.7696034,107.2317573	0.57
C2	H20	16.7767357,107.2299659	0.42
C2	H21	16.7781041,107.2313992	0.28
C2	H22	16.7244424,107.2383810	0.35
C2	H23	16.7713189,107.2255412	0.42
C2	H24	16.7755361,107.2311598	0.35
C2	H25	16.7746992,107.2280340	0.33
C3	H26	16.7980505,107.2213614	0.12
C3	H27	16.7980505,107.2213614	0.05
C3	H28	16.7962374,107.2219535	0.09
C3	H29	16.7962374,107.2219535	0.09
C3	H30	16.7962374,107.2219535	0.11
C3	H31	16.7962374,107.2219535	0.10
C3	H32	16.7962374,107.2219535	0.02
C3	H33	16.7980505.107.2213614	0.09
C3	H34	16.7980505.107.2213614	0.06
C3	H35	16.7980505.107.2213614	0.09
C3	H36	16.7928373,107.2213319	0.14
C3	H37	16.7928373,107.2213319	0.08
C3	H38	16.7928373,107.2213319	0.13
C3	H39	16.7928373,107.2213319	0.12
C3	H40	16.7928373,107.2213319	0.11
C3	H41	16.7922149,107.2216715	0.13
C3	H42	16.7913588,107.2212189	0.08
C3	H43	16.7918933,107.2209677	0.13
C3	H44	16.7915620,107.2218378	0.06
C3	H45	16.7902739,107.2224225	0.07
C3	H46	16.7922672,107.2213325	0.09
C3	H47	16.7915566,107.2222217	0.17
C3	H48	16.7917967,107.2209793	0.16
C3	H49	16.7903118,107.2208279	0.13
C3	H50	16.7894968,107.2208880	0.09
C3	H51	16.7926607,107.2214418	0.14
C3	H52	16.7933264,107.2218827	0.08
C3	H53	16.7926774,107.2215065	0.15
C3	H54	16.7900274,107.2163973	0.07
C3	H55	16.7900274,107.2163973	0.04
C4	H56	16.7730367,107.2162182	0.20
C4	H57	16.7730367,107.2162182	0.26
C4	H58	16.7730367,107.2162182	0.16
C4	H59	16.7730367,107.2162182	0.13
C4	H60	16.7218046,107.214124	0.33
C4	H61	16.7218046,107.214124	0.20
C4	H62	16.7724242,107.2164955	0.20
C4	H63	16.7724582,107.2149039	0.13
C4	H64	16.7724582,107.2149039	0.20
C4	H65	16.7724582,107.2149039	0.16
C4	H66	16.7724582,107.2149039	0.13
C4	H67	16.7724582,107.2149039	0.26
C4	H68	16.7730367,107.2162182	0.20
C4	H69	16.7720197,107.2142123	0.20
C4	H70	16.7720197,107.2142123	0.33
C4	H71	16.7720197,107.2142123	0.13
C4	H72	16.7720197,107.2142123	0.20
C4	H73	16.7720197,107.2142123	0.20
C4	H74	16.7724242,107.2164955	0.23
C4	H75	16.7724242,107.2164955	0.16
C5	H76	16.7780075,107.2485590	0.16
C5	H77	16.7855281,107.2476138	0.07
C5	H78	16.7799056,107.2451197	0.20

(continued on next page)

(*continued*)

Cluster	Household	Location (coordinates)	Demand (tonnes)
C5	H79	16.7789638,107.2474026	0.20
C5	H80	16.7795807,107.2488550	0.19
C5	H81	16.7795332,107.2474680	0.16
C5	H82	16.7839163,107.2494622	0.20
C5	H83	16.7781744,107.2500754	0.16
C5	H84	16.7855281,107.2476138	0.06
C5	H85	16.7799056,107.2451198	0.19
C5	H86	16.7855477,107.2480423	0.19
C5	H87	16.7239168,107.2494622	0.19
C5	H88	16.7797165,107.2457316	0.16
C5	H89	16.7851744,107.2490555	0.12
C5	H90	16.7850142,107.2495276	0.13
C5	H91	16.7787336,107.2468950	0.10
C5	H92	16.7848749,107.2493760	0.13
C5	H93	16.7850633,107.2502045	0.06
C5	H94	16.7789638,107.2474026	0.16
C5	H95	16.7781744,107.2500754	0.16
C6	H96	16.7817382,107.2565828	0.27
C6	H97	16.7779459,107.2553785	0.44
C6	H98	16.7773228,107.2549564	0.36
C6	H99	16.7775128,107.2538691	0.27
C6	H100	16.7785503,107.2554563	0.36
C6	H101	16.7777404,107.2548565	0.36
C6	H102	16.7771093,107.2551502	0.27
C6	H103	16.7781940,107.2557446	0.71
C6	H104	16.7783250,107.2549792	0.71
C6	H105	16.7778945,107.2548923	0.27
C7	H106	16.7789577,107.2414893	0.38
C7	H107	16.7785439,1072421435	0.56
C7	H108	16.7773616,107.2423587	0.66
C7	H109	16.7785660,107.2395441	0.84
C7	H110	16.7785099,107.2421367	0.56

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