

DESIGNING A VACCINE COLD CHAIN NETWORK IN NORTHERN THAILAND USING THE MAX-MIN ANT SYSTEM

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Abstract

Metaheuristic approaches have become one of the most popular methods for big data of the optimization problem. This paper applies a nature inspired algorithm called the max-min ant system (MMAS) to design a vaccine cold chain network in northern Thailand. The research scope is focused on the Office of Disease Prevention & Control Area 1. This area office transports vaccines to provincial health offices and to hospitals within its geographical area of responsibility. This research aimed to rearrange routes to minimize the distances involved. The optimal parameters of the MMAS employ statistical experiment theory, namely a full factorial design. Statistical tools to design the experiment and for the analysis were adopted to investigate the factors affecting the performance of this algorithm.

Keywords: Metaheuristic approaches, max- min ant system, vaccine cold chain, full factorial design

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Introduction

Vaccines are highly useful to prevent and treat diseases in both children and adults. However, the effectiveness of vaccines depends on appropriate storage and transportation, which are difficult to control. As a result, the World Health Organization (WHO) is serious about the importance of transportation and what is sometimes referred to as the immunization supply chain. The WHO defines the vaccine cold chain (VCC) as the maintenance of vaccine products' quality from the point of manufacture until the point of administration by ensuring that the vaccines are stored and transported within a defined temperature range. Maintaining a reliable VCC for a system and storing vaccines within a defined temperature range require that all VCCs and the transportation from outreach sites follow the WHO's recommendations. Vaccines are sensitive biological products and may be sensitive to freezing, heat, and light. The VCC system that is used to store vaccines in good condition consists of a series of links designed to keep the vaccines within a temperature range of between $+2^{\circ}\text{C}$ to $+8^{\circ}\text{C}$ (World Health Organization, 2015). In Thailand, the VCC begins with international vaccine manufacturers delivering vaccines by plane. These vaccines and those from domestic manufacturers are shipped to the Department of Disease Control, and they are then distributed in refrigerated vehicles to all 13 area offices of the Office of Disease Prevention & Control (ODPC), which are located throughout the country. The 13 ODPC offices distribute the vaccines throughout the country to provincial health offices (PHOs) from where they are sent to hospitals or contracting units for primary care (CUPs). Primary care centers acquire vaccines from the CUPs as the final step in the supply chain (Thachathawat, 2012) (Figure 1). Since each type of vaccine must be stored in a refrigerated vehicle that has different temperature-controlled cabinets, the transportation distance and delivery time affect the quality of the vaccine.

This paper is organized as follows. The optimization algorithm is explained in the

second section, and then the max-min ant system (MMAS) theory is presented in the third section. The VCC network concept and equations are displayed in the fourth section. In the fifth section, the MMAS for a VCC network is described. The sixth section then presents the experiment's design and results. Finally, the seventh section concludes the paper.

Optimization Algorithm

The optimization algorithms theory can be classified into 2 categories: the conventional optimization approach and the approximation optimization approach. The conventional optimization approach is based on mathematics and finding the best solution, but this requires dynamic programming. The approximation optimization approach is based on intelligent random searches using a large scale and complex problems. Both types are constructive approaches that use specific rules for approximation and stochastic search approaches using bio-inspired theory for each method.

In the recent decades, a variety of proposed metaheuristic search methods have attracted considerable attention to solve large-scale optimization problems (Holland, 1992). Typical metaheuristic approaches are commonly based on physics, chemistry, sociology, ethnomusicology, and biology (Sujaree, 2017).

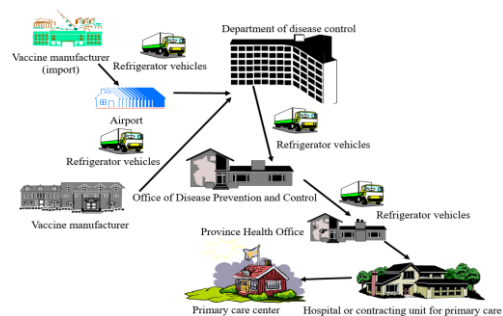


Figure 1. Vaccine cold chain network in Thailand

Many proposed versions are population-based techniques such as the genetic algorithm (Goldberg, 1989), particle swarm optimization (Kennedy and Eberhart, 1995), harmony search algorithm (Lee and Geem, 2005), cuckoo search (Yang and Deb, 2010), and artificial chemical reaction optimization algorithm (Alatas, 2011) among others. Further, a number of proposed methods are random-based techniques such as the ant colony optimization (ACO) (Dorigo *et al.*, 1996), central force optimization (Formato, 2007) and so on. There are 5 algorithms of ant colony optimization comprising the ant system (AS), elitist ant system, max-min ant system (MMAS), rank-based ant system, and ant colony system. This research study presents the metaheuristic approach MMAS, which was inspired by ant behavior because it is a better solution to the traveling salesman problem than other ant algorithms (Stutzle and Hoos, 1997).

Max-Min Ant System

The MMAS is the third algorithm from the ACO set of algorithms (Dorigo and Gambardella, 1997). The principles of the algorithm are that it imitates collaborative artificial ants to find the shortest path between the nest and the source of food by following and depositing a chemical substance, called a pheromone, on the paths. The MMAS was developed from the ant system by Stutzle and Hoos in 1997. The structure of the MMAS can be divided into 2 parts. The first part is the process of tour construction that is completed by individual ants. The second part is the pheromone update trails of an ant. An initial amount of pheromone (t_0) for all sub-tours can be roughly estimated using the following equation $t_{ij} = t_0 = m/C_{mn}$ ($\forall_{ij}$) where m is the number of ants and C_{mn} is the total distance of the first tour solution using the nearest neighborhood rule (Dorigo and Stutzle, 2004). To construct a tour, the probability (p) of an ant k moving from a current node i to a neighboring node j is determined according to Equation 1:

$$p_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{j \in N_i^k} [\tau_{ij}]^\alpha [\eta_{ij}]^\beta} \text{ If } j \in N_i^k \quad (1)$$

where τ_{ij} is the amount of the pheromone deposited from node i to node j . Meanwhile, α and β are the weight of the pheromone trail and the weight of the heuristic information, respectively. Next η_{ij} is the available heuristic information between node i and node j , and N_i^k is a set of nodes which ant k has not visited yet. The roulette wheel method is an approach for selecting the next node until all nodes have been visited. Once all the ants have completed their tour construction, the next step is to determine the best solution for all the ants and select the best solution so far for a representative of τ_{ij}^{best} . If the path that the ants walk through is in the path of the best route, then let τ_{ij}^{best} be $1/C^{best}$ else τ_{ij}^{best} be 0. The second part of the pheromone update process involves evaporation of the pheromone and the deposition of a new pheromone. The updated pheromone level τ_{ij}^{new} is computed according to Equation 2:

$$\tau_{ij}^{new} = (1 - \rho)\tau_{ij}^{old} + \sum_{k=1}^m \Delta\tau_{ij}^{best}, \quad \forall (i,j) \in L \quad (2)$$

where ρ (with $0 < \rho < 1$) is a fraction of the pheromone evaporation and L is the possible paths. Thus, $(1-\rho)$ is a fraction of the remaining trail. On the right of Equation 2, the first term corresponds to the pheromone evaporation, while the second term is the amount of the pheromone deposition. The advantages of the MMAS are different from the other ant algorithms, with the upper pheromone range (τ_{max}) and lower pheromone range (τ_{min}) being defined according to Equations 3 and 4:

$$\tau_{max} = \frac{1}{\rho C^{best}} \quad (3)$$

$$\tau_{min} = \frac{\tau_{max}}{2 n_c} \quad (4)$$

where C^{best} is the best-so-far distance and n_c is the number of cities. In this study, C^{best} is set to 1 in order to avoid τ_{max} (Dorigo and Stutzle, 2004). After completing the monitoring process and controlling the pheromone, the MMAS collects the best solution and returns to the first step until the required number of iterations has been completed.

Vaccine Cold Chain Network and Equations

Vaccines are presently delivered by ODPCs to PHOs and they are then transported to CUPs. Each ODPC transports vaccines to the provinces and areas under its responsibility; for example, ODPC 1 is responsible for the provinces of Chiang Mai, Chiang Rai, Nan, Phayao, Mae Hong Son, Lamphun, Lampang and Phrae. There are 102 public hospitals in the area for transportation of the vaccines. The simple VCC network is described in Figure 2.

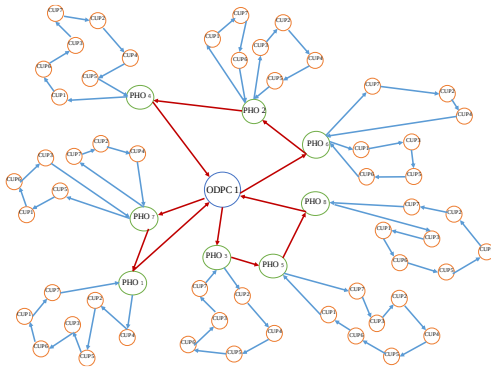


Figure 2. The simple vaccine cold chain network

Normally, ODPC 1 uses a single refrigerated vehicle to support each PHO. The objective of this research is to reduce the total distance from ODPC 1 to the CUPs by arranging a new route. Google Maps is used to calculate the distances between ODPC 1, the PHOs, and CUPs. The distances from the PHOs to the CUPs are stored in the form of a symmetric matrix.

The following equations detail the mathematical model and notations for the VCC network considered in this paper.

Indices:

Z	denotes total distances
i ,	denotes the ODPC i
j	denotes the PHO j
m	denotes the CUP m
k	denotes the refrigerated vehicles k from ODPC to PHO
l	denotes the refrigerated vehicles l from PHO to CUP
p	is a PHO (1,2,3,...,N)
q	is a CUP (1,2,3,...,M)
c	is the capacity of the refrigerated the vehicles
a	is the demand

Parameters:

d_{ij}	is the distance from ODPC i to PHO j
d_{jm}	is the distance from PHO j to CUP m
N	is the number of the PHO
M	is the number of the CUP
K	is the number of the refrigerated vehicles from ODPC1 to the PHOs
L	is the number of the refrigerated vehicles from the PHOs to the CUPs
V	are the vaccines from ODPC1 to the PHOs
y	are the vaccines from the PHOs to the CUPs

Decision variables:

X_{ij}^k	= 1 if vehicles k from ODPC i to PHO j , otherwise 0
X_{jm}^l	= 1 if vehicles l from PHO j to CUP m , otherwise 0
Y_i^k	= 1 if vaccines loaded in vehicles k , otherwise 0
Y_j^l	= 1 if vaccines loaded in vehicles l , otherwise 0
U_i, U_j, U_m	= Auxiliary variable ≥ 0

Objective function:

$$\text{Min} Z = \sum_{i=1}^N \sum_{j=1}^N \sum_{k=1}^K d_{ij} X_{ij}^k + \sum_{j=1}^N \sum_{j=1}^M \sum_{m=1}^M \sum_{l=1}^L d_{jm} X_{jm}^l \quad (1)$$

Representation by:

$$\sum_{j=1}^N X_{ij}^k \leq 1 \quad (k = 1, 2, 3, \dots, K) \quad (2)$$

$$\sum_{m=1}^M X_{jm}^l \leq 1 \quad (l = 1, 2, 3, \dots, L) \quad (3)$$

$$\sum_{i=0}^N X_{ip}^k - \sum_{j=0}^N X_{pj}^k = 0 \quad (p = 1 \dots N) \quad (4)$$

$$\sum_{j=0}^M X_{jq}^l - \sum_{m=0}^M X_{mq}^l = 0 \quad (q = 1 \dots M) \quad (5)$$

$$\sum_{k=1}^K Y_i^k = 1 \quad (i = 1, 2, 3 \dots K) \quad (6)$$

$$\sum_{l=1}^L Y_j^l = 1 \quad (j = 1, 2, 3 \dots L) \quad (7)$$

$$\sum_{i=1}^N c_i^v Y_i^K \leq a_k^v \quad (k = 1 \dots K) \quad (8)$$

$$\sum_{j=1}^M c_j^v Y_j^L \leq a_L^v \quad (l = 1 \dots L) \quad (9)$$

$$Y_i^k \leq \sum_{i=1}^N X_{ij}^k \quad (i = 1 \dots N), (k = 1 \dots K) \quad (10)$$

$$Y_j^l \leq \sum_{j=1}^M X_{jm}^l \quad (j = 1 \dots M), (l = 1 \dots L) \quad (11)$$

$$\sum_{k=1}^K \sum_{i=0}^N X_{ij}^k \geq 1 \quad (j = 1, 2, 3 \dots N) \quad (12)$$

$$\sum_{l=1}^L \sum_{j=1}^M X_{jm}^l \geq 1 \quad (m = 1, 2, 3 \dots M) \quad (13)$$

$$U_i - U_j + N \sum_{k=1}^K X_{ij}^k \leq N - 1, \quad \forall_{i,j} = (2, \dots, N), i \neq j \quad (14)$$

$$U_j - U_m + N \sum_{l=1}^L X_{jm}^l \leq N - 1, \quad \forall_{j,m} = (2, \dots, N), j \neq m \quad (15)$$

Equation 1 is a sum of the distance from ODPC1 to the PHOs. Constraints (2) and (3)

represent the refrigerated vehicles travelling from ODPC1 to the PHOs and from the PHOs to the CUPs, respectively. The vaccines are only delivered upon requirements that are ensured by constraints (4) and (5). Likewise, constraints (6) and (7) are that only the refrigerated vehicles deliver to the PHOs and CUPs. Constraints (8) and (9) ensure that the vaccines are less than or equal to the capacity limitations of the refrigerated vehicles in the PHO and CUP network. To ensure that the refrigerated vehicles k and l take a route through PHO j and CUP m by constraints (10) and (11) on at least 1 occasion, both PHO j and CUP m get vaccines as ensured by constraints (12) and (13). The remaining constraints prevent a sub-tour in the PHO and CUP network.

MMAS for Vaccine Cold Chain Network

In this research, the MMAS was adopted to design a VCC network. The MMAS consists of 2 main phases: the ants' solution construction and the pheromone update. According to the MMAS concept, the pseudocode of the MMAS to solve the VCC network problem is represented in Figure 3.

Input: Problem information such as distance ODPC1 to PHOs and PHOs to CUPs, vehicle capacity, number of vehicles. MMAS parameters such as Number of iteration, Number of ant, Weight of pheromone, Weight of heuristic information, Evaporation rate.
For $i \leq 1$ to maximum iteration For $a \leq 1$ to maximum number of ant Selection ODPC1 is initial node and end node Random (PHOs, CUPs) according probability equation Create route and checking constraint Calculate the objective function (Minimize distance) End for ant Sorting objective function from ant in iteration Update pheromone trails Checking upper and lower pheromone (MMAS theory) To compare the best ant with the best so far Selection best so far End for iteration Output the minimize objective function (Ant best so far) and routing of ODPC1 to PHOs to CUPs

Figure 3. Pseudocode of the MMAS for vaccine cold chain network

The MMAS iteratively constructs the exploration by stages depending on the amount of the pheromone which is deposited on the route taken by the ants. After the moving iterations, the amount of the pheromone on the

Table 1. Experimental factors and levels

Factors	Levels		
	Low	Medium	High
Number of Iterations and ants (<i>i/a</i>)	50/200	100/100	200/50
Weight of Pheromone (<i>WP</i>)	0.5	1.5	2.5
Weight of Heuristic information (<i>WH</i>)	1	3	5
Evaporation Rate (<i>ER</i>)	0.1	0.5	0.9

route not taken by the ants will decrease according to the pheromone evaporation rate. Conversely, the route taken by the ants has a greater pheromone value which encourages biasing the exploration. The MMAS was derived from the ant system (AS) according to the following modifications: i) only either the iteration-best ant or the best-so-far ant was allowed to deposit a pheromone; ii) the possible range of the pheromone trail values was controlled by the upper and lower pheromone limits (τ_{max} and τ_{min}); iii) the pheromone trails were initialized to the upper pheromone trail limit with a low pheromone evaporation rate (ρ); and iv) when the system approaches stagnation or the generated exploration is not improved upon for a certain number of consecutive iterations, the pheromone trails are then reinitialized (Stutzle and Hoos, 2000).

Experiment Design and Results

There are several factors impacted by these algorithms. In the present study, the statistic of experiment theory was used to design the experiment in terms of 3-level full factorial design due to the need to analyze the covered factors and to reduce the required computational time for each solution. This approach was applied when there were k factors to consider. Each factor consists of 3 levels: high, medium, and low. One experiment was composed of 3^k data which is called the 3^k factorial design. The MMAS was used to design the VCC network, which included 1 ODPC, 8 PHOs, and 102 CUPs. The application was developed in Visual Basic Express Edition and was calculated on a computer with an Intel Core i7 3.40 GHz processor and 8 GB of

RAM. The design of the experiment was evaluated in a trial version of Minitab 18.1.

A two-step sequential experiment was adopted in this work. The first experiment was designed to investigate the appropriate settings for the MMAS parameters including the numbers of iterations (i), the numbers of ants (a), the weight of the pheromone (WP), the weight of the heuristic information (WH), and the evaporation rate (ER). Each parameter was considered to have 3 levels which are shown in Table 1.

A full factorial design (3^k) was adopted in this experiment (Montgomery, 2001). It should be noted that these parameters contain a combination of numbers of iterations and ants (i/a) that determine the number of generated candidate solutions, which directly imply the number of searches in the solution space. Higher values for these parameters mean that there is a greater chance of getting better solutions, although this requires longer computational times. The combination of these

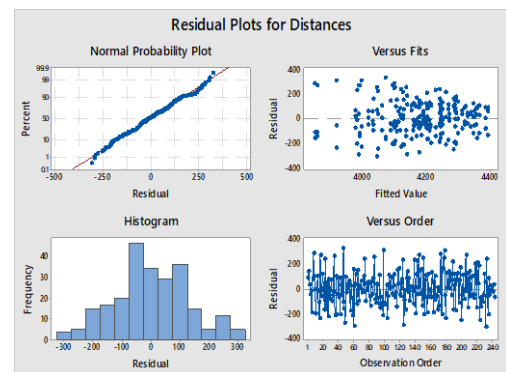


Figure 4. Displays of the normal distribution of data in a residual plot

factors was fixed to 10,000 candidate solutions. The experiment was repeated 3 times using different random seed numbers, which could be a potential nuisance factor. The residual plot represents the normal distribution pattern of the distance data and is shown in Figure 4.

The computational results obtained from 243 (34*3) runs are shown in Table 1 and were analyzed using a general linear form of analysis of variance (ANOVA) including source of variation, degree of freedom (DF), sum of square(SS), mean square (MS), F values, and P values. A factor with $P < 0.05$ is statically significant with a 95% confidence level. From Table 2, it can be seen that only a single factor called the weight of the heuristic information (WH) was statically significant for this problem. The remaining factors including the numbers of iterations and ants (*i/a*), the weight of the pheromone (WP), and the evaporation rate (ER) in the range considered were not significant with a 95% confidence level.

The main effect plots shown in Figure 5 represent that the appropriate setting of the MMAS parameters (*i/a*, WP, WH, ER) should be 50/200, 1.5, 5, and 0.5 respectively. Given these parameters, the objective function was to find a good solution. The final aim was to compare the experimental results obtained from the MMAS with the real system that was

used to determine the shortest path method from the PHOs to the CUPs. The MMAS parameters settings in this sequential experiment were recommended by analysis of variance of the computational results from the previous experiment. It should be noted that the total number of searches for each method conducted in the computational runs was fixed at 10,000 generated candidate solutions to make a reasonable comparison by determining the number of candidate solutions based on Yamane's principle (Yamane, 1973).

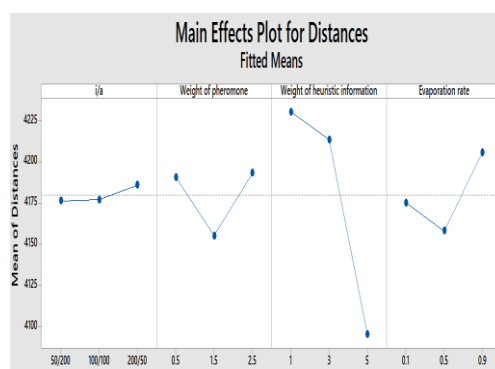


Figure 5. The average distance displayed for each parameter

Table 2. ANOVA on experimental results obtained from the MMAS

Source	DF	SS	MS	F	P
<i>i/a</i>	2	4716	2358	0.09	0.912
WP	2	73576	36788	1.43	0.242
WH	2	881098	440549	17.14	0.000
ER	2	94724	47362	1.84	0.162
<i>i/a</i> *WP	4	187747	46937	1.83	0.126
<i>i/a</i> *WH	4	237817	59454	2.31	0.06
<i>i/a</i> *ER	4	293608	73402	2.86	0.025
WP*WH	4	124505	31126	1.21	0.308
WP*ER	4	265520	66380	2.58	0.039
WH*ER	4	17207	4302	0.17	0.955
<i>i/a</i> *WP*WH	8	104739	13092	0.51	0.848
<i>i/a</i> *WP*ER	8	97486	12186	0.47	0.873
<i>i/a</i> *WH*ER	8	103537	12942	0.5	0.852
WP*WH*ER	8	349568	43696	1.7	0.102
<i>i/a</i> *WP*WH*ER	16	671007	41938	1.63	0.066
Error	162	4163395	25700		
Total	242	7670249			

In the real world, vaccines are transported by the shortest path method which means that CUPs are selected based on the closest distance. The total distance travelled from ODPC 1 to all the CUPs is approximately 3,923 km. (Sujaree, 2018). Usually, the vaccine delivery route will always be chosen for the nearest delivery point from the previous location. The summary of the objective function obtained from MMAS was able to reduce the distance to 3,826 km. Therefore, the best-so-far result obtained from MMAS was better than the real system.

Conclusions

This research applied an algorithm inspired by ant behavior called the max-min ant system (MMAS) to minimize the total distance within a VCC network involving ODPC 1, the PHOs, and CUPs. The algorithm performance was found to depend on the parameters' settings. The experiment was based on a full factorial design aiming to investigate the appropriate MMAS parameters' settings, which were then used in the experiment with the intention of comparing the performance of this algorithm with the real system. The experiment showed that the MMAS produced a shorter route by total distance than the real system. The VCC network may be applicable to solve other algorithms or to be applied to a local search to improve the efficiency of finding solutions. However, there are many constraints for transportation, for example, some CUPs have sufficient vaccines while others lack vaccines. Therefore, it is recommended that the stock of CUPs is checked in real time and the distance data is entered to access the application for more accurate processing.

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