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Improved Transportation Systems Based on Evolved Business Intelligence

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ABSTRACT

Intelligent transportation systems offer various services to all parties involved in transportation activities. Route planning is a common and challenging problem in transportation. Therefore, the quality of metaheuristic approaches to this problem is crucial, as it is now a planning module in almost all intelligent transportation systems available. On the other hand, improving the structure of intelligent transportation systems using business intelligence can address management challenges. The purpose of this paper is to analyze and apply business intelligence, specifically a combined genetic algorithm with a harmony search algorithm, to solve a transportation problem. The transportation problem is chosen as a challenging computational experiment in this research. To evaluate the behavior of the investigated methods, two examples of medium-sized intelligent transportation systems that cover large areas have been proposed. The research approach is based on a factor-based model. Agent-based modeling is used, which is an approach based on the idea that a system is composed of individual decentralized 'agents' that interact with each other according to local knowledge. The text also mentions special types of artificial agents that are created by simulating nature models.

1. INTRODUCTION

In today's world, communication, data transfer, and transportation are accomplished quickly. Many demands are met through technology and equipment development and application, some of which were once unimaginable. Due to the growth and development of technology, modern transportation engineering has made significant advancements through close communication and cooperation between scientists and manufacturers of advanced equipment. When the idea of using a cylindrical object or something similar to facilitate movement was first conceived, it is unlikely that its impact on future generations was fully realized [1-5]. Currently, with the growing population and urban development, transportation and related issues have become increasingly important. One major challenge for drivers is finding the most efficient route. This often requires significant time and financial investment for companies and organizations to ensure timely delivery of shipments. Transport fleet drivers in the country face several challenges, including cars returning empty, long queues to find cargo, the presence of middlemen, finding suitable cargo for loading, and optimal routing [6]. Considering these factors, various parameters play a role in load selection, including

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the type of load, weight and volume, loading origin, transport route, freight, and so forth. These challenges currently exist in transportation companies [7], and this research aims to address these issues. One of the sustainable solutions to efficient resource utilization is optimizing the transportation system. Nowadays, transportation systems are often determined arbitrarily and based on individuals' opinions, which is not an optimal choice. Therefore, an effective method must be adopted to model this issue.

On the other hand, when the number of vehicles and loads for transportation is high, the problem's search space expands, making the use of mathematical algorithms challenging. This problem is recognized as difficult or NP-Hard, and often Metaheuristic methods are employed for its resolution [8]. However, on the flip side, deploying an intelligent mechanism based on Business Intelligence (BI) can be an intriguing solution to address shortcomings in the intelligent transportation system [8].

Business intelligence has also evolved into competitive intelligence with the growth of new management tools and the competitiveness of the economy [10]. The creation of value through business intelligence is only possible when it is correctly applied and utilized by experts [11]. Business intelligence is a concept that encourages the entire organization to effectively use provided information systems to obtain timely and quality information for decision-making. This concept should be supported by senior managers and used throughout the organization. It creates an effective flow of information within the organization and encourages the participation of all employees in the improvement process, ultimately leading to improved communication [13]. Business intelligence aims to improve business decisions by utilizing multiple sources of process information and applying experience and hypotheses to provide a correct understanding of business dynamics [14]. Business intelligence combines data analysis with decision support systems to provide information to all stakeholders. [15]

The utilization of business intelligence in the banking sector involves the analysis of a vast set of financial data, encompassing various aspects such as customer transactions, credit scores, and financial market trends. One critical element in this context is the effective management of data, including both structured and unstructured data. The strategic handling of data is crucial for enhancing decision-making processes and gaining valuable insights into the dynamic financial landscape. Among the essential components of business intelligence, key focus areas include Data Warehouse, Data Mining, Extraction Transformation Load (ETL), and Online Analytical Processing (OLAP). These components collectively contribute to the comprehensive understanding and utilization of data for informed decision-making within the banking sector.

This research specifically emphasizes the role of cluster-based data mining as a pivotal component for implementing business intelligence in the banking sector. The integration of clustering techniques plays a significant role in uncovering patterns and trends within the extensive dataset, facilitating strategic decision-making and optimizing banking operations. Improving transportation systems is a complex optimization problem, specifically a variation of the traveling salesman problem. The weight of the edges on the graph represents the cost of travel between warehouses. The problem involves determining the most efficient routes for a given number of vehicles, each located at a specific warehouse, to travel between nodes represented by warehouses on a graph. The weight of the edges on the graph represents the cost of travel between warehouses. The weight of the edges on the graph represents the cost of travel between warehouses. The goal is to minimize cost while maximizing efficiency. The weight of the edges on the graph represents the cost of travel between warehouses. The objective is to identify distinct rounds for each device, ensuring that these rounds encompass all nodes and minimize the total cost of the rounds [18].

For this purpose, in this research, an attempt has been made to reduce the search space of the problem using an intelligent method. Subsequently, a cluster-based Business Intelligence mechanism, relying on the Genetic Algorithm population, is employed to search for optimal goods for transportation on each route as a cluster for drivers. However, one of the challenges of the Genetic Algorithm is the selection of suitable operators for problem conditions. Therefore, combining it with another algorithm can address the weaknesses of the Genetic Algorithm. In this study, the Harmony Search Algorithm (HAS) is used. It has been attempted to improve the problem-solving conditions and reduce the time to reach the optimal solution by employing suitable and innovative Crossover and Mutation operators. Using this developed algorithm in the Business Intelligence framework, the problem, while being responsive, converges to the optimal solution with fewer iterations compared to the Genetic Algorithm with simple operators. Moreover, it possesses a higher repeatability test.

2. AN OVERVIEW OF THE RESEARCH BACKGROUND

Numerous studies have been conducted on transportation systems to mitigate traffic congestion and improve management. This section examines various models that share the same objectives as this research. In reference [19], a fuzzy controller was introduced to regulate the traffic volume of an intersection with three entrances and one exit. This method checks every 0.11 seconds, starting seven seconds after the green light is turned on, whether the light duration can be extended (provided it does not exceed the maximum time for the green light) or if a higher priority input light should be turned on. Simulation results demonstrate the positive impact of this method on traffic control. This study presents one of the initial approaches to traffic control using fuzzy logic. In their work, authors in [20] proposed a traffic prediction and control system based on fuzzy logic that considers traffic volume as the only parameter of its fuzzy law. The fuzzy rule of this system determines the extension or interruption of the green light status of each route based on the traffic at the beginning of its route. The simulation results indicate that this method performs well when traffic occurs simultaneously on each route. The two previously presented solutions only consider the traffic volume parameter and do not take into account factors such as stop records, periods, and route size. In his subsequent research (reference [21]), the author presented a fuzzy traffic control system. This system can control intersection traffic in two-way routes by using the parameters of the length of time periods and the difference between periods, in addition to the traffic volume parameter. This method is effective in reducing the average traffic delay. All previous fuzzy methods are only capable of processing the direct movement of cars and are ineffective in cases where the direction of the car's changes.

In their study [22], the authors presented a traffic volume prediction system that utilizes the second type of fuzzy logic. This method efficiently sets the control parameters and membership function, and due to the nature of type 2 fuzzy logic, better distinguishes between traffic conditions. The method is particularly effective in heavy traffic conditions, with an average error rate of 12% in blockage mode and 5% in normal mode. In reference [23], a traffic volume prediction system was presented. The system has the ability to adapt to different traffic and movement conditions. The presented model uses a multi-layer fuzzy architecture to estimate the traffic volume ahead. Simulation results demonstrate its efficiency for timing traffic control guide lights. The research provides an adaptive platform for traffic control using fuzzy logic. The use of fuzzy logic in combination with other solutions can enhance the efficiency of traffic prediction and control systems.

In [24], they presented a traffic prediction system using fuzzy rules and combining it with Support Vector Machine (SVM). This system generates various scenarios based on current traffic conditions. After each scenario is generated, the output from the fuzzy state is used to classify new conditions using Support Vector Machine. This process updates the parameters of traffic conditions for subsequent analyses. Simulation results demonstrate that by completing parameters and fuzzy conditions after several iterations, the system exhibits satisfactory performance with an average error of 5%.

In [25], a model for tracking the movement history of vehicles and predicting their motion characteristics is proposed using fuzzy logic. This model utilizes a Division Unit (DVU) and its reaction delay as inputs to the fuzzy model. The presented fuzzy model predicts the expected reaction of the vehicle (driver) based on stimulus conditions and, by aggregating all results, predicts traffic conditions. In addition to predicting movement direction, this model has the ability to predict features such as acceleration and stops with an acceptable error of 4%.

In [26], they used the Takagi Sugeno Kang (TSK) fuzzy model to predict traffic volume. Their algorithm is a combination of fuzzy logic and the Flow Iteration Algorithm. The aim of introducing this method was to identify the structural and parametric characteristics of the tested system. Fuzzy rules were used to identify the structural features of the system, and mathematical rules of the flow iteration algorithm were used to determine and specify system parameters. The process of this model involves determining the initial conditions of the system, data analysis, finding optimal factors, and iterating the algorithm to minimize the average error.

In [27], they introduced a traffic volume prediction system with Reinforcement Learning (RL) based on Neural Networks (NNs). The system operates in an iterative loop for reinforcement learning. At the beginning of each iteration, conditions such as current time, day of the week, weather conditions, and temperature are considered to make the generated model more adaptable to real traffic systems. This model also includes a database capable of storing traffic records for the past three months. The use of this feature enables the generation of more proportional parameters for the processing system. In this approach, input parameters undergo adaptive filtering after generation and are then stored in the database. Subsequently, they are used as input for the neural network. In [28], they presented a multi-layer neural network based on the genetic algorithm for predicting traffic volume. The use of this algorithm provides the ability to predict traffic in both time intervals and sections. This capability has been achieved by modifying the architecture of the multi-layer neural network. The simulation of this model has performed well under both single-variable and multi-variable traffic conditions, demonstrating that the capabilities of neural networks, when combined with genetic algorithms for adjusting network parameters, have satisfactory performance. In [29], a similar model is utilized, benefiting from the same architecture. This model, employing a genetic algorithm, adjusts the initial weights and thresholds of the Back Propagation Error Neural Network (BP NN) and exhibits good performance in sectional traffic conditions, achieving a 4% average error. In summary, the extensive use of the genetic algorithm strategy along with neural networks for predicting network traffic has been widely employed, and the exploration of these research areas is beyond the scope of this study.

All of the reviewed works aim to predict traffic occurrences, but they typically do not perform well in predicting traffic duration. In [30], a two-part model consisting of two neural networks was presented, which can predict the time intervals of heavy traffic and road blockages. This model utilizes two neural networks to predict heavy traffic time and the length of road blockage periods. The neural networks periodically update their states from the time of traffic occurrence. Real-time processing of information is a major challenge in traffic forecasting. In [31], an architecture based on neural networks was presented, which works well for real-time processing and decision-making of parameters. The presented architecture utilizes the GPS system to receive information on cars on the road. It then predicts the movement pattern of the cars by producing speed parameters, analyzing the volume of current traffic, and assessing the capacity of the road using a neural network. Traffic prediction parameters are generated through the use of a repetition field in the neural network. This model encompasses the phases of data collection, pre-processing, data normalization, parameter extraction, classification, and decision-making. The effectiveness of this architecture may be limited in certain real-world scenarios due to the necessity of a GPS platform. In [32], the presented model concentrates on traffic analysis in suburban highways and predicts future traffic conditions by utilizing a database of previously recorded traffic data. This model utilizes a multilayer neural network to predict outcomes based on input parameters such as speed, current traffic volume, and current time.

In [33], using a neural network with self-adaptive capability, they have created a model for predicting and controlling the traffic of urban intersections. The use of self-adaptive neural network will make the network more stable to deal with uncertainty in the path. This model works correctly only if the intersection is isolated and does not work properly in coordinated mode.

Different types of neural networks have been employed in traffic volume prediction research. For instance, in [34], they utilize a backpropagation neural network for the prediction process. Additionally, [35] uses the Hermit Iterational Neural Network for traffic prediction. To account for noise effects, sectional data obtained from the environment is classified into time series using an Electro Motive Division unit, and noise effects are applied to each series. After generating the output of the Hermit neural network, its value is combined with the time series data to achieve better adaptability. The combined data is then used for subsequent iterations of the neural network and the learning process. In [37], a traffic prediction system using Neuro-Fuzzy (ANFIS) is introduced, incorporating the driver's reaction delay as a key parameter in predicting vehicle movement. This model also provides an idea for estimating reaction delay. The delay parameter is used as input for the neuro-fuzzy model, and other inputs and outputs are extracted based on this parameter. Simulation results indicate that the presented model exhibits good compatibility with real-world conditions. Generally, the use of neuro-fuzzy networks alone in coordinated systems does not yield satisfactory performance. To address these shortcomings, complementary algorithms like Game Theory can be employed. In [38], a neural-fuzzy model for urban traffic volume prediction is presented, consisting of a Port Network and an Expert Network. The port network classifies input data using fuzzy logic, while the expert network, based on a neural network, determines the relationship between inputs and outputs. In other words, while the port network classifies traffic patterns with similar features into one category, the expert network models the specific relationship between each category. The neural network in this model employs online and batch learning to maintain satisfactory adaptability to the environment.

In a previous study [39], a traffic volume prediction model was presented using a special category of neural-fuzzy networks called outer-product networks (POPFNN). This model has a five-layer structure, with each layer named based on the phase activities it performs. The five layers involved in the process are: input fuzzification, condition determination, rule combination, logical inference, and output transformation. The presented model combines fuzzy logic and neural network, allowing it to adapt to the environment. In a study by [40], a neuro-fuzzy model was used for real-time traffic prediction. The model presented comprises of two parts: a fuzzy network for fuzzy classification and a neural network, which is a single layer, to determine the relationship between input and output. Each resulting branch introduces a traffic pattern. The fuzzy network supervises the learning of the neural network, making the learning process more efficient. The simulation of this model demonstrates that the presented method performs well with an acceptable average error.

In [41], a self-organizing model for traffic forecasting was presented using the Sogno fuzzy type neural-fuzzy network. The model adapts regularly and periodically by receiving input data from the environment. The process consists of two steps: structure recognition and parameter understanding. In the structure recognition stage, the classification algorithm based on median changes calls the entire database to form the initial structure .

Using a reduction algorithm, the fuzzy neurons that were removed will be disabled. Once the structure detection phase is complete, the neural network's learning parameters will be adjusted, and it will enter the prediction phase. The fuzzy neural network presented comprises four input layers, a membership function, a fuzzy rule layer, and an output. In a previous study [42], transportation systems were investigated as an industrial process control model. A traffic system has distinct characteristics compared to industrial processes. Due to its direct connection with humans, uncertainty and randomness of events are more prominent. Forecasting and industrial control systems are not efficient enough in the field of traffic systems. Traffic volume prediction algorithms pose two main challenges: traffic system modeling and optimization. Despite extensive research, a model that completely addresses both of these needs has not yet been presented.

In their study, [43] proposed a hybrid approach that combines genetic algorithm and optimal particle swarm algorithm to solve vehicle routing problems with time windows. The proposed algorithm's improvements include the use of the real numerical encoding method of particles to decode the path, reducing the calculation load. Additionally, the algorithm uses a linear reduction function based on the number of iterations to balance global and local exploration capabilities. Finally, it integrates with the combination operator of the Genetics algorithm to prevent premature convergence and local solutions. The experimental results indicate that the proposed algorithm is not only more efficient than other published results, but it can also obtain more optimal solutions for solving the heterogeneous vehicle routing problem. In reference [44], an evolutionary version of the firefly algorithm was presented to solve the known routing problem with a time window. The objective of this algorithm is to reduce the number of solution paths in the search process by selecting and reading fewer nodes. The new operators analyze all paths of the current solution, increasing the diversity of the search process compared to traditional nodes. In [45], an adaptive variable neighborhood search (AVNS) algorithm was proposed, which includes neighborhood search (LNS) as a diversity strategy and addresses the routing problem. This method comprises of two phases: a learning phase and a multi-level local search with an adaptive aspect integrated into it. A set of highly successful searches will be selected through an intelligent selection mechanism. Additionally, the combination of LNS with AVNS prevents local solutions, as the aim is to find a global solution in the optimization problem. In this method, a flexible and straightforward data structure is embedded, along with a neighborhood reduction scheme. Finally, a new search is conducted, and an appropriate solution is found.

In their study [46], the authors developed a model for the Vehicle Routing Problem with Simultaneous Pickup and Delivery (VRPSPD) that takes into account heterogeneous vehicles. They presented a hybrid local search algorithm that includes a forbidden search strategy. The algorithm uses an adaptive threshold function that adjusts itself and is simple to implement, requiring only the length of the banned list as a parameter. The article's authors utilized a set of randomly generated samples for evaluation and experimentation. In a previous study, an experimental approach was presented that measures the execution time behavior to convert control parameter values for successful use. This method is a manual adjustment rather than heuristic, and has shown good performance in cases where the problem is larger. In [48], a new mathematical model was introduced for the time-dependent routing problem (TDVRP) as one of the sub-problems of routing green vehicles. Additionally, the article discusses the optimal routing of customers while avoiding heavy routes. The model aims to reduce carbon emissions by minimizing travel time. Therefore, this paper presents a new two-way mathematical model that considers air tension, road conditions, vehicle characteristics, travel time, and fuel consumption. The model minimizes time and accounts for vehicle weight and load. To solve this complex problem, we propose a new method based on the optimal particle swarm algorithm. In their study [49], the authors presented a method for online routing in an international supermarket chain's online shopping service, which utilizes time windows. Customers can select a delivery time window for their online order, and vehicle tours are updated in real-time accordingly.

This presents two challenges: placing new customers in a suitable location on an existing tour and entering new customers in real-time due to the high request rate. To address these challenges, a low-cost, two-step approach has been implemented, consisting of an entry step and an improvement step. An experimental study has demonstrated the effectiveness of this method based on a different set of criteria. In [50], a solution has been designed to minimize distribution costs by utilizing the capacity of vehicles, which is known as a vehicle routing problem. The distance matrix is calculated and saved based on the location of the customer or the route where the customer is located to obtain a wide vehicle routing. The main objectives of this article are to reduce the total distance and the total number of vehicles used to deliver goods to customers. The algorithm proposed is based on the K-means clustering method, which is commonly used in data mining. It reduces the total distance and the number of vehicles assigned to each route. This method can improve the storage matrix method of Chopra and Meindl and the storage matrix method of Clark and Wright.

3. THE PROPOSED METHOD

To model the problem of improving heterogeneous transportation systems, a business intelligence platform based on data mining principles has employed the combination of two harmony search algorithms to reduce the search space and a genetic algorithm for optimal load transportation in each cluster. Therefore, it is essential to understand these two algorithms for this modeling. However, first, it is necessary to establish a set of devices under the category of 'car' in a specific dimension. Therefore, to determine their distance, we use the Euclidean distance formula (1).

$$r_1 + r_2 = \sqrt{((x_2 - x_1)^2 + (y_2 - y_1)^2)} \tag{1}$$

As seen in relation (1), it can be said that the Euclidean distance is considered. Based on the conditions for the sharing operation between two cars $v1$ and $v2$, relation (2) will exist.

$$r_1 + r_2 \le \sqrt{((x_2 - x_1)^2 + (y_2 - y_1)^2)} \tag{2}$$

Several special cases need to be considered. Relation (3) exists when the sensing range of two cars is separated from each other, and relation (4) exists when one car is within the range of other cars. Similarly, when two cars only touch without creating a coverage area, they share with each other, and relation (5) exists.

$$distance(v1,v2) > r_1 + r_2 \tag{3}$$

$$distance(v1,v2) < (r_1 + r_2) \quad , \quad and\ \ r_1 > r_2 \tag{4}$$

$$distance(v1,v2) = r_1 + r_2 \tag{5}$$

It is crucial to consider three conditions outlined in relations (3) to (5). Additionally, determining an appropriate area for car sharing is of utmost importance. When two car intervals result in sharing, an area is formed as described in relation (6). If the shared area is represented as a hatched area, the shared area between two hatched areas can be defined using relations (7) and (8).

$$r_1 - r_2 < distance(v1,v2) < r_1 + r_2 \tag{6}$$

$$x^2 + (y-1)^2 = 1 \tag{7}$$

$$(x-1)^2 + y^2 = 1 \tag{8}$$

It is evident that drawing a line between the two coordinate areas x and y as y=x creates a gap in the sharing area, which is divided into two equal parts. The cut section of a hatched area has a radius of one and an area of $\pi/4$. Therefore, equation (9) provides the total sharing area.

$$2 \times \pi - \frac{2}{4} = \pi - 2/2 \tag{9}$$

Now that the sharing area has been identified, it is possible to determine the degree of coverage between the vehicles in their routes. When two cars overlap, the degree of coverage between them, denoted as v1 and v2, is equal to one, as defined by coverage. This relationship is also expressed in the form of proven relation 10.

$$(v1 \cap v2 = x)\ and\ v1 \cup v2 = |v1 - v2| + |v2 - v1| + |v1 \cap v2| = 1 - x + 1 - x + x \rightarrow 2 - 2x + x = |v1 \cup v2| \rightarrow 2 - x = v1 \cup v2 \rightarrow 2 - v1 \cup v2 = x \rightarrow 2 - v1 \cap v2 = v1 \cap v2 \tag{10}$$

When a vehicle is in motion, it is assumed to cover an area. The degree of coverage is equal to one. If two moving vehicles cover an area, the degree of coverage is equal to two. This is calculated using equation (11), which is commonly used in routing for cargo transportation to determine the optimum coverage.

$$|v1 \cup v2| = |v1| + |v2| - |v1 \cap v2| = 1 + 1 - 2 = 0 \rightarrow |v1 \cup v2| = 0 \tag{11}$$

Relation (2) defines the Euclidean distance between sets v1 and v2, where $|v1 \cup v2|=0$ and $|v1 \cap v2|=2$. This relationship demonstrates that the coverage degree of the area shared by the car interval is equal to two. The next step is to establish both coverage and connection. As previously mentioned, this study considers a set of K predetermined potential positions and a set of N targets for deploying vehicles. The objective is to find the most cost-effective route for routing the vehicles. The study employs a combination of two harmony search algorithms and a genetic algorithm within the context of business intelligence. Theoretical explanations are provided as necessary. Harmony Search is a type of intelligent and meta-innovative computing algorithm. It is inspired by the improvisations of jazz musicians, where the musician rapidly improvises an individual and introduces a variety of musical steps to create a beautiful harmony in their music. In this algorithm, each player corresponds to a characteristic of the candidate solution of the problem domain, and each instrument corresponds to the bounds on its decision variable. The musicians' harmony is considered a complete candidate solution within a given time frame, and the audience perceives the aesthetic sense of harmony as a specific cost function problem. Musicians strive for harmony in music through small changes and improvisations that enhance the cost function. The Harmony Search Algorithm is a general optimization method that can be applied to continuous, discrete, and constrained optimization problems. It has been successfully utilized in various optimization problems.

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$$x' \leftarrow x + range \times \in \quad (11)$$

The user's parameter controls the size of the changes within a specific range of Novak's bandwidth. The symbol $\in$ represents a uniformly random number between -1 and 1. This function is used to perform routing improvement operations. The rate $\in[0,1]$ controls the information used or generated from the random number of the harmony memory. The harmonic memory that considers a rate is called HMCR. The algorithm's convergence rate is controlled by the harmony memory, which is configured to be between 0.7 and 0.95. The frequency of the novak, which corresponds to the frequency control of the novak selected from the memory, is tuned to be between 0 and 1. Typically, it is configured to be between 0.1 and 0.5. The regulation of the novak rate is called PAR, and a high value can lead to premature convergence of the search. The adjustment rate and method of Novak are generally constant and have a linear effect over time. When creating a new harmony, the algorithm takes the sum of notes from all players in the harmony memory. Updating the harmony memory is typically a greedy process, prioritizing similarity over variety. The algorithm aims to reduce data dimensions and search space for the next goal, which is to optimize load transportation by drivers. The objective of optimizing cargo transportation is to minimize both time and costs. To achieve this, a genetic algorithm is utilized to optimize cargo transportation by drivers. The algorithm involves an initial population with chromosomes and genes, as well as combination and mutation operations in a specific iteration round. The best solution is chosen from the optimal load of drivers to transport cargo from the origin to the destination and reach a fitting function. The genetic algorithm used in this research consists of six stages:

1. Creating a random population and evaluating them (each answer that is generated is calculated at the same moment as its cost function)
2. Choosing parents and combining them to create a population of children (such as combining the ideas of two people and obtaining a better idea)
3. Selection of population members to apply mutations and create a population of mutants.
4. Merging the main population, children and mutants and creating a new main population (in fact, we collected this new population from three sources)
5. If the termination conditions are not met, we repeat from step 2.
6. The end

The problem of optimal transportation, aimed at reducing time and costs, can be modeled using the harmony search algorithm and genetics. It is important to ensure equalization by having the same number of musicians (Harmony Search Algorithm) as the number of initial population or chromosomes (Genetic Algorithm), which is equivalent to the number of nodes or cars in an environment. The search space in both algorithms is the area where routing takes place. Routing is considered the fitting function with the minimum time and the most optimal state in the shortest paths, which is also the termination condition. The memory of candidate solutions (harmony search algorithm) and their combination and mutation (genetic algorithm) are known as paths. Both algorithms include an iterative round. In the case of routing cars for optimal load carrying, there is also a theorem for shortening the route and minimizing time. Novak's adjustment rate and adjustment method (harmony search algorithm) and combination operation (genetic algorithm) are used to identify a path that is better than the others in various iterations. The most optimal route is then selected as the main route. The optimal state may not always be achievable due to the randomness of evolutionary algorithms and crowd intelligence. Different iterations of the implementation can result in various outcomes, including the initial deployment of heterogeneous vehicles. Table (1) shows the equation.

Table 1. Equivalence of Genetic Algorithm and Harmony Search Algorithm Parameters with the Research Problem Statement

The problem of optimal load carrying by drivers	Genetic algorithm	Harmony search algorithm
The number of nodes or vehicles in an environment	The number of primary population or community	The number of musicians
The area where routing takes place	Search space	Search space
The minimum time and the most optimal mode possible in the short paths during routing	fit function	fit function
routes	Leap operation	Memory of candidate solutions
Determining a route that is better than the rest of the routes in various iterations	Combination operation	The face of setting and setting method
Repeat round	Repeat round	Repeat round
The minimum time and the most optimal mode possible in the short paths during routing	Reaching the termination condition= satisfying the fitting function	Reaching the termination condition= satisfying the fitting function

Therefore, the combined algorithm of harmony and cultural search can be used to define the number of nodes or cars in the model. The problem of routing heterogeneous vehicles can be considered a search space and is a difficult problem. The application of these two evolutionary algorithms and crowd intelligence is interesting. The reasons for using these two algorithms in combination include their effectiveness in solving complex problems.

- ✓ The closeness of the problem statement to the cultural algorithm
- ✓ High execution speed of harmony search algorithm
- ✓ Fast convergence of cultural optimization algorithm
- ✓ Not getting trapped in the local optimum when combining harmony and cultural search algorithms
- ✓ Ability to solve difficult problems for hybrid evolutionary algorithms and crowd intelligence, such as heterogeneous vehicle routing problem

In evolutionary algorithms and swarm intelligence, the initial population is defined and placed in a specific iteration with operators such as Crossover and Mutation. The best generations are selected from the answers obtained in the round of iterations. If it is possible to select the optimal generation that provides a better solution to the intended answer, as well as the methods already presented in this field, it can be considered as the termination condition of the program. The Fitness Function is satisfied when this occurs. In the problem of heterogeneous vehicle routing, node and route information is utilized during routing, along with correlation and search capabilities in heterogeneous vehicles. These are the main goals of the upcoming research. Thus, the hybrid algorithm assumes each car or heterogeneous node in the vehicle system as the initial population. The harmony search algorithm refers to the initial population as the number of musicians, while the cultural algorithm refers to it as the number of the community or the initial population of the community. In fact, the combined mode for defining the initial population is N_{pop}. Now, it is necessary to place N_{pop} in the case of heterogeneous vehicle routing, so to speak, N_{pop} is placed in the search space.

Now, it is necessary to explore the search space by N_{pop} in order to fulfill the mentioned goals, for this, $N_{pop}$is placed in Iteration for Finding Anwer with N_{pop}, that is, it falls in the iteration round. There is a need to have a series of paths that are in the two algorithms of harmony and cultural search, named memory of candidate solutions and fertile space, respectively. In fact, this is the combination operation. So N_{pop} becomes Crossover for Routes with N_{pop}. Then, it is necessary to provide the mutation operation during the combination to find the answer in the round of iterations. The mutation operation in the harmony search algorithm is called Novak adjustment rate along with its adjustment type, and in the cultural algorithm, it is called the combinatorial operation of communities. Actually, after combining the proposed approach, the mutation is done with the two mentioned operators, which is done as Mutate for Best Genes in Iteration after Crossover with Initial N_{pop}. If the main objectives of the research can be reached, it is stated that the fitting function is satisfied, otherwise, the operation is performed again to obtain the best solution for the routing of heterogeneous vehicles.

4. SIMULATION AND RESULTS

This study employs a dataset for driver load selection to enhance the transportation system using business intelligence. The data contains various features, including columns for registration ID, tracking code, bill of lading number and serial, time and date of issue, sender information (code, title, name and surname, national code, postal code, and phone number), recipient information (code, title, and name), origin city, and origin address. Recipient information includes the last name, national code, postal code, address, and phone number. Additionally, the driver's name and national code, postal code, address, telephone number, insurance number, health credit, certificate, and place of issue are provided. It is unnecessary to utilize all of these features as some are considered irrelevant in smart systems. The dataset consists of 100 entries. When choosing the load of drivers, the registration ID and bill of lading number are crucial in determining their location. Additionally, the source and destination addresses of the sender and receiver are important for routing purposes and to identify the drivers' movement path.

The simulation was conducted in the MATLAB environment on a system with a 4-core processor, 6 MB cache, 3.4 GHz, and 16 GB of memory. All results were obtained using this computer. Each car starts from a point and is expected to reach the destination with the shortest possible time. The research problem involves selecting the load of drivers to reduce traffic in transportation and scheduling. The route can only be crossed once, and a repeated route cannot be selected. A randomly generated M×N matrix is used to display the positions on a two-dimensional surface, with n representing the number of vehicles. The output will display M as the column and N as the row. In the vehicle routing problem, the distance between each point is referred to as the DMatrix or distance matrix. The initial population of the hybrid harmony search and genetics algorithm is equal to the number of homogeneous and heterogeneous vehicles. This is because there is one species from the initial population of two harmony and genetic search algorithms for each type of vehicle. The matrix at the outset is 88×2, providing a set of predefined positions for the problem on a two-dimensional plane of x and y. The combined harmony search and genetics algorithm is repeated for 5000 rounds. For the driver load selection problem, the initial number of homogeneous and heterogeneous cars considered is 4 out of 100 (based on 100 data). The genetics and harmony search algorithm begins with an initial population of 100 and repeats the process to create new generations with 4 elites in each round.

The number of paths between homogeneous and heterogeneous vehicles is set to 25 by default. Therefore, the candidate solution memory for the harmony search algorithm and the belief space with its mutation in the genetic algorithm are also limited to 25. Similarly, the optimal rate for setting Novak and its corresponding method in the harmony search algorithm, as well as the combination operation in the genetic algorithm, should be determined for each round of iteration. It is important to choose a specific path that is better than the others, which is equal to one. The defined parameters are presented in Table 2.

Table 2. The main parameters of the problem

Heterogeneous vehicle routing problem	Genetic algorithm	Harmony search algorithm	Number
The number of nodes or vehicles in an environment	Primary population or chromosome number	The number of musicians	100
The area where routing takes place	Search space	Search space	perimeter and dimensions in the form of a 88×2 matrix
The minimum time and the most optimal mode possible in the short paths during routing	fit function	fit function	Optimal time and route (short)
routes	jump	Memory of candidate solutions	25
Determining a route that is better than the rest of the routes in various iterations	Combination operation	The face of setting and setting method	1
Repeat round	Repeat round	Repeat round	5000
The minimum time and the most optimal mode possible in the short paths during routing	Reaching the termination condition = satisfying the fitting function	Reaching the termination condition = satisfying the fitting function	Optimal time and route (short)

When the simulation is executed with the mentioned parameters, the placement position of homogeneous and heterogeneous vehicles for the driver's load selection problem in the potential positions defined as the data set entered into the system will be as shown in Figure 1.

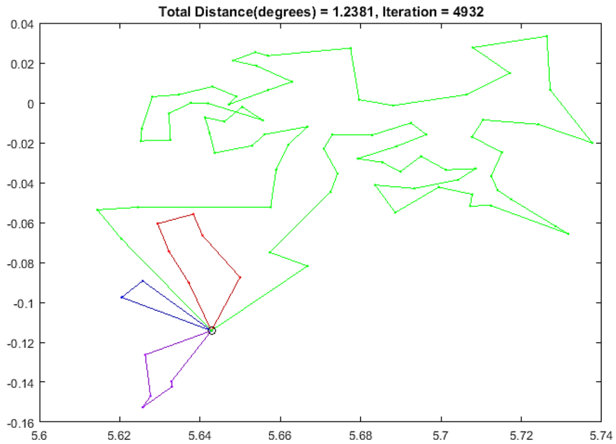

Fig. 1. shows the potential positions for drivers' load selection problem and the positioning of homogeneous and heterogeneous vehicles.

Based on Figure 1, the environment deploys four general categories of vehicles: the customer node position generated in the cluster (blue), the randomly generated customer node positions (red), the group where half of customer node positions are randomly generated (purple), and the number of homogeneous and heterogeneous vehicles (green). Based on Figure 2, several cars are positioned for optimal time and accuracy in the shortest route.

Therefore, the operation is performed with the combined algorithm of Harmony Search and Genetic Algorithm, and the proposed approach is known as HS-GA DLSP Algorithm or Harmony Search-Genetic Algorithm Driver Load Selection Problem.

The sum of the routes that are read and the routing performed with the mentioned parameters is also shown in figure (3).

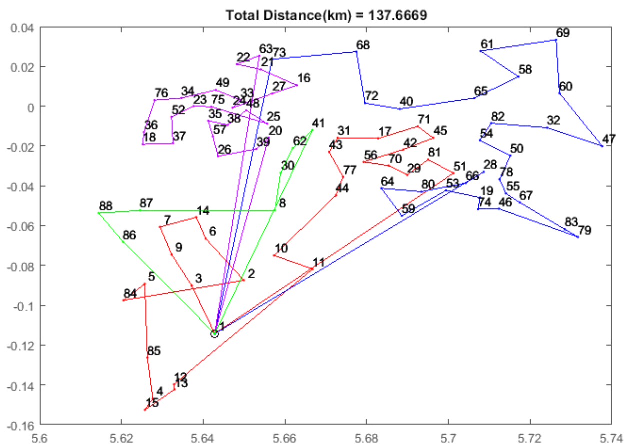

Fig. 2. Routing of Homogeneous and Heterogeneous Vehicles for the Drivers' Load Selection Problem

Based on the output of Figure 2, it can be observed that four main categories of vehicles, namely C, R, RC, and HV, have been precisely and thoroughly routed. In general, for each of C, R, RC, and HV, a total of 25 vehicles are considered, which are strategically placed and routed within the pathways. The overall results of one of the best scenarios for C, R, RC, and HV can be seen in Table 3.

Table 3. Overall Results of One of the Best Scenarios for C, R, RC, and HV

Move from the path	execution time	CPU consumption	HVRP modes
2-4-16	0.5 seconds	1	The best C
11-12-14	0.2 seconds	1	The BestR
31-28-27	0.4 seconds	1	The best RC
10-9-8-7	0.2 seconds	1	The best HV

The execution time of the proposed algorithm may exhibit variations in different runs. However, in the initial run, where the aforementioned outputs were obtained, the execution time was 58.82 seconds, with an average time of 56.32 seconds over 10 runs. Similarly, the accuracy rate in detecting positions and navigating optimal and elite paths, considering the operators of the presented composite algorithm, is illustrated in Figure 3.

```
-15           (Accuracy : 56.0%)
[1]-16-4-2          (Accuracy : 93.0%)
[1]-5-6          (Accuracy : 98.0%)
[1]-7-8-9-10          (Accuracy : 100.0%)
[1]-14-12-11          (Accuracy : 99.0%)
[1]-19-24          (Accuracy : 80.0%)
[1]-21-22-18-3          (Accuracy : 84.0%)
[1]-17-23          (Accuracy : 93.0%)
[1]-25          (Accuracy : 87.0%)
[1]-20-26          (Accuracy : 89.0%)
[1]-27-28-31          (Accuracy : 89.0%)
[1]-29-30-32          (Accuracy : 92.0%)
[1]-13          (Accuracy : 65.0%)
```

Fig. 3. Accuracy Rate in Position Detection and Navigation of Optimal and Elite Paths Considering the Operators of the Presented Composite Algorithm

It can be observed that the presence of a greater number of paths does not have a significant impact on accuracy. Instead, the increase in the number of paths has resulted in optimizing the routing. For instance, paths 20 to 26 exhibit an accuracy of 89%, while traversing paths 10-9-8-7 demonstrates 100% accuracy.

5. CONCLUSION

Transportation, as one of the most crucial economic and commercial sectors, holds a prominent position in various countries. It can be argued that a portion of the gross domestic product (GDP) of different nations is generated and secured by their transportation systems. Therefore, optimizing routes, eliminating unnecessary paths, and establishing an efficient routing mechanism with minimal time and cost are endeavors that researchers have undertaken. On the other hand, the distribution of products is considered one of the key activities for companies and organizations. Improving the physical distribution system, in addition to cost reduction, can enhance productivity and efficiency.

Hence, there exists a significant issue known as the "drivers' load selection problem," which is important from two perspectives. Firstly, it is a practical challenge, and devising better solutions leads to economic savings. Secondly, the problem of drivers' load selection serves as a search space in an environment categorized as NP-Hard or challenging problems. In essence, the problem involves determining a set of routes for a fleet of vehicles that operate independently in one or more regions to serve a set of customers (nodes) scattered in various points of the city (set). The overall goal of the drivers' load selection problem is to optimize and reduce time and costs during movement and traffic, as well as minimizing the traveled distance.

In this research, for presenting an optimal transportation model, the selection of drivers' load is performed through the combination of two optimization algorithms, namely Harmony Search and Genetic Algorithm, in a business intelligence framework. The primary parameters of the combined algorithm, Harmony Search, and Genetic Algorithm need to be precisely considered and initialized to correspond to the drivers' load selection problem. Thus, the parameters of the Harmony Search algorithm include the number of improvisations, search space, fitting function, memory consideration for candidate solutions, pitch adjustment rate, pitch adjustment method, iteration cycle, and the termination condition and program stop. These parameters are equivalently mapped to the parameters of the Genetic Algorithm, which include the initial population or chromosomes, search space, fitting function, fertility space and mutation, crossover operation, iteration cycle, and the termination condition and program stop.

These parameters in the drivers' load selection problem involve the number of nodes or vehicles in an environment, the region where routing occurs, the minimum time, and the optimal possible state in minimizing the paths' length during routing. The paths, specifying a better route than others in diverse iterations, repetition cycles, and minimum time and optimal possible state during routing, are determined.

Based on the observed results, four main categories of vehicles are deployed in the environment, including the customer node's position (C), randomly generated customer node positions (R), customer nodes positions generated with half random states (RC), and predefined placement of heterogeneous vehicles (HV). Their routing optimization is performed using the combined Harmony Search and Genetic Algorithm, referred to as the HS-CA DLSP algorithm. The results indicate a 95% average reduction in the routing rate along with improved accuracy in routing, with an average execution time of 56.32 seconds over 10 runs for the proposed approach.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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