

Artificial Carbon Nanotube Synthesis Optimization to Address the Vaccine Cold Chain Network Problem

Kanon Sujaree

Abstract—In this research study, a novel metaheuristic approach using nanotechnology is proposed, known as Artificial Carbon Nanotube Synthesis Optimization (ACNSO), in order to develop a vaccine cold chain network in north of Thailand. The scope of the study emphasizes Area 1 of the Office Disease Prevention and Control in the Chiang Mai region. Vaccines must be transported both to the Provincial Health Offices and hospitals in the region. This study seeks to arrange the transportation routes involved in order to achieve the shortest possible total distance. The algorithm must first of all assess the travel conditions between each point in the network, and then generate the starting solution. Efficient solutions to this problem will cut the total processing time. The study then made a comparison between the results produced by ACNSO algorithm and those of other algorithms used in earlier studies. Full factorial design was the statistical approach used to evaluate the optimal parameters for the algorithm. The experiment was designed to examine the various factors which influence the algorithm performance. The results showed that ACNSO algorithm found the best solution in experimental algorithms and 3rd processing time.

Index Terms—Vaccine cold chain network, metaheuristic approach, full factorial design, nanotechnology, artificial carbon nanotube synthesis optimization.

I. INTRODUCTION

Transport is a very important consideration in the vaccination supply chain according to the Vaccine Cold Chain (VCC) is to ensure that the quality of the vaccine is sustained throughout the process from manufacturing until it reaches the patient. This is achieved by controlling the storage temperatures within an acceptable range throughout the journey. Vaccines are a vital element in the prevention of disease, but their effectiveness can be adversely affected by inadequate conditions during storage or transportation. These conditions can be difficult to control, and vaccines tend to be very sensitive to temperature changes or the wrong kind of lighting since they are complex biological products [1]. In Thailand, international vaccine producers have started VCC, using aircraft to bring vaccines into the country where they are delivered to the Department of Disease Control (DDC). From the DDC, the vaccines are then sent to the 13 regional Disease Prevention and Control (ODPC) using refrigerated carriers. The ODPCs are then responsible for distributing the vaccines to the Province Health Office (PHO), where they are sent on hospitals or to Contracting Units for Primary Care (CUP). In the final stage of the chain, the Primary Care

Centre obtains the vaccines from the CUP.

Under the current system, the ODPCs must take responsibility for transporting the vaccines to the PHO and CUP within their own geographical areas. Chiang Mai is served by ODPC 1, along with Chiang Rai, Nan, Phayao, Mae Hong Son, Nan, Lamphun, Phrae, and Lampang and Phrae [2]. A total of 102 public hospitals then use the vaccines. Fig. 1 shows the basic vaccine cold chain network. ODPC 1 normally allocates one refrigerated vehicle for each PHO, and then employs Google Maps to perform the distance calculations in the region between origins and destinations for the vaccines. The information collected about distances to PHOs and CUPs is then saved in a symmetric matrix.

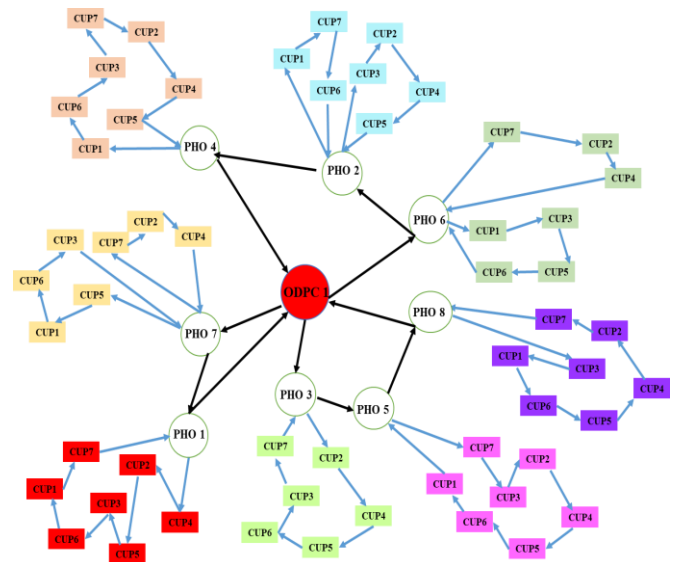


Fig. 1. In this basic vaccine cold chain network, ODPC 1 is the starting point for the refrigerated vehicle, which then delivers to each PHO before coming back to ODPC 1. Each PHO then has a refrigerated vehicle for deliveries to the local CUPs before completing its journey at the PHO. It is not possible to exceed the capacity of the refrigerated vehicle.

The vaccine cold chain network is sometimes known as the capacitated Vehicle Routing Problem (VRP) and has similarities with the classical VRP. In this case, the optimal routes form a single path and use a single depot of origin. Several variants of VRP have been studied to address the wide variety of conditions in the real world [3]. For example, capacitated VRP (CVRP) [4], Heterogeneous fleet VRP (HVRP) [5], Multi depot VRP (MDVRP) [6], VRP with time windows (VRPTW) [7], VRP with simultaneous pickup and deliveries (VRPSPD) [8]. The VRP aim is to minimize the cost or the distance, while there is one vehicle visiting one customer, and the journey begins and ends at the same point. Crucially, the vehicle capacity sets the delivery content limit [9]. It is difficult to optimize solutions in problems where

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large road networks are used in real time and the problem is time-dependent, since the computational time required grows dramatically if the road network size increases [10]. The equations which follow describe the detail the mathematical model employed in studying the vaccine cold chain network along with the notations used.

Indices

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

Parameters

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

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 load in vehicles k , otherwise 0
- $Y_j^l = 1$ if vaccines load in vehicles l , otherwise 0
- U_i, U_j, U_m = Auxiliary variable ≥ 0

Objective function

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

Representation by

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

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

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

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

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

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

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

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

$$Y_i^k \sum_{i=0}^N X_{ij}^k (i = 1, \dots, N), (k = 1, \dots, K) \quad (10)$$

$$\sum_{j=0}^M X_{jm}^l (j = 1, \dots, M), (l = 1, \dots, L) \quad (11)$$

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

$$\sum_{i=1}^K \sum_{j=1}^N X_{ij}^k \geq 1 (m = 1, 2, 3, \dots, M) \quad (13)$$

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

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

Equation 1 determines the total of the distances from ODPC1 to the PHOs. The constraints given by (2) and (3) indicate the refrigerated vehicles which link the ODPC1 to the PHOs and onwards to the CUPs. Constraints (4) and (5) determine that the vaccines are delivered only when required, while constraints (6) and (7) ensure that only refrigerated vehicles can be used for delivery to the PHOs and CUPs. The role of constraints (8) and (9) is to limit the quantity of vaccine to no more than the capacity of the vehicles used in the network. Constraints (10) and (11) set the route of the refrigerated vehicles k and l to PHO _{j} and CUP _{m} by constraints (10) and (11), on at least one time both PHO _{j} and CUP _{m} while constraints (12) and (13) ensure that PHO _{j} and CUP _{m} receive the vaccines. Sub-tours are prevented within the network by the remaining constraints.

This study is organized as follows. Section II presents a reviews of metaheuristic approaches. Section III describes the new metaheuristic technique which makes use of carbon nanotubes synthesis (ACNSO). This algorithm can be applied to address the problem of the vaccine cold chain network as explained in Section IV. The results of the experiment along with the parameters employed are described in Section V, while the conclusion is presented in Section VI.

II. METAHEURISTIC APPROACHES

Today's optimization problems are often addressed using metaheuristic approaches because of the speed required when attempting to process larger quantities of data which must be processed simultaneously through numerous techniques. Many metaheuristic techniques have their inspiration in physics or biology. The term 'heuristic' is Greek, and refers to a trial and error approach to reaching a quick solution [11]. The aim of heuristic techniques is to rapidly determine a near-optimal solution rather than to guarantee the best possible outcome or indeed one which is feasible. Algorithms which take an approach based on heuristics offer the advantage of being much faster than classical methods. The Greek prefix 'meta' has the meaning of 'beyond' and

suggests a higher level approach. In this context, metaheuristic methods serve to modify and update algorithms and solutions when searching for the near optimal answer. Metaheuristic approaches were first researched by Glover. The local search approach relies on many iterations of a process being used to find neighboring solutions to the latest solution, and thus seeking to continually improve upon the current solution in local steps [12]. One advantage of metaheuristic algorithms is their ability, via their stochastic properties, to avoid becoming trapped in a local optimum [13]. Every metaheuristic step requires a balance to be found between the concepts of diversification and intensification. Diversification allows the algorithm to explore a wider search space and to generate more solutions. A higher degree of diversification can enhance the likelihood of finding the global optimum, but the convergence rate will be slow and the process is rather time-consuming. This was seen when using the Genetic Algorithm. It is vital that the algorithm avoids traps and does not become caught in a local optimum. The role of intensification is to provide better signal information which can help to generate better solutions. However, if intensification is too strong, the convergence rate will be rapid and the result is often a local optimum, as other possibilities are ignored. Without effective intensification, however, the computation time is extended and it can take a very long time to discover a global optimum. This was seen in the process of updating pheromones in the Ant colony optimization. Intensification therefore plays a key role in ensuring that the right amount of signal information is used in the process. There are nine different categories which can be used to classify the various metaheuristic techniques, including Physics-based, Music-based, Social-based, Biology-based, Swarm-based, Mathematics-based, Chemical-based, Sport-based and hybrid [14]. A number of algorithm types have been based on physics, including the Elevator Kinematics Optimization algorithm [15], Gravitation Search algorithm [16], Electromagnetism-like algorithm [17], Central Force optimization [18], Intelligent Water Drops algorithm [19], Big Bang-Big Crunch algorithm [20], and Galaxy-Based algorithm [21]. Social-based algorithms include the Imperialist Competitive algorithm [22] and Teaching Learning based optimization [23]. Algorithms based on biology include the Genetic algorithm [24], Artificial Immune Systems [25], and Biogeography-based optimization [26] while one example of a chemical-based algorithm is the Artificial Chemical Reaction optimization algorithm [27]. Music is the basis for the Harmony search algorithm [28] while biology forms the inspiration for the Ant Colony optimization [29], Particle Swarm optimization [30], Cat Swarm optimization [31], Monarch Butterfly optimization [32], Cuckoo Search [33] and Whale optimization algorithm [34]. The Matheuristic [35] and Base Optimization algorithms [36] are inspired by mathematics, while metaheuristic algorithms can sometimes be based on more than one underlying type, such as the Cultural algorithm [37] which has both social and biological bases, as is the case for Colonial Competitive difference evolution [38] and the two-phased approximation for the bat algorithm [39]. While many of these algorithms have worked effectively on

particular problems, improvements in the field can only be achieved through the successful development of metaheuristic techniques. No algorithm has yet been designed which is capable of giving the best outcomes in all scenarios, and for this reason there is a continuous series of artificial intelligence proposals offered to move closer to this goal. In most optimization the aim is to determine the best approach among all solutions. For example, the task might involve the optimization of the route from A to B. The algorithms created to address such optimization problems have seen little change since their introduction almost fifty years ago. These earlier approaches followed a step-by-step procedure in which the number of steps required would be in direct proportion to the quantity of data involved. This research created a new metaheuristic which incorporates the concept of Genetic algorithm, Cuckoo search and Ant colony optimization with detail in next section.

III. ARTIFICIAL CARBON NANOTUBES SYNTHESIS OPTIMIZATION (ACNSO)

Nanotechnology is a term which establishes that the design, production, and application of all materials, systems, and equipment will occur at the nanoscale, which refers to sizes in the range of 1–100 nm. Nanotechnology is a broad and complex area of study focusing on the varying properties and structures of materials on the nanoscale [40]. Some major applications include nanoparticles, carbon nanotubes, nanoparticles, and Buckminster fullerene. Carbon nanotubes (CNTs) are formed by rolling graphene sheets into tubes of diameter 3–30 nm., and were first brought to attention in 1991 by Iijima in 1991 [41]. There are two main structural forms of carbon nanotubes: single-walled carbon nanotubes (SWCNT) and multiple-walled carbon nanotubes (MWCNT). As might be expected, the principal difference lies in the fact that the SWCNT involves just one graphene layer, allowing easy characterization, whereas the MWCNT comprises numerous single-walled tubes placed in a complex arrangement inside each other. The SWCNT is normally not as wide as the MWCNT and has a typical diameter of 1–2 nm. Three roll types of graphene are well-known: armchair carbon nanotubes, zigzag carbon nanotubes, and chiral carbon nanotubes. The tube chirality is used to describe the carbon nanotubes, and this will be determined by the chiral angle, θ , and the chiral vector.

First of all, one graphene sheet is created using a specified chiral angle and vector. The description of the given using the

Lattice translational indices (n , m) along with the unit vectors a_1 and a_2 as indicated in $Ch = na_1 + ma_2$. The extent to which the tube twists is determined by the chiral angle (θ), defined as the angle (θ) between vectors Ch and a_1 , and which lies in the range of $0^\circ \leq |\theta| \leq 30^\circ$. Carbon nanotubes types differ in the way the graphene sheet is rolled up when they are created. The carbon bond geometry at the tube circumference is constrained by two limiting cases, which depend upon the chiral tubes. These are armchair ($\theta = 30^\circ$) and zig-zag ($\theta = 0^\circ$).

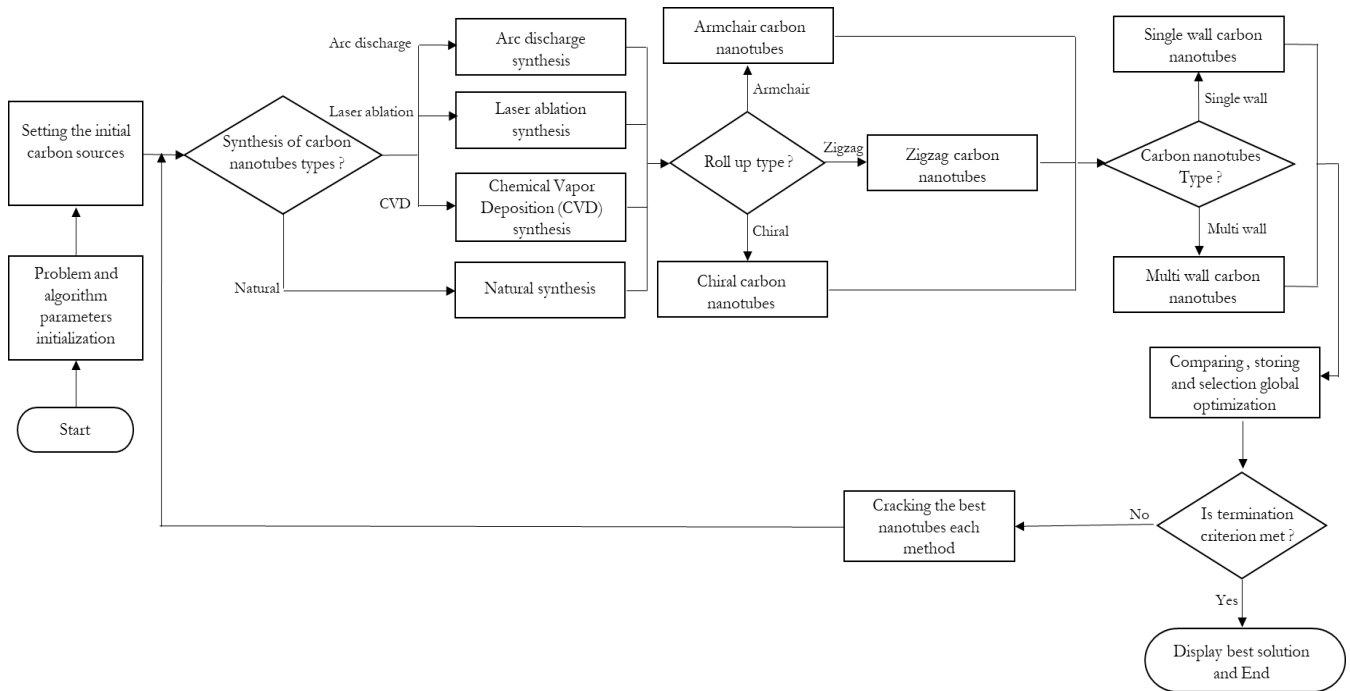


Fig. 2. The flowchart of the ACNSO algorithm.

Moreover, when $0^\circ < |\theta| < 30^\circ$, the nanotube is known as chiral. A number of methods have been applied for the synthesis of carbon nanotubes. The most frequently used approaches are arc discharge [42], laser ablation [43], and chemical vapor deposition [44]. It is also possible for carbon nanotubes to be formed naturally [45]. In order for carbon nanotubes to form, certain elements are required. These include T carbon source to act as the raw material for synthesis, a catalyst, and an adequate supply of energy. The synthesis of carbon nanotubes has been achieved through various m, often using hydrocarbons including methane and acetylene as precursors. Other sources of carbon can also be sued, including graphite, coal, or other kinds of hydrocarbon.

An algorithm can simulate the synthesis of carbon nanotubes, and then after adaptation can be applied to solve specific problem types. The carbon sources encoding can be done as

Binary, real string, and so forth. This study makes use of asymmetric strings. The encoding plan influences the carbon atoms from the carbon sources as can be seen in Figure 2. In the case of ACNSO, the process opens with an initial carbon source set in a solution.

A. Initialization of the Problem and Algorithm Parameters

In this part, the input data used for the application are described. The algorithm in this study sets four variable parameters for investigation, while determining the number of Carbon Sources (CS), and Repetitions (R), as well as the Percentage of Carbon Nanotubes types (PCN) and the Proportion of Roll-up types (PR). At the start, CS and R are set for one parameter establish the proportion which is suitable for the solution. The Proportion of Synthesis Carbon Nanotubes types will determine the laser ablation, arc discharge, chemical vapor deposition and natural using a ratio of 30:30:30:10 respectively (with regard to a set constant). PR reveals the carbon nanotubes probability as indicated: Armchair carbon nanotubes, Zigzag carbon nanotubes and Chiral carbon nanotubes. PCN denotes the overall proportion of single to multi-wall carbon nanotubes.

B. Initial Carbon Sources Settings

Any carbon atom carbon material which comprises molecules which can be used for organic synthesis can be termed a carbon source. The algorithm in this study makes use of initial carbon sources which are randomly positioned within the feasible search area. They do not, however, represent an initial solution, since this would make the difference in carbon source string size as shown in Fig. 4. A random approach sets the number of carbon sources as well as the number of string carbons. It is usually the case that the applicable number of carbon sources will be suitable for the solution space size. Once the first iteration in the process is complete it is normally the case that the strongest carbon nanotube structure will form the likely to be the substrate for the subsequent solution on the basis of the roulette wheel method.

C. Carbon Nanotubes Synthesis

The process of synthesizing carbon nanotubes is very complex and can be approached in many different ways, but three methods can actually take place naturally.

1) Arc discharge

Carbon nanotubes were first generated through an arc-discharge evaporation technique in 1991. This method echoed that used in the earlier synthesis of fullerene. The process involved carbon needles of 1 mm in length and 4-30 nanometers in diameter. The equipment assembly used for an arc-discharge comprises a pair of thin vertical electrodes anode and cathode – which are placed in the middle of the chamber. The cathode is the lower electrode, and has shallow dip designed for the purpose of holding a small piece of iron in place as evaporation takes place. Generation of the arc-discharge occurs by passing a 200 A DC current of 200 A at 20 V between two graphite the two electrodes which are fully immersed in an inert gas. The use of the carbon source allows the deposition of carbon nanotubes at the cathode, taking the appearance of soot. The carbon source thus fixes at the cathode, allowing the formation of carbon nanotubes

from the carbon molecules. The initial arc- discharge is random, but then connection with the other carbon source takes place, allowing the connection point to be switched. The solution is created by the random method in the case where the conditions are not met at the start, as shown in Fig. 3.

2) Laser ablation

Richard Smalley and colleagues first made use of laser ablation in 1995 in order to grow nanotubes of superior quality. The carbon target is ablated by highly intense pulses from the laser, and then heated to 1200°C in a tube furnace. This process serves to destroy the carbon source through the use of high temperatures. The carbon molecules can then take the form of bonded carbon nanotubes. The carbon molecules stay in remains in the carbon form while no fewer than two atoms are sent to the carbon source pool. Within the carbon source pool, the random technique then generates further carbon nanotubes, as shown in Fig. 4.

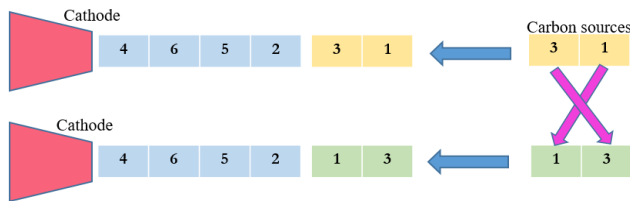


Fig. 3. Carbon nanotubes of arc discharge synthesis

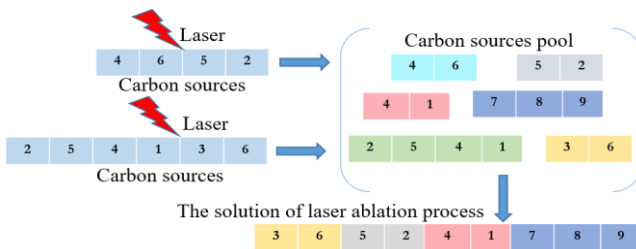


Fig. 4. Carbon nanotubes used in laser ablation synthesis

3) Chemical vapor deposition

The easiest and most common approach to growing carbon nanotubes under laboratory conditions involves chemical vapor deposition (CVD). Such CVD systems operate by injecting a vaporized hydrocarbon compound, such as methane or ethane, into a furnace. The hot zone within the furnace has a substrate upon which there has been deposited a thin film which may contain iron, cobalt, or nickel, which has either undergone separation or has been pre-patterned into nanoscale metal islands. These islands serve as catalysts for the carbon nanotube growth. The catalyst is critical, and therefore must be very carefully deposited. This CVD approach composition of the molecule from the carbon source, catalyzed by the metal which thus initiates the growth of the carbon nanotube. The catalysts are able to break down the carbon atoms, while the carbon molecules create the nanotube structure as shown in Fig. 5.

4) Natural

Carbon nanotubes have long existed in nature, but until recently the microscopes required for their observation were not available. Therefore, the natural process offers a random approach in the absence of a carbon source pool. The outcome is the creation of many dual carbon atoms whose

composition involves carbon nanotubes.

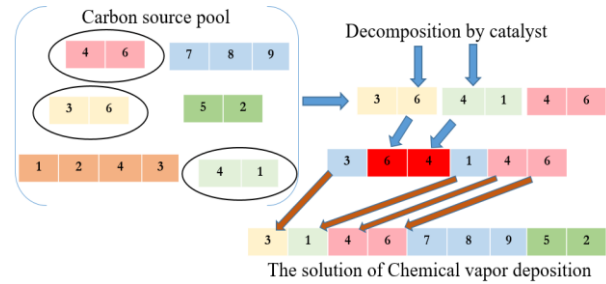


Fig. 5. Carbon nanotubes used in chemical vapor deposition synthesis

D. Roll-up Types Selection

The formation of carbon nanotube structures arises in zigzag, armchair and chiral configurations. The differences among them lie in diameters and chiral angles, as well as their electrical properties. Armchair nanotubes have similar electrical properties to those of metals while zigzag and chiral nanotubes have electrical properties which more closely resemble those of semiconductors. Other differences occur at the nanoscale in three different directions, whereby the roll-up of the armchair sees uniform carbon atom arrangement as 180-120-180-120 degrees. Meanwhile, the zigzag carbon nanotubes show an angle pattern of 120-240-120-240 degrees. Chiral carbon nanotubes may have uncertain angles of arrangement, while the armchair roll-up can establish the upper – lower bound random value in the form of an even number. The upper – lower random approach is applied for every position in the zigzag roll-up, while the chiral roll-up makes use of upper – lower bound randomly, alternating with ignorance. The algorithm in this study sets the upper and lower values as +3 and -3 respectively. The armchair, zigzag, and chiral random methods used in this process can be seen in Fig. 6. For the armchair new solution, number 3 had previously been used to find a new solution with no duplication of the preceding position, while number 6 was the maximum and had been used already in the creation of a new solution.

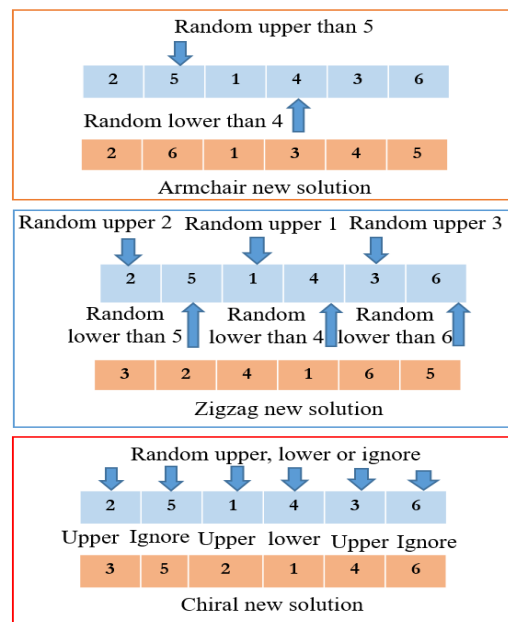


Fig. 6. The novel solution for Armchair, Zigzag and chiral.

E. Carbon Nanotube Types Selection

Single wall and multi-wall carbon nanotubes differ insofar as the multi-walled carbon nanotube has a number of concentric graphene cylinders, whose appearance is dependent on the graphene sheet rolling in the case of armchair, zig-zag, and chiral types. This study makes use of both single and multi-walled carbon nanotubes as solutions for the process of synthesis. The multi-walled carbon nanotubes for two wall layers and are therefore known as double-wall carbon nanotubes, which have a difference of one position in their diameter as can be seen in Fig. 7. Expansion of these double-wall carbon nanotubes arises when 1 is added to each position. In cases where the number duplicates an earlier value, this results in a new position on a random basis. Because of this, new solutions can be created by double-wall carbon nanotubes as the tube expands.

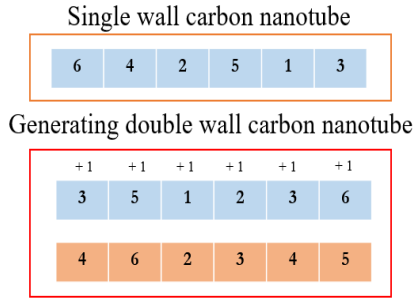


Fig. 7. Generation of a new solutions of single and double wall nanotubes.

The maximum is number 6, which can be used without the need to duplicate the earlier position which was replaced by a unique number.

F. Comparing, Storing and Selecting Global Optimization

This is due to each procedure being capable of producing the solution and not always having to finalize another. The comparison is to take the solution of each process and choose the best solution and collect the solution as the carbon source for the next iteration. The selection of global optimization is to choose the best so far from past to present iterations. However, this must be compared with the best of the current iterations to select the new best so far.

G. Cracking the Optimal Nanotubes Solution for each Method

For every process, the best solution must be based on the good outcomes in the present iteration, as the basis for each future solution is the outcome of the current solution. Cracking is used to destroy carbon nanotubes, returning them to the original carbon source. Working randomly, the carbon nanotubes are cracked into around 2-5 carbon atoms which are sent back to the carbon sources in order to form new carbon nanotubes. Repetition of the algorithm takes place until determination is complete.

IV. ACNSO FOR VACCINE COLD CHAIN NETWORK PROBLEMS

At the start, the parameters must first be set for both the vaccine cold chain network problem and the ACNSO algorithm. Then the CS, R, and random carbon source size must have their parameters defined. The integers, representing hospitals, are then generated into the carbon source string using a random approach. Four of the

synthesized carbon nanotube types must then be selected in proportion, along with the random roll-up types which include armchair, zigzag and chiral carbon nanotubes. In the next step, carbon nanotubes of both single and multiple wall types are randomly selected. The role of the application is then to assess the objective function from Equation 1, which is to achieve the minimum distance. Then the sorting process takes place by the objective function which serves to choose the optimal global solution for data storage, which is represented by a strong structure, while the weak structures of the carbon nanotubes are destroyed. In the last step, the carbon nanotubes are cracked from the remaining solution, and termination of the ACNSO occurs upon meeting the termination criteria. The optimal solution is then reported by the application if possible. Alternatively, the algorithm would be repeated. The detail and figures are shown in the artificial carbon nanotube synthesis optimization topic presents the figures involved and the details, while Fig. 8 shows the pseudo-code of the ACNSO when solving the vaccine cold chain network problem.

V. EXPERIMENTAL DESIGN AND RESULTS

The use of the algorithms in this study was guided by the statistics related to experiment theory, and the experiment was designed in terms of full factorial design 3 level. This was because it was necessary to conduct analysis of the factors covered while cutting the computational time required for each solution. The approach was used when it was necessary to take into consideration k factors, where each factor has three levels, given as high, medium and low. One experiment used 3^k data which is known as 3^k factorial design. ACNSO was employed in designing the vaccine cold chain network, comprising one ODPC, eight PHOs and 102 CUPs [46]. Application development was carried out in Visual Basic Express version and calculations were performed by computer using an Intel Core i7 3.40 GHz processor with 8 GB of RAM. Experimental design was assessed in trial version of Minitab 19. The experimental approach adopted for this study was thus a two-step sequential process [47]. The initial experiment was planned to examine the suitable settings for the parameters of ACNSO, encompassing the number of Carbon Sources (CS) and, Repetitions (R), the Percentage of Carbon Nanotube types (PCN), and the Proportion of Roll-up types (PR). Every parameter was investigated at three levels, as shown in Table I, while the experiment used full factorial design (3^k). The combined number of repetitions and carbon sources controls the number of candidate solutions which are found, and by extension the extent of the search in the solution space.

When these parameters have higher values, the probability of a good solution is increased, but the time taken for computation is extended. The factors were therefore fixed in combination to permit 10,000 candidate solutions so that it was possible to make a fair comparison of the findings with those of other algorithms.

TABLE I: EXPERIMENTAL FACTORS AND IT LEVEL

Factors	Levels		
	Low	Medium	High
R/CS	50/200	100/100	200/50
PCN	20/40/40 (%)	40/20/40 (%)	40/40/20 (%)
PR	25/75 (%)	50/50 (%)	75/25 (%)

Input: Problem data such as distance between nodes, vaccine demand, vehicle capacity, number of vehicles
Algorithm parameters such as number of repetition, number of carbon sources, proportion of synthesis carbon nanotubes types, percent of carbon nanotubes type, proportion of roll up type.

```

For i <= 1 to maximum repetition do
  If i = 1
    Random integer (nodes) to the string (Carbon source)
  End if
  While termination criterion not met do
    Get random x in interval {0,1} ( Synthesis of carbon nanotubes )
    If x <= 0.3 then
      "Arc discharge"
    else if 0.3 <= x <= 0.6 then
      "Laser ablation"
    else if 0.6 <= x <= 0.9 then
      "Chemical Vapor Deposition"
    else
      "Natural"
    End if
    Calculate the objective function and storage the solution (Method 1)
    Get random y in interval {0,1} ( Selection roll up types )
    If y <= Percentage of armchair rollup then
      "armchair rollup "
    else if Percentage of armchair rollup <= y <= Percentage of zigzag rollup then
      "zigzag rollup "
    else
      "chiral rollup"
    End if
    Calculate the objective function and storage the solution (Method 2)
  End if
  Get random y in interval {0,1} (Selection carbon nanotube types)
  If y <= 0.33 then
    "single wall carbon nanotube"
  else
    "double wall carbon nanotube"
  End if
  Calculate the objective function and storage the solution (Method 3)
  Comparing solution each method and selection the best solution
End while
Cracking the best nanotubes (solution) in each method
End for

Output the minimize objective function and routing from ODPC 1 to all nodes

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Fig. 8. Pseudo code of ACNSO for vaccine cold chain network problem.

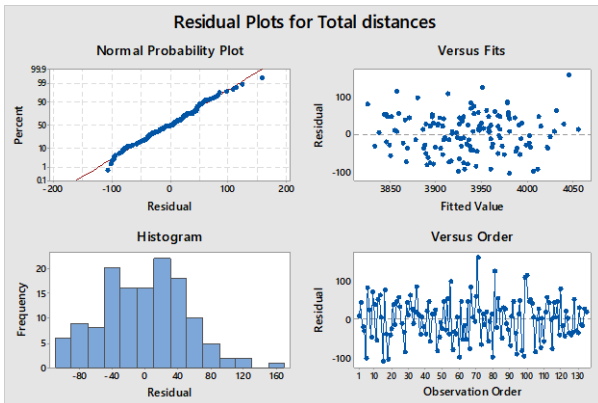


Fig. 9. Residual plot analysis for the vaccine cold chain problem.

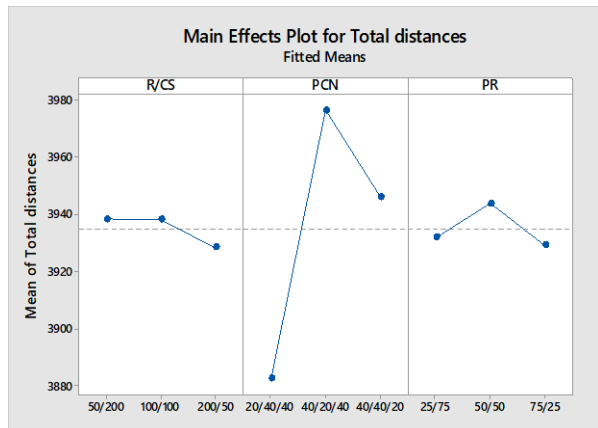


Fig. 10. Vaccine cold chain problem main effect plot.

The experiment was performed five times; each repetition used differing seed numbers chosen randomly, serving as a potential nuisance factor. The findings derived from 135 runs

($3^3 \times 5$) as presented in Table II underwent analysis which applied a general linear version of analysis of variance (ANOVA) and made use of Source of Variation, Sum of Squares (SS), Degree of Freedom (DF), Mean Square (MS), and F and P values and P values. Statistical significance was deemed to be $p \leq 0.05$ for a confidence level of 95%. Residual plot analysis takes into account normal probabilities and the histogram plot. The graphs for the normal distribution Versus fits and Versus order indicate a normal distribution for the data, which are shown to be independent as indicated in Fig. 9.

Table II demonstrates that only one factor was statistically significant for every problem size: Percentage of Carbon Nanotubes (PCN). Various solutions are presented by the Zigzag and Chiral nanotubes when string positions are switched, while the other remaining factors were not found to be statistically significant at the 95% level of confidence, among which were the number of carbon sources and repetitions (R/CS) and the proportion of roll-up types (PR).

TABLE II: ANOVA ON EXPERIMENTAL RESULTS DERIVED FROM ACNSO ADDRESSING THE VACCINE COLD CHAIN PROBLEM

Source	DF	SS	MS	F	P
R/CS	2	2848	1424	0.41	0.667
PCN	2	207730	103865	29.7	0.000
PR	2	5471	2736	0.78	0.460
R/CS * PCN	4	12763	3191	0.91	0.460
R/CS * PR	4	17320	4330	1.24	0.300
PCN * PR	4	13268	3317	0.95	0.439
R/CS * PCN * PR	8	39347	4918	1.41	0.203
Error	108	363892			
Total	134	717538			

The main effect plots represented in Fig. 10 indicate that the appropriate setting of ACNSO parameters should be

20/40/40 (%) for Percentage of Carbon Nanotubes type (PCN). This is the technique of the solution of both zigzag and chiral can find new solutions better than for the armchair. The remaining parameters can be adjusted as appropriate.

However, this algorithm was designed to compare the experimental results obtained from Max-Min Ant System (MMAS), Central Force Optimization (CFO), Artificial

Chemical Reaction Optimization Algorithm (ACROA), Hybrid Central Force Optimization (HCFO) and Hybrid Artificial Chemical Reaction Optimization Algorithm (HACROA). The appropriate parameters from the full factorial design use to 10 times to analyse route distance. These algorithms are based on Random technique. As a result, the route distance is not equal as shown in Table III.

TABLE III: THESE ALGORITHMS PRESENT THE AVERAGE CALCULATION TIME AND TOTAL DISTANCE FROM THE APPROPRIATE PARAMETERS

Times	MMAS (22.77 sec.)	CFO (21.36 sec.)	HCFO (24.65sec.)	ACROA (20.36 sec.)	HACROA (23.48 sec.)	ACNSO (22.12 sec.)
1	3848	3898	3848	3881	3832	3826
2	3867	3872	3854	3872	3849	3804
3	3898	3826	3867	3826	3854	3838
4	3826	3854	3838	3854	3872	3792
5	3881	3872	3848	3867	3826	3832
6	3838	3906	3872	3848	3804	3792
7	3854	3867	3804	3906	3816	3854
8	3826	3854	3898	3838	3898	3826
9	3906	3849	3804	3881	3792	3838
10	3854	3881	3826	3898	3814	3804

Vaccines must travel today via the shortest path, which involves carefully selecting the CUPs to minimize distance. The sum of the distances from ODPC 1 to all of the required CUPs is around 3923 km. In summary, the objective function derived from ACNSO and HACROA could achieve a distance of 3,792 km, but the processing time for ACNSO was shorter than that of the HACROA algorithm.

VI. CONCLUSION

The inspiration underpinning this algorithm lay in the synthesis of carbon nanotubes, known as Artificial Carbon Nanotube Synthesis Optimization (ACNSO). There are various ACNSO techniques which can find solutions through four types of synthesis: arc discharge, laser ablation, chemical vapor deposition, and natural. Among the types produced are the roll forms of carbon nanotubes, armchair, zigzag, and chiral, and the single and double walled types. One major benefit of the algorithm is that carbon sources are created, for the initial solution and single node, so that solutions can be quickly found which are not in the local search, and hence an optimal solution is reached rapidly. The method employed is able to solve the vaccine cold chain network problem through a two-step sequential experiment. Algorithm performance is dependent upon the settings for the parameters, and hence the experiment employed full factorial design so as to examine the various ACNSO parameter settings. The ideal setting was found to be 20/40/40 (%) for the Percentage of Carbon Nanotubes type (PCN). This setting was then applied for the next experiment which compared the algorithm in question with the performance of alternative algorithms such as MMAS, CFO, ACROA, HCFO and HACROA. The objective function was shown to be calculated to achieve a lower distance by ACNSO than by most other algorithms. The same result was also achieved by the HACROA algorithm which did so using less time for computation. However, it is possible to use this algorithm to solve different problems of vehicle routing, or to create a hybrid algorithm capable of solving problems with improved efficiency.

CONFLICT OF INTEREST

The author declares no conflict of interest.

AUTHOR CONTRIBUTIONS

The author conducted the whole of this research.

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