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Logistic optimization of the blood delivery routing problem in the Lower Southern region of Thailand

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Abstract

This study discusses a blood delivery routing problem faced by a regional blood centre (RBC). The RBC meets the requests of 21 hospitals for blood and blood products. Each hospital can request product deliveries throughout the day, but the RBC has a cut-off time for its transportation round and manually designates a specific route for the transport van, which is available only during working hours. This vehicle routing problem operates under vehicle time restriction constraints. The aim of the research is to use a metaheuristic method to find the optimal transport route to deliver blood and blood products at minimal total cost. This paper proposes a novel hybrid metaheuristic method that combines the firefly algorithm (FA) as the main structure, a crossover operator in differential evolution (DE) and a new local search (NLS); is called the HFA+NLS algorithm. The exact solution of the mathematical model and current practice are used for comparisons of the quality of the solutions. Four existing algorithms are also employed to compare the search performance. The paired t-test is used to compare the means of the search performance measures of any two methods. Different sizes of problem are considered by generating a set of nine test instances (small, medium and large problems) and a real-world case study to verify the competitive performance of the proposed algorithm. The computational results reveal that the HFA+NLS algorithm has a superior performance to other methods in the number of test instances for which the optimal, or the best known, solution was successfully found. The HFA+NLS algorithm determines the best route for a blood transport van with a total blood transportation cost reduction of 66.46%.

Keywords: Blood delivery routing, Firefly algorithm, Crossover, Local search, Hybrid metaheuristic

1. Introduction

Blood is an extremely important resource for saving the lives of accident victims, and is also needed by patients for the treatment of some diseases. Government organizations dealing with blood management, such as hospitals and national blood centres, provide effective value-added services by optimizing the delivery of requested blood products. Non-profit organizations oversee the blood supply chain in some countries around the world, and attach great importance to blood management [1]. The blood supply chain relates to activities and material flows among the network elements. Blood units are collected from donors, after their registration, screening and testing, at either fixed or temporary blood donation facilities to avoid the transmission of diseases through blood transfusions. The blood units are then tested for different types of blood diseases and compatibility before being used in blood transfusions. The blood products are shipped to hospitals to fulfil orders received by the blood centre, by a blood transportation vehicle on a specified route [2].

Some authors have developed mathematical approaches to optimize blood supply chain network models. Zahiri et al. [3] presented a bi-objective mixed-integer model for the integrated planning of the main processes (collection, screening, production, distribution and delivery route) for blood products. Total cost and the freshness of the blood products were optimized using a multi-stage stochastic programming approach to take into account the uncertain nature of supply and demand. A multi-objective self-adaptive differential evolution and variable neighbourhood search (named MSDV) was proposed to solve this highly complex problem. Mousavi et al. [4] used bi-objective programming to design a supply chain network for blood products, considering social and environmental factors affecting blood decomposition. They applied four metaheuristic approaches, multi-objective simulated annealing (MOSA), multi-objective particle swarm optimization (MOPSO), multi-objective social engineering optimization (MOSEO), and a non-dominated

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ranking genetic algorithm, to verify the behavior of the model. Their results showed that the overall cost was increased by the social effects of blood decomposition.

The literature on the logistics of the upstream activities for blood and its components was studied to design a specified route for blood product delivery by addressing the vehicle routing problem (VRP) in blood supply chain. Şahinyazan et al. [5], using a two-stage IP-based heuristic algorithm, proposed a mobile collection model, based on the VRP, with the goal of increasing blood collection levels. In this model, a new vehicle (shuttle) was integrated into the system to visit bloodmobiles (vehicles with medical staff and equipment for collecting blood from donors) in the field and transfer the collected blood to the depot, while the bloodmobiles continued to perform their tours without having to make daily returns to the depot. The blood pickup routing problem (BPRP), presented in [6, 7], focuses on the upstream activities of blood logistics to pick up blood bags at fixed blood bank donation sites. The authors modelled the problem on the VRP and solved the model using CPLEX optimization software along with simulated annealing (SA) to minimize the total distance travelled. Özener and Ekici [8] developed a blood platelet collection model using the vehicle routing approach to optimize the number of donations for platelet production, while Haitam et al. [9] applied the VRP with time windows to the collection of medical samples (blood and/or urine tubes) from sick people at home and their transportation to a laboratory in Morocco. Karakoc and Gunay [10] studied priority-based vehicle routing for agile blood transportation between donor/client sites, and the VRP, with simultaneous delivery and pickup and time windows, was applied to products in home healthcare logistics, such as chemotherapy drugs and blood products [11].

Some studies have focused on the downstream activities of blood logistics for serving designated hospitals in the blood supply chain network. Ganesh et al. [12] proposed a VRP to distribute and collect blood for a public healthcare system. They clustered the nodes to be visited and then assigned vehicle routes to each cluster using a metaheuristic approach by combining genetic algorithms (GAs) and SA. Rabbani et al. [13] introduced bi-objective mathematical programming for the collection of blood from donors by bloodmobiles. They applied multi-objective fuzzy programming and the VRP to determine the optimal routes, and solved the problem using CPLEX with the SA approach. The VRP was also used to determine distribution routes for a blood transfusion unit in Indonesia, obtaining a reduction in both distance and time [14]. Jafarkhan and Yaghoubi [15] developed an inventory routing model for distributing red blood cells in hospitals using a real case study with a consideration of uncertain demand and supply. They solved this problem using the robust stochastic optimization method, while Ghasemi and Bashiri [16] developed a two-stage stochastic inventory vehicle routing model for the distribution of blood products that optimized the holding cost and the blood collection and transportation costs. A production-inventory-routing problem for blood products was studied in [17] and solved by heuristic (local search) and metaheuristic (adaptive large neighbourhood search (ALNS)) methods.

Blood transportation in the Bangkok metropolitan region of Thailand was studied in [18], and the transport for the delivery of blood products by a third-party logistics service provider, modelled as a VRP, was introduced in [19] with the aim of minimizing the total route time (the sum of the total travel time and the total length of stay time). The model was solved using CPLEX. Sujaree and Jirawongnuson [20] studied the blood routing problem in the northern region of Thailand from blood donation centres to hospitals in the relevant area. The problem was modelled as a VRP and solved by the hybrid cuckoo search algorithm, which is a combination of cuckoo search (CS), tabu search, and neighbourhood search. A location-routing problem with emergency referral (LRPER) model was developed in [21] to determine the logistical locations of blood banks and the distribution of blood products, and was solved by a hybrid genetic algorithm (HGA) that minimized the total fixed cost of the local blood banks, the total periodic delivery costs and the emergency delivery costs. Intapan et al. [22] investigated the blood routing problem using a small-scale case study in the southern region of Thailand. They implemented the VRP to determine the optimal route using a hybrid differential evolution algorithm, and their results showed a reduction in transportation costs.

Recently, several metaheuristic approaches have been developed for solving different variants of the VRP, including the artificial bee colony (ABC), the artificial fish swarm (AFS), the genetic local search algorithm, the variable neighbourhood search algorithm, tabu search (TS), the iterated local search algorithm (ILS), particle swarm optimization (PSO), the large neighbourhood search heuristic, the GA, SA, CS, differential evolution (DE), the firefly algorithm (FA) and the shuffled frog leaping (SFL) algorithm [23-25]. Variants of recent metaheuristic algorithms have also been applied to solve the VRP for blood logistics; these include the GA, SA, CS, DE and PSO. However, there have been limited applications of other existing metaheuristic approaches for solving blood delivery routing problems in the blood supply chain network.

The Thai Red Cross Society is a charitable organization that undertakes humanitarian activities such as blood supply chain management in Thailand. The blood services include the blood transfusion and blood donation service, which is coordinated by the National Blood Centre and collects, processes and provides sufficient blood and blood components to hospitals nationwide. The National Blood Centre has established twelve Regional Blood Centres (RBCs) for regional blood management operations [26]. According to the National Blood Centre [27], the daily blood requirements throughout Thailand, divided using the ABO blood group system, are 500 units of group A, 550 units of group B, 800 units of group O and 150 units of group AB, with one unit being approximately 400 ml of blood. High levels of blood demand in Thailand require efficient transportation and delivery. Here, the blood supply chain is evaluated in terms of cost, time and distance as a vehicle routing problem for the efficient delivery of blood and blood products to meet the demands of each hospital under vehicle time restriction constraints. Experiments are conducted on nine generated test instances and one case study collected from real-life situations experienced by the 12th RBC in Songkhla Province (Southern Thailand).

The 12th RBC for blood supply chain management delivers blood and blood products to 89 hospitals in seven provinces in the south of Thailand. This study analyzed data collected from just 21 hospitals in Songkhla Province, for the case study because different blood distribution policies apply elsewhere. When blood and blood products requested by hospitals have been approved by the Chief of the 12th RBC in Songkhla Province, a vehicle (hospital van) with a driver is allocated for delivery and return as a single-trip journey, as shown in Figure 1.

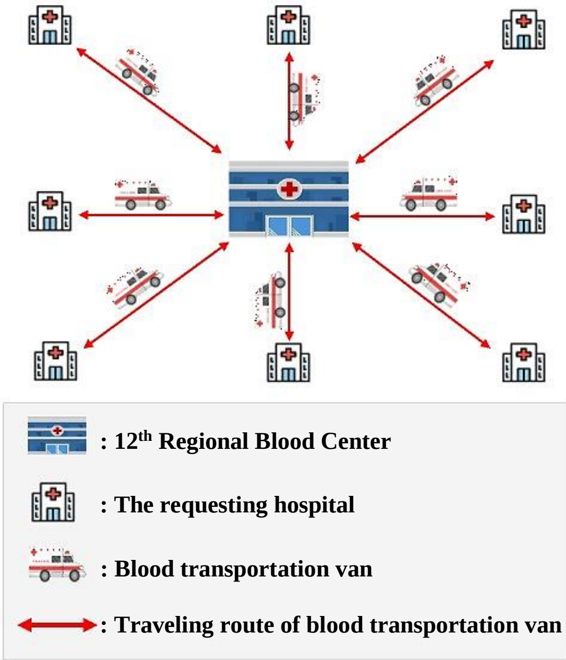

Figure 1 Blood distribution policy

However, in the context of a cost-efficient supply chain, single-trip transportation leads to high costs of physical distribution in the blood supply chain because the empty leg means there is inefficient use of the transport vehicle. This paper considers blood transportation as a vehicle routing problem (VRP), considering how the 12th RBC can operate to efficiently deliver blood and blood products to meet the demands of each hospital under vehicle time restriction constraints. A new metaheuristic algorithm is proposed to optimize blood delivery transportation costs. The main contributions of this paper are threefold. First, the problem is based on the VRP, and is called the Blood Delivery Routing Problem with time constraints (BDRP-TC); it assesses the optimal routing of a fleet of vehicles to deliver blood bags between the blood centre and the requesting hospitals. BDRP-TC is an extension of the well-known VRP. Unlike the VRP for other products, in BDRP-TC a set of vehicle routes is constructed to minimize total cost. Time-driven activity-based costing is implemented in the transportation cost function to ensure minimal vehicle time use. Each hospital site is allocated the same pickup time window for blood transport delivery and return. If the available vehicle time-of-use is exceeded, the delivery is scheduled for the next day.

Second, the BDRP-TC model uses a hybridized firefly algorithm, a crossover operator in differential evolution, and a new local search. No publications have previously applied this hybrid scheme for blood delivery routing.

Third, this paper scales up the problem size on the nine generated test instances and presents a new larger-scale case study based on real-life situations to test the performance of the algorithm.

In order to summarize the research background and review of the literature focusing on the research topic in the context of blood logistics, Table 1 provides a coding classification system of the relevant literature using seven major characteristics. Table 2 illustrates the characteristic features of the relevant papers that were reviewed.

Table 1 Classification of literature on optimization of blood logistics

1. Blood type		**4. Output**	
Platelet	PLC	Location/allocation	LA
Plasma	PLA	Delivery routes	DR
Red blood cell	RBC	Number of productions	NP
Whole blood	WB	Inventory level	IL
Blood products and blood components	BP	Integrated blood collection	IBC
Blood bag	BB	Ordering policy	OP
2. Objective function		**5. Problem variants**	
Min. cost	MC	Vehicle routing problem with time window	VRPTW
Max. remaining bloods	MRS	Location routing problem	LRP
Min. distance	MD	Blood collection, production, distribution and routing planning	BCPDRP
Min. delays	MDL	Selective-covering-inventory-routing	SCIR
Min. time	MT	Vehicle routing problem	VRP
Min. delivery time	MDT	Special collecting vehicles	SCV
Min. inventory-routing transfusion	MIT	Selective vehicle routing problem	SVRP
Min. production costs	MPC	Blood pickup routing problem	BPRP
Max. number collected and processed	MCP	Maximum blood collection problem	MBCP
3. Modelling		Pickup and delivery problem	PDP
Stochastic dynamic programming	SDP	Vehicle routing problem with backhaul	VRPB
Mixed integer linear programming	MILP	Vehicle routing problem with delivery and collection	VRPDC
Mixed integer nonlinear programming	MINLP	Location routing problem with emergency referral	LRPER
Statistical modelling and analysis	SM	Flexible and robust inventory-routing	FRIR

Table 1 (Continued) Classification of literature on optimization of blood logistics

5. Problem variants (continued)		**7. Method / Method for performance comparison** (continued)	
Capacitated vehicle routing problem	CVRP	IBM ILOG CPLEX	CPLEX
Capacitated vehicle routing problem with time window	CVRPTW	LINGO software	LINGO
Inventory-routing problem	IRP	Greedy heuristic / Generation heuristic	GH / GEH
Vehicle routing problem cold supply chain	VRPCSC	Pattern generation heuristic / Incremental pattern generation heuristic	PGH / IPGH
Blood delivery routing problem with time constraints	BDRP-TC	Tabu search	TB
6. Type of solution method		Neighbourhood search	NS
Exact	EX	Genetic algorithm	GA
Heuristic/ Metaheuristic	HE	Hybrid genetic algorithm	HGA
7. Method / Method for performance comparison		Hybrid cuckoo search	HCS
Simulated annealing	SA	Artificial chemical reaction optimization	ACROA
Harmony search	HS	Differential evolution	DE
Local search / Iterated local search	LS / ILS	Differential evolution with new local search	DE+NLS
General algebraic modelling system	GAMS	Adaptive large neighbourhood search	ALNS
Multi-objective self-adaptive differential evolution algorithm	MSDV	Hybrid metaheuristic algorithm including genetic algorithms and local search	GANLS
Multi-objective simulated annealing	MOSA	Sweep algorithm	SWA
Multi-objective particle swarm optimization	MOPSO	Saving algorithm	Saving
Multi-objective social engineering algorithm	MOSEO	Hybrid firefly algorithm	HFA
Non-dominated ranking genetic algorithm	NSGA-II	Hybrid firefly algorithm with new local search	HFA+NLS
Simulated annealing heuristic with restart strategy	SARS		

Table 2 A summary of the articles reviewed in the context of blood logistics optimization

Reference article	Year	1. Blood type	2. Objective function	3. Modelling	4. Output	5. Problem variants	6. Solution method		7. Performance comparison
							EX	HE	
Eskandari-Khanghahi et al. [2]	2018	PLC	MC	MILP	LA, DR	VRPTW, LRP	CPLEX	SA	HS
Zahiri et al. [3]	2018	PLC, PLA, RBC, WB	MC, MRS	MILP	NP, IL, OP, DR	BCPDRP	GAMS	MSDV	-
Mousavi et al. [4]	2021	BP	MC	MILP	DR	VRP, SCV	-	MOSA, MOPSO, MOSEO, NSGA-II	-
Şahinyazan et al. [5]	2015	WB	MC	SM	DR	SVRP	GOROBI	HE	-
Iswari et al. [6]	2016	WB	MC	MILP	DR	VRPTW	CPLEX	SA	-
Yu et al. [7]	2018	WB	MD	MILP	DR	BPRP	CPLEX	SARS	SA
Özener and Ekici [8]	2018	PLC	MCP	SDP	DR	MBCP	-	GH	GEH, PGH, IPGH
Haitam et al. [9]	2021	WB	MDL	MILP	DR	PDP, VRPTW	CPLEX	TB, NS	-
Karakoc and Gunay [10]	2017	BP	MDT	MILP	DR	CVRP	-	GANLS	-
Liu et al. [11]	2013	BP	MC	MINLP	DR	VRPTW	-	GA, TB	-
Ganesh et al. [12]	2014	WB	MC	MILP	DR	VRPB, VRPDC	-	GA, SA	-
Rabbani et al. [13]	2017	PLC	MC	MILP	DR	VRP	CPLEX, GAMS	SA	-
Lestari et al. [14]	2021	BP	MDT, MT	MILP	DR	VRP	-	SWA	-
Jafarkhan and Yaghoubi [15]	2018	RBC	MC	MILP	DR, IL	FRIR	CPLEX, GAMS	ILS	ALNS
Ghasemi and Bashiri [16]	2018	PLC	MC	SDP	LA	SCIR	CPLEX, GAMS	-	-
Mousazadeh and Darestania [17]	2019	BP	MIT, MPC	MILP	IBC, IL	VRP, IRP	-	LS	ALNS
Pathomsiri and Sukhaboon [18]	2011	BB	MD	MILP	DR	VRP	-	Saving	-
Taweeugsornpun and Raweewan [19]	2017	RBC	MT	MILP	DR	VRP	CPLEX	-	-
Sujaree and Jirawongnuson [20]	2018	BP	MD	MILP	DR	CVRP	-	HCS	GA, CS, ACROA
Banthao and Jittamai [21]	2018	BP	MC	MILP	LA	LRPER	-	HGA	GA
Intapan et al. [22]	2022	PLC, PLA, RBC, WB	MC	MILP	DR	CVRP	-	DE+NLS	SA, DE, HCS
Our paper	2023	PLC, PLA, RBC, WB	MC	MILP	DR	BDRP-TC	LINGO	HFA+NLS	SA, DE+NLS, HFA, HCS

2. Vehicle routing for blood delivery

This section provides details of the mathematical model for the blood delivery routing problem with time constraints (BDRP-TC). The objective is to minimize the total cost of blood transportation from the Regional Blood Centre to the requesting hospitals as the sum of the transportation costs based on distance and the time-of-use of the vehicles. In addition, time limitations are an important consideration in the decision support system for blood delivery, particularly in emergency blood transport. In the real situation of this case, if emergency blood products are requested they are picked up by the requesting hospital from the 12th RBC and are excluded from the delivery routing.

In the general situation of blood delivery, according to [28], the time limitation for temporarily maintaining blood quality outside a permanent blood storage room (i.e., during transportation) is no more than 24 hours. In this paper, we study the blood delivery routing only in the real situation under the 12th RBC's delivery management policy. This policy directs that the time limit for blood transportation must not exceed the 8 working hours of a day, which is equal to the working time of a driver, and this is set as a parameter of the delivery time in the BDRP-TC model. This model can handle a delivery time of up to 24 hours according to the maximum time limit suggested in [28] by changing the parameter value for working hours per day. In this case, the overtime, if any, based on the hourly driving rate for a driver should be calculated and included in the transportation cost based on the time-of-use of the vehicle. When blood product requests for hospitals are approved each day by the Chief of the Regional Blood Centre, the routing planner will manually assign all requesting hospitals to the route as far as possible within the day requested. Each hospital is visited exactly once by only one blood delivery vehicle. However, in practice, it is possible that a requesting hospital may not be included in the route. It will then be assigned to a new route on the next working day, or if necessary it will directly pick up the blood products requested from the 12th RBC using its own hospital vehicle. In this model, the requesting hospitals will receive their delivery on a new route on the next working day if they cannot be assigned to a route within the requested day. Blood and blood product bags are packed into single-size foam boxes for each hospital and then assigned to the designated traveling route for shipping to that hospital. The maximum number of boxes that can be loaded into a blood transportation van is 40 boxes. The model assumptions are summarized in the list below.

(1) The locations of the blood centre and the hospital points are known.
(2) The amount of blood in the requests for blood products is determined.
(3) Each route assigned to a blood delivery vehicle takes the blood centre as its starting point, and returns to the blood centre.
(4) All the blood requests of a hospital must be met at the same time (i.e., splitting blood requests for one hospital is not allowed).
(5) The total number of blood boxes packed for each route must not exceed the maximum load of the blood delivery vehicle (i.e., there must be no more than 40 boxes).
(6) Each hospital is served exactly once by only one blood delivery vehicle, but one blood delivery vehicle can serve multiple hospitals within its route.
(7) The sum of the traveling time for each route must not exceed the predefined value for the maximum delivery time (i.e., it must be no more than 8 hours of working time).

The indices, parameters, decision variables and objective function used in the formulation are explained in detail below.

Indices

i	Hospital i, $i = 1, 2, ..., I$
j	Hospital j, $j = 1, 2, ..., J$
k	Blood transport vehicle k, $k = 1, 2, ..., K$

Parameters

I, J	Number of hospitals
K	Number of blood transport vehicles
T	Working hours per day
d_{ij}	Traveling distance from i to j (kilometres, km)
t_{ij}^k	Traveling time from i to j (hours), calculated as the traveling distance divided by the average vehicle speed (km/hour), which is calculated from the historical driving data
c_d	Transportation cost based on traveling distance (Baht/km)
c_t	Transportation cost based on time-of-use of the vehicle (Baht/min)
q_i	Blood request (number of boxes for all products) of hospital i
a_k	Capacity of the blood transport vehicle k

Decision variables

U_i^k	Variable to eliminate incomplete loop paths or to prevent incomplete loop delivery paths
X_{ij}^k	$\begin{cases} 1 & \text{if the blood transport vehicle } k \text{ drives from hospital } i \text{ to hospital } j \\ 0 & \text{Otherwise} \end{cases}$
Y_i^k	$\begin{cases} 1 & \text{if the blood request for hospital } i \text{ is carried by blood transport vehicle } k \\ 0 & \text{Otherwise} \end{cases}$

Objective function:

$$Min \quad Z = \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} \left(c_d d_{ij} + c_t t_{ij}^k \right) X_{ij}^k \tag{1}$$

Subject to

$$\sum_{j=1}^{N} X_{0j}^k \leq 1 \qquad , k = 1,2,...,K \tag{2}$$

$$\sum_{i=0}^{N} X_{ih}^k = \sum_{j=0}^{N} X_{hj}^k \qquad , h = 1,2,...,N;\ k = 1,2,...,K \tag{3}$$

$$\sum_{k=1}^{K} Y_i^k = 1 \quad , i=1,...,N \tag{4}$$

$$\sum_{i=1}^{N} q_i Y_i^k \leq a_k \quad , k=1,2,...,K \tag{5}$$

$$Y_i^k \leq \sum_{j=0}^{N} X_{ji}^k \quad , i=1,...,N;\ k=1,2,...,K \tag{6}$$

$$\sum_{k=1}^{K} \sum_{i=0}^{N} X_{ij}^k = 1 \quad , j=1,2,...,N \tag{7}$$

$$\sum_{i=0}^{N} \sum_{j=0}^{N} t_{ij}^k X_{ij}^k \leq \mathrm{T}, \quad k=1,2,...,K \tag{8}$$

$$U_i^k \geq U_j^k + q_i - a_k + \left(a_k\left(X_{ij}^k + X_{ij}^k\right)\right) - X_{ij}^k(q_i + q_j), \quad k=1,2,...,K;\ i=0,...,N;\ j=1,2,...,N;\ i \neq j \tag{9}$$

$$U_i^k \leq a_k - X_{0i}^k(a_k - q_i) \quad , k=1,2,...,K;\ i=1,...,N \tag{10}$$

$$U_i^k \geq q_i + \sum_{j=1}^{N} q_j X_{ji}^k \quad , k=1,2,...,K;\ i=1,...,N \tag{11}$$

$$X_{ij}^k = \{0,1\} \quad , i=0,...,N;\ j=0,2,...,N;\ k=1,2,...,K \tag{12}$$

$$Y_i^k = \{0,1\} \quad , i=0,...,N;\ k=1,2,...,K \tag{13}$$

$$U_i^k \geq 0 \quad , i=0,...,N;\ k=1,2,...,K \tag{14}$$

The objective function (1) minimizes the total cost of delivering blood and blood products from the Regional Blood Centre to the requesting hospitals. This sum function of the transportation cost is based on the distance and the time-of-use of the vehicle. The transportation cost based on distance is calculated as a function of the average cost of the van, the fuel cost, the maintenance cost and the cost of tyre changes, multiplied by the traveling distance from the Regional Blood Centre or from hospital i to hospital j. The cost based on time-of-use of the vehicle is computed as the product of the time-activity-based cost for transportation (including driver's wages, depreciated cost, vehicle tax and insurance) and the time-of-use of the vehicle. Constraint (2) ensures that no blood transport vehicle departs from the Regional Blood Centre (Location no. 0) more than once. Constraint (3) ensures that when the blood transport vehicle travels to a particular hospital it then travels out from that hospital. Constraint (4) ensures that the blood request for hospital i is carried out only once by the blood transport vehicle k. Constraint (5) ensures that the blood transport vehicle loads boxes of blood products that do not exceed its capacity. Constraint (6) guarantees that delivery to hospital i is possible only if blood transport vehicle k travels through hospital i from one of the hospital j. Constraint (7) ensures that hospital j will only be visited once by any blood delivery vehicle on the route from any hospital i. Constraint (8) ensures that the total traveling time for each route does not exceed the specified working time, and Constraints (9) to (11) are equations to prevent subtours. Constraints (12) to (14) set the boundary values for the decision variables.

3. Hypotheses and methodology

A wide variety of algorithms has been developed using metaheuristic methods rather than mathematical methods to solve the complexity of the VRP, because these methods are simpler and more flexible. For this reason, the research goal is formulated as using a new hybrid metaheuristic method to determine the transport route with minimal total cost for blood and blood products delivery. Two research hypotheses (RHs) were posited as follows:

RH1: The search performance of the novel hybrid metaheuristic algorithm is better than or comparable to existing metaheuristic methods for solving the BDRP-TC.

RH2: If the route planning staff of the 12th RBC use the novel hybrid metaheuristic algorithm to design a specific route for blood delivery, they will be better prepared for blood delivery management, with a cost saving on transportation.

The research team conducted this study on nine generated test instances, with different numbers of hospitals requesting blood products, to investigate the search performance of the proposed method. One case study, a real-life situation experienced by the RBC in Songkhla Province, was used to examine whether the new proposed method can provide a cost saving on transportation for blood products.

3.1 A novel hybrid metaheuristic algorithm to solve the BDRP-TC

The proposed algorithm is a hybridization of the firefly algorithm (FA), the crossover operator in differential evolution (DE) and a new local search (NLS), and is called the HFA+NLS algorithm. The FA is a metaheuristic algorithm that was introduced by Yang [29] in 2008 for optimization problems, and was bio-inspired by the flashing behaviour of fireflies at night. The FA has been successfully implemented to solve many optimization problems. It has good population diversity, but the search performance needs to be enhanced for the aspects of exploitation capability and fast convergence. Wang et al. [30] suggested that the binomial crossover operator of DE should be incorporated with evolutionary algorithms to improve search performance. Here, the binomial crossover operator is employed to enhance the exploitation ability of the proposed method. NLS is an effective local search strategy introduced by Intapan et al. [22], and is a modified version of the new local search of Kongkaew and Wittayasilp [31]. In this paper, the HFA+NLS allows a possible solution to access a new local search procedure to escape the trap and/or obtain a new improved solution. Details of these methods are given in the following subsections.

3.2 Design of the HFA+NLS algorithm

In this paper, we develop a new method that is a hybridization of the FA, the crossover operator of DE and NLS. The FA is the main structure of the algorithm, while the crossover operator of DE and NLS are applied to improve the search performance. The step-by-step procedures of the proposed algorithm are described below.

Step 1. (Initialization): Set the FA parameters, choose a stopping criterion, and randomly generate the initial population of fireflies (x_i) to represent a routing solution in the BDRP-TC problem.

Step 2. (Brightness): Compute the light intensity (l_i) for each firefly member i, which is determined by the objective function $f(x_i)$. Decode the space coordinates of each firefly member i (x_i) in the current population using the largest-ranked-value (LRV) method, to represent a group of possible routes. Evaluate the objective function $f(x_i)$, which is the total cost of blood transportation, of each firefly using Eq. (1).

Step 3. (Movement of fireflies): This step moves less bright fireflies towards brighter ones. If the brightness (i.e., light intensity) of firefly member j (l_j) is more attractive (brighter) than the brightness of firefly member i (l_i), then firefly member i is attracted to firefly member j. The movement of the fireflies is determined by

$$x_i(t+1) = x_i(t) + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha(rand - 0.5) \tag{15}$$

where x_i and x_j are the space coordinates of firefly members i and j. The second term is associated with the attractiveness, based on the distance between the two fireflies. The third part is the randomization term. The step α and *rand* represent the random number generator uniformly distributed in the range [0, 1].

Step 4. (Crossover operation): Apply the binomial crossover operator to implement a discrete recombination of the fireflies after the movement ($x_i(t+1)$) and the parent fireflies (x_i) to produce offspring.

Step 5. (Updating the light intensity): Update the light intensity of the firefly members in the population.

Step 6. (Local search): Apply the new local search procedure to all fireflies in the population. Details of the new local search method are presented in the next subsection.

Step 7. (Evaluating and ranking the fireflies): Decode the space coordinate of each firefly member in the population to represent a group of possible routes and then evaluate the objective function of each firefly using Eq. (1). After evaluation, rank the fireflies to find the current best solution.

Step 8. (Checking for the stopping criterion): Terminate the algorithm if the number of generations has reached the stopping criterion, then report the outputs.

The HFA+NLS procedure can be summarized as the pseudocode depicted in Figure 2.

Algorithm HFA+NLS for the BVRP-TC

Initialization:

Set the FA parameters: light absorption coefficient (γ), number of population (*NP*), maximum number of generations (*MaxGen*)

Randomly generate the initial population of fireflies x_i (i = 1, ..., *NP*).

Apply the LRV rule to decode the space coordinates of firefly member i (x_i) to represent the group of routes.

Assume that $f(x_i)$ is the objective function.

Light intensity l_i at x_i is determined by $f(x_i)$.

Define light absorption coefficient γ.

while (t < *MaxGen*) **do**

for i = 1 to *NP* (all *NP* fireflies) **do**

for j = 1 to *NP* (all *NP* fireflies, inner loop) **do**

  If ($l_j > l_i$) **then**

    Move firefly i towards j in n-dimension using Eq. (15);

  End

Vary attractiveness with distance r via $exp\left(-\gamma r^2\right)$

Apply the crossover operator of DE.

Evaluate new solutions and update light intensity.

End for j

End for i

Apply the new local search operation based on five neighborhood structures.

Rank the fireflies and find the current best.

End while

Postprocess results and visualization

Figure 2 Pseudocode of the HFA+NLS

3.3 Detail of the NLS procedure

According to the movement in the search space, the solution can move from one solution to another in many different directions to improve the space of only the feasible solutions. The NLS procedure provides a systematic change of five neighbourhood structures to explore the solution space with the ability to avoid being trapped in local minima. According to the search enhancement with the local search, the local search can be applied either to only the top members or to all the members in the population. In this paper, the NLS procedure with five moves is applied to all the members in the population. This is because the NLS procedure enables the members in the population with worse solutions to have a chance to evolve towards a better solution in the search space region. The NLS procedure with these structures is depicted in Figure 3.

Procedure New Local Search (NLS)

Begin
x_i represents the space coordinates of the firefly i to be enhanced.
Apply the LRV rule to decode the space coordinates of firefly member i (x_i) to represent the group of routes.
Evaluate the objective function $f(x_i)$.
for $k = 1$ to $n\times(n-1)$
  $h = 1$;
  while $h \le 5$
    If $h = 1$
    Randomly select two different positions of space coordinates u and v of the firefly i;
    Execute swap operation for the firefly member i (x_i), and obtain the new firefly member i (x_{i_new});
    Elseif $h = 2$
    Randomly select two different positions of space coordinates u and v of the firefly i;
    Execute insert operation for the firefly member i (x_i), and obtain the new firefly member i (x_{i_new});
    Elseif $h = 3$
    Execute reverse operation for the firefly member i (x_i), and obtain the new firefly member i (x_{i_new});
    Elseif $h = 4$
    Execute random walk operation for the firefly member i (x_i), and obtain the new firefly member i (x_{i_new});
    Elseif $h = 5$
    Insert the average of the value of best firefly operation for the firefly member i (x_i), and obtain the new firefly member i (x_{i_new});
    End if.
    Apply the LRV rule to decode the space coordinates of new firefly member i (x_{i_new}) to represent the group of routes.
    Evaluate the objective function $f(x_{i\_new})$.
      If $\left(f(x_{i\_new}) - f(x_i) \le 0\right)$
        $x_i = x_{i\_new}; f(x_i) = f(x_{i\_new})$
        Continue
      Else $h = h + 1$;
      End if.
  End while.
  End for.
    End.

Figure 3 Pseudocode for the NLS method

The solution quality (i.e., total cost of transportation) and computational time of the algorithms were investigated to verify the research hypotheses. The algorithm generated a reduced total cost of transportation, with a higher solution quality executed in a faster computational time. The statistical parameters used in this study include the average total transportation cost, the average computation time and the average improvement rate. The graphical analysis approach and the statistical paired t-test are also employed for comparison.

4. Computational results and comparisons

4.1 Experiment settings and performance comparison

The efficiency of the proposed HFA+NLS algorithm for solving the BDRP-TC problem was analyzed in terms of the total cost and computational time. The mathematical model was solved for the optimal solution, or the best known feasible solution, obtained using optimization software (Lingo v.20 on Windows). The best known feasible solution was used if the optimal solution was not found after 24 hours (i.e., 86,400 seconds) of runtime. The proposed HFA+NLS method was tested and compared with the optimal solution (or best known feasible solution) obtained from Lingo and the solution based on current practice of the 12th RBC. Previous studies used simulated annealing (SA) [6], hybrid cuckoo search (HCS) [20] and hybrid differential evolution (DE+NLS) [22] to successfully deduce, in a short period of time, near-optimal solutions of the VRP for blood transportation. All five of the metaheuristic algorithms considered (including the HFA) were coded in Java computer language with NetBeans IDE 8.2 and run on a computer with Intel Core i5 CPU 2.40 GHz and Ram DDR4 8 GB. All six methods and the current practice were tested with nine generated test instances and a real-world case study, making ten test instances in total. In this paper, we consider only the total cost of the current procedure operated by the 12th RBC. The ten test instances were divided into three groups (small, medium and large test problems) depending on the number of hospitals. Details of the ten test instances are illustrated in Table 3.

Table 3 Information for the test instances

Test instance	No. of hospitals	Test instance	No. of hospitals
S1	5	M3	52
S2	7	L1	60
S3	10	L2	68
M1	40	L3	72
M2	46	Case study	21

For the experimental settings, all test instances were repeated five times for each algorithm and once for the current practice. The maximum number of generations was used as the stopping criterion in the experiments for all the five algorithms under consideration. When the generation number reached the predefined maximum value, the best known solution was reported. In order to develop a robust algorithm, in Table 4, the 2^k full factorial design method with 2 replications (i.e., 2*2*2*2 = 16 runs) was applied for tuning the parameters for the HFA+NLS method (with the test instance M3) to determine the best values of the three parameters: step size (α), light absorption coefficient (γ) and crossover rate (CR). Table 5 shows the analysis of variance for the parameter tuning. For the two-way interaction between two factors S-S (step size) and L-A (light absorption coefficient), using a significance level of 0.05, the p-value (= 0.031) was less than 0.05. This indicates that there was significant interaction between these two factors. For the single-factor result for the light absorption coefficient (L-A), the p-value (< 0.000) was less than 0.05, meaning that there was a significant difference in yield (total cost) between the two levels of this factor. In Figure 4, using the response optimizer in Minitab software, it was clear that there was better performance and robustness of HFA+NLS when the parameters α, γ and CR were set to 1, 0.5 and 0.95, respectively. The parameter values of HFA were the same as those of HFA+NLS. In addition, the parameter values of SA, HCS and DE+NLS were obtained from the works of Iswari et al. [6], Sujaree and Jirawongnuson [20] and Intapan et al. [22], respectively. The parameter settings used in all five algorithms are shown in Table 6.

Table 4 Parameters for HFA+NLS and their levels

Factor	Name	Low level (-)	High level (+)
S-S	Step size (α)	0.2	1
L-A	Light absorption coefficient (γ)	0.5	1
C-R	Crossover rate (CR)	0.7	0.95
Response	**Name**		
T-C	Total Cost		

Table 5 Analysis of variance for the parameter tuning experiment

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	718213	102602	8.07	0.004
Linear	3	598496	199499	15.70	0.001
S-S	1	35592	35592	2.80	0.133
L-A	1	560623	560623	44.12	0.000
C-R	1	2281	2281	0.18	0.683
2-Way Interactions	3	105295	35098	2.76	0.111
S-S*L-A	1	86732	86732	6.83	0.031
S-S*C-R	1	7406	7406	0.58	0.467
L-A*C-R	1	11157	11157	0.88	0.376
3-Way Interactions	1	14422	14422	1.13	0.318
S-S*L-A*C-R	1	14422	14422	1.13	0.318
Error	8	101660	12708		
Total	15	819873			
Model Summary					
S	R-sq	R-sq(adj)	R-sq(pred)		
112.728	87.60%	76.75%	50.40%		

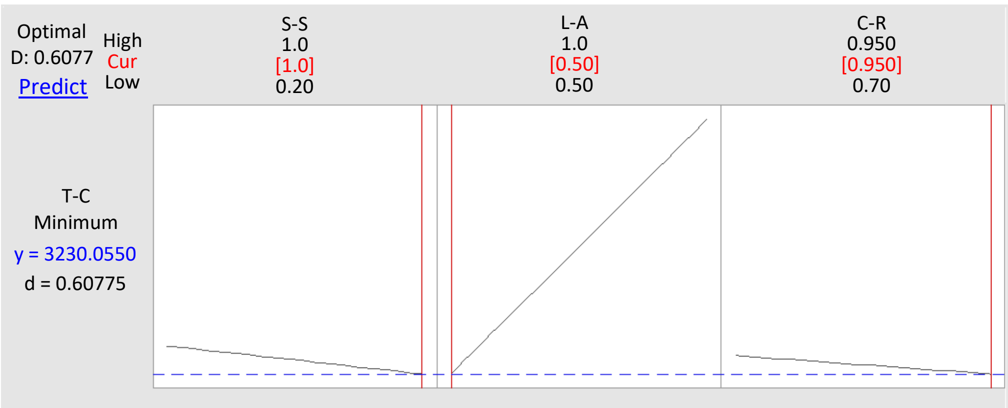

Figure 4 The plots obtained from the response optimizer

Table 6 Details of parameters used in each algorithm

Parameter	Algorithm				
	SA	HCS	DE+NLS	HFA	HFA+NLS
Step size (α)	-	-	-	1	1
Light absorption coefficient (γ)	-	-	-	0.5	0.5
Scaling factor (F)	-	-	0.9	-	-
Crossover rate (CR)	-	-	0.7	0.95	0.95
Initial temperature (T_0)	150	-	-	-	-
Final temperature (T_{final})	0.001	-	-	-	-
Cooling rate (β)	0.99	-	-	-	-
Lévy flight (λ)	-	3	-	-	-
Probability to discover (P_a)	-	0.45	-	-	-
Number of populations	-	100	100	100	100
Maximum number of generations	100	100	100	100	100

4.2 Computational results and discussion

The results for all the methods under consideration (total cost and running time) are presented in Table 7, with the improvement rates in transportation costs for blood products provided by the proposed HFA+NLS method compared with the current practice by the route planning staff of the 12th RBC shown in Table 8. Statistical tests on the total cost and computational time were conducted to determine any significant differences between the means of the proposed HFA+NLS approach and the competitive method using the paired t-test at a significance level of 0.05, with the results reported in Table 9. A plot of the convergence behavior against the generation number of all the methods considered for the case study is depicted in Figure 5. Table 10 illustrates the best, worst, and mean results obtained with the standard deviations over 100 times of running the algorithm over the problem set.

Table 7 Computational results generated by the seven methods considered

Instance	No. of hospitals	Current practice	Lingo		SA		HCS		DE+NLS		HFA		HFA+NLS	
		Cost	Cost	Time	Cost	Time	Cost	Time	Cost	Time	Cost	Time	Cost	Time
S1	5	1636.2	1300.4	0.07	**1300.4**	1.40	**1300.4**	3.60	**1300.4**	2.00	**1300.4**	1.40	**1300.4**	1.60
S2	7	1735.4	1091.9	0.16	**1091.9**	2.20	**1091.9**	4.20	**1091.9**	3.20	**1091.9**	3.00	**1091.9**	2.80
S3	10	3246.2	1333.3	0.52	1366.1	4.40	1358.6	8.40	1353.4	6.80	1361.3	5.80	**1350.6**	7.00
M1	40	11891.5	2524.8	1440	2595.5	50.20	2567.9	83.80	**2563.5**	74.40	2585.9	65.00	2571.3	70.60
M2	46	13515.9	3048.4	86400	3559.2	69.80	3474.5	95.80	3480.8	81.00	3488.7	76.80	**3470.2**	81.60
M3	52	15238.3	2789.7	86400	3619.2	87.20	3417.9	113.20	3365.9	86.80	3358.1	82.80	**3321.9**	91.60
L1	60	16532.8	2729.7	86400	3536.2	84.20	3274.4	118.00	3330.6	87.60	3344.8	89.00	**3238.0**	89.60
L2	68	17767.9	2388.8	86400	3522.4	88.00	3331.9	116.20	3326.3	86.20	3306.7	86.80	**3217.9**	90.20
L3	72	18470.0	2320.3	86400	3628.2	88.20	3344.0	107.80	3403.2	90.40	3402.1	87.20	**3300.2**	92.40
Case study	21	6464.9	1671.1	5480.41	1918.9	23.20	1730.6	36.40	1754.0	33.80	1804.4	33.60	**1728.1**	34.00
Average		10649.9	2130.7	52388.12	2613.8	49.88	2489.2	68.74	2497.0	55.22	2504.4	53.14	**2459.1**	56.14

Remark: Unit of "Cost" is Thai Baht (THB), where 36 Baht is approximately 1 US dollar (USD), and unit of "Time" is seconds.

Table 8 Improvement rate for total cost by the HFA+NLS

Instance	Total cost (THB)		Improvement rate (%)
	Current practice	HFA+NLS	
S1	1636.2	1300.4	20.52
S2	1735.4	1091.9	37.08
S3	3246.2	1350.6	58.39
M1	11891.5	2571.3	78.38
M2	13515.9	3470.2	74.33
M3	15238.3	3321.9	78.20
L1	16532.8	3238.0	80.41
L2	17767.9	3217.9	81.89
L3	18470.0	3300.2	82.13
Case study	6464.9	1728.1	73.27
		Overall average	66.46

As seen in Table 7, all the metaheuristic methods considered can achieve the optimal solutions (solved by Lingo v.20) for instances S1 and S2. The HFA+NLS method outperformed all the metaheuristic methods and the current practice in the number of test instances for which it successfully determined the best known solution. The HFA+NLS found the solution in 9 out of the 10 test instances. The total number of successful test instances for the HFA, DE+NLS, HCS and SA methods was 2, 3, 2 and 2, respectively. For all the small test instances, the optimal solution or best known solution was obtained by the proposed HFA+NLS, while the SA, HCS, DE+NLS and HFA methods were successful in some test instances. For the medium-sized problems, the HFA+NLS method successfully found the best known solutions in two test instances (M2 and M3). The DE+NLS method achieved the best known solution for only one test instance (M1), while the SA, HCS and HFA methods did not find any of the best known solutions. For the large problems and the case study, the HFA+NLS method successfully found the best known solutions for all the test instances.

The results in Table 8 show that the HFA+NLS algorithm reduces the total blood transportation cost by 66.46%, and achieves a better route for the blood transport van than the current practice.

Table 9 P-values of the test of significance

Methods	Costs	Times
HFA+NLS vs. Current practice	0.002	-
HFA+NLS vs. Lingo	0.015	0.004
HFA+NLS vs. DE+NLS	0.029	0.264
HFA+NLS vs. HFA	0.009	0.012
HFA+NLS vs. SA	0.008	0.012
HFA+NLS vs. HCS	0.053	0.004

The results in Table 9 shows the statistically significant differences in total cost and computational time using the paired-t test. For the tests on the total cost of the pair HFA+NLS vs. Lingo, there was a significant difference in the means, and it was found that the better solutions were accomplished by Lingo, according to Table 7. For the other pairs, there was a significant difference in the mean total cost almost always, except for the pair HFA+NLS vs. HCS. This indicates that the performance of HFA+NLS in searching for solutions was better than the current practice, SA, DE+NLS and HFA, while the performance of HFA+NLS and HCS in searching for solutions was equivalent. The results show no statistically significant difference in the computational time between HFA+NLS and DE+NLS, indicating the equivalence of these methods, while significant differences were found for the other pairs. Therefore, the comparative numerical results show the competitiveness of the proposed HFA+NLS algorithm in solving the blood delivery routing problem with time constraints (BDRP-TC).

Figure 5 shows a convergence plot for all five algorithms in solving the case study. The proposed HFA+NLS algorithm outperformed SA, HCS and HFA after reaching the 27th generation. HFA+NLS showed slower convergence than DE+NLS for the first 57 generations but then achieved optimal performance. In addition, the HFA+NLS algorithm provides superior results to the other algorithms in solution quality, since HFA+NLS can explore more new solutions from the solutions obtained after the movement of firefly step in Eq. (15) by applying the DE crossover operator, leading to new best solutions because of the effectiveness of the DE crossover operator. The hybridization with NLS can speed up the process of finding a lower total cost by using information from the five neighbourhoods search space to enhance the algorithm's ability to avoid being trapped in a local optimal solution. As seen in Figure 5, the HFA hybridized with NLS can lead to a faster convergence than the HFA without NLS. Thus, the proposed HFA+NLS method is very efficient, with fast convergence. To compare the performance with DE+NLS, the HFA+NLS performs better than DE+NLS since it can generate solutions more from two successive methods. The first solutions set is generated by using Eq. (15). Then, the obtained solutions set will be re-explored by the DE crossover operator to be new solutions. In contrast to the DE+NLS, there is only a set of solutions generated by the DE crossover operator. Therefore, HFA+NLS can find more solutions than DE+NLS even though the same NLS method is used, leading to better performance of the algorithm.

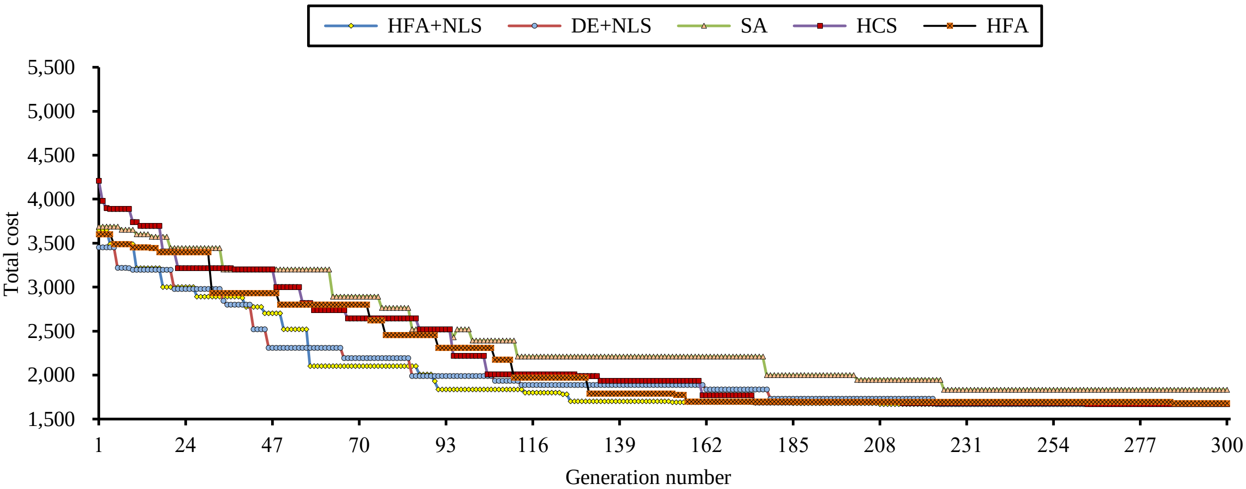

Figure 5 The behavior plot of the case study

Table 10 Best, worst, mean and standard deviations among 100 times of running HFA+NLS

Instance	No. of hospitals	Best	Worst	Mean	Standard deviations
S1	5	1300.4	1300.4	1300.4	-
S2	7	1091.9	1415.1	1138.6	99.4
S3	10	1351.2	1420.5	1373.8	21.3
M1	40	2589.4	4725.3	3072.6	513.7
M2	46	3511.2	4992.4	3824.8	399.0
M3	52	3421.4	4870.4	3879.4	471.4
L1	60	3367.8	5201.3	4149.5	471.9
L2	68	3211.2	4893.3	3911.3	512.6
L3	72	3421.1	5339.4	4200.8	570.0
Case study	21	1838.0	3653.2	2569.2	542.1

In Table 10, the results show less variability in the solutions obtained for the small problem, and instance S1 has no variability. When the problem size increases, the variability in the solutions obtained becomes larger. The range between the best value and the worst value also becomes larger when the instance size increases. Therefore, the HFA+NLS needs its search capability to be further enhanced with an efficient strategy in order to reduce the variability and the range of solutions obtained.

The novel hybrid metaheuristic algorithm, HFA+NLS, successfully solved the BDRP-TC and determined a shorter transportation route to deliver blood and blood products. Therefore, RH1 was satisfied, and the HFA+NLS algorithm performed significantly better than the other methods. For RH2, the HFA+NLS algorithm reduced the total cost of blood transportation, with a cost saving of 66.46%. Thus, this method was beneficial for the Chief of the 12th RBC to design specific blood delivery routes.

5. Conclusions

Blood is an extremely important resource for saving the lives of accident victims, and is also needed by patients for the treatment of some diseases. Many academics and practitioners have highlighted the importance of the blood supply chain to handle supply and demand more efficiently. The blood delivery routing problem with time constraints (BDRP-TC) was formulated as a vehicle routing problem with time constraints to minimize the total cost of delivering blood and blood products. A novel hybridization of the firefly algorithm (FA), a crossover operator in differential evolution (DE) and a new local search (NLS), called the HFA+NLS algorithm, was developed and tested using nine generated test instances and a real-world case study. The solution (total cost) for the HFA+NLS method was compared with current practice and the optimal solution, or best known solution, obtained from the Lingo v.20 optimization software. In addition, the performance of the HFA+NLS algorithm was compared with four other existing methods: simulated annealing (SA), hybrid cuckoo search (HCS), hybrid differential evolution (DE+NLS) and the hybrid firefly algorithm (HFA), in terms of solution quality and computational time. The HFA+NLS method provided the most promising and competitive search performance, with good exploitation ability and fast convergence to solve blood delivery routing problems with time constraints. The HFA+NLS algorithm was proved to be a useful approach for optimizing blood delivery management at a regional blood centre, with cost savings in product transportation.

In addition to the previously mentioned contributions, our study can fill a research gap in the literature in three ways. First, a mathematical model for the blood delivery routing problem with time constraints (BDRP-TC) has been developed and solved for optimal solutions by using the Lingo optimization software. Second, a hybridization of the firefly algorithm, a crossover operator in differential evolution, and a new local search has been introduced and used to successfully solve the BDRP-TC. Third, the performance of the algorithm was tested with different problem sizes for nine generated test instances and a new case study based on a real-life situation for the BDRP-TC.

The current knowledge can be extended to develop user-friendly mobile application software and data visualization according to the Industry 4.0 concept, by using the HFA+NLS as the solution method to determine the best blood delivery route, and then transferring the knowledge to the 12th RBC's routing planner for practical use in a real situation. In addition, future research can extend this research in two directions. The first will be to extend the model to cope with other characteristics in real-world situations, including time windows, travel routes under violence situation (e.g., arson, bombing and other attacks) and travel possibilities, vehicle speeds depending on traffic conditions and uncertain demands. The second will be to improve the performance of the metaheuristic techniques or to develop new techniques. A comparison of the performance with other existing metaheuristic techniques may also be made.

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