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Optimization of the allocation of dynamic vehicle routing with considering traffic

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Abstract

In the light of the impact of transportation management and logistics on the economy and extending the efficiency in the systems of production, the well-timed supply of materials and products is a momentous prerequisite for economic and environmental extension. In addition, since the optimality usage of communication networks and detecting optimal routes to decrease traffic volume and travel time in the logistics network by discovering optimal routes for vehicles to attain the destination, is an fundamental challenge and a goal in the smart transportation system, hence, in this paper, we accomplish a new model targeted to minimize the costs of customer service for a dynamic transport network in a safe solution in regard to monitor the dynamic production process and achieve the instantaneous information dependent upon the traffic situation of an advanced evolutionary genetic algorithm. Besides, the Logit function is used to obtain probability and assign routes in the model. Eventually, So that to evaluate the proficiency and feasibility of the suggested model, a number of numerical examples accompanied with sensitivity analysis are demonstrated.

Keywords: Logistics, dynamic routing, traffic, improved evolutionary genetic algorithm

1- Introduction

Transportation, as a non-value-added activity, expends a lot of resources and costs. Reducing transportation costs has turn into a paramount issue for intensifying competition in various industries, as an example of e-commerce, retail, and manufacturing (Gainanov et al., 2016). Nowadays, vehicle routing is decisive in logistics, transportation, and related industries. This has interested a large variety of scholars and specialists in diverse fields of study, understand as the VRP (Sabar et al., 2019). VRP has been given an introduction by Dantzig and Ramser (1959) as a mathematical model for transport management. Classical VRP is a renowned hybrid optimization problem that has been extensively investigated so far (Toth and Vigo, 2014). VRP contains a collection of customers that are geographically to spread out widely in disparate areas and is a fleet of vehicles.

One of the necessities and goals of transport management is to fulfill to all customers at the lowest cost (for example, travel distance, time, fuel, etc.) with restrictions (Ghannadpour et al., 2014; Kilby et al., 1998).

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Furthermore, on account of the nature of routing issues and not the same constraints, there are well-known types of VRP introduced types of VRP consist of: I) the problem of routing capacity-limited transport vehicles (CVRP), which takes into consideration the capacity of transport vehicles as a paramount limit (Toth and Vigo, 2014), II) the problem of routing vehicles with time window (VRPTW , Where each customer can receive their services in just a predetermined time window (Bräysy and Gendreau, 2005), III) The problem of routing transport vehicles with multiple trips (VRPMT), that a vehicle can conduct greater one trip or task (Vidal et al., 2013). In these vehicle routing scenarios, travel time from one point to another is constant (Sabar et al, 2019).

As a matter of fact, the nature of the majority transportation systems and logistics are dynamic (Pillac et al, 2013). In the following words, only limited information is ready to be used at the commencement of the journey, and new information is attained over time. For instance, a customer's new order may be registered when a vehicle is serving the customer (Montemanni et al, 2005). Besides, traffic situation is one more substantial factor that may vary meaningfully in diverse times of the day or simultaneously on different days, which engenders it very arduous to forecast traffic density levels (Pillac et al, 2013). This takes one to a realistic and challenging type of VRP dynamic, describe as dynamic vehicle routing (DVRP). The DVRP was first accomplished by Psaraftis (1988) that recognized after the presentation of collection of criteria by Kilby et al (1998), as an appropriate platform for the application of optimization methods (Okulewicz and Mańdziuk, 2019). In DVRP, the accurate time amid customers is not widely known clearly and established upon the level of traffic congestion on the route, which expresses that after manufacturing a set of route plans and after the vehicle goes away the warehouse to serve customers, the time to travel among customer may be modified. When a change comes to pass, the optimization algorithm must adjust to it and attain a new solution with minimal cost. However, DVRP is comparatively unknown despite its theoretical momentousness and practical values (Sabar et al, 2019).

Due to inaccurate information and lack of analysis of executive results, routing optimization systems cannot be continuously improved and repeated on the basis of customer necessities to counter the dynamics of scenarios, hence goes to the failure of these systems in practice (Shao et al, 2019). In this paper, a dynamic vehicle routing model (DVRP) has been accomplished take into consideration non-random travel time under traffic. The travel time duration through two nodes may change dynamically and accidentally at various times, depending upon the traffic conditions. In this vein, a Markov decision-making process model and a solution-based approach are developed. We additionally probe the estimated distribution of the probability of cargo travel from arcs, which represents the reality of diverse parts of the road. Accordingly, real-world research has been conducted by Logistics / Singapore Delivery (Kim et al, 2016). So that enhance the proficiency of vehicle route chain planning on the Internet and minimize traffic congestion, a model of dynamic vehicle route guidance via Internet vehicles has introduced adaptive optimization established upon global planning. They also applied a regional network segmentation method to design and program vehicle nodes. The conclusions revealed that the implemented method in this work intensified the traffic volume by 42.8% and decreased the travel time by greater than 50% when driving a dynamic vehicle on the Internet (Respen et al, 2019).

In an investigation that Liu et al (2020) addressed the issue of Windows Vehicle Routing (TDVRPTWW) in the car emissions. The aim of this study is to make less the fixed cost of the vehicle and the cost of drivers, fuel consumption and carbon dioxide emissions. To prevent congestion throughout the time of traffic hours, on the basis of the TDVRPTW model, an ant colony algorithm has been established with an IACACAA method. The outcomes suggest that the proposed IACACAA can reduce traffic congestion further efficaciously reduce traffic congestion (Wasa and Tanaka, 2019).

In a study, they taken into account the optimal path in random and nonlinear road traffic environments. Next, in this case, the optimality control of integral path formalism and the impressiveness of control synthesis established upon Mont Carlo forward sampling back then provided by integral path control by way of numerical studies have been fulfilled. In addition, in order to be more effectual, creative strategies have been presented in the development of information and communication technology (Abbatecola et al, 2016). Ulmer et al (2019), illustrated a model for dynamic vehicle routing problems (DVRPs). The DVRP literature includes the shortage in models that associated with real-world applications to solution methods. To tackle to this gap, a path-based MDP model has been formulated that extends the conventional MDP model for dynamic and random optimization problems by specify again normal operating space to work in route (programs.aka, 2019). Utilization of effectual vehicle new formation systems fulfills a pivotal role in the increasing progression of vehicles. Today, the design of a vehicle rerouting system is recognized to be a momentous problem in transportation because of its dynamic nature in vehicles. In an article (Ho et al, 2019) developed a time-based and travel-based (PTPR) system. First of all, with travel time and vehicle density details, the PTPR system anticipated subsequent congestion levels. Further, they distributed vehicles in varied directions in order that balanced the traffic. The target of usage this pheromone model is to intensify the efficiency of the PTPR system. Kim et al (2005), intend for integrate instantaneous traffic data and historical information into the entry and exit of drivers and routes in a randomized investigation environment. The study established a Markov-based formula and implemented by real-world data from Southeast Michigan to confirm the value of immediate traffic information. Gayialis and Tatsiopoulos (2004), probed in a routing optimization system to design oil delivery routes from diverse distribution centers to the latter customer. Instantaneous location information was applied to achieve support to distributors on the route of vehicles and planning. Ng et al (2017) accomplished an online vehicle routing (OVRP) research in which instantaneous traffic data made arrangements by IoT devices to diminish delivery risk, particularly in regions with the traffic volume. In fact, a reorientation strategy dependent upon instantaneous IoT information to combat traffic congestion is developed, and a bee colony algorithm is designed to efficaciously solve the problem. Tsang et al (2018), presented IoT-based system planning so that formulated a multi-temperature packing model to prosper momentary monitoring of productions throughout transport. Shao et al (2019), conducted a smart product service system (SPSS) approach in order that made plans for an IoT-based routing optimization system, which states that a routing optimization system should be updated with primary data. Xu et al (2019), implemented a cloud-based fleet management platform by combining the profits of IoT and cloud technology. To deal with the momentary interactions amid various members of organizations in an industrial town, Qiu et al (2015), introduced an IoT supply hub model to intensify the proficiency of physical services.

Sabar et al (2019) carried out an automated evolutionary algorithm in light of traffic density for dynamic routing system. The established algorithm evolves through adaption to the values of the parameters and types of operators of the evolutionary algorithm in order that fulfill dynamic changes efficaciously in addition to produce high quality solutions. Ghannadpour et al (2014) in a multi-objective model associated with dynamic vehicle routing problem with taking into consideration time windows to solve the problem, a solution algorithm based on genetic algorithm was offered. In the conducted model, the size of the essential fleet, the whole travel distance and the expecting time enforced on the vehicles are diminished and the overall customer preferences in this way are maximized. The importance of green routing problem (GVRP) with capacity limitation is not indisputable, thus, a new model was implemented by Zoe et al (2019), in order that decreases carbon emissions and enhances customer satisfactory by regarding soft time windows, fuel consumption operation, the speed of vehicle variable amid programming period and traffic density.

In the current study, a new model intends for minimize the costs of customer service in light of a dynamic transportation system and taking into account time windows in a safe solution to monitor the dynamic procurement process and attain instantaneous information established upon the situation. Traffic offers an improved evolutionary genetic algorithm. The continuation of this research is organized in the following order. In Section 2, the problem is defined and the proposed model is presented. Section 3 describes the methodology and approach to the proposed solution. In section 4, the conclusions of the model are analyzed. Eventually, section 5 is devoted to concluding and making suggestions for future research.

2- Definition of the problem

After reviewing the concept on the literature and considering the gaps in the problem, in this investigation, a problem of dynamic vehicle routing with customer service time window have conducted. Moreover, taking into consideration the traffic congestion situation of the transportation network changes over time on the basis of a random process; in this evolution, non-constant random travel times are determined. In fact, various traffic conditions represent the average vehicle speed, thus, the more appropriate the traffic situation, the faster the vehicle will move. In addition, in each node and environment, the real time of the information perceived by the Logit function is the primary principles of the proposed model.

2-1- Problem assumption

In this section, first of all, the problem definition and the mathematical modeling are established by describing the assumptions.

- ✓ The travel time is taken account to be non-constant and dependent upon the speed and distance traveled.
- ✓ Traffic congestion situation conforms a random process.
- ✓ The traffic situation determines the average speed of the vehicle.
- ✓ Each vehicle removes the customer from the point of origin at which the customer is located and delivers it to the desired destination.
- ✓ It is assumed that there are a number of vehicles at each origin to serve customers every time.
- ✓ For each customer, a high limit of time to reach the destination is specified, and the customer wants to attain the desired destination up to that time. Therefore, if this does not happen, the customer's satisfaction with the service will decrease and the violation penalty will be considered excessive.
- ✓ It is supposed that the average speed in the direction of the entire length of a route is the same to the elementary speed at the time of entering the route.

2-2- Proposed model

In this section, at the beginning, the definitions, parameters and decision variables are described; next the proposed model is introduced with the definition of purpose and limitations.

Sets and Indices:

I	Sets of source nodes
J	Sets of destination nodes
R	Sets of nods between transportation routes
$N \in K\{I, J, R\}$	Sets of all nodes
C	Sets of customers
T	Sets of time period (According to minutes)
K	Sets of vehicle

Parameters:

dis_{ij}	The distance between node i and j
$b_{nn'}$	If there is a route from n to n' node, therefore equal to 1, otherwise 0
a_{ijct}	If the costumer c at the time t aimed to move from source i to destination j, thus, equal to 1, otherwise 0
$NV_{nn't}$	The number of machines in the n to n' route at the moment t that follows the random distribution.
$K_{nn'}$	The capacity of route in n to n' node.
U_i	The upper limit of the time window of node i
CL	The cost of late payment of customer service
TC	The cost of customer service in per unit of time
L	A large positive number

$VMax_{nn't} \begin{cases} random(10,30); \text{ if } MT_{nn't} = Very\ heavy \\ random(30,50); \text{ if } MT_{nn't} = Heavy \\ random(50,80); \text{ if } MT_{nn't} = Moderate \\ random(80,110); \text{ if } MT_{nn't} = Light \\ random(110,140); \text{ if } MT_{nn't} = Very\ light \end{cases}$	Maximum speed allowed on the n to n' route at the time t

Decision variables

AT_{nc}	The arrival time of customer *c* to the node *n*
$X_{inn'ck}$	If the *n* to *n'* route is traveled by the vehicle *k* to deliver the customer *c*, which starts from the source *i*, equal to 1 and otherwise 0
FE_{jc}	The duration of the customer's delivery to the destination *j*

Mathematical model

$$MinZ = \sum_c \sum_j FE_{jc}.CL + \sum_c \sum_j AT_{jc}.TC \tag{1}$$

$$X_{inn'ck} \le b_{nn'} \qquad \forall n, n', i, c, t \tag{2}$$

$$\sum_n \sum_k X_{iinck} = a_{ijcb} \qquad \forall i, j, c, t \tag{3}$$

$$\sum_n \sum_k X_{injck} = a_{ijct} \qquad \forall i, j, c, t \tag{4}$$

$$\sum_{n'} \sum_k X_{inn'ck} - \sum_{n'} \sum_k X_{in'nck} = 0 \qquad \forall t, i, c, k, n \ne \{i, j\} \tag{5}$$

$$AT_{nc} \ge \frac{dis_{in}}{VMax_{int}} \left(1 + 0.15 \left(\frac{NV_{nn'b}}{k_{nn'}} \right)^4 \right) - L \times (1 - X_{iinck}) \qquad \forall i, n, k, c, b \in \{t\} \tag{6}$$

$$AT_{nc} \le \frac{dis_{in}}{VMax_{int}} \left(1 + 0.15 \left(\frac{NV_{nn'b}}{k_{nn'}} \right)^4 \right) + L \times (1 - X_{iinck}) \qquad \forall i, n, k, c, b \in \{t\} \tag{7}$$

$$AT_{n'c} \ge AT_{nc} + \frac{dis_{nn'}}{VMax_{nn't}} \left(1 + 0.15 \left(\frac{NV_{nn'b} + AT_{nc}}{k_{nn'}} \right)^4 \right) - L \times \left(1 - \sum_i X_{inn'ck} \right) \qquad \forall n, n', k, c, b \in \{t\} \tag{8}$$

$$AT_{n'c} \le AT_{nc} + \frac{dis_{nn'}}{VMax_{nn't}} \left(1 + 0.15 \left(\frac{NV_{nn'b} + AT_{nc}}{k_{nn'}} \right)^4 \right) + L \times \left(1 - \sum_i X_{inn'ck} \right) \qquad \forall n, n', k, c, b \in \{t\} \tag{9}$$

$$AT - FE_{jc} \le U_j \qquad \forall j, c, t \tag{10}$$

Equation (1) be evidences of the objective function of the problem, which is to minimize the costs of customer service. The foremost phrase attempts to minimize the cost of violating the customer's desired time to attain the destination, and the secondly phrase tries to decrease the total cost of transferring the customer to the destination. As can be observed, by minimizing costs, we will achieve sub-objectives, including minimizing travel duration between the two nodes. On the other side of view, on account of the accidental traffic situation and the reduction of costs, it decreases the environmental affect as well as increases the service. Constraint (2) indicates that it is conceivable to transport from one node to another if there is a path (road, highway, alley, etc.) between the two nodes. Constraints (3) and (4) assure that if there is a demand from the customer to go from one source to another, a route must be established by a vehicle from source to destination. Constraint (5) is the restriction of route formation. Constraints (6) to (9) estimate the time it takes for each node to reach the vehicle to transport the customer on the route, at which time the distance traveled on each route depends on the speed of the vehicle. Constraint (10) represents the amount of violation above the time limit for each customer to obtain the favorable destination.

3- Solving approach

Population-based algorithms are identified as one of the greatest and appropriate solutions for dynamic problems, containing the DVRP problem, which is frequently referred to as evolutionary algorithms like for example genetic algorithms (Martarelli and Nagano, 2018; Ji et al, 2017, Gholizadeh et al,2020a; Gholizadeh and Fazlollahtabr, 2020; Gholizadeh et al,2020b). One of the fundamental challenges determined in evolutionary algorithms is adaptive configuration, which provides the search process to be adjusted established upon the current situation (Razavi et al, 2020). In order to develop DVRP dynamic changes, such as the combination of operators and the succession of operator releases, an integrated genetic algorithm is presented. Next, the settings of the genetic algorithm are configured to achieve more efficient DVRP solutions to search and make progress the convergence of a wide range of evolved operators. Therefore, the introduced algorithm leads to a reduction of manual settings and configuration adjustment in accordance with the dynamic changes that lead to the appropriate solution space. As mentioned, the proposed algorithm dynamically formulates the genetic algorithm, which contains cross-sectional operators, mutations, and DVRP-appropriate parameters. In this vein, the suggested algorithm extends applying complex interactions between settings and employing configuration with the initial population. Furthermore, diverse configurations for random changes to tackle with DVRP, obtain a higher quality solution. The following diagram (figure 1) illustrates the steps for implementing the algorithm.

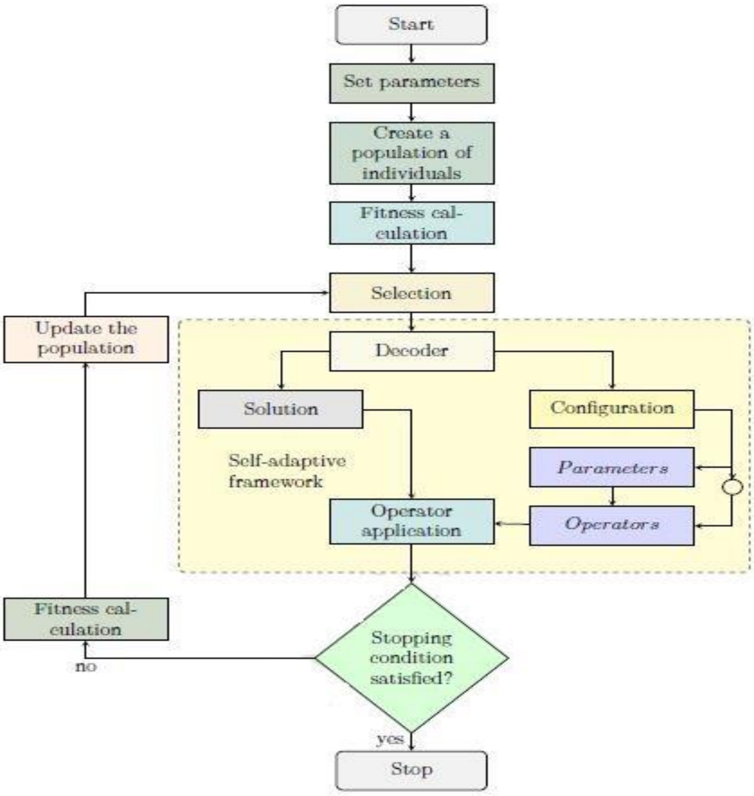

Fig 1. Suggested algorithm framework

Each chromosome has a one-dimensional array in the proposed algorithm, which contains three parts, such as figure 2.

Part 1									Part 2		Part 3		
D	C1	C3	C4	D	C2	C6	C5	D	P1	P2	OP1	OP2	OP3

Fig 2. Display the solution

As you can see in figure 2, at the outset part, the path determinants reveal a DVRP solution using the path representation, then indicate the commencement and end of the path with a succession of customer indicators with determinants. We give for instance | D | C1 | C3 | C4 | D | C2 | C6 | C5 | D | There are two paths that exist, the first path, customers C1 | C3 | C4 | They visit in order and secondly, customers | C2 | C6 | C5 | Which starts at C2 and ends at C5. Here D specifies the separate paths. The proposed algorithm endeavors to create a new DVRP solution in the course of a search by using a DVRP solution with an evolved configuration. In the second part, the intersection and mutation parameters represent the possible values taken into account for the cross-operator {0.2,0.4,0.6,0.8,1} and for the mutation operator {0.1,0.3,0.5,0.7,0.9} . It should be stated that the operator of the mutation and the cross are considered independent of each other. To conclude, there is no limit to the total number of mutations that can be 100%. On the other side of view, the proposed algorithm assigns a value to provide a set for each parameter. The third part devotes the operators. In the proposed algorithm, we have supposed 3 types of operators.

Operator 1 (OP1): it may be inferred that it is various from cross-operators, which proves chromosomes so that discover precise solutions for creating children and exchanging them. The three diverse types of these operators are clarified as follows. Furthermore, it is proper to mentioned that in order to ensure feasibility, existing cross-sectional operators prepare the conditions by removing duplicate customers and inserting lost routes.

- In the order-based operator, two intersecting points are randomly adjusted on a selected solution, copying the children in the middle of the two points, and subsequently applying the corresponding elements of the second selected solution, fulfills the remaining parts.
- In the route-based operator, the effective and most reasonable routes are adopted from both solutions and the selected routes are passed on to the children, and the remaining routes make full with customer sequences for the better solutions.
- In the succession-based operator, it seek to address routes from both solutions, but between the two solutions, it replaces with one on either side routes, eliminates repetitive customers, and puts the lost routes in the par excellence possible position.

Operator 2 (OP2): This operator, which is identifying with the mutation operator, moves the mutation rate of one or several locations in the given children to effectual locations established upon the given probabilities. For this purpose, three diverse operators for the mutation are presumed to be represented as follows.

- The random mutation operator removes the customer's N mutation and next allocates them to varied positions.
- The mutant operator with the worst elimination removes N customer with the most cost savings and moreover assigns them in the best position to save the cost.
- Reverse mutation operator, this operator randomly selects a route and as well as changes the customers on the basis of the cost.

Operator 3 (OP3): This operator functions according to the DVRP solution recurrently as a local search operator. The solution prepared by a local operator is modified to seek out more efficacious values with better options. This operator performs in three various ways and necessities to be improved in 10 consecutive repetitions, which are as is explained in below.

- Two customers repetitively select and switch in the middle of the two diverse paths. If the replacement conclusions in a better states, the search will continue dependent upon the new solution presented by the replacement.
- A customer repeatedly is selected fortuitously and transferred in a various direction. In this regard, the only better solution will be established.
- Frequently, it accidentally determines two customers and moves them in a varied direction. Only solutions that make progress are acceptable.

In the course of the research process, the proposed algorithm of compounding these operators, an operator of any type and succession of their application expands.

4- Computational results

In this section, the outcomes got hold from solving the mathematical model using the proposed algorithm put on displayed. To do this, to begin with, the indispensable data to solve the problem are estimated.

4-1- Data generation

This section describes how to estimate the data that necessitated solving a research problem. It should be noted that analogous and reasonable research has been executed to generate the essential data. How to generate data is revealed as a function of uniform distribution in the below table:

Table 1. Production of random data

Uniform[10,150]	dis_{ij}
Uniform[1,6]	$NV_{nn't}$
Uniform[3,10]	$K_{nn'}$
300	U_i
Uniform[100,1000]	CL
Uniform[500,3000]	TC
1000000	L

4-2- Results

In this section, the answer of the problem is discovered in various dimensions and the consequences of the report are analyzed. For this purpose, 14 problems are designed in several dimensions and the values attained from the proposed algorithm are compared with the exact solution method (GAMS software). Moreover, in order to precise measure the proficiency of the proposed algorithm, the problem is solved with the traditional genetic algorithm and the answers are evaluated. Table 2 represents the dimensions of 14 issues:

Table 2. Dimensions of designed issues

problem size	Number of vehicles	Number of nodes	problem size	Number of vehicles	Number of nodes
1	4	7	8	4	11
2	3	8	9	5	11
3	4	8	10	5	12
4	3	9	11	4	13
5	4	9	12	5	13
6	3	10	13	5	14
7	4	10	14	6	14

Table 2 indicates the conclusions of solving the mathematical model with the established algorithm, the traditional genetic algorithm and the exact method. It should be stated that in this table, GAP1 represents the percentage of deviation of the answers achieved from the algorithms compared to the exact solution method and GAP2 shows the amount of percentage deviation of the answers obtained from the two algorithms relative to each other. The following relationships are the answer obtained from the algorithm, the answer got hold from the GAMS software and the best answer acquired between the two algorithms. It is also worth noting that the time solved in the table is 2 seconds.

$$GAP1 = \frac{ALg_{sol} - GAMS_{sol}}{GAMS_{sol}} \times 100 \tag{11}$$

$$GAP2 = \frac{Best_{sol} - ALg_{sol}}{Best_{sol}} \times 100 \tag{12}$$

Table 3. The outcomes obtained from solving the mathematical model

Problem No.	**Traditional Genetic algorithm**				**Proposed algorithm**				**GAMS**	
	CPU Time	GAP2	GAP1	Z	CPU Time	GAP2	GAP1	Z	CPU Time	Z
1	14.68	0	0	1865.25	18.35	0	0	1865.25	180.4	1865.25
2	15.42	0.6	0.60	2959.83	19.28	0	0	2942.18	321	2942.18
3	17.38	0.88	0.88	2368.66	21.71	0	0	2348	293.1	2348
4	20.2	1.02	1.02	4066.18	25.25	0	0	4025.12	498.2	4025.12
5	25.93	1.43	1.43	3022.53	32.42	0	0	2980.90	538.6	2980.90
6	28.08	1.72	1.72	4842.89	35.10	0	0	4761	1175.2	4761
7	33.39	1.95	1.95	3569.78	41.74	0	0	3051.50	2795.8	3501.5
8	36.26	2.14	2.14	4150.52	45.33	0	0	4063.56	4268.1	4063.56
9	42.54	1.85	2.58	3418.25	53.18	0	0.64	3356.22	6053.5	3334.88
10	46.88	1.81	2.71	3674.26	58.60	0	0.88	3608.79	9725.3	3577.31
11	50.32	1.7	-	5608.25	62.90	0	-	5514.62	10000<	-
12	52.42	1.45	-	4472.33	65.53	0	-	4408.40	10000<	-
13	60.57	1.66	-	5078.54	75.72	0	-	4995.43	10000<	-
14	78.68	2.16	-	4393.73	98.35	0	-	4300.89	10000<	-

Table 3 shows that the proposed algorithm can produce optimum or near-optimum responses at a vastly greater appropriate time than the exact solution method. As exhibited in Table 3, the resolution time of the GAMS software intensifies nonlinearly as the dimensions of the problem enhance, so that for problems 12 to 15, the software has not been capable to solve the model after more than 10,000 seconds. Table 2 additionally indicates that the proposed algorithm did not fulfill much better than the traditional genetic algorithm in connection with the quality criterion of the answers attained (percentage of deviation). Figures 3 and 4 compare the performance of the algorithms regarding response quality criteria (GAP1 and GAP2). Figures 5 and 6 furthermore put on view the analysis of the variance of the answers achieved dependent upon the quality criterion of the answer. All of these forms well illustrate the superiority of the proposed algorithm over the traditional genetic algorithm in producing optimality or near-optimality responses. Figure 7 compares the duration of solving the exact method, the proposed algorithm, and the traditional genetic algorithm. Figure 7 demonstrates that the traditional genetic algorithm executes more valuable than the proposed algorithm in terms of solution time criteria.

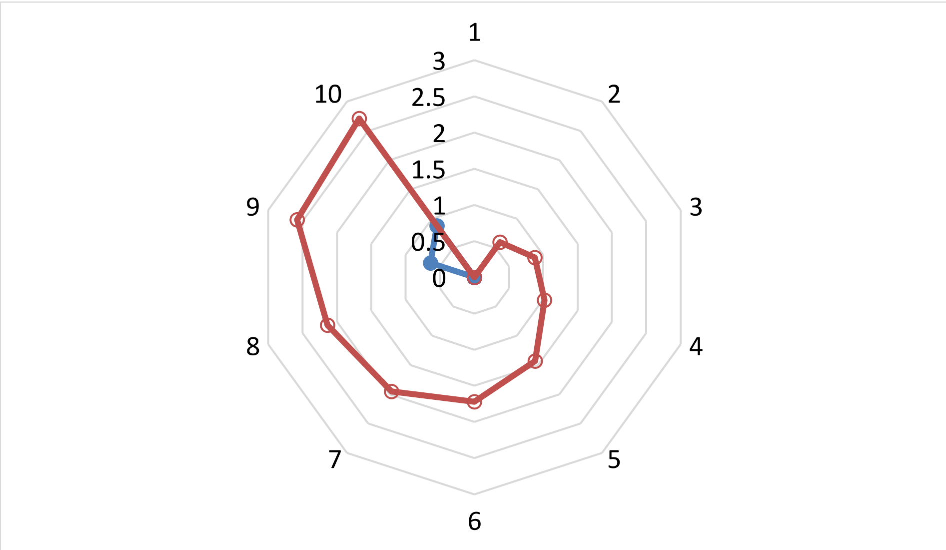

Fig 3. Comparison of algorithms on the basis of GAP1 (red line for genetic algorithm and blue line for the proposed algorithm)

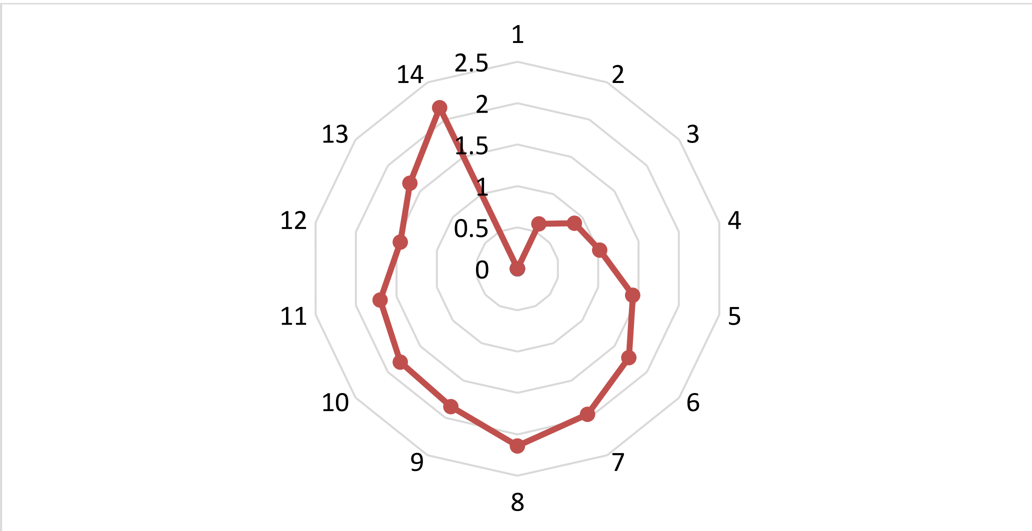

Fig 4. Comparison of algorithms on the basis of GAP2 (red line for genetic algorithm and blue line for the proposed algorithm)

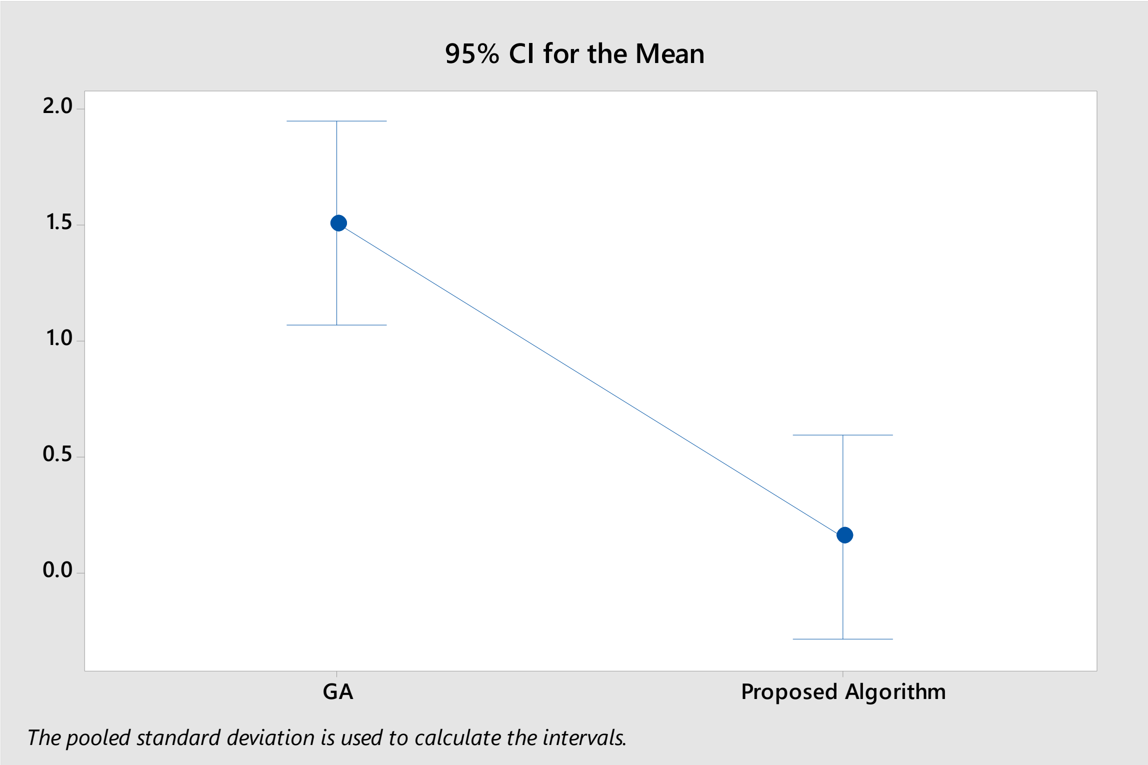

Fig 5. Statistical comparison of algorithms on the basis of GAP1

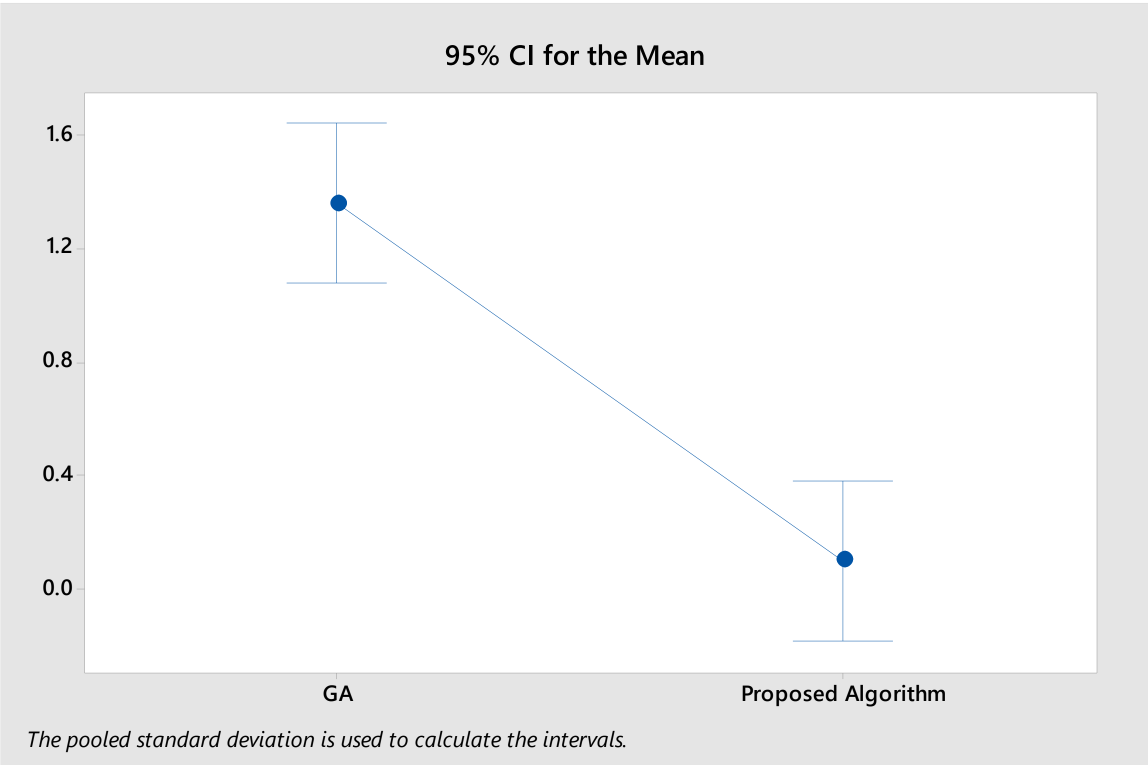

Fig 6. Statistical comparison of algorithms on the basis of GAP2

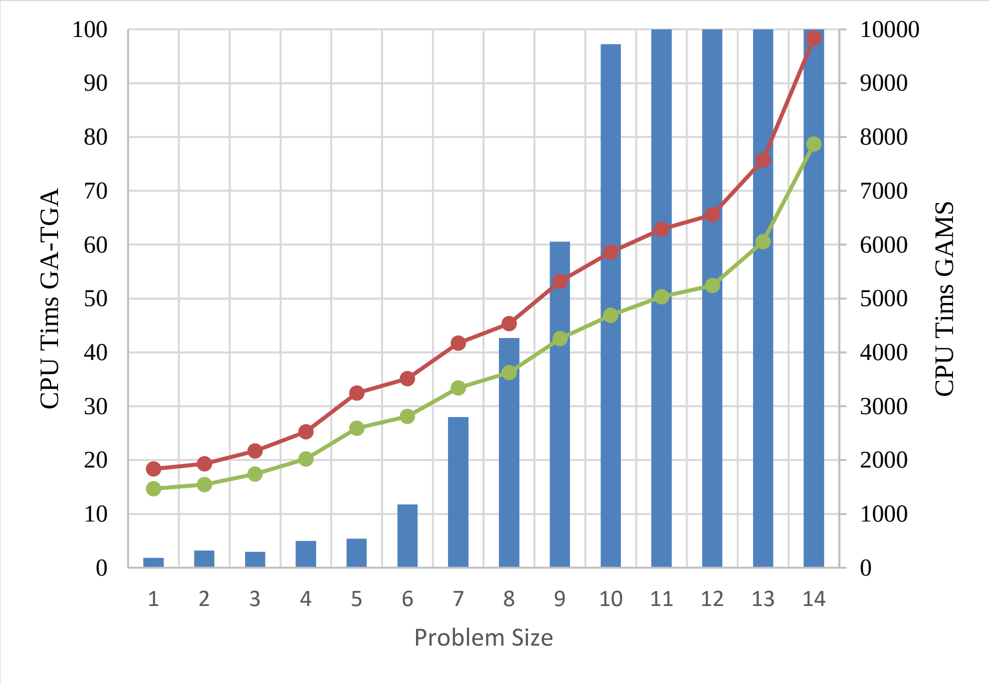

Fig 7. Comparison of algorithms solving time

To enhancement the efficiency of the proposed method for the DVRP problem, we modified a traditional genetic algorithm, and to prove the performance of the proposed algorithm two dimensions after the solution time, we taken into consideration the value of the objective function and the percentage of deviation of the GA. Hence, it is proper to mentioned that our proposed modified GA in very small size and problems operates close to the exact method and goes on the other side of the exact method for larger sizes, because the exact method cannot obtain outcomes in a reasonable time (see table 3). It is indisputable that the values of the modified GA objective function perform better than the classical GA. The existence of this performance is owing to the activation of local search in GA, where it discovers a better initiative solution for multiplying GA operators. Other analyzes have been accomplished on the solution time of the two algorithms. The comparison of the solution time is revealed in Figure 7. Solved time in modified GA problems has much more time than classic GA. On account for the elimination of additional solutions through local search and moreover due to the selection of varied operators, as the size of the population and the solution time intensified. These comparisons affect the proficiency of GA in tactical decisions and DVRP indicates an effective suggestion. Managers and policymakers be obligated to be conscious the values of decision variables, in addition to the dynamics of traffic, both economically and in a timely manner. Besides, Operational decisions required to be made in regard to minimize the cost of DVRP.

4-3- Sensitivity analysis

In this section, the sensitivity analysis of the objective function is comparable to the diverse traffic conditions of the model to specify the effect of the variation in the value of the objective function. The impression on of traffic conditions, as referred to, will accidentally affect the speed of the vehicle and the amount of travel time, which will have a complete impact on costs. As far as you can see in Figure 8, the application of traffic conditions and the non-application of traffic conditions increase or decrease the objective function. This indicates the momentousness of traffic conditions and planning at the procurement and transportation levels, and additionally demonstrates the capability of the proposed algorithm to tackle dynamic changes with the advancement of variety configurations for use at diverse decision points. Moreover, it is notable that in the absence of traffic, the target cost is reduced by 14.25% compared to the applied traffic conditions.

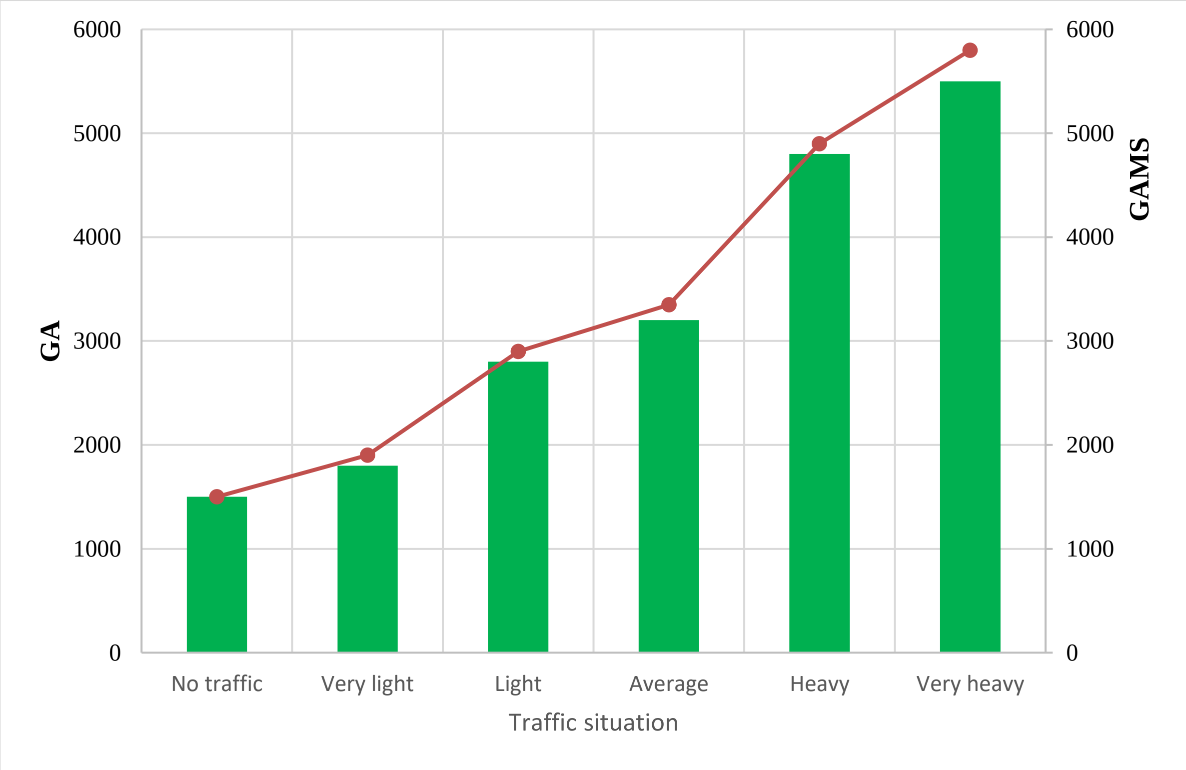

Fig 8. Traffic conditions analysis

5- Conclusion

In this study, in order to optimize logistics systems and system's efficiency intend for minimizing the costs of customer service for a dynamic transport network, an advanced optimization model with Logit function to attain the probability and allocate routes in view of the diverse traffic conditions accomplished. Therefore, this paper has taken into consideration the routing of a dynamic vehicle to accompany with the service window to customers limited to the process of vehicle implementation in a logistics transportation system. In this case, on account of different of traffic conditions, vehicle speed and the time of travel are regarded without prior planning. Also, to solve the proposed model in varied sizes, an improved evolutionary genetic algorithm has been conducted and its conclusions have been evaluated with GAMS commercial software for the precise method and traditional or classical genetic algorithm. Sensitivity analysis for traffic conditions was also performed for optimality policies for decision making. The result of calculating the expected arrival time can be used to make passengers decide on the route and departure time. Transport system operators, on the other hand, have to strike a balance between passenger satisfaction and travel time when providing information on waiting times to arrive.

Managers can benefit from the model outputs by using these models and creating optimal facilities for transportation in assessing the traffic conditions of routes, in relation to the optimal route allocation to customers, effective decisions in the transportation industry. Since dynamism in the transportation system is inevitable, it is necessary to be prepared to face different scenarios in the transportation system. In some cases, the interaction between scenarios is important. Consider, traffic increases, costs increase, and customer dissatisfaction happens at the same time. Then, the manager must know what degree (feature) of the route, such as the type of detour routes and how long to reach the destination and with what traffic conditions to maximize customer satisfaction and increase revenue, while at the same time overall costs are rising; also, due to the speed of fluctuations, the level of dynamics changes and leads to the nature of quick decisions to maintain a competitive market.

Suggestions for future research include uncertainty in problem parameters and scenario-based optimization approaches. Therefore, taking into account a case study for the effectiveness of the proposed method can be developed as future research.

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