Research Article

A Novel Approach for Optimizing the Supply Chain: A Heuristic-Based Hybrid Algorithm

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Managing the distribution of goods is a vital operation for many companies. A successful distribution system requires an effective distribution strategy selection and optimum route planning at the right time and minimum cost. Furthermore, customer's demand and location can vary from order to order. In this situation, a mixed delivery system is a good solution for it and allows the use of different strategies together to decrease delivery costs. Although the "distribution strategy selection" is a critical issue for companies, there are only a few studies that focus on the mixed delivery network problem. There is a need to propose an efficient solution for the mixed delivery problem to guide researchers and practitioners. This paper develops a new "modified" savings-based genetic algorithm which is named "distribution strategy selection and vehicle routing hybrid algorithm (DSSVRHA)." Our new algorithm aims to contribute to the literature a new hybrid solution to solve a mixed delivery network problem that includes three delivery modes: "direct shipment," "milk run," and "cross-docking" efficiently. It decides the appropriate distribution strategy and also optimal routes using a heterogeneous fleet of vehicles at minimum cost. The results of the hybrid algorithm are compared with the results of the optimization model. And the performance of the hybrid algorithm is validated with statistical analysis. The computational results reveal that our developed algorithm provides a good solution for reducing the supply chain distribution costs and computational time.

1. Introduction

Today's organizations are trying to find better distribution strategies that reduce supply chain costs and enhancing customer satisfaction to survive in the competitive supply chain environment. Therefore, delivery with the most cost-effective distribution strategy has recently become a critical focus of logistics systems.

There are several types of distribution strategies: direct shipment, cross-docking, milk run, and mixed delivery. In direct shipment, all products are carried out from suppliers to customers or producers or directly to retailers. This strategy is economical if there is a full truck of shipment. Milk run reduces transportation costs by combining shipments from multiple locations with a single truck [1]. Milk run can be daily or weekly depending on the business model and the geographic location of the customers [2]. Small lot size and high frequency are characteristics of milk runs and are often used to deploy the just-in-time (JIT) strategy in logistical systems [3]. This strategy has been used in various industries. In a cross-docking strategy, the products are received and collected at a cross-docking center. And afterward, they are delivered to the customer destinations directly from a cross-docking center. Cross-docking is an appropriate distribution strategy in cases where each truck is fully or almost fully loaded. Cross-docking can reduce total inventory costs and lead time and improve customer service level and the relationships with

suppliers [4]. A mixed delivery system allows implementing two or three distribution strategies together. A mixed distribution strategy is the best strategy in satisfying customer demand flexibility.

In recent years, vehicle routing problem along with selecting the right distribution strategy has become an important problem. Distribution locations and quantities vary from order to order. Selecting an appropriate vehicle route for distribution is extremely difficult. In the literature, there exists a wide variety of exact techniques and efficient heuristics for the vehicle routing problem. Earlier exact techniques include ones such as branch-and-bound algorithm [5, 6], branch and cut [7], and branch and price [8]. Exact techniques are simple, and their solutions are based on integer and mixed-integer programming. Dondo et al. [9] studied multiechelon distribution networks with the cross-docking strategy and presented a mixed-integer linear mathematical formulation. Hasani-Goodarzi and Tavakkoli-Moghaddam [10] proposed a mixed-integer linear programming (MILP) model for the vehicle routing problem, considering split deliveries, with the cross-docking strategy. Santos et al. [11] implemented an integer program (IP) and a branch-and-price-algorithm for solving the pickup and delivery problem with the cross-docking strategy. Agustina et al. [12] modeled a mixed-integer linear program for solving the vehicle scheduling and routing problem at a cross-docking center. Exact algorithms are efficient for solving small-scale vehicle routing problems. It is difficult to find a solution in a limited time frame with the exact algorithms for large-scale vehicle routing problems. That is what motivated the researchers to develop heuristic algorithms. Two earlier heuristics for vehicle routing problems are savings algorithm [13] and sweep algorithm [14]. These heuristics quickly produce feasible solutions. Xu et al. [15] studied a mixed delivery system that allows direct shipment, cross-docking, and milk run strategies. They developed a heuristic algorithm, based on Clark and Wright's algorithm, to determine the right distribution strategy and vehicle routes. This study proves that a mixed delivery system is more cost-effective than a pure delivery system. Dondo and Cerdá [16] proposed a sweep heuristic-based algorithm for the vehicle routing problem with the cross-docking strategy. They determined vehicle routes and schedules simultaneously at the cross-dock center. Mei et al. [17] developed an improved version of Clarke and Wright's algorithm for modeling vehicle routing problems with the milk run strategy. The study results show that the improved algorithm seeks to complete all goods distribution requirements efficiently.

Heuristics that developed recently are intelligent techniques, and they produce better solutions than the earlier heuristics or optimal solutions. These techniques are powerful especially when solving combinatorial optimization problems. Intelligent heuristic algorithms for vehicle routing problems commonly include genetic algorithm, simulated annealing algorithm, tabu search algorithm, and ant colony algorithm [18]. Lee et al. [19] proposed a heuristic algorithm based on a tabu search algorithm for vehicle routing scheduling with the cross-docking strategy. Wen et al. [20]

studied vehicle routing problem with cross-docking and developed a tabu search heuristic that embedded within an adaptive memory procedure to solve the problem. Musa et al. [21] formulated an integer programming (IP) model for the distribution problem of cross-docking, and they solved it using an ant colony optimization (ACO) algorithm. Moghadam et al. [22] proposed a hybrid algorithm combining the ant colony algorithm and the simulated annealing algorithm to solve the vehicle routing scheduling problem with the cross-docking strategy. Mousavi and Tavakkoli-Moghaddam [23] developed a two-stage hybrid algorithm with simulated annealing and tabu search algorithms to solve location-routing scheduling problems with cross-docking. Hosseini et al. [24] presented a hybrid algorithm that combines the simulated annealing and the harmony search algorithm to find a solution for the vehicle routing problem with cross-docking and milk run strategies. Sadjadi et al. [25] solved milk run problem by using the genetic algorithm (GA), and the results indicate that the proposed method significantly reduces the cost of logistics. Baniamerian et al. [26] introduced three echelon supply chain problems with cross-docking and proposed a two-phase genetic algorithm (GA) focusing on customer satisfaction. Baniamerian et al. [27] studied a heterogeneous vehicle routing problem with cross-docking and developed a hybrid genetic algorithm with modified variable neighborhood search. When the results were compared with the simulated annealing (SA) algorithm and artificial bee colony (ABC) algorithm, the proposed hybrid algorithm had given significantly better results than the others.

The main contributions are summarized as follows:

(1) In a competitive supply chain environment, a mixed delivery system is the best solution that allows using different distribution strategy combinations in reducing logistics costs. As we can see from the literature review, the mixed delivery system has not been emphasized enough. There is a need to propose an efficient solution for the mixed delivery problem to guide researchers and practitioners. This paper focuses on a mixed delivery system network problem that allows three delivery modes: cross-docking, milk run, and direct shipment. A hybrid algorithm is proposed combining the genetic algorithm and Clarke and Wright's algorithm to solve this mixed delivery network problem. This algorithm aims to contribute to the literature a new hybrid solution to solve the mixed delivery system problem efficiently. The new algorithm decides on an appropriate distribution strategy and optimum vehicle routes while significantly reducing logistics costs.

(2) To the best of our knowledge, this is the first time the genetic algorithm has been hybridized with Clarke and Wright's algorithm for the heterogeneous vehicle routing problem with mixed delivery strategies. The study of Clarke and Wright [13] satisfies all distribution requirements efficiently with minimal vehicles, the shortest mileage, and the lowest cost. The following papers are proof of this: [15, 17].

Clarke and Wright's algorithm provides good solutions for small-size instances. For large-size instances, developing a hybrid algorithm provides better results. The genetic algorithm is an intelligent heuristic technique for solving vehicle routing problems by reducing delivery costs significantly, and the following papers prove this: [25–27]. Thus, this paper chooses two well known and proven algorithms to solve the mixed delivery problem efficiently.

(3) Today, many businesses see the use of 3PL (third-party logistics) provider as an option to reduce costs and improve customer service. The authors of References [21, 28] employed this approach in their paper with a homogeneous and unlimited number of vehicles. In this paper, the 3PL (third-party logistics) provider in a mixed distribution system with heterogeneous and unlimited number of vehicles are employed as a different approach.

Figure 1 shows the flow of the paper. The paper starts with an introduction and proceeds with the literature review. Section 3 defines optimization model of the problem. Section 4 presents the proposed hybrid algorithm. Section 5 shows a case study of the proposed algorithm. The last section presents the conclusions and gives a brief regarding the direction of future research.

2. Literature Review

A supply chain is an integrated system that includes a variety of distribution actors such as facilities, suppliers, manufacturers, and distributors. In supply chain management, multiple organizations participate in a collaborative task via a business process [29]. Supply chain design with energy and sustainability issues is a popular research topic [30]. Zhao et al. [31] focused on developing minimization of risks in green logistics based on a multiobjective optimization model. Wang et al. [32] emphasized application of the technology equipment's for the optimization of renewable energy resources. Zhang et al. [33] stated that energy management problems can be formulated as an optimization problem. Li et al. [34] emphasized the importance of energy problem whose major purpose is to maximize the resource allocation profits or minimize the energy costs while meeting the coupled matrix constraint and a set of system operation constraints. This type of optimization problems arises in a broad range of applications including energy management and electric vehicle aggregator [35]. Apte and Viswanathan [36] stated that 30% of the supply chain costs occurred during the distribution process [19]. At this point, an efficient distribution strategy selection and optimum vehicle route planning are necessities. A vehicle routing problem (VRP) is a well-known important combinatorial optimization problem in distribution management [37]. Efficient methods and optimization algorithms should be developed to solve this problem. Optimization models and methods for supply chain design are of great interest among industry and academic researchers [30]. There are many review papers
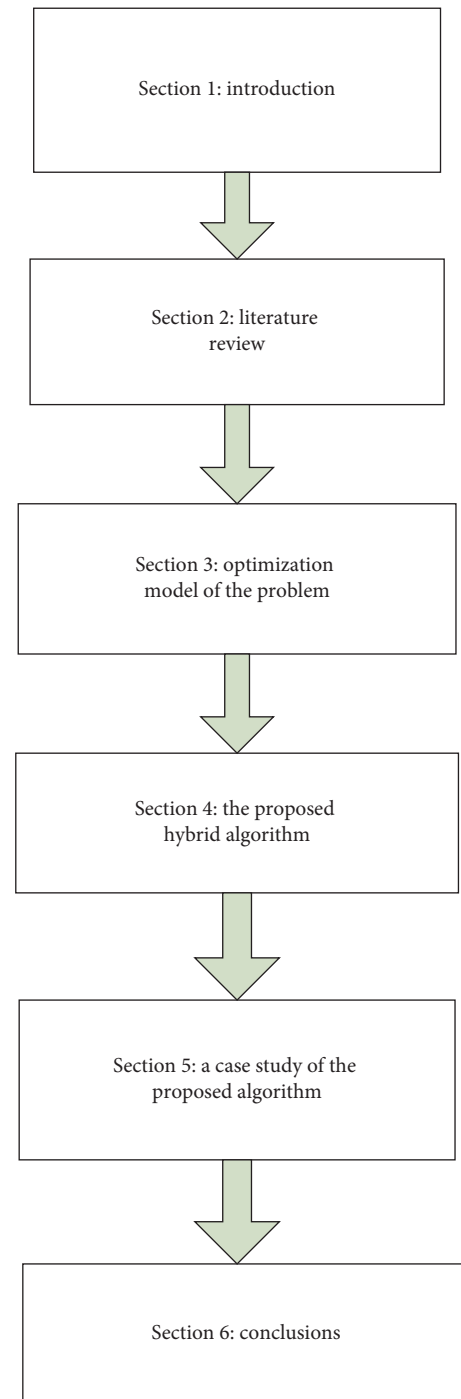
Figure 1: The flow of the paper.

about the optimization methods for vehicle routing problems, see the following papers for more information: [38–42]. The scope of our literature review is limited to the following distribution strategies for vehicle routing problems: cross-docking, milk run, and mixed delivery.

There has been extensive research on the vehicle routing problem (VRP) with cross-docking strategy. The cross-docking is an efficient strategy that reduces inventory, transportation, and holding costs. It requires lower stock levels and less storage space. Lee et al. [19] developed a

mathematical model and a heuristic method, based on the tabu search algorithm, for both cross-docking and vehicle routing with time windows. They randomly generated problems and found optimal solutions that were close to optimal with a 4% error within a reasonable time.

Wen et al. [20] addressed the vehicle routing with cross-docking, where the data of homogeneous vehicles are used. They formulated a mixed-integer programming model considering time window constraints. And they implemented a tabu search heuristic method that embedded within an adaptive memory procedure. They tested the heuristic method on datasets provided by Danish consultancy Transvision. The results show that the heuristic method can give high-quality solutions within a short time.

Liao et al. [43] implemented a model that integrates cross-docking into the vehicle routing problem using a set of homogeneous, capacity, and number limited vehicles. In their paper, they developed a new tabu search heuristic method, and they proved that the new algorithm performs better than a tabu search algorithm.

Hasani-Goodarzi and Tavakkoli-Moghaddam [10] examined the capacity-limited vehicle routing problem for multiproduct cross-docking with allowing split deliveries, and the problem is formulated as a mixed-integer linear programming (MILP) model for small-sized problems.

Mousavi and Tavakkoli-Moghaddam [23] suggested a two-stage hybrid algorithm (HSA), which is the combination of simulated annealing, and a tabu search algorithm, for location-routing scheduling problems with cross-docking. Santos et al. [11] proposed a branch-and-price algorithm and linear programming branch-and-bound (LPBB) method for a cross-docking problem considering homogeneous, number, and capacity-limited vehicles.

Mousavi et al. [44] offered a hybrid fuzzy possibilistic-stochastic programming solution for the location-routing problem of cross-docking centers.

Agustina et al. [12] studied the vehicle routing problem with cross-docking for food delivery considering just-in-time strategy. They modeled the problem as a mixed-integer linear program with a time window.

Baniamerian et al. [26] solved the cross-docking vehicle routing and scheduling problem focusing on improving customer satisfaction and time windows by developing a mixed-integer programming (MIP) model and a two-phase genetic algorithm.

Wang et al. [45] presented a new vehicle routing problem with cross-docking, considering split deliveries and heterogeneous and capacity-limited vehicles. They established a mixed-integer linear programming model and proposed a solution method combining a constructive heuristic approach and two-layer simulated annealing and tabu search. Their experimental results show that the proposed method solves large-size problems effectively within a reasonable time.

Ahkamiraad and Wang [46] studied a distribution problem with multiple cross-docks, where a set of homogeneous, number, and capacity-limited vehicles with time window was considered. They modeled the problem as mixed-integer linear programming and proposed a hybrid of the genetic algorithm and particle swarm optimization. It has been proven that the proposed hybrid algorithm provides better solutions than the exact method for small-size problems.

Milk run, which is another efficient distribution strategy, has been successfully applied to the logistics activities of various industries. The milk run strategy has the advantages of reducing distances and logistics costs by providing a high delivery frequency. Milk run routing problems with homogeneous, capacitated, and limited vehicle fleets were studied in the following papers: [17, 25]. Sadjadi et al. [25] implemented a mixed-integer programming model and the genetic algorithm (GA) considering homogeneous-, number-, and capacity-limited vehicles to solve the milk run problem of the auto industry. The GA results indicate that the use of GA can produce a near-optimal solution and significantly reduce lower supply chain costs. You and Jiao et al. [47] presented the milk run distribution problem of the express company. They improved the traditional Clarke and Wright's algorithm and then tested the algorithm with 10 distribution nodes. They stated that the algorithm could effectively reduce the distance and costs with reasonable route planning. Mei et al. [17] proposed an improved version of Clarke and Wright's algorithm for a milk run vehicle routing problem of the Anji logistics company considering time window. The results show that the improved approach reduces logistics costs and it could provide reduced these costs for other companies in the business also.

In real life, suppliers and customers are located randomly, and delivery quantities vary from order to order. In this case, a mixed delivery system can be a better distribution option than a pure delivery system. However, a mixed distribution system has received less attention in the literature [15]. Xu et al. [15] studied a mixed delivery system with both hub-and-spoke and direct shipment. They developed a heuristic approach based on Clarke and Wright's algorithm. Their experiments indicate that the mixed system is more effective than using a pure system. They provided researchers with a direction, to have better solutions, for trying different methods like a genetic algorithm and/or tabu search. Berman and Wang [48] proposed a Greedy heuristic, a Lagrangian relaxation heuristic, and a branch-and-bound algorithm to select the appropriate distribution strategy (decision of cross-docking or direct shipment) and vehicle routes for inbound logistics planning. Branke et al. [49] developed an evolutionary algorithm (EA) by combining savings heuristic to solve transport channel selection and vehicle routing problem simultaneously. They proved that their hybrid algorithm could significantly reduce the transportation cost better than simple heuristics. Musa et al. [21] studied the distribution planning problem that determines the loads to be delivered by direct shipment or cross-docking from the supplier to customers. In this study, the distribution is carried out with third-party logistics (3PL) providers, where the vehicles are ready for use when necessary. They proposed a novel ant colony optimization (ACO) algorithm to solve this problem. The results showed that the proposed algorithm provides better solutions than branch-and-bound (B&B) solutions. Dondo et al. [9] studied

the vehicle routing problem (VRP) with hybrid strategies combining direct shipping, warehousing, and cross-docking. They presented a mixed-integer linear programming model where the following constraints are taken into account: heterogeneous vehicle, vehicle capacity limitation, travel distance limitation, and time window. Charkhgard and Yahya Tabar [28] extended the paper [21], which focused on distribution planning with the decisions of direct shipment or cross-docking by implementing third-party logistics providers. In this paper, a mixed-integer nonlinear programming (MINLP) model is formulated, and a simulated annealing (SA) heuristic algorithm is applied. Hosseini et al. [24] offered an integer programming model and a hybrid heuristic method based on harmony search (HS) and simulated annealing (SA) for the transportation problem which consists of direct shipment, cross-docking, and milk run. They pointed out that the hybrid approach has better performance in reducing computational and transportation costs for large-size instances. Cóccola et al. [50] solved a real vehicle routing problem with developing a branch-and-price solution-algorithm to determine which of the two different delivery options (direct delivery or cross-docking) would be used. Goodarzi and Zegordi [51] proposed a metaheuristic algorithm named biogeography-based optimization (BBO) for the location-routing problem of cross-docking. The algorithm determines cross-docking locations and vehicle routing with selecting one of the transportation strategies (direct shipment or shipment through cross-dock). Meyer and Amberg [52] developed a mixed-integer linear programming model addressing the transport concept selection problem of automotive manufacturers, which includes milk run, area forwarding, and point-to-point transport. Their study showed how to establish a mixed distribution network.

Figure 2 presents a brief review of our literature review. The "distribution characteristics" column indicates the papers that have the following vehicle routing constraints: time window, travel time limitation, travel distance limitation, vehicle capacity limitation, homogeneous/heterogeneous vehicle, limited/unlimited number of vehicles, and split deliveries. The "distribution strategies" column presents the papers that have the following distribution strategies: cross-docking/area Forwarding/hub-and-spoke, direct shipment milk run, and groupage service. "The use of the genetic algorithm and Clarke Wright algorithm" column presents the papers that employ the genetic algorithm and Clarke and Wright algorithm. The "solution method" column presents the exact/heuristic/metaheuristic method of the papers. The "distribution strategy selection" column presents the papers that are interested in distribution strategy selection.

As illustrated in Figure 2, a mixed distribution system, which consists of cross-docking, direct shipment, and milk run, has not been emphasized enough in the literature. In real life, suppliers and customers are located randomly, and delivery quantities vary from order to order. Although the hybrid distribution system has received less attention in the literature, a mixed distribution system may be a better distribution option than practicing a single distribution option [15]. So, there is a need to propose an efficient solution for the mixed delivery problem to guide researchers

and practitioners. This paper proposes a hybrid algorithm to solve a mixed delivery network problem. The algorithm determines the best distribution strategy and optimum vehicle routes while significantly reducing costs.

To the best of our knowledge, this is the first time the genetic algorithm has been hybridized with Clarke and Wright's algorithm for the heterogeneous vehicle routing problem with mixed delivery strategies, which consists of cross-docking, milk run, and direct shipment. Clarke and Wright's algorithm is one of the popular and simple algorithms that reduce travel distance and logistics costs efficiently with minimal vehicle requirements. As we mentioned above, Xu et al. [15] proposed a heuristic method based on Clarke and Wright's algorithm for a mixed delivery system. Their studies indicate that the use of Clarke and Wright's algorithm, with reasonable route planning, reduced the distance and costs for small-size instances. They gave a direction for researchers to try different methods like a genetic algorithm or tabu search, to reach better results. The genetic algorithm is a well-known and powerful algorithm to solve different vehicle routing problems, reducing delivery costs significantly by producing better solutions. The following papers are proof of this: [25–27, 46]. And Branke et al. [49] showed that the hybrid algorithm could better reduce logistics costs than simple heuristics by developing an evolutionary algorithm (EA), combining savings heuristic for transport channel selection and vehicle routing problem. In this paper, inspired by the studies mentioned above, and for having better results, we hybridized two well-known and proven algorithms (genetic algorithm and Clarke and Wright's algorithm) to solve a mixed delivery network problem with heterogeneous vehicles efficiently.

A simple way to increase the efficiency of the supply chain is to outsource third-party logistics (3PL) companies that operate at high-efficiency levels [50]. The authors of References [21, 28] implemented this approach in their paper by homogeneous and an unlimited number of vehicles. In this paper, we implemented a 3PL (third-party logistics) provider in a mixed distribution system by employing a heterogeneous and an unlimited number of vehicles as a different approach.

Table 1 presents the abbreviations of the solution methods which are shown in Figure 2.

3. Optimization Model of the Problem

We, considering the literature discussed in the previous section, studied a two-stage distribution network problem. In this scenario, finished goods are distributed to customers/retailers from manufacturer/supplier with three available distribution methods: "direct shipment," "cross-docking," and "milk run" (Figure 3). The distribution network in this paper consists of a manufacturer/supplier, a cross-docking center, and customers. This type of distribution network is common for the automotive industry, food industry, and electronic manufacturing industry. In this paper, the mixed delivery network problem is studied to offer an efficient distribution solution to minimize the total distribution costs.

Author	Year	Objective function	Distribution strategy selection	Exact	Heuristic/metaheuristic	Exact method	Heuristic/metaheuristic method	GA	CW	GA + CW	Homogenous vehicles	Heterogeneous vehicles	Unlimited number of vehicles	Limited number of vehicles	Vehicle capacity limitation	Split deliveries	Travel distance limitation	Travel time1 limitation	Time window	Cross-docking/area forwarding/hub-and-spoke	Direct shipment	Milk run	Groupage service
Berman and wang	2006	Min total cost (transportation + inventory costs)		x	x	BB	GH + LRH				x			x	x					x	x		
Branke and schmidt	2006	Min total transportation cost			x		EA + CW		x		x			x	x					x		x	x
Schöneberg et al.	2010	Min total cost		x	x	MIP	PH				x			x	x	x				x			
Mokhtarinejad et al.	2015	Min travel cost + Min travel time		x	x	MIP	GA + ML	x			x			x	x					x			
Mohtashami et al.	2015	Min. Time + Min. transportation cost + Min. Number of transportations		x	x	MINLP	NSGA-II + MOPSO	x			x			x	x					x			
Meyer and amberg	2018	Min transport cost		x		MILP						x		x	x			x		x	x		
Cóccola et al.	2015	Min total routing cost		x		MILP + BP					x			x	x			x		x			
Hosseini et al.	2014	Min transportation cost		x	x	IP	HS + SA				x			x	x					x	x		
Liu et al.	2003	Min travel distance		x	x		CW		x		x		x	x						x	x		
Mei et al.	2017	Min total travel distance			x		ICW		x		x					x	x			x			
Goodarzi and zegordi	2016	Min total cost		x	x	MINLP	BBO				x			x			x	x		x	x		
Baniamerian et al.	2017	Min total cost (transportation cost + early/tardy deliveries)			x	MIP	GA	x			x			x					x				
Ahkamiraad and wang	2018	Min. total cost (transportation cost + fixed cost)			x	MILP	GA+PSO	x			x			x	x			x		x			
Sadjadi et al.	2009	Min transportation cost			x	MIP	GA	x			x			x							x		
Baniamerian et al.	2019	Max total profit			x	MILP	GA + MVNS + SA + ABC	x				x		x					x				
Fardin et al.	2015	Min total cost (travel cost + purchasing cost + holding cost)			x	MINLP	Hybrid GA	x			x			x	x				x				
Gumus and bookbinder	2004	Min total cost			x						x			x	x					x			
Lee et al.	2006	Min total cost (travel cost + vehicle fixed cost)		x	x	MM	TS				x			x	x		x	x	x	x			
Wen et al.	2009	Min travel time		x	x	MIP	TS				x			x	x				x	x			
Musa et al.	2010	Min travel cost	x	x	x	BB	ACO				x	x		x					x	x		
Liao et al.	2010	Min total cost (travel cost + operation cost)			x		TS				x			x			x		x				
Dondo et al.	2011	Min transportation cost		x		MILP					x			x	x	x	x		x				
Charkhgard and yahya tabar	2011	Min transportation cost		x	x	MINLP	SA				x	x		x	x				x				
Santos et al.	2011	Min transportation cost		x	x	BB + BP					x			x	x				x				
Hasani-goodarzia and tavakkoli-moghaddama	2012	Min total cost		x		MILP					x			x	x			x		x			
Mousavi and tavakkoli-moghaddam	2013	Min transportation cost		x	x	MIP	SA + TS				x			x	x		x	x	x				
Santos et al.	2013	Min total cost		x	x	BP + LPBB					x			x					x	x			
Tarantilis	2013	Min travel distance			x		AMRTS				x			x	x				x	x			
Mousavi et al.	2013	Min cross-dock numbers + min travel cost + min operation cost		x		MIP	FP				x			x	x				x				
Dondo and cerdá	2013	Min travel cost + min makespan		x	x	MILP	SW				x			x	x			x	x				
Dondo and cerdá	2014	Min travel cost + min makespan + Min distribution time		x	x	MILP	SW				x			x	x		x		x				
Agustina et al.	2014	Min total cost (earliness & tardiness + inventory holding cost + travel cost)		x		MILP					x			x	x			x	x				
Moghadam et al.	2014	Min total cost (travel cost + load and unload cost)		x	x	MINLP	SA + ACO				x			x	x	x			x				
Mousavi et al.	2014	Min total cost		x		FMILP					x			x	x				x				
Morais et al.	2014	Min total cost			x		ILS				x			x	x				x				
You and jiao	2014	Min total cost and min travel distance			x		IS		x		x			x	x				x			x	
Rahbari et al.	2019	Min total cost (penalty costs + inventory costs + transportation costs), Max the total weighted freshness		x		MILP						x		x	x			x	x				
Dondo and cerdá	2015	Min total cost (travel cost + makespan + distribution time)		x	x	MILP	SW				x		x	x		x		x				
Wang	2017	Min total cost		x	x	MILP	CH + SA, CH + TS					x		x	x				x				
Yu et al.	2016	Min total cost		x	x	MILP	SA				x			x	x				x	x			
Yin et al.	2016	Min total cost		x	x	NLP	AMABC				x			x	x		x		x				
Maknoon and laporte	2016	Min total cost		x	x	NILP	ALNS				x			x	x				x				
Nikolopoulou et al.	2016	Min total travel distance		x	x	MIP	AMP+ TS				x			x	x	x			x	x			
Grangier et al.	2017	Min total delivery cost		x	x	MIP	LNS				x			x	x				x	x			
Mousavi and vahdani	2017	Min total cost (holding cost + transportation cost)		x	x	MILP	SAICA				x			x	x		x		x				
This article		Min distribution cost	x	x	x	ILP	MSGA (GA + CW)	x	x	x	x	x		x	x		x	x	x	x	x	x	

FIGURE 2: The brief review of the literature review.

TABLE 1: Abbreviation table.

| Abbreviation	Description
FMILP	Fuzzy mixed-integer linear programming
NLP	Nonlinear programming
NILP	Noninteger linear programming
ILP	Integer linear programming
IP	Integer programming
MIP	Mixed-integer programming
MILP	Mixed-integer linear programming
MINLP	Mixed-integer nonlinear programming
B&B	Branch-and-bound algorithm
GH	Greedy heuristic
LRH	Lagrangian relaxation heuristic
ACO	Ant colony optimization
SA	Simulated annealing
TS	Tabu search
HS	Harmony search
ALNS	Adaptive large neighborhood search
AMP	Adaptive memory programming
AMABC	Adaptive memory artificial bee colony
PSO	Particle swarm optimization
GA	Genetic algorithm
NSGA-II	Nondominated sorting genetic algorithm
MOPSO	Multiobjective particle swarm optimization
ML	Machine learning
BP	Branch and price
LPBB	Linear programming-based branch and bound
BBO	Biogeography-based optimization
AMRTS	Adaptive multirestart tabu search
PH	Primal heuristics
CW	Clarke and Wright's algorithm
CG	Column generation
EA	Evolutionary algorithm
FP	Fuzzy programming
SW	Sweep algorithm
ILS	Iterated local search
MSGA	Modified savings-based genetic algorithm
IS	Improved saving
ICW	Improved Clarke and Wright's algorithm
ABC	Artificial bee colony
MVNS	Modified variable neighborhood search
SAICA	Self-adaptive imperialist competitive algorithm
CH	Constructive heuristic approach
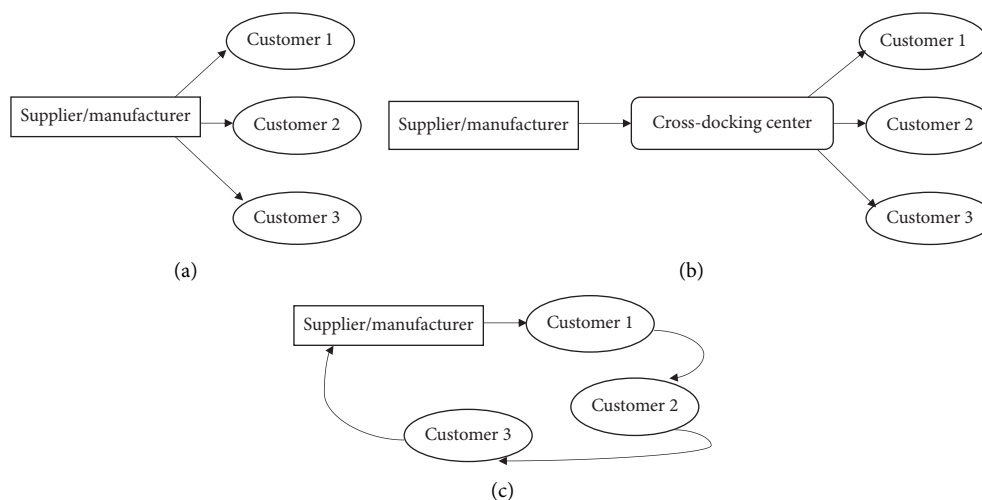
FIGURE 3: Distribution strategies. (a) Direct shipment. (b) Cross-docking. (c) Milk run.

We developed a new mathematical model, shown below, with the help of the models developed by Laporte [41] and Hosseini et al. [24]. The mathematical model determines the proper distribution strategy and optimal routes.

The mathematical model makes the following assumptions:

(1) Customer orders are not split, so only one vehicle can be assigned to each customer.

(2) The vehicle fleet is heterogeneous, and all vehicles have a different capacity.

(3) There are no limits to the number of vehicles, assuming that each type of vehicle is ready for use when needed (this is only possible with the use of a third-party logistics (3PL) provider).

(4) In milk run, the stop costs are incurred when the vehicles stop at each customer.

(5) Customer orders are not delayed and are satisfied daily. Therefore, penalty costs are not incurred.

(6) The milk run route length of the vehicle is bounded by a given distance due to the driver's legal driving times.

(7) Customer demand quantities are deterministic and known.

(8) The total load shipped by each vehicle cannot exceed the vehicle capacity.

(9) The manufacturer/supplier capacity is sufficient to meet the demand of all customers.

(10) There is one cross-docking center, and there is no stock in the cross-docking center.

(11) The cross-docking transportation from the manufacturer/supplier to the cross-docking center is made by truck. The shipments are distributed from the cross-dock to the customers directly with smaller trucks, and this direct shipment cost is priced according to customer's demand volume.

The parameters and the definitions used in the model are as follows:

(i) Indices

N_0 = set of nodes with manufacturer/supplier {$i, j = 0, 1, 2, 3, \ldots, n$}
N = set of customer nodes {$i, j = 1, 2, 3, \ldots, n$}
V = set of vehicles {$V = 1, 2, 3, 4, \ldots, v$}.
K = cross-docking center

(ii) Parameters

K_v: the maximum loading capacity of the vehicles (m³) {$v = 1, 2, 3, 4, \ldots, v$}.
d_j: the volume of customer j shipments (m³), $j \varepsilon N$
C_{ij}: total distance between customer i and customer j (km)
S: truck capacity for cross-docking center
D: milk run tour length (km)
Lv: rental cost of vehicle {$v = 1, 2, 3, 4, \ldots, v$}

O: fixed cost of transportation from the manufacturer/supplier to a cross-docking center
W: milk run stop cost (milk run stop cost arises when the vehicle delivers a product to the customers. It is considered as the cost of the time it takes to deliver the product to the customer)
T: direct shipment cost from the cross-docking center to customers.
P: cost per unit of gasoline consumed per km

(iii) Decision variables

$X_{ijv} = \begin{cases} 1 \\ 0 \end{cases}$ if vehicle v travels from customer i
to customer j 1, otherwise 0; $i\varepsilon$No, $j\varepsilon$No ve $i \neq j, v$
εV
$Z_{jv} = \begin{cases} 1 \\ 0 \end{cases}$ if vehicle v travels directly to customer
j 1, otherwise 0; $j\varepsilon N$ ve $v\varepsilon V$
$Y_j = \begin{cases} 1 \\ 0 \end{cases}$ if customer j
demand is transported with cross −
docking 1, otherwise 0; $j\varepsilon N$
M = number of trucks used for shipment from the manufacturer/supplier to the cross-docking center

(iv) Objective value

Min Z = direct shipment cost + milk run cost + cross-docking cost
Direct shipment cost = Total rental cost of vehicles + total gasoline consumption of direct shipment = $\sum_{i=0, j\varepsilon N} \sum_{v\varepsilon V} Z_{jv} \cdot (L_v + C_{ij} \cdot P_v)$
Milk run cost = total rental cost of vehicles + total gasoline consumption of milk run route + total milk run stop cost = $\sum_{i=0, j\varepsilon N} \sum_{v\varepsilon V} X_{ijv} \cdot (L_v + C_{ij} \cdot P_v) + \sum_{i\varepsilon N} \sum_{j\varepsilon N} \sum_{v\varepsilon V} X_{ijv} \cdot C_{ij} \cdot P_v + \sum_{i\varepsilon N0} \sum_{j\varepsilon N} \sum_{v\varepsilon V} W \cdot X_{ijv}$
Cross-docking cost = total cost for shipment from the manufacturer/supplier to the cross-docking center + direct shipment cost from the cross-docking center to customers = $M \cdot O + \sum_{j\varepsilon N} T \cdot Y_j$

The model formulation is as follows:

$$\text{Min } Z = \sum_{i=0, j\varepsilon N} \sum_{v\varepsilon V} Z_{jv} \cdot \left(L_v + C_{ij} \cdot P_v\right)$$
$$+ \sum_{i=0, j\varepsilon N} \sum_{v\varepsilon V} X_{ijv} \cdot \left(L_v + C_{ij} \cdot P_v\right)$$
$$+ \sum_{i\varepsilon N} \sum_{j\varepsilon N} \sum_{v\varepsilon V} X_{ijv} \cdot C_{ij} \cdot P_v + \sum_{i\varepsilon N0} \sum_{j\varepsilon N} \sum_{v\varepsilon V} W \cdot X_{ijv}$$
$$+ M \cdot O + \sum_{j\varepsilon N} T \cdot Y_j,$$

$$(1)$$

$$\sum_{i\varepsilon \text{No}} \sum_{v\varepsilon V} X_{ijv} + \sum_{v\varepsilon V} Z_{jv} + y_j = 1, \quad \forall j \varepsilon N, i \neq j,$$

$$(2)$$

$$\sum_{i \varepsilon \text{No}} \sum_{j \varepsilon N} d_j \cdot X_{ijv} \le K_v, \quad \forall v \varepsilon V, V = 1, 2, 3, 4, \dots, v, i \neq j, \tag{3}$$

$$\sum_{i \varepsilon S} \sum_{j \varepsilon S \setminus \{i\}} X_{ijv} |S| - 1, \quad \forall S \subset N, |S| \ge 2, V = 1, 2, 3, 4, \dots, v, \tag{4}$$

$$\sum_{v \varepsilon V} X_{ijv} + \sum_{v \varepsilon V} Z_{iv} + Y_i \le 1, \quad \forall i \varepsilon N, j = 0, \tag{5}$$

$$\sum_{v \varepsilon V} X_{jiv} + \sum_{v \varepsilon V} Z_{iv} + Y_i \le 1, \quad \forall i \varepsilon N, j = 0, \tag{6}$$

$$\sum_{j \varepsilon N} X_{jiv} + \sum_{j \varepsilon N} Z_{jv} \le 1, \quad \forall v \varepsilon V, i = 0, j \neq 0, i \neq j, \tag{7}$$

$$\sum_{i \varepsilon \text{No}} X_{ijv} - \sum_{l \varepsilon \text{No}} X_{jlv} = 0, \quad \forall j \varepsilon N, \forall, v \varepsilon V, i \neq j, 1 \neq j, \tag{8}$$

$$d_i \cdot \sum_{i \varepsilon N} Z_{iv} \le K_v, \quad \forall i \varepsilon N, \forall v \varepsilon V, V = 1, 2, 3, 4, \dots, v, \tag{9}$$

$$\sum_{j \varepsilon N} d_j \cdot Y_j \le M \cdot S, \quad s \varepsilon S, \tag{10}$$

$$\sum_{i \varepsilon \text{No}} \sum_{j \varepsilon \text{No}} C_{ij} \cdot X_{ijv} \le D, \quad \forall v \varepsilon V, i \neq j, \tag{11}$$

$$\sum_{j \varepsilon N} Y_j \le N, \tag{12}$$

$$X_{ijv} \varepsilon \{0, 1\}, \tag{13}$$

$$Z_{iv} \varepsilon \{0, 1\}, \tag{14}$$

$$Y_{iv} \varepsilon \{0, 1\}. \tag{15}$$

Formula (1) is the objective function and aims to minimize the total distribution costs. Constraint (2) ensures that customer demands are met via one of the three available distribution strategies. Constraint (3) ensures that the sum of the amounts carried in the milk run tour does not exceed the vehicle capacity. Constraint (4) eliminates subtours. Constraints (5) and (6) guarantee that only one of the direct, cross-docking, or milk run distribution strategies will be available. Constraint (7) restricts the same vehicle from making both direct shipment and milk run tour. Constraint (8) guarantees that the same vehicle completes the milk run tour. Constraint (9) provides the assignment of the appropriate vehicle to meet the demands of the customer by direct shipment. Constraint (10) guarantees that the total amount shipped to the cross-docking center will meet customer demands. Constraint (11) restricts milk run route length. Constraint (12) guarantees that the assignment to the cross-docking center can be as much as the maximum number of customers. Constraints (13)–(15) provide that the variables take binary values of 0 or 1.

4. Proposed Hybrid Algorithm

The vehicle routing problem is one of the more widely studied problems in combinatorial optimization. It comprises the traveling salesman problem (TSP) which includes a Hamiltonian cycle. Held and Karp [53] had shown that the TSP is an NP-hard (nondeterministic polynomial-time hard) problem as is the Hamilton path [54]. Because of this, the proposed mathematical model cannot solve large-size vehicle routing problems in a reasonable time.

We can see from the literature that the "genetic algorithm" has been used successfully to solve problems which integrate VRP and cross-docking [27, 44, 55]. On the contrary, the "Clarke and Wright" algorithm has been used successfully for solving the vehicle routing problem (VRP) [15, 17]. Therefore, we propose a novel hybrid algorithm named "distribution strategy selection and vehicle routing hybrid algorithm" (DSSVRHA) combining Clarke and Wright's algorithm and genetic algorithm. This algorithm contributes to the literature a new hybrid solution to solve a mixed delivery network problem efficiently.

Our hybrid algorithm selects the optimal distribution strategy and determines optimal routes for milk run to provide the minimum total distribution costs. It consists of two subalgorithms: genetic and modified savings. The algorithm starts with GA. First, the genetic algorithm assigns distribution strategies to customers randomly. The modified savings algorithm creates the milk run route and selects the proper vehicle type and also calculates the distribution costs. The hybrid algorithm is explained in the following sections.

Step 1. GA—generate random population

   (i) Initialization of the population: DeJong [56] and Grefenstette [57] proposed a population size of 100. The population size of the papers in the literature varies from 20 to 100 [58]. In this paper, population size is determined as 100 according to these papers.

   (ii) Assigning distribution strategies to customers randomly: the value coding approach is used in chromosome representation. The chromosome representation indicates which distribution strategy is assigned to customers: (1) cross-docking; (2) direct shipment; (3) milk run. The length of the chromosome is determined by the total number of customers. Distribution strategies are randomly assigned to customers. Figure 4 represents a sample chromosome for ten customers.

Step 2. Apply modified savings algorithm if method is equal to milk run

Clark and Wright [13] proposed a simple method for optimal routing of a fleet of vehicles, which have varying capacities, used for delivery from a depot to delivery points. The traditional savings method has three basic steps before starting route creation: (i) calculate savings between customers i and j with the [13] formula $S_{ij} = d_{i0} + d_{0j} - d_{ij}$ (the formulation is shown as below where d_{ij} denotes travel

3	3	3	3	3	3	1	1	1	2
1	2	3	4	5	6	7	8	9	10

FIGURE 4: A sample chromosome representation.

distance from customer i to j and "0" stands for the depot), (ii) sort savings in the descending order (iii) select customers i and j with the largest savings value. The developed modified procedure starts with traditional savings method Steps (i) and (ii), but it differentiates in Step (iii). Instead of selecting customers that have the maximum savings, the random selection procedure is applied when creating the routes. Thus, it is possible to create different milk run routes by avoiding local solutions. In the traditional savings method, there is possibly one customer on the route, but our modified procedure does not allow for only one customer on the route. When there is one customer on the route, the customer is served by the direct shipment strategy. The flowchart of the proposed modified savings algorithm is given in Figure 5.

The pseudocode of the modified savings is given below:

(1) [Traditional savings heuristic] Calculate savings for each customer pair i-j that are assigned to the milk run in the chromosome.

(2) [Traditional savings heuristic] Rank S_{ij} values in the descending order.

(3) [Modified savings heuristic] If unserved customers > 1,

   (a) Generate random numbers in the range [0, 1] and go to Step 4.
   (b) If there is only one customer in the route,

      (i) Serve customers by direct shipment, and calculate the milk run cost and end procedure.
      (ii) Else calculate the milk run cost and end procedure.

(4) [Modified savings heuristic] If generated random number is >0.9 (0.9 is defined as the threshold value)

   (a) Select customers i and j that are in the first rank in the savings list.
   (b) Else select customers i and j that are in the next saving in the savings list.

(5) [Traditional savings heuristic] If customers i and j are the members of the route,

   (a) Check if customers i and j are on the same route,

      (i) Remove saving of customers i and j from the savings list and go to Step 3.
      (ii) Else check if customer i or j is the first or last customer on one of the routes.
      (iii) Check if total demand of routes < vehicle capacity?, go to iv, else go to Step 3.
      (iv) Check if total travel distance < the milk run tour length, merge the milk run routes, else go to Step 3.

   (b) Else check if total demand of customers i and j < vehicle capacity? go to step c, else go to Step 3.
   (c) Check if total travel distance < the milk run tour length? create new route, else go to Step 3.

The modified savings procedure is explained with the chromosome indicated in Figure 4. The modified savings algorithm is applied for the customers that are randomly assigned to the milk run strategy in the chromosome, as shown below.

The objective is to identify and create milk run routes by minimizing the total distance. Because of the driver's legal driving time limit, the total travel distance is limited to 900 kilometer to satisfy customer demands daily. The distance matrix, demands of customers, and vehicle characteristics are presented in Tables 2–4. Savings calculation and modified savings results are shown in Tables 5 and 6.

Routes created by a modified savings algorithm are shown in Figure 6. Customer 3 is not on one of the milk run routes because when this customer is added into the routes, it causes a violation in vehicle capacity and travel distance. In the modified savings algorithm, when there is single customer in the route, the milk run route is canceled, and the customer is served by direct shipment.

Table 7 presents the traditional savings results, and Figure 7 shows routes that can be created by traditional savings. Table 8 indicates the improvement obtained by the modified savings algorithm. When we compare traditional savings results and modified savings results, we can see that our modified savings algorithm decreases the total distance by creating different routes based on random creation procedure.

After creating the milk run routes with the modified savings algorithm, the chromosome is repaired as indicated in Figure 8. Figures 8 and 9 indicate the chromosome representation before and after applying the modified savings algorithm ((1) cross-docking; (2) direct shipment; (3) milk run).

Step 3. Apply direct procedure if method is equal to direct shipment

   (i) Assign proper vehicle type: for the customers assigned to a direct shipment strategy in the chromosome solution, the proper vehicle type is assigned according to customer demands. Figure 10 shows the customers are served by direct shipment.

   (ii) Calculate direct shipment cost: direct shipment cost is calculated. It involves the fixed cost of the vehicle type and travel distance costs.

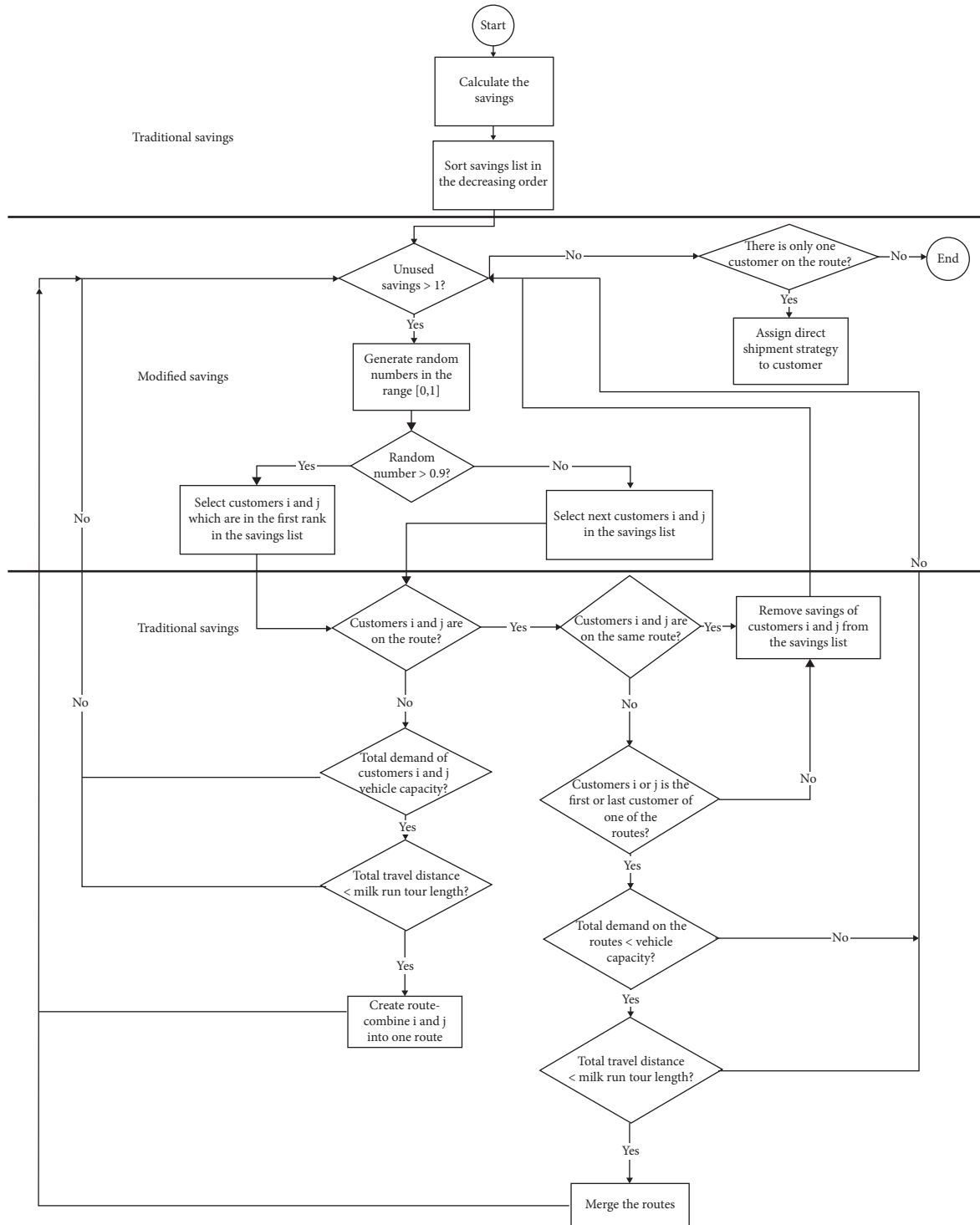*Step 4.* Apply cross-docking procedure if method is equal to cross-docking

FIGURE 5: The flow of the modified savings algorithm.

(i) Consolidate customer demands to be shipped to cross-docking center: for the customers assigned to a cross-docking strategy in the chromosome solution, the total volume of demands is calculated. It is assumed that a sufficient number of trucks are used for shipment to cross-docking center. Figure 11 shows the customers that are served by cross-docking.

(ii) Calculate cross-docking cost: this cost involves shipment cost to cross-docking center and direct shipment cost from the cross-docking center to the customer. Direct shipment cost from the cross-docking center to the customer is a fixed cost, varying according to the volume of customer demands.

TABLE 2: Distance matrix (km).

d_{ij}	0	1	2	3	4	5	6
0	0	420	200	175	230	155	300
1	420	0	175	330	300	165	180
2	200	175	0	305	403	185	190
3	175	330	305	0	280	149	300
4	230	300	403	280	0	55	100
5	155	165	185	149	55	0	45
6	300	180	190	300	100	45	0

TABLE 3: Demand (m^3).

Customers	Demand (m^3)
1	10
2	20
3	23
4	5
5	10
6	30

TABLE 4: Vehicle characteristics.

Vehicle type	Capacity (m^3)	Vehicle cost ($)
1	9	86
2	25	123
3	30	137
4	50	172

Step 5. GA—evaluate the fitness value

The fitness value is the distribution cost of solutions, and it is calculated according to (1) (Section 3). Distribution cost involves direct shipment cost, cross-docking cost, and milk run cost. The costs are ranked in the descending order since it is a minimization problem. The lowest cost is kept as the optimum cost.

Step 6. GA—create new population

(i) Selection: the selection process is applied in GA to select parent chromosomes based on their fitness function value. The roulette-wheel selection procedure proposed by Goldenberg [59] is used for selecting chromosomes in the selection process. The selection probability is calculated by $p_i = f_i \sum_i^N f_i$ where f_i is the fitness value of chromosome and N is the population size.

(ii) Crossover: in the literature, crossover rate varies between 50% and 95%, and mutation rate varies between 5% and 70% [60, 61]. A single-point crossover operator is used in the crossover process. This is illustrated in Figure 12.

Step 7. GA—replace

Replacement is applied with the elitist strategy. The chromosome with the best fitness value is carried directly to the newly generated population.

(iii) Mutation: a single-point mutation is performed. The mutation procedure is shown in Figure 13, and

TABLE 5: Savings calculation.

Savings calculation	Savings in descending order	
	Customer i-j	Savings value
$S_{16} = 900 = 420 + 300 - 180$ $(d_{10} + d_{06} - d_{16} = d_{01} + d_{60} - d_{16})$	S_{16}	900
$S_{12} = 445 = 420 + 200 - 175$ $(d_{10} + d_{02} - d_{12} = d_{01} + d_{20} - d_{12})$	S_{12}	445
$S_{46} = 430 = 230 + 300 - 100$ $(d_{40} + d_{06} - d_{46} = d_{04} + d_{60} - d_{46})$	S_{46}	430
$S_{56} = 410 = 155 + 300 - 45$ $(d_{50} + d_{06} - d_{56} = d_{05} + d_{60} - d_{56})$	S_{56}	410
$S_{15} = 410 = 420 + 155 - 165$ $(d_{10} + d_{05} - d_{15} = d_{01} + d_{50} - d_{15})$	S_{15}	410
$S_{14} = 350 = 420 + 230 - 300$ $(d_{10} + d_{04} - d_{14} = d_{01} + d_{40} - d_{14})$	S_{14}	350
$S_{45} = 330 = 230 + 155 - 55$ $(d_{40} + d_{05} - d_{45} = d_{04} + d_{40} - d_{45})$	S_{45}	330
$S_{26} = 310 = 200 + 300 - 190$ $(d_{20} + d_{06} - d_{26} = d_{02} + d_{60} - d_{26})$	S_{26}	310
$S_{13} = 265 = 420 + 175 - 330$ $(d_{10} + d_{03} - d_{13} = d_{01} + d_{30} - d_{13})$	S_{13}	265
$S_{35} = 181 = 175 + 155 - 149$ $(d_{30} + d_{05} - d_{35} = d_{03} + d_{50} - d_{35})$	S_{35}	181
$S_{36} = 175 = 175 + 300 - 300$ $(d_{30} + d_{06} - d_{36} = d_{03} + d_{60} - d_{36})$	S_{36}	175
$S_{25} = 170 = 200 + 155 - 185$ $(d_{20} + d_{05} - d_{25} = d_{02} + d_{50} - d_{25})$	S_{25}	170
$S_{34} = 125 = 175 + 230 - 280$ $(d_{30} + d_{04} - d_{34} = d_{03} + d_{40} - d_{34})$	S_{34}	125
$S_{23} = 70 = 200 + 175 - 305$ $(d_{20} + d_{03} - d_{23} = d_{02} + d_{30} - d_{23})$	S_{23}	70
$S_{24} = 27 = 200 + 230 - 403$ $(d_{20} + d_{04} - d_{24} = d_{02} + d_{40} - d_{24})$	S_{24}	27

a sample for mutation is shown in Figure 14, where a gene is randomly selected. Random numbers are generated between the range [0, 1]. For mutation, 0.5 is accepted as a threshold value, and the following procedure is applied:

(1) If the gene distribution strategy value is cross-docking and generated a random number, that is, <0.5, direct shipment is assigned as the distribution strategy, else the milk run is assigned

(2) If the gene distribution strategy value is direct shipment and generated a random number, that is, <0.5, cross-docking is assigned as a distribution strategy, else the milk run is assigned

(3) If the gene distribution strategy value is milk run and generated a random number, that is, <0.5, cross-docking is assigned as a distribution strategy, else direct shipment is assigned

Step 8. GA—terminate algorithm

Maximum iteration number is used as the termination condition (iteration number = 1000).

TABLE 6: Modified savings results.

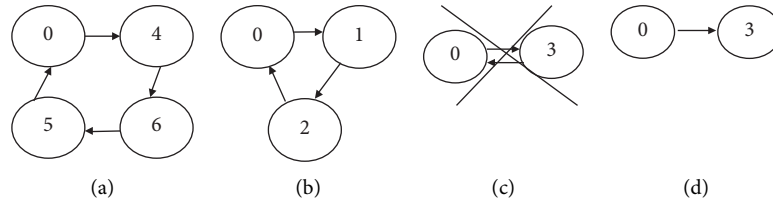| S_{ij}	Savings	Random number	Route	Total demand	Total distance	Vehicle capacity type	Random number >0,90	Violation	
								Vehicle capacity	Travel distance
S_{12}	445	0,58	0-1-2-0	30	795	30–3			
S_{46}	430	0,61		35	630	50–4			
S_{56}	410	0,22	0-4-6-5-0	45	675	50–4			
S_{16}	900	0,99	—	—	—	—	x		
S_{15}	410	0,98				—	x	x	x
S_{45}	330	0,15	—	—	—	—			
S_{26}	310	0,77	—	—	—	—			
S_{13}	265	0,42			880	—		x	
S_{14}	350	0,92				—	x	x	x
S_{36}	175	0,73	—	—	—	—			
S_{25}	170	0,76				—		x	x
S_{35}	181	0,97				—	x	x	
S_{23}	70	0,22				—		x	x
S_{24}	27	0,71				—		x	x
S_{34}	125	0,48			755	—		x	

FIGURE 6: Routes created by the modified savings algorithm. (a) Route 1. (b) Route 2. (c) Route 3 canceled. (d) Direct shipment.

TABLE 7: Traditional savings results.

S_{ij}	Savings	Route	Total demand	Total distance	Vehicle capacity type	Violation	
						Vehicle capacity	Travel distance
S_{16}	900		40	720	50–4		
S_{12}	445	0-2-0	20	855 400	25–2	x	
S_{46}	430		45		50–4		x
S_{56}	410	0-1-6-5-0	50	800	50–4		
S_{15}	410	—	—	—	—		
S_{14}	350				—	x	x
S_{45}	330				—	x	x
S_{26}	310	—	—	—	—		
S_{13}	265			885	—	x	
S_{35}	181				—	x	x
S_{36}	175	—	—	—	—		
S_{25}	170				—	x	x
S_{34}	125	0-3-4-0	28	685	30–3		
S_{23}	70		48		50–4		x
S_{24}	27		48		50–4		x

The flow of the new approach is shown in Figure 15. The pseudocode of the new approach is given below:

(1) [Step 1] Generate a random population

    (i) Initialize population (population size = 100)

    (ii) Assign distribution strategy to customers randomly

(2) [Step 2] If method = milk run, apply modified savings algorithm steps

(3) [Step 3] Else if method = direct shipment, apply direct procedure

(4) [Step 4] Else method = cross-docking, apply cross-docking procedure
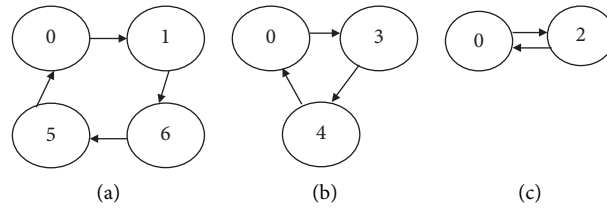
FIGURE 7: Routes created by the traditional savings algorithm. (a) Route 1. (b) Route 2. (c) Route 3.

TABLE 8: Savings obtained by the modified savings algorithm.

	Traditional savings					Modified savings				
Route	Distance	Vehicle cost	Total distance	Total cost	Route	Distance	Vehicle cost	Total distance	Total cost	Savings cost ($/km)
0-1-6-5-0	800	172			0-4-6-5-0	675	172			
0-3-4-0	685	137	1885	2317	0-1-2-0	795	137	1645	2077	240
0-2-0	400	123			0–3	175	123			
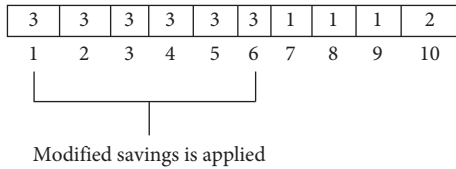
FIGURE 8: The chromosome representation before applying the modified savings algorithm.
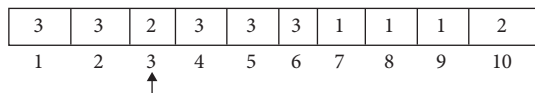
FIGURE 9: The repaired chromosome representation after applying the modified savings algorithm.
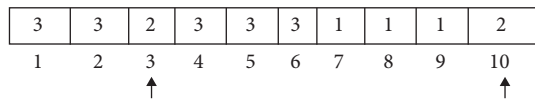

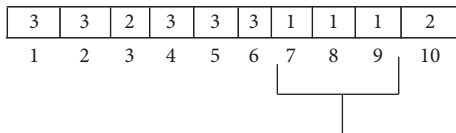FIGURE 10: Customers assigned to the direct shipment strategy.

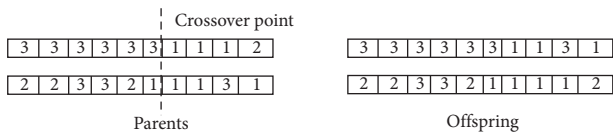FIGURE 11: Customers assigned to the cross-docking strategy.

FIGURE 12: Crossover procedure. (1) Cross-docking; (2) direct shipment; (3) milk run.

(5) [Step 5] Evaluate the fitness value

   (i) Calculate the total distribution costs
   (ii) Rank the costs in descending order

(6) [Step 6] Create new population

   (i) [Selection] Select two parent chromosomes according to their fitness value
   (ii) [Crossover] Apply single-point crossover to form a new offspring
   (iii) [Mutation] Apply a single-point mutation to form a new offspring
   (iv) [Placement] Place new offspring in a new population

(7) [Step 7] Stop creating a new population. If population size = 100, finish forming a new offspring else go to Step 6

(8) [Step 8] Replace-Apply the elitist strategy and use newly generated population

(9) [Step 9] Terminate algorithm if iteration number = maximum iteration number, finish algorithm, and return the best solution, else go to Step 2

5. Case Study of the Proposed Algorithm

In this section, the effectiveness of the proposed algorithm is confirmed by a case study. The case study is conducted on a global electronics manufacturing company. The company's products are mainly electronic components. The company has 380,000 employees and makes 1,502,000,000 deliveries annually. Following steady growth, the company management is trying to find a better route planning solution for its distribution network to meet the market demands and extend its business scope.

For the case study, a project team was established with the SCM director (15 years of experience), the business analyst (10 years of experience), and the authors. Some of the company's staff was invited to attend the meetings when
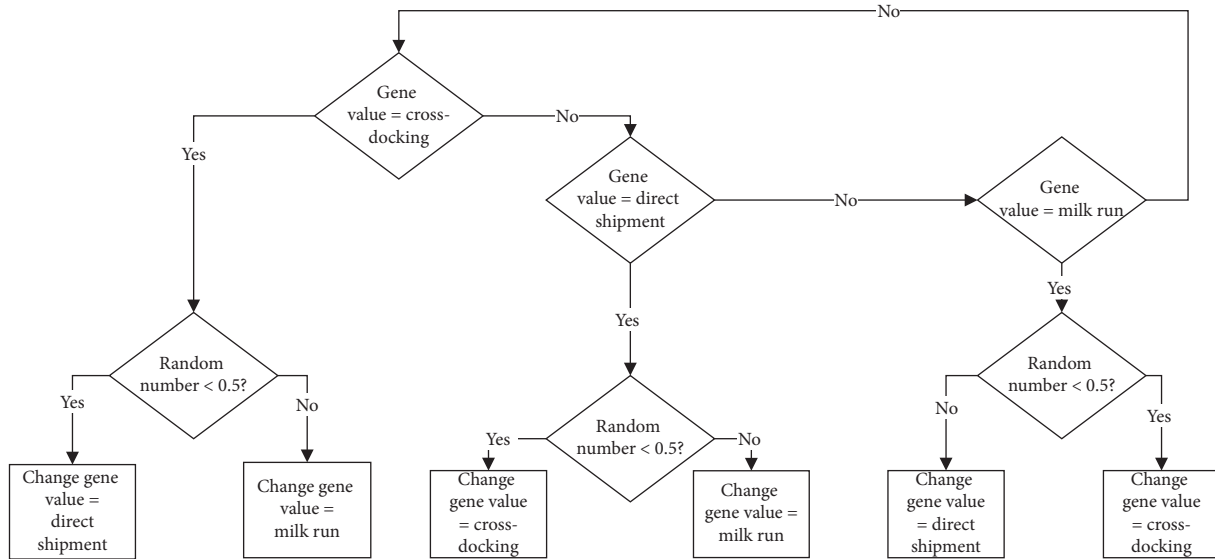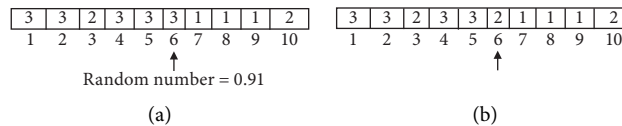
Figure 13: Mutation procedure.

Figure 14: Mutation sample. (a) Before mutation. (b) After mutation.

needed. One of the authors, a former project manager, acted as a consultant (15 years of experience) for the value study. The team met biweekly (4 hours per meeting) to discuss the distribution process and agreed to work on the process. Figure 16 presents a sample of the distribution network that is worked on.

A data sample involving up to 50 customer's distribution requests is used as a problem dataset. Table 9 presents the data sample, including shipment size, the Cartesian coordinates of the customer locations, and direct shipment costs from the cross-docking center for each customer request. Table 10 presents vehicle characteristics, and Table 11 presents other characteristics.

Lingo 15.0 package program is used to obtain the optimal solutions. The software language used in the development of the proposed algorithm is Visual Studio 2013 C sharp. Minitab 15 and SPSS 17.0 package programs are used for performing statistical tests and evaluating statistical results. In addition to this, Minitab 15 is used to apply the Taguchi method. A 64-bit PC with Core i-7-8550U CPU and 8 GB RAM is used to solve the dataset sample.

The genetic algorithm was run 30 times for each data sample. In the determination of the genetic algorithm parameters, the literature was used. In the literature, the population size ranges from 20 to 100 [58], the crossover rate ranges from 50% to 95%, and the mutation rate ranges from 5% to 70% [60, 61]. Therefore, five levels were determined for these three factors. They are for population size, 20, 30, 40, 50, 100; for crossover rate, 0.5, 0.6, 0.7, 0.8, 0.9; and for mutation rate, 0.01, 0.05, 0.1, 0.2, 0.3. The Taguchi method,

an experimental design technique, is used to determine the optimum parameters because it would take too long to test these parameter combinations for each customer data sample.

5.1. Optimization of GA Parameters with Taguchi Method.
The Taguchi method is a statistical method developed by Taguchi and Konishi [62]. The Taguchi method is a helpful method for determining the best combination of different parameters and levels. Taguchi suggests that there is a loss function value converted to a signal-to-noise ratio (S/N) to measure performance characteristics deviations from the target value. In the analysis of the S/N ratio, there are three categories of performance characteristics: nominal best, largest best, and smallest best.

5.1.1. Determination of Control Factors and Levels.
At this stage, the factors and levels that affect performance characteristics are determined. Population size, crossover rate, and mutation rate are the control factors. There are five levels for each factor. Table 12 shows the levels defined for the factors.

5.1.2. Selection of Orthogonal Array.
The most important feature of the orthogonal order is to be able to evaluate factors with a minimum number of tests. In this paper, an L25 orthogonal array is used.
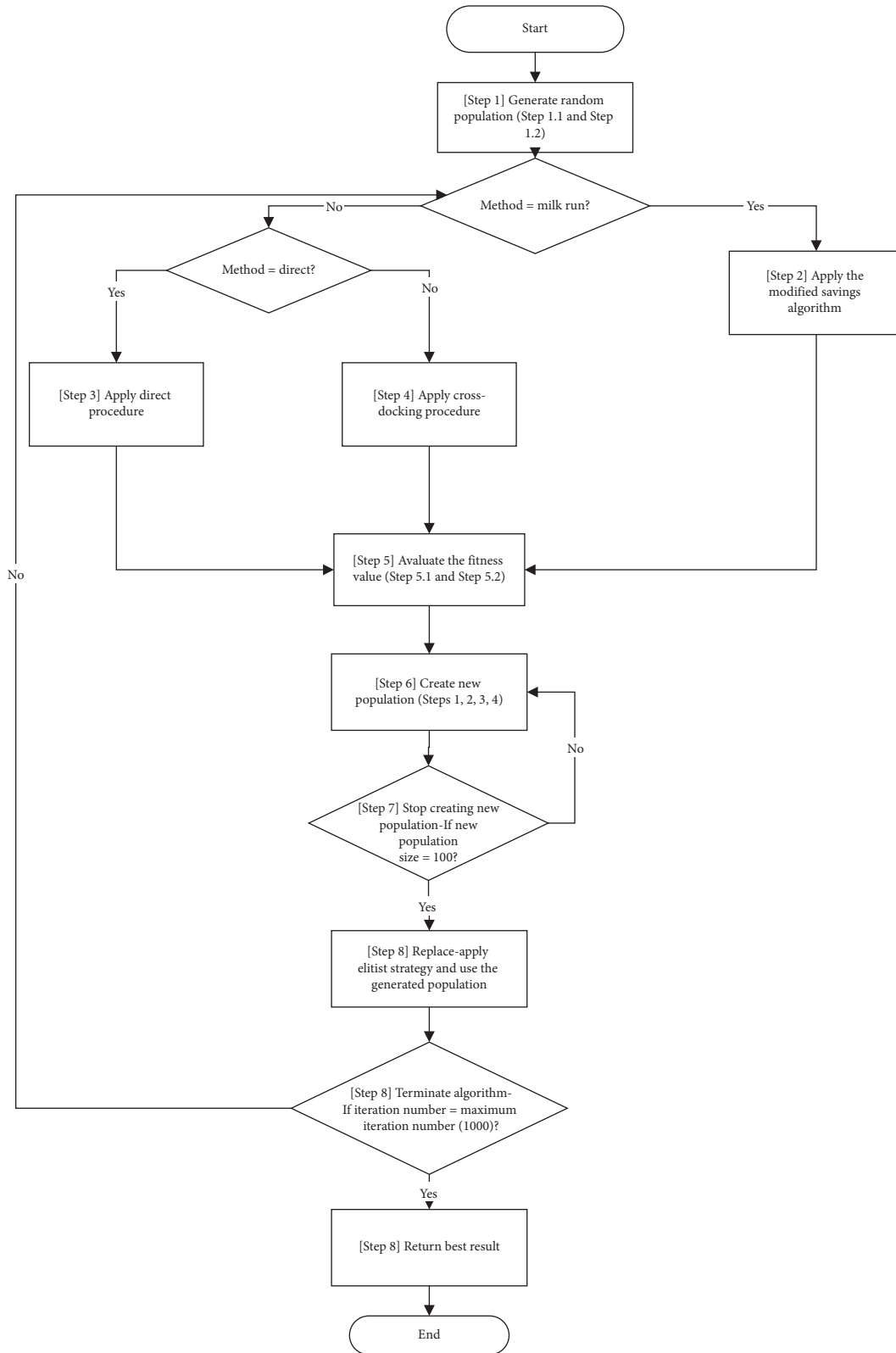
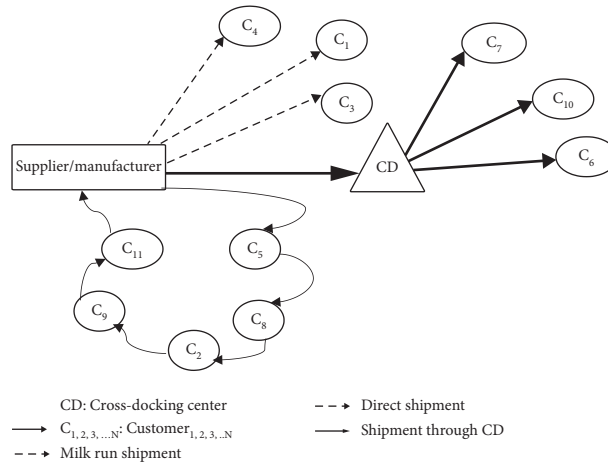FIGURE 15: The flow of the proposed hybrid algorithm.

CD: Cross-docking center   – – ➤ Direct shipment

⟶ $C_{1, 2, 3, ...N}$: Customer$_{1, 2, 3, ..N}$ ⟶ Shipment through CD

– – ➤ Milk run shipment

FIGURE 16: A sample of the distribution network for the case study.

TABLE 9: Dataset sample involving up to 50 distribution requests.

| Customer number | Load (m³) | Customer location | | Direct shipment cost from the cross-docking center (load ∗ 1.5 $) |
		X coordinate	Y coordinate	
1	10	101	195	15
2	15	184	115	22,5
3	13	140	49	19,5
4	10	110	98	15
5	26	114	52	39
6	2	184	189	3
7	25	83	50	37,5
8	4	298	99	6
9	16	75	260	24
10	18	250	38	27
11	24	94	298	36
12	12	246	41	18
13	11	167	58	16,5
14	32	99	255	48
15	8	270	80	12
16	17	98	256	25,5
17	13	217	167	19,5
18	10	200	180	15
19	40	160	64	60
20	42	154	128	63
21	50	207	57	75
22	17	187	265	25,5
23	29	168	234	43,5
24	12	292	291	18
25	15	189	118	22,5
26	38	148	261	57
27	50	155	240	75
28	23	287	80	34,5
29	12	81	243	18
30	18	156	56	27
31	19	43	221	28,5
32	22	193	119	33
33	6	70	269	9
34	19	290	231	28,5
35	29	253	247	43,5
36	33	136	86	49,5
37	20	228	138	30
38	40	80	209	60
39	9	298	272	13,5

TABLE 9: Continued.

| Customer number | Load (m³) | Customer location | | Direct shipment cost from the cross-docking center (load * 1.5 $) |
		X coordinate	Y coordinate	
40	21	65	262	31,5
41	19	148	229	28,5
42	21	31	252	31,5
43	15	89	56	22,5
44	12	182	100	18
45	15	76	180	22,5
46	16	176	127	24
47	14	126	194	21
48	22	270	130	33
49	18	53	56	27
50	17	169	250	25,5

Manufacturer/supplier Cartesian coordinates: $X = 125$, $Y = 35$; cross-dock Cartesian coordinates: $X = 400$, $Y = 200$.

TABLE 10: Vehicle characteristics.

Vehicle type	Capacity (m³)	Vehicle cost ($)
1	9	86
2	25	123,8
3	30	137,6
4	50	172

TABLE 11: Other characteristics.

Truck capacity for cross-docking (m³)	Truck fixed cost for cross-docking ($)	Milk run stop cost ($)	Milk run limited tour distance (km)
45	172	9,6	900

TABLE 12: Control factors determined at different levels.

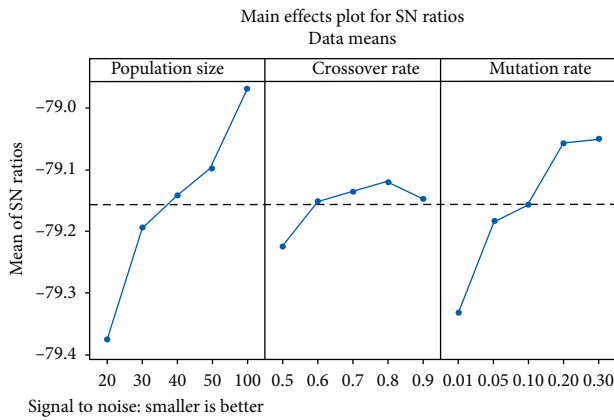| Factors	Level 1	Level 2	Level 3	Level 4	Level 5
Population size	20	30	40	50	100
Crossover rate	0.50	0.60	0.70	0.80	0.90
Mutation rate	0.01	0.05	0.1	0.2	0.3

FIGURE 17: S/N result graph for Taguchi experiments.

5.1.3. *Calculation of Loss Function and S/N Ratio.* The proposed algorithm tries to minimize the Z value, which is the objective function value. The function value is used to calculate the loss function value. The objective function is the smallest best for this paper.

The S/N ratio is calculated using the formula in equation (16) where the smallest is the best:

$$ S/N = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n} yi^2\right). \tag{16} $$

5.1.4. *Construction and Analysis of Experiments.* Experiments are determined by the Taguchi method. L25 orthogonal array is applied, and 25 experiments are executed. For one customer data sample, each experiment is repeated 30 times to obtain the best values in the solution of the proposed algorithm. Since it is the minimization problem, the values with the biggest S/N ratio are the best values. According to Figure 17, the best values for population size, crossover rate, and mutation rate, respectively, are 100, 0.8, and 0.3.

Table 13: Solutions of the data samples.

Data sample size (number) C: customer	Optimal cost ($)	Optimal CPU (s) S: second	Heuristic solution ($)	Heuristic CPU (s) S: second	Milk run tour(s)	Direct tour(s)	Customer(s) serviced by cross-docking shipment	The fleet composition (capacity (m³)-shipment type) M: milk run, D: direct shipment	The number of a used vehicle for milk run and direct shipment
4C	587,40	1,00	587,40	0,06	0-4-1-2-3-0			50-M	1
5C	745,00	1,00	745,00	0,03	0-3-2-1-4-0	0-5		50-M, 30-D	2
6C	796,60	5,00	796,63	0,08	0-4-1-6-2-3-0	0-5		50-M, 30-D	2
7C	965,40	8,00	965,62	0,11	0-3-2-6-1-4-0	0-5 0-7		50-M, 25-D, 30-D	3
8C	981,50	30,00	981,51	0,08	0-5-3-0	0-7	1, 2, 4, 6, 8	50-M, 25-D	2
9C	1193,90	266,00	1194,03	0,06	0-2-4-7-0	0-5	1, 3, 6, 8, 9	50-M, 30-D	2
10C	1409,20	8330,00	1409,31	0,10	0- 10-2-3-0	0-5 0-7	2, 5, 7, 9, 10	50-M, 25-D, 30-D	3
11C	1633,10	25211,00	1633,10	0,08	0-3-4-5-0	0-7	2, 3, 7, 9, 10, 11, 12	50-M, 25-D	2
12C	1849,00	203009,00	1849,10	0,13	0-5-3-0-0-7-4-2-0		2, 7, 9, 10, 11, 12, 13	50-M, 50-M	2
13C	—	—	1900,80	0,18	0-4-2-13-3-0	0-5 0-7	1, 6, 8, 9, 10, 11, 12	50-M, 25-D, 30-D	3
14C	—	—	2294,80	0,19	0-4-2-13-3-0	0-5 0-7 0-14	1, 6, 8, 9, 10, 11, 12	50-M, 25-D, 30-D, 50-D	4
15C	—	—	2399,68	0,15	0-10-12-13-0 0-3-5-0	0-7 0-14	1, 2, 4, 6, 8, 9, 11, 15	50-M, 50-M, 25-D, 50-D	4
16C	—	—	2561,83	0,22	0-12-10-15-13-0 0-5-4-3-0	0-7 0-14	1, 2, 6, 8, 9, 11, 16	50-M, 50-M, 25-D, 50-D	4
17C	—	—	2788,97	0,15	0-3-13-5-0	0-2 0-7 0-14	1, 4, 6, 8, 9, 10, 11, 12, 15, 16, 17	50-M, 25-D, 25-D, 50-D	4
18C	—	—	2859,80	0,30	0-4-2-13-3-0	0-5 0-7 0-14	1, 6, 8, 9, 10, 11, 12, 15, 16, 17, 18	50-M, 25-D, 30-D, 50-D	4
19C	—	—	3076,80	0,22	0-4-2-13-3-0	0-5 0-7 0-14 0-19	1, 6, 8, 9, 10, 11, 12, 15, 16, 17, 18	50-M, 25-D, 30-D, 50-D, 50-D	5
20C	—	—	3345,80	0,32	0-4-2-13-3-0	0-5 0-7 0-14 0-19 0-20	1, 6, 8, 9, 10, 11, 12, 15, 16, 17, 18	50-M, 25-D, 30-D, 50-D, 50-D, 50-D	6
21C	—	—	3602,80	0,27	0-4-2-13-3-0	0-5 0-7 0-14 0-19 0-20 0-21	1, 6, 8, 9, 10, 11, 12, 15, 16, 17, 18	50-M, 25-D, 30-D, 50-D, 50-D, 50-D, 50-D	7
22C	—	—	3831,04	0,33	0-10-12-2-0 0-3-13-5-0	0-7 0-14 0-19 0-20 0-21	1, 4, 6, 8, 9, 11, 15, 16, 17, 18, 22	50-M, 50-M, 25-D, 50-D, 50-D, 50-D, 50-D	7
23C	—	—	4141,68	1,00	0-2-17-18-4-0 0-12-10-15-13-0 0-3-5-0	0-7 0-14 0-20 0-21 0-23	1, 6, 8, 9, 11, 16, 22	50-M, 50-M, 50-M, 25-D, 50-D, 50-D, 50-D, 30-D	8
25C	—	—	4475,53	0,45	0-13-25-2-0 0-5-4-3-0	0-7 0-19 0-20 0-21	1, 6, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 22, 23, 24	50-M, 50-M, 25-D, 50-D, 50-D, 50-D	6

TABLE 13: Continued.

| Data sample size (number) C: customer	Optimal cost ($)	Optimal CPU (s) S: second	Heuristic solution ($)	Heuristic CPU (s) S: second	Milk run tour(s)	Direct tour(s)	Customer(s) serviced by cross-docking shipment	The fleet composition (capacity (m³)- shipment type) M: milk run, D: direct shipment	The number of a used vehicle for milk run and direct shipment
30C	—	—	5853,24	2,34	0-10-12-30-0 0-4-17-2-13-0 0-3-5-0	0-19 0-20 0-23 0-26 0-27 0-28 0-7 0-21	1, 6, 8, 9, 11, 14, 15, 16, 18, 22, 24, 25, 29	50-M, 50-M, 50-M, 50-D, 50-D, 30-D, 50-D, 50-D, 25-D, 25-D, 50-D	11
35C	—	—	6982,65	2,80	0-15-28-10-0 0-2-32-3-0 0-13-30-0	0-5 0-7 0-14 0-23 0-19 0-20 0-21 0-26 0-27 0-35	1, 4, 6, 8, 9, 11, 12, 16, 17, 18, 22, 24, 25, 29, 31, 33, 34	50-M, 50-M, 30-M, 30-D, 25-D, 50-D, 30-D, 50-D, 50-D, 50-D, 50-D, 50-D, 30-D	13
40C	—	—	8081,06	6,45	0-25-37-2-0 0-10-13-30-0 0-3-36-0	0-5 0-7 0-14 0-23 0-19 0-20 0-21 0-26 0-27 0-28 0-32 0-38	1, 4, 6, 8, 9, 11, 12, 15, 16, 17, 18, 22, 24, 29, 31, 33, 34, 35, 39, 40	50-M, 50-M, 50-M, 30-D, 25-D, 50-D, 30-D, 50-D, 50-D, 50-D, 50-D, 50-D, 25-D, 25-D, 50-D	15
45C	—	—	8958,50	6,09	0-15-28-10-0 0-25-32-44-0 0-7-43-4-0 0-3-13-5-0	0-19 0-20 0-21 0-26 0-27 0-30 0-36 0-38	1, 2, 6, 8, 9, 11, 12, 14, 16, 17, 18, 22, 23, 24, 29, 31, 33, 34, 35, 39, 40, 41, 42, 45	50-M, 50-M, 50-M, 50-M, 50-D, 50-D, 50-D, 25-D, 50-D, 50-D, 50-D, 50-D	12
50C	—	—	10092,87	10,16	0-37-17-6-47-0 0-2-32-44-0 0-7-49-0 0-4-36-0 0-13-30-3-0 0-5-43-0	0-19 0-20 0-21 0-26 0-27 0-38 0-48	1, 8, 9, 10, 11, 12, 14, 15, 16, 18, 22, 23, 24, 25, 28, 29, 31, 33, 34, 35, 39, 40, 41, 42, 45, 46	50-M, 50-M, 50-M, 50-M, 50-M, 50-M, 50-D, 50-D, 50-D, 50-D, 50-D, 25-D, 50-D	13
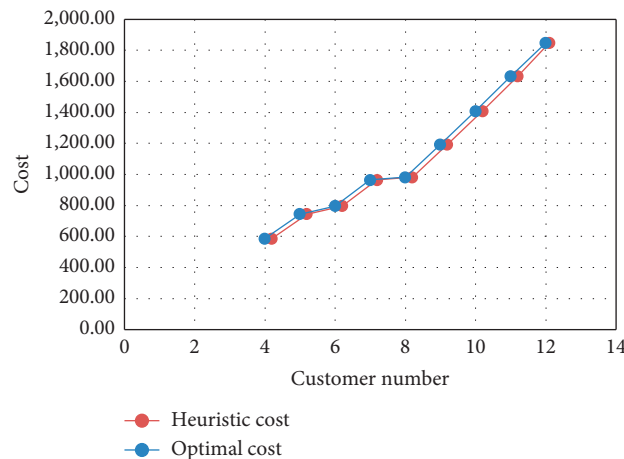
FIGURE 18: The comparison of solutions.
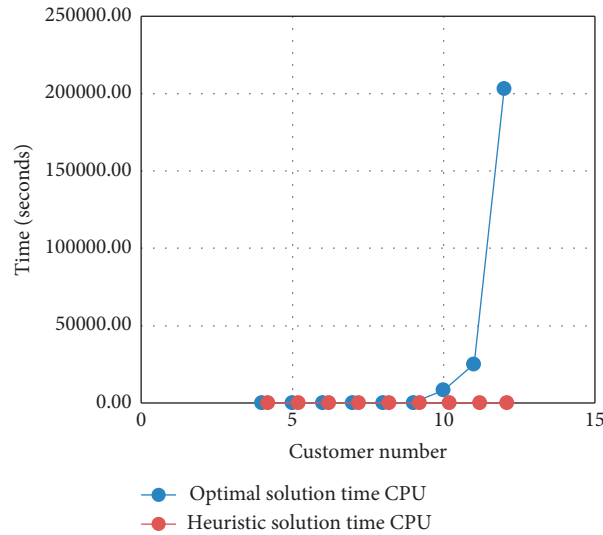
FIGURE 19: The comparison of CPU run times.

Tests of normality						
	Kolmogorov–Smirnov[a]			Shapiro–Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Difference value between solutions	0.237	9	0.155	0.843	9	0.063

[a]Lilliefors significance correction

FIGURE 20: Tests of normality results.

Paired samples test								
Paired differences								
				95% Confidence interval of the difference				
	Mean	Std. deviation	Std. error mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1 optimal solution-heuristic solution	−0.06667	0.07778	0.02593	−0.12646	−0.00688	−2.571	8	0.033

FIGURE 21: Paired samples test results.

5.2. Computational Results and Statistical Analysis. This section presents the solutions of the data sample shown in Table 9 and statistical analysis for comparing the solutions. The solutions of the data samples are summarized in Table 13.

The solutions for the data sample involving up to 12 customers are created with both the optimization model and the proposed heuristic algorithm. As we can see from Table 13, the optimal time solution of the data sample involving up to 12 customers is 203009 seconds and that is nearly three days. Because of the long solution time, the solutions for the data sample involving more than 12 customers are created with the proposed heuristic algorithm. The comparisons of solutions are depicted in Figure 18. The two methods have given similar solutions for small-size samples.

Figure 19 shows the CPU run times for both methods. It can be observed that for small-size samples, the two methods have approximately the same running time. For the large-size samples, the optimization method's running time increases exponentially. So for large-size samples, the heuristic method is necessary to obtain solutions within a reasonable time.

The paired sample t-test is applied for the data samples involving up to 12 customers to compare the solutions. Before applying this test, the Kolmogorov–Smirnov test has been applied to control normality.

As shown in Figure 20, the significance level (Sig.) is 0.155 for the Kolmogorov–Smirnov test, and 0.063 for the Shapiro–Wilk test. These values are greater than 0.05 ($p > 0.05$), so the paired sample t-test can be applied for comparing solutions. In Figure 21, the significance value is 0.033. Since the value is greater than 0.01 ($p > 0.01$), the null hypothesis is not rejected. Therefore, the two solutions produce similar solutions. It can be concluded from the

statistical test that the proposed heuristic algorithm can produce good solutions.

6. Conclusions

Distribution plays an important role in supply chain management. Milk run added distribution network models reduce the number of vehicles and travel distances by increasing the loading rates at the possible levels. This kind of mixed logistics model requires accurate management based on the operational plan and a suitable combination of delivery methods to increase distribution reliability. The overall supply chain cost can be minimized by using an optimized mixed system.

In the literature, a few studies address a mixed delivery system, which consists of three delivery modes: milk run, direct shipment, and cross-docking shipment. Additionally, there is no developed heuristic solution based on Clarke and Wright's algorithm and the genetic algorithm to solve this mixed delivery network problem. This paper develops a "modified" savings-based genetic algorithm which is called distribution strategy selection and vehicle routing hybrid algorithm (DSSVRHA). Our algorithm contributes a new hybrid solution to the literature in order to solve this mixed delivery network problem efficiently which consists of two subproblems: distribution strategy selection and vehicle routing. Our new algorithm decides the selection of an appropriate distribution strategy and optimal routes using a heterogeneous fleet of vehicles at minimum cost.

Population size, mutation rate, and crossover rate parameters in the proposed algorithm have been determined by the literature review. The most optimal parameter values were determined by the Taguchi method, which is a statistical method for the correct combination of parameter values to make the study more reliable. The optimum parameter values found were used to generate a solution for all customer data samples.

Solutions for data samples involving up to 12 customers were obtained with both a linear programming model and the proposed algorithm. The performance of results was validated with statistical analysis. The paired sample t-test was performed to test whether the results obtained by the two methods gave similar results. The results of the paired sample t-test show that the two methods produce similar results. Therefore, it has been proved that our developed algorithm provides a good solution in reducing the supply chain distribution costs and computational time, especially for large-size problems.

Some future research points of this study would be as follows:

   (i) The proposed heuristic algorithm in this paper can be used to solve similar network structure problems

  (ii) Backhaul delivery strategy can be added to the models studied in this paper

 (iii) When the number of vehicles is limited, the recommended routes, costs, and effects on the solution times can be examined

 (iv) Distribution strategies allowing split shipment can be studied

  (v) Uncertain situations for demand and time can be taken into consideration

 (vi) In case of need, opening or closing of additional distribution centers can be examined

Data Availability

The data set is added in the manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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