Artificial Carbon Nanotubes Synthesis Optimization: A Novel Nanoscience Based Metaheuristic Approach for Blood Vehicle Routing Problems

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***Abstract*—This paper demonstrates a novel computational method intended to develop inspiration from a synthesis of carbon nanotubes. The proposed method is Artificial Carbon Nanotubes Synthesis Optimization (ACNSO). In this paper, one of the first applications has been executed in the blood vehicle routing problem and has been demonstrated. This algorithm was tested on three sizes of benchmarking datasets of the blood vehicle routing problem. The advantage of this algorithm is to check the travel conditions between the points before creating the initial solution. As a result, the overall processing time is reduced. However, this research presented a definition of the appropriate parameters of this algorithm for the optimal solution. The design of the experiment is adopted to investigate the factors affecting the performance of the algorithm. The experiments were conducted to compare the efficiency of the other algorithms in previous research in terms of the distance.**

***Index Terms*—Metaheuristic approach, artificial carbon nanotubes synthesis optimization, blood vehicle routing problem, design of experiment.**

I. Introduction

Nowadays, metaheuristic approaches are used for solving optimization problems due to the speed requirements when using big data which must be processed through several techniques simultaneously. Mostly the concept of metaheuristic approaches is inspired by biology and physics, Heuristic is a root word derived from Greek and means to find or to discover through exploration by a trial and error method [1]. As a result, the heuristic approaches search for the near-optimal solution of the problem without being able to guarantee either optimality or feasibility. The main algorithm characteristic of heuristic based direct search techniques for the specific problem is that a heuristic is a technique designed for solving a problem more quickly when classical methods are too slow. The prefix “meta” in Greek means beyond, denoting a higher level or upper-level methodology. Metaheuristic approaches are the strategic key that can modify and update the algorithm for the searching solution. Sir Glover introduced metaheuristic in a research paper. Local search is basically an iterative-based method to search for a neighbor of a solution and hence trying to enhance the best current solution by local movement [2]. Each metaheuristic process depends on balancing between two essential components including diversification and intensification. The diversification phase ensures that the algorithm explores the search space more efficiently and helps to generate solutions. However, when diversification is too much it will increase the probability of finding the optimal globally solutions. However, this process will often be too slow with low rate convergence of the problem as seen in the initial population process in the Genetic Algorithm. The key to this process is to avoid a solution being the trap or becoming stuck in the local optimum. The intensification process is the signal information in the search process to generate better solutions. However, if there is too much intensification this will induce convergence rapidly usually to local optimum and will reduce the probability to survey the global optimum solutions. Meanwhile, if there is too little intensification it will take a long computational time to find the global optimum solutions as seen in the update pheromone process in the Ant Colony Optimization. The importance of the intensification process is to control the amount of signal information to the appropriate level [3]. Nowadays, metaheuristic approaches can be classified into nine different groups as Physics-based, Social-based, Biology-based, Chemical-based, Music-based, Swarm-based, Mathematics-based, Sport-based and hybrid [4]. Examples of algorithm that were inspired by physics are the Elevator Kinematics Optimization algorithm [5], Gravitation Search algorithm [6], Electromagnetism-like algorithm [7], Central Force optimization [8], Intelligent Water Drops algorithm [9], Big Bang-Big Crunch algorithm [10], and Galaxy-Based algorithm [11]. The Imperialist Competitive algorithm [12] and Teaching Leaning based optimization [13] are social-based. The Genetic algorithm [14], Artificial Immune Systems [15], and Biogeography-Based optimization [16] are biology based. The Artificial Chemical Reaction optimization algorithm [17] is chemical-based. The Harmony search algorithm [18] is music based. The Ant Colony optimization [19], Particle Swarm optimization [20], Cat Swarm optimization [21], Monarch Butterfly optimization [22] and Cuckoo Search [23] are all biology based. Both Matheuristic [24] and Base Optimization algorithms [25] are mathematics- based. Some metaheuristic algorithms can be classified as both biology based and social-based such as the Cultural algorithm [26] and Colonial Competitive difference evolution [27]. Although the many algorithms are successful for many optimization problems, the design and implementation of new metaheuristics is an important task under the philosophy of improvement in a scientific field to create better technique. The best algorithm that gives the best results for all the

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problems has not yet been designed, and that is why new artificial intelligence optimization algorithms are constantly proposed. Optimization problems seek to find the best way from all possible solutions, such as mapping the fastest route from point A to point B. Many algorithms designed to solve optimization problems have not changed since they were first described in the 1970s. Previous optimization algorithms generally worked in a step-by-step process, with the number of steps proportional to the amount of data analyzed

The organization of this research is as follows. In Section II, the carbon nanotubes and synthesis are described. In Section III, the novel metaheuristic approach is presented with its computational operators inspired by the synthesis of carbon nanotubes (Artificial Carbon Nanotubes Synthesis Optimization: ACNSO). The blood vehicle routing problem is presented in Section IV. The application of this algorithm for the blood vehicle routing problem is presented in Section V. The parameters and experimental results are in Section VI. Finally, Section VII concludes this research.

II. The Synthesis of Carbon Nanotubes

Norio Taniguchi coined the word nanotechnology in 1974, in Japan. The meaning of nanotechnology is the design, characterization, production, and application of materials, devices, and systems by controlling shape and size at the nanoscale. The nanoscale consensually refers to the range of 1–100 nm. Nanotechnology is a vast field, which explores many facts about the structures and properties of materials [28]. There are many applications at the nanoscale such as carbon nanotubes, nanoparticles, and Buckminster fullerene. Carbon nanotubes (CNTs) are graphene sheets rolled to form tubes with a diameter of 3-30 nm. They were discovered by Iijima in 1991 [29]. Carbon nanotubes are classified into two basic structure types: single-walled carbon nanotubes (SWCNT) and multiple-walled carbon nanotubes (MWCNT). The difference between two tubes is that SWCNTs are a single layer of graphene, easy to characterize and evaluate, while MWCNTs consist of many single-walled tubes stacked one inside the other and have a very complex structure. Normally, SWCNTs are narrower than MWCNTs with diameters in the range of 1-2 nm. There are three roll types of graphene including armchair carbon nanotubes, zigzag carbon nanotubes, and chiral carbon nanotubes. The atomic structures of the carbon nanotubes are described by the tube chirality defined by the chiral vector, C_h, and the chiral angle θ in Fig. 1.

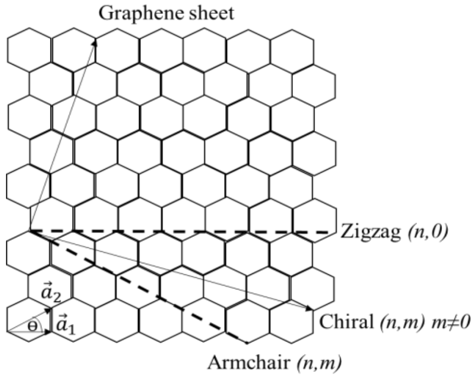

Fig. 1. Unit vector a_1, a_2 and angle.

A graphene sheet is formed with defined chiral vector and angle. The chiral vector is described in terms of the lattice translational indices (n, m) and the unit vectors a_1 and a_2 as shown in $C_h=na_1+ma_2$. The chiral angle (θ), determines the degree of twisting of the tube, and is defined as the angle (θ) between the vectors C_h and a_1, which varies in the $0^o \le |\theta| \le 30^o$ range. The differences in carbon nanotubes types are generated depending on how the graphene sheet is rolled up during the creation process. Fig. 2 shows the three different roll up type of SWCNTs. Based on the geometry of the carbon bonds around the circumference of the tube, there are two limiting cases, corresponding to the chiral tubes, known as armchair ($\theta = 30^o$) and zig-zag ($\theta = 0^o$). In addition, when $0^o < |\theta| < 30^o$, the nanotube is called chiral.

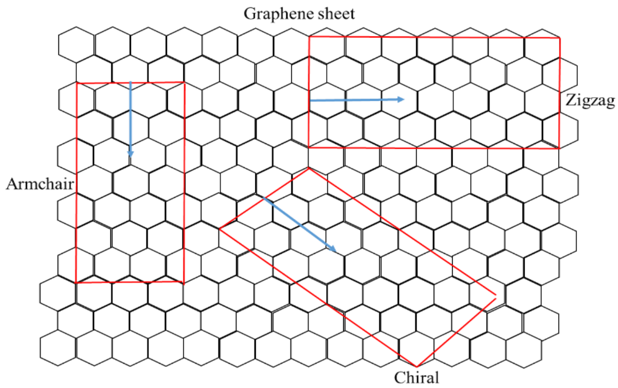

Fig. 2. Carbon nanotube types: armchair, zigzag, and chiral.

Several techniques have been used to synthesize the carbon nanotubes. There are three techniques most commonly employ: arc discharge, laser ablation, and chemical vapor deposition. However, carbon nanotubes can also be generated in nature. The basic elements for the formation are catalyst, a source of carbon, and sufficient energy.

A. Arc Discharge

In 1991, carbon nanotubes were produced using an arc-discharge evaporation method similar to that used for fullerene synthesis in the past. Carbon needles with diameters ranging from 4 to 30 nm. And lengths up to 1 mm were used. The arc-discharge assembly includes two vertical thin electrodes (anode, cathode) installed in the center of the chamber. The lower electrode (cathode) has a shallow dip to hold a small piece of iron during the evaporation phase. The arc-discharge can be generated by running a DC current of 200 A at 20 V between the two electrodes. After the arc discharge process the carbon nanotubes are found at the cathode. The yield for this method is up to 30% by weight and it produces both SWCNTs and MWCNTs [30].

B. Laser Ablation

In 1995 Richard E. Smalley and his group used laser ablation for the first time to grow high quality nanotubes. Intense laser pulses ablate a carbon target, which is placed in a tube-furnace heated to 1200 ℃. During the process, some inert gas like helium or argon flows through the chamber to carry the grown nanotubes to the copper collector. After the cooling of the chamber the nanotubes and the by-products can be collected, including the fullerenes and amorphous carbon over-coating on the sidewalls of nanotubes [31].

C. Chemical Vapor Deposition

The most popular and simplest way to grow carbon nanotubes in the laboratory is to use chemical vapor deposition (CVD). A CVD system for CNT growth injects a vaporized hydrocarbon compound (methane or ethane are common) into a high temperature zone in a furnace. The hot zone contains a substrate on which has been pre-deposited a thin film of iron, nickel or cobalt that has either separated or been pre-patterned into nanoscale islands of the metal. These nanoscale islands catalyze the growth of the carbon nanotubes. The catalyst is the key to the whole process and careful attention must be given to its deposition. Both single and multi-walled CNTs can be produced via CVD [32].

D. Natural

Carbon nanotubes which do not use the high-tech laboratories are commonly formed in such mundane places as ordinary flames produced by burning methane, ethylene, and benzene. They have been found in soot from both indoor and outdoor air. However, these naturally occurring varieties can be highly irregular in size and quality because the environment in which they are produced is often highly uncontrolled [33].

III. Artificial Carbon Nanotubes Sythesis Optimization (ACNSO)

The carbon source is an important raw material for the synthesis of carbon nanotubes. Several techniques have been used in the synthesis of carbon nanotubes where hydrocarbons such as methane and acetylene are commonly used as precursors. However, there are many carbon sources for the production of carbon nanotubes such as coal, graphite and other hydrocarbon. Algorithm can be considered as a simulation of carbon nanotubes in synthesis and can be modified or adapted to suit specific problem requirement. Encoding of carbon sources can be binary, real string, etc. In this case they are asymmetric string. These encoding schemes play a role in the carbon atoms of carbon sources (Fig. 3). ACNSO begins with a set of initial carbon sources in a solution.

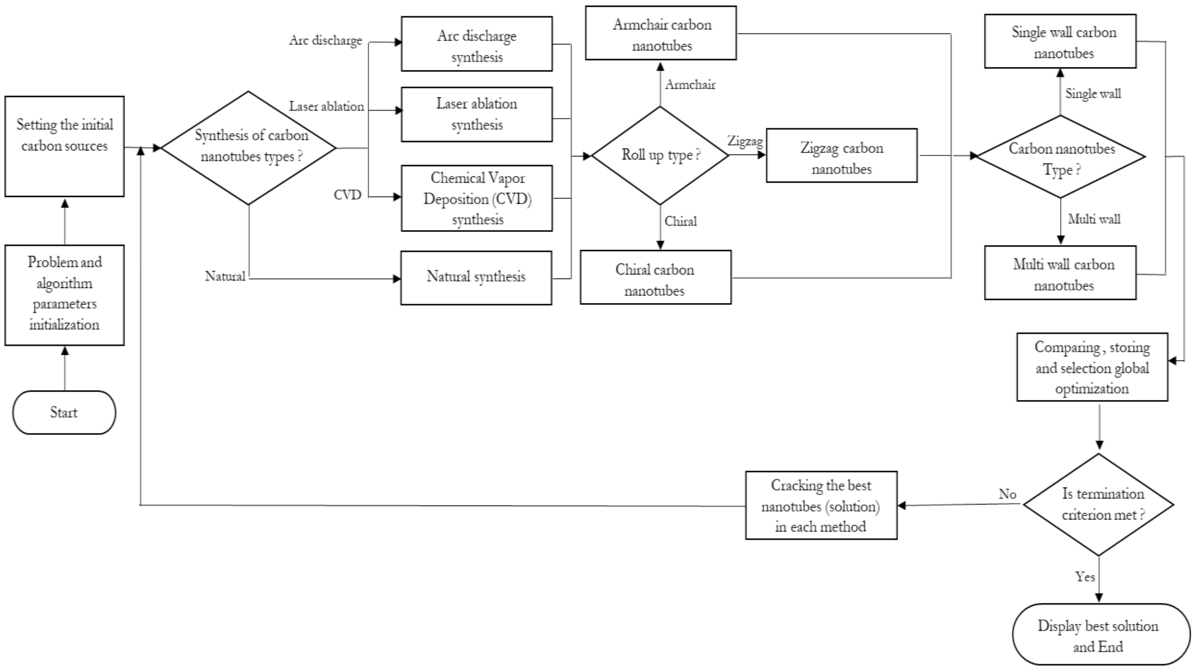

Fig. 3. The flowchart of the ACNSO algorithm.

A. Problem and Algorithm Parameters Initialization

This section provides details about input the data of the problem into the application. The proposed algorithm defines four parameters and one constant parameter for evaluation including the number of Carbon Sources (CS), number of Repetitions (R), Percentage of Carbon Nanotubes type (PCN) and Proportion of Roll up type (PR). Initially, CS and R are set to one parameter and determine the appropriate proportion of the solution. The Proportion of Synthesis Carbon Nanotubes types defines arc discharge, laser ablation, chemical vapor deposition and natural in the ratio of 30:30:30:10 respectively (set to a constant). PR shows the probability of carbon nanotubes as follows: Armchair carbon nanotubes, Zigzag carbon nanotubes and Chiral carbon nanotubes. PCN is the proportion of single wall and multi-wall carbon nanotubes.

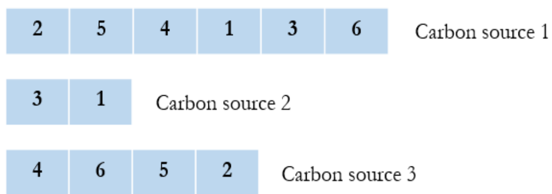

Fig. 4. The string size of carbon nanotubes.

B. Setting the Initial Carbon Sources

Carbon source refers to any carbon atom carbon containing molecules and uses to the synthesis of its organic molecules. In the proposed algorithm, the initial carbon sources are randomly arranged in the feasible searching space. However, they are not an initial solution which makes the difference in string size of the carbon source as shown in Fig. 4. The random technique is to define both the number of carbon source and number of string carbons. Generally, the number of carbon sources is appropriate to the size of solution space. After the first iteration of processing, the structure of the strongest carbon nanotube is likely to be the substrate of the next solution according to the roulette wheel method.

C. Synthesis of Carbon Nanotubes

Nowadays, the carbon nanotube synthesis process has many approaches and complex steps. However, there are three main methods that also occur naturally.

Arc discharge

This process is to be applie across two graphite electrodes immersed in an inert gas. When the carbon source is used, carbon nanotubes are deposited on the cathode in the form of soot. Similarly, the carbon source fixes at the cathode and then the carbon molecules to form carbon nanotubes. The arc discharge occurs randomly initially and then connects with the other carbon source which can switch the connection point. The random method creates the solution if the conditions are not initially met (Fig. 5).

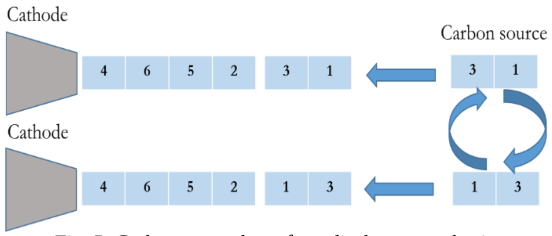

Fig. 5. Carbon nanotubes of arc discharge synthesis.

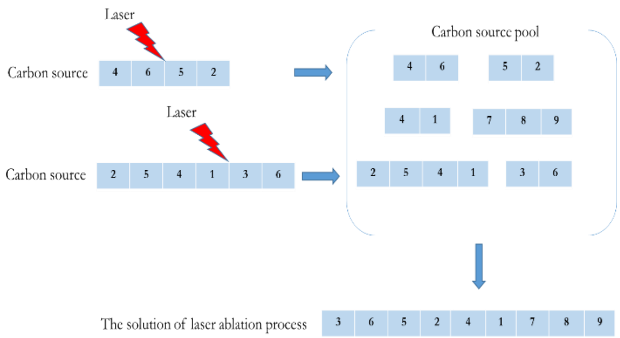

Fig. 6. Carbon nanotubes of laser ablation synthesis.

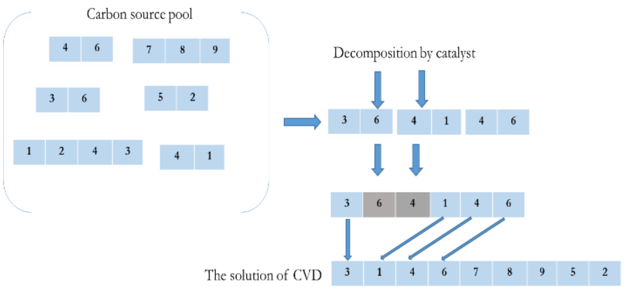

Fig. 7. Carbon nanotubes of chemical vapor deposition synthesis.

Laser ablation

The laser ablation process is to destroy the carbon source in the laser oven with high temperatures. Afterwards, the carbon molecule takes the bonded carbon nanotubes form. The carbon molecule remains in the carbon form with at least 2 atoms which are sent into the carbon source pool. The random technique in the carbon source pool is to generate carbon nanotube (Fig. 6).

Chemical Vapor Deposition

The CVD technique involves the composition of the molecule of the carbon source, catalyzed by the metallic particle which also serves for the initiation of carbon nanotube growth. The catalysts break down carbon atoms like the carbon atoms of the carbon molecule whereby carbon molecules formed carbon nanotube structure (Fig. 7).

Natural

Naturally, occurring carbon nanotubes have existed for a long time, but the microscope technology had not yet seen this phenomenon. Consequently, this process provides a random technique without a carbon source pool. However, many dual carbon atoms are created and are composed of carbon nanotubes.

D. Selection Roll up Types

Carbon nanotube structures form in armchair, zigzag and chiral configurations. They differ in chiral angle and diameter: armchair carbon nanotubes share electrical properties similar to metals. The zigzag and chiral carbon nanotubes possess electrical properties similar to semiconductors. The difference is only at the nano scale along three different directions as shown in Fig. 8.

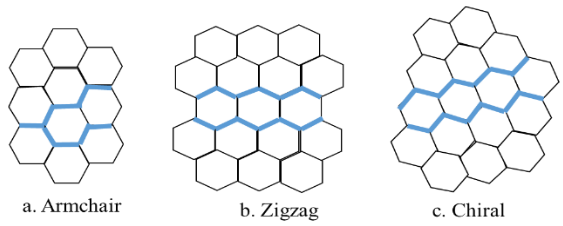

Fig. 8. The carbon atoms arrangement is the direction of alignment on Armchair, Zigzag, and Chiral. The bold line is to present the bonding of carbon atoms.

The armchair roll-up has a uniform arrangement of the carbon atoms as 180-120-180-120 degrees. The zigzag carbon nanotube has a pattern of angles as 120-240-120-240 degrees. Uncertain angles of arrangement of carbon atoms are a form of chiral carbon nanotube. Similarly, armchair roll-up defines the upper - lower bound random value as even number. The upper lower random technique applies with all positions in the zigzag roll-up. The chiral roll-up uses upper-lower bound random with ignorance alternately. In this work, the proposed algorithm sets +3 and –3 for the upper and lower values respectively. Fig. 9 shows the armchair, zigzag and chiral random methods in this process.

E. Selection of Carbon Nanotube Types

The difference between the single wall and multi-wall carbon nanotubes is the single graphene cylinder whereas a multi-walled carbon nanotube comprises several concentric graphene cylinders, depending on the rolling of the graphene sheets, for armchair, zig-zag and chiral type. In this work, both Multi-wall and single wall carbon nanotubes are the solution of the synthesis process. However, multi-wall carbon nanotubes create two layers of wall called double-wall carbon nanotubes to the form difference in diameter by one position as shown in Fig. 10. Double-wall carbon nanotubes expand by the addition of 1 to each position. If the number is a duplication of a previous value that creates a new position randomly. As a result, double-wall carbon nanotubes can create a new solution from the expansion of the tube.

F. Comparing, Storing and Selecting Global Optimization

After the synthesis procedure of carbon nanotubes, selection of roll up types and selection of carbon nanotube types, there are many solutions from these processes. 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 Best Nanotubes (Solution) in Each Method

The optimal solution in each process must respect the good results from the current iteration. Causes for these solutions are precursors for the next iteration. The cracking is to destroy carbon nanotubes (solution) back to the original as the carbon sources. The random approach to crack the carbon nanotubes into at least 2-5 carbon atoms is to return to carbon sources to generate new carbon nanotubes. This algorithm is to be repeated until complete determination.

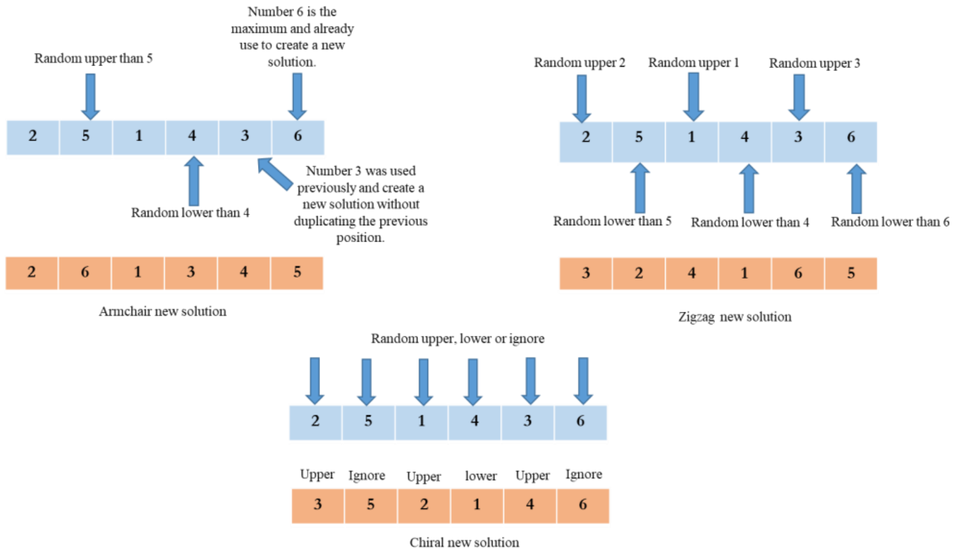

Fig. 9. Armchair, Zigzag and Chiral strategy for generating a new solution.

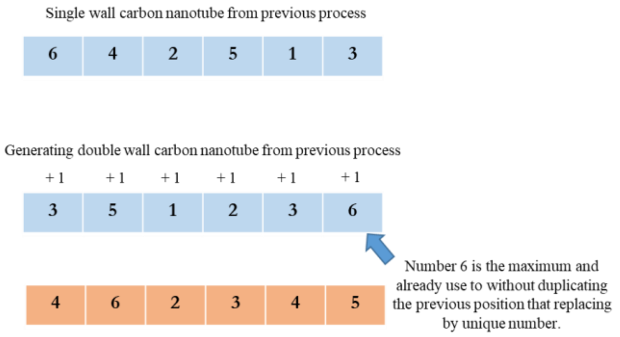

Fig. 10. Single and double wall carbon nanotubes strategy for creating a new solution.

IV. Blood Vehicle Routing Problem

The importance of blood vehicle routing networks has been widely recognized. Effective management of blood vehicle routing can reduce distance and improve responsiveness to changing hospital demand. Vehicle routing may be defined as the art of bringing the right product in the right quantity to the right place at the right time while minimizing distance. The Vehicle Routing Problem (VRP) is a Nondeterministic Polynomial time problem (NP-hard problem) [34]. VRP has been previously tackled using various methods. Efficient, exact algorithms are only for small size problems. Based on the full enumerative search within this algorithm, the optimal solutions are always guaranteed. However, the approach might need exponential computational time [35]. This research focuses on the Chiang Mai blood donation center to support the hospitals in the north of Thailand. It is responsible for donating and delivering blood to hospitals in Chiang Mai, Chiang Rai, Phrae, Nan, Lam pang, Lamphun, Phayao and Mae Hong Son. The number of hospitals that receive blood is 112 hospitals [36]. Google Maps is used to calculate the distance of each hospital for data processing. The mathematical model and its notations for blood vehicle routing considered in this paper involve the following equations.

Indices:

Z: denotes total distances for blood vehicle routing

i: denotes hospital i

j: denotes hospital j

k: denotes blood vehicles k

Parameters:

dij: is distance from hospital i to hospital j

N: is number of hospitals

K: is number of blood vehicles

p: is hospital (1, 2, 3, …..N)

A: is blood group A

B: is blood group B

AB: is blood group AB

O: is blood group O

ak: is capacity of blood vehicles k

q_i^A : is blood group *A* demand of hospital *i*

q_i^B : is blood group *B* demand of hospital *i*

q_i^{AB} : is blood group *AB* demand of hospital *i*

q_i^O : is blood group *O* demand of hospital *i*

Decision variables:

X_{ij}^k = 1 if vehicles *k* from *i* to *j*, otherwise 0

Y_i^k = 1 if blood load in vehicles ***k***, otherwise 0

U_i^k is the variable for protection if it is not possible to supply all hospitals

Objective function

$$Min\, Z = \sum_{k=1}^{K}\sum_{j=0}^{N}\sum_{i=0}^{N} d_{ij} X_{ij}^k \tag{1}$$

Representation by

$$\sum_{j=1}^{N} X_{oj}^k \le 1 \quad (K = 1,2,3,\ldots\ldots..K) \tag{2}$$

$$\sum_{i=0}^{N} X_{ip}^k - \sum_{j=0}^{N} X_{pj}^k = 0 \,(p = 1\ldots N) \tag{3}$$

$$\sum_{k=1}^{K} Y_i^k = 1 \qquad (i = 1,2,3\ldots K) \tag{4}$$

$$\sum_{i=1}^{N} q_i^A Y_i^K \le a_k^A \qquad (k = 1\ldots.K) \tag{5}$$

$$\sum_{i=1}^{N} q_i^B Y_i^K \le a_k^B \qquad (k = 1\ldots.K) \tag{6}$$

$$\sum_{i=1}^{N} q_i^O Y_i^K \le a_k^O \qquad (k = 1\ldots.K) \tag{7}$$

$$\sum_{i=1}^{N} q_i^{AB} Y_i^K \le a_k^{AB} \qquad (k = 1\ldots.K) \tag{8}$$

$$Y_i^k \le \sum_{i=1}^{N} X_{ji}^k \;(i = 1\ldots.N),(k = 1\ldots.K) \tag{9}$$

$$\sum_{k=1}^{K}\sum_{i=0}^{N} X_{ij}^k \ge 1 \qquad (j = 1,2,3\ldots.N) \tag{10}$$

$$U_i^k \ge U_j^k + q_i - a_k + \left(a_k\left(X_{ij}^k + X_{ij}^k\right)\right) - X_{ij}^k\left(q_i + q_j\right) \tag{11}$$

$$U_i^k \le a_k - X_{0i}^k\left(a_k - q_i\right) \tag{12}$$

$$U_i^k \le q_i + \sum_{j=1}^{N} q_j X_{ji}^k \tag{13}$$

$$X_{ij}^k = \{0,1\} \quad (i=1\ldots N),(j=1\ldots N),(k=1\ldots K) \tag{14}$$

$$Y_i^k = \{0,1\}\; (i=1\ldots.N),(k=1\ldots.K) \tag{15}$$

$$U_i^k \ge 0 \quad (i=1\ldots.N),(k=1\ldots.K) \tag{16}$$

Equation 1 is the sum of the distance from the blood donation center to all hospitals. Constraint 2 represents the blood delivery vehicles transportation from the blood donation center only. Constraint 3 ensures that the blood is delivered to only the hospitals requiring it. Likewise, Constraint 4 is for only the blood vehicles delivering to the hospitals. Constraints 5 to 8 ensure that blood groups A, B, AB and O are less than or equal to the capacity limitation of the blood vehicles. Constraint 9 ensures that blood vehicle *i* takes a route through hospital *j*. Constraint 10 ensures that the hospital *j* has been transported at least 1 time. Constraints 11 to 13 prevent detours and guarantee the supporting of all hospitals requiring blood. Constraints 14 and 15 are decision variables 0 or 1. If it is 0, the value of the equation is 0. If the variable is 1, the value of equation is the original value, while the Remaining constraint defines to be greater than or equal to 0.

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Input: Problem data such as distance between hospitals, blood demand, vehicle capacity, number of vehicles
       Algorithm parameters such as number of Repetition (R), number of Carbon Sources, Proportion of Roll up type (PR), Percent of Carbon
       Nanotubes type (PCN)

For i <= 1 to maximum repetition do
  If i = 1
    Random integer (hospitals) to the string (Carbon source)
  End if
  While termination criterion not met do
    Get random x in interval {0,1} (Proportion of Synthesis Carbon Nanotubes types = 30:30:30:10 ) (Constant)
        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} Proportion of Roll up type (PR = 0,1)
        If y <= PR1 then
          "armchair rollup "
        else if PR1 <= y <= PR2 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} Percent of Carbon Nanotubes type (PCN = 0,1)
        If y <= PCN1 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 blood center to all hospitals
```

Fig. 11. Pseudo code of ACNSO for blood vehicle routing network problem.

V. ACNSO FOR BLOOD VEHICLE ROUTING PROBLEMS

At the beginning, the initial process is the setting parameters for both the ACNSO algorithm and the blood vehicle routing network problem. The second step is defining the parameters as CS, R and random carbon source size. After that, the process generates the integers (hospitals) into the carbon source string by a random technique. The third step is the selection of four of the synthesized carbon nanotube types in proportion. The fourth step is the random roll up types including armchair, zigzag and chiral carbon nanotubes. Both single and multiple wall carbon nanotubes are randomly selected in the fifth step. Henceforward, the application evaluates the objective function from Equation 1 (minimizing distance). The sixth step is sorting by the objective function that selects the best global solution (strong structure) in data storage and destroys the weak structures of carbon nanotubes.

The final step is cracking the carbon nanotubes from the remaining solution. The ACNSO is terminated when the termination criterion has been met. The application reports the best solution. Otherwise, the algorithm is repeated. The detail and figures are shown in the artificial carbon nanotube synthesis optimization topic. According to the ACNSO algorithm concept, the pseudo-code of the ACNSO for solving the blood vehicles routing network problem is represented in Fig. 11.

VI. Experiment and Results

Nowadays, there are several factors impacting the algorithm. The research objective is to find factors that have an influence in order to find the objective function for the application. This paper has to use statistics of experimental theory to design the experiment in terms of full factorial design 3 level. This method is used when there are k factors to consider. Each of the factors consists of 3 levels including high, intermediate and low. Each experiment is composed of 3^k data which is called 3^k factorial design. In this present work, ACNSO was used to design the blood vehicle routing network. Three sizes of benchmarking are shown in the next sentence. The small size problem involves 26 hospitals (only Chiang Mai Province). The medium size problem supports 38 hospitals (Chiang Mai, Lamphun, Mae Hong Son) and 112 hospitals are contained in the large size problem [36], [37]. A two-step sequential experiment was adopted in this research [38]. The experiment was designed to investigate the appropriate setting for ACNSO parameters including the number of Carbon Sources (CS), number of Repetitions (R), Percentage of Carbon Nanotubes types (PCN) and Proportion of Roll up type (PR)[39]. Since each parameter was considered at three levels (see Table I), full factorial design (3^k) was adopted in this experiment. It should be noted that the combination of number of repetitions and number of Carbon Sources (R/CS) determine the number of candidate solution generated, which are directly implied the amount of searching in the solutions space. The higher values of these parameters mean that there is more chance of getting good solutions but this requires longer computational time. The combination of these factors was fixed to 10,000 candidate solutions in order to fairly compare the obtained results with other algorithms.

The experiment was repeated five times using different random seed numbers, which could be potential nuisance factors. The computational results obtained from 135 runs (3^3x5) shown in Table II to Table IV were analyzed using a general linear form of analysis of variance (ANOVA) including Source of Variation, Degree of Freedom (DF), Sum of Squares (SS), Mean Square (MS), F values and P values. A factor with $p <= 0.05$ is statically significant with a 95% confidence level. The analysis of the residual plot considers the normal probability and the histogram plot. The normal distribution Versus fits and Versus order graphs show that the data are normally distributed and independent as shown in Fig. 12–Fig. 14.

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 (%)

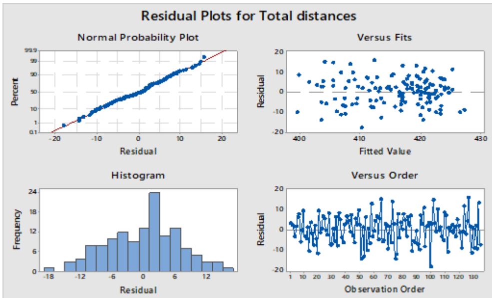

Fig. 11. The analysis of the Residual plot of the small size problem.

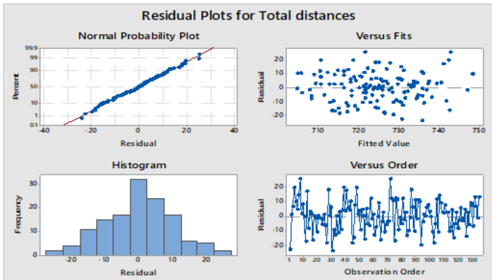

Fig. 12. The analysis of the Residual plot of the medium size problem.

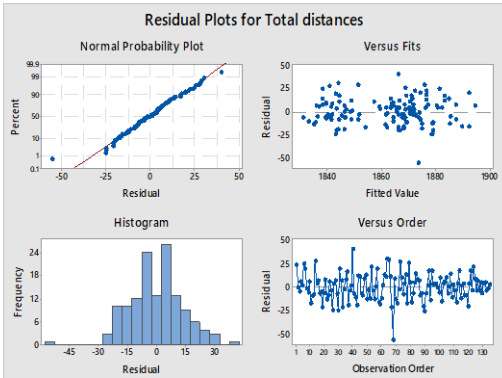

Fig. 13. The analysis of the residual plot of the large size problem.

TABLE II: ANOVA on Experiment Results Obtained from ACNSO Using Small Problem

Source	DF	SS	MS	F	P
R/CS	2	1.1	0.56	0.01	0.991
PCN	2	4780.8	2390.42	39.28	0.000
PR	2	71.6	35.49	0.58	0.56
R/CS * PCN	4	32.6	8.14	0.13	0.970
R/CS * PR	4	385.6	96.41	1.58	0.184
PCN * PR	4	99.9	24.98	0.41	0.801
R/CS * PCN *PR	8	337.5	42.18	0.69	0.697
Error	108	6328.5			
Total	134	12375.3			

From Table II-Table IV, it can be seen that only one single factor called Percentage of Carbon Nanotubes (PCN) was statically significant on all problem sizes. The Zigzag and Chiral solutions can create a variety of solutions from switching string positions. The remaining factors including the number of repetitions and number of carbon sources (R/CS) and proportion of roll up types (PR) in the range considered were not significant with a 95% confidence level.

TABLE III: ANOVA ON EXPERIMENT RESULTS OBTAINED FROM ACNSO USING MEDIUM PROBLEM

Source	DF	SS	MS	F	P
R/CS	2	725	362.50	2.73	0.07
PCN	2	5912.6	2956.3	22.23	0.000
PR	2	498.3	249.16	1.87	0.159
R/CS * PCN	4	236.8	59.21	0.45	0.776
R/CS * PR	4	57.8	14.44	0.11	0.979
PCN * PR	4	695.0	173.74	1.31	0.273
R/CS * PCN *PR	8	1537.7	192.22	1.45	0.187
Error	108	13831.6	133.0		
Total	134	26103.2			

TABLE IV: ANOVA ON EXPERIMENT RESULTS OBTAINED FROM ACNSO USING LARGE PROBLEM

Source	DF	SS	MS	F	P
R/CS	2	347.5	173.8	17.87	0.501
PCN	2	26230.7	13115	52.55	0.000
PR	2	173.6	86.8	0.35	0.707
R/CS * PCN	4	1371.4	342.8	1.37	0.248
R/CS * PR	4	1330.3	332.6	1.33	0.263
PCN * PR	4	1034.8	258.7	1.04	0.392
R/CS * PCN *PR	8	1862.4	232.8	0.93	0.493
Error	108	25955.6	249.6		
Total	134	59108			

The main effect plots represented in Fig. 14-Fig. 16 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 Genetic Algorithm (GA), Cuckoo Search (CS), Artificial Chemical Reaction Optimization Algorithm (ACROA) and Hybrid Cuckoo Search (HCS) reported by Sujaree. K and Jirawongnusorn S. [37].

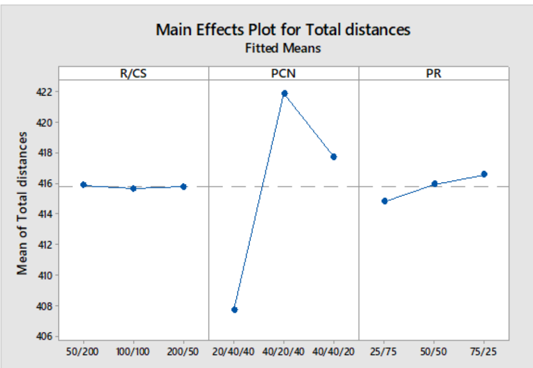

Fig. 14. Main effect plot of the small size problem.

The summary of the objective function obtained from GA, CS, ACROA, HCS and ACNSO is shown in Table V. It can be seen that for small size problems GA, CS, ACROA, HCS and ACNSO were able to find the minimized distances. For medium size problems, the CS, ACROA, HCS and ACNSO algorithms produced minimized distances lower than the GA. Whereas for large size problems, the best-so-far results obtained from ACNSO and HCS were better than GA, CS and ACROA respectively [37]. However, the computational times of ACNSO are shorter than HCS.

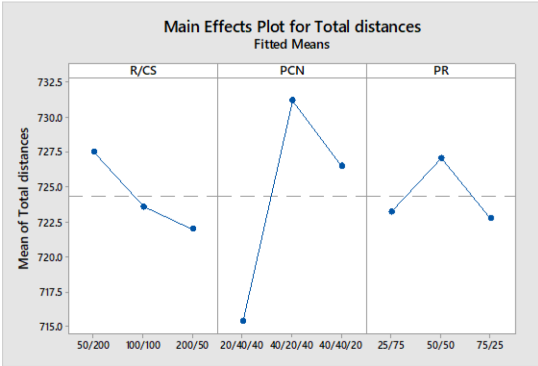

Fig. 15. Main effect plot of the medium size problem.

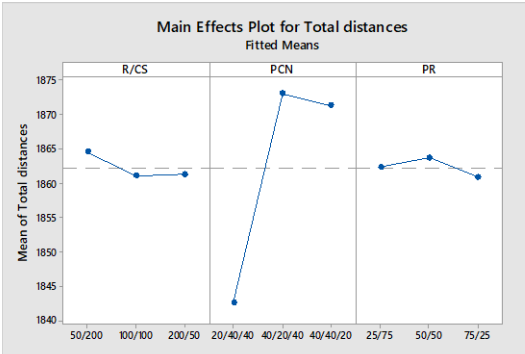

Fig. 16. Main effect plot of the large size problem.

TABLE V: THE SUMMRY OF RESULTS OBTAINED FROM GA, CS, ACROA, HCS AND ACNSO

Problem size	Best-so-far solution				
	GA	*CS*	*ACROA*	*HCS*	*ACNSO*
Small size (26 hospitals)	389 km.	389 km.	389 km.	389 km.	389 km.
Computational times	18.4 Sec.	19.2 Sec.	23.3 Sec.	26.1 Sec.	24.6 Sec.
Medium size (38 hospitals)	735 km.	697 km.	697 km.	697 km.	697 km.
Computational times	41.7 Sec.	43.5 Sec.	49.2 Sec.	55.6 Sec.	50.4 Sec.
Large size (112 hospitals)	1968 km.	1836 km.	1832 km.	1818 km.	1818 km.
Computational times	191.5 Sec.	213.6 Sec.	231.7 Sec.	264.3 Sec.	234.8 Sec.

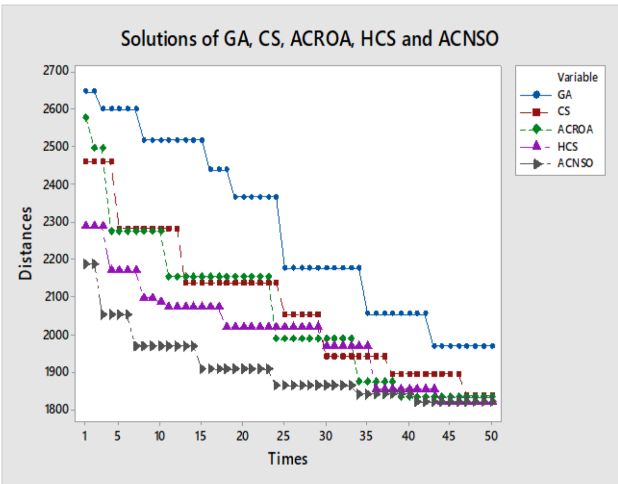

Fig. 17. The convergence to optimal solution in large size problem.

Fig. 17 shows only plots of a large size problem due to similarity in all problem sizes. One experiment was assigned per algorithm with brake criteria of 50 replications. In the experiment, ACNSO and HCS have the ability to quickly find the objective function towards the minimizing of distance with faster solution convergence compared to ACROA, CS, and GA. This implies that ACNSO and HCS have a strong capability in terms of speed of objective function convergence for each problem size. However, ACNSO takes less time to process a solution than the HCS algorithm.

VII. Conclusion

This algorithm was inspired by the synthesis of carbon nanotube method called Artificial Carbon Nanotube Synthesis Optimization (ACNSO). The ACNSO has many techniques to generate solutions consisting of four synthesis types (Arc discharge, Laser ablation, Chemical vapor deposition and Natural). These types include the roll form of carbon nanotube (Armchair, Zigzag, Chiral) and the layers of walls of carbon nanotubes (single and double wall). The advantage of this algorithm is the creation of carbon sources, not both the initial solution and the single node, which makes it possible to find solutions not in local search and to create an optimal solution quickly. The proposed approach solved the blood vehicle routing network problem and was tested on three sizes of benchmarking datasets. The two-step sequential computational experiment was adopted in this paper. Since the performance of an algorithm depends on its parameter settings, the experiment was based on full factorial design aiming to investigate the appropriate setting of ACNSO parameters, which was then used in the second experiment intending to compare the performance of the proposed method with other algorithms including GA, CS, ACROA and HCS. It was also found that ACNSO calculated the objective function with a lower distance than those obtained from other methods especially for the large size problem. However, the HCS algorithm could find the same solutions but required less computational time. However, this algorithm can be used to solve other vehicle routing problems or can be developed into a hybrid algorithm to increase the efficiency of finding solutions.

Conflict of Interest

The author declares no conflict of interest.

Author Contributions

The author conducted the whole of this research.

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