Knowledge-Based Learning for Solving Vehicle Routing Problem

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Abstract
In this study, we have developed a method that applies machine learning in combination with an optimization heuristic algorithm such as a genetic algorithm (GA) for solving the vehicle routing problem (VRP). Further, we developed a knowledge-based algorithm for a knowledge learning system. The algorithm learns to classify coordinates (unlabeled) into regions. Consequently, dividing routing calculations into regions (clusters) provides many benefits over traditional methods, and can result in an improvement in routing cost over the traditional company method by up to 25.68% and over the classical GA by up to 8.10%. It is also shown that our proposed method can reduce traveling distance compared to previous methods. Finally, the prediction of future customer regions has an accuracy of up to 0.72 for the predicted unlabeled customer coordinates. This study can contribute toward creation of more efficient and environmentally friendly urban freight transportation systems.

Author Keywords
Vehicle routing problem; Learning algorithm; Genetic algorithms; Neural networks; Geolocation clustering

ACM Classification Keywords
H.2.8 Database Application: data mining, spatial databases, and GIS

Introduction

The rapid growth of freight transportation in urban areas poses many challenges for transit and logistics agencies to optimize their expense base for each of their business units and create more efficient routing plans. In this study, we have developed a method that applies machine learning in combination with a well-known optimization heuristic algorithm such as a genetic algorithm (GA) for solving the vehicle routing problem (VRP). Further, we developed a knowledge-based algorithm for constructing a learning system for better route planning. The techniques used in this study are an improvement of a hybrid approach. One was introduced by Jean-Yves Potvin [6] to create a delivery region clustering for coordinate agent and the other was developed by Barış Koçer and Ahmet Arslan to do a transfer learning in each agent [3]. The purpose of this system is to transfer knowledge of a coordinate agent to a route agent. The benefit of using transfer learning is that it makes a machine understand and behave in a manner similar to a human being, who is capable of creating an improved new task by learning from past experiences. For example, the routing optimization problem uses past knowledge to create the route planning and adapt it to changes in routing conditions such as customer demands, travel time, and incidents. This behavior is unlike that of the current classical method which needs to formulate a new problem whenever the routing conditions change.

This paper is organized as follows. The literature review section presents the reviews of the VRP, clustering methods, and transfer learning. In the methodology section, we discuss the classical optimization method and our proposed method. The result and discussion section puts forth the performance comparison of the classical method and our proposed method. The final chapter discusses the summary of our findings, the conclusion drawn based on the research objectives, and possible improvements to this study.

Literature Review

1. Vehicle Routing Problem

The objective of a VRP is to minimize the travel distance and time for delivering goods from the warehouse to the customer via the capacity limit of a vehicle and service time windows. The VRP is an NP hard optimization problem, which is more complex than the traditional travelling salesman problem. Many extensions of the VRP have been developed such as the capacitated vehicle routing problem (CVRP), which deals with a fleet truck capacity while carrying the production demand to the desired destination [2]. The construction of a pick-up and delivery problem (PDP) The method uses multiple depots for each trip as considered in multi-depot VRP (MDVRP). It also has more models, which can be referenced from the survey by Lin [4]. We also discovered that this field of study deals with activities related to the environment such as fuel consumption and pollution. Statistics show that fuel cost constitutes a significant part of the total transportation cost [9]. This is a sensitive issue in the logistics policy; therefore, research communities have developed many models to deal with such types of problems. Sustainability is increasingly seen as an essential requirement for delivering long-term environmental benefits. This model, which is known as the green vehicle routing problem (GVRP) considers impact factors such as fuel consumption and pollution emission. This study focuses on reducing consumption costs rather than minimizing the travel distance [1][8].

However, as discovered by Sevgi Erdogan and Elise Miller-Hooks, the region of delivery is also important in route optimization because it can reduce the travel distance and save energy[8]. They used "Density-Based Clustering Algorithm" to cluster customer coordinates. Instead of running this algorithm every time we initialize the problem, our proposed method uses the benefits of machine learning to perform geo-coordinate clustering and learn the characteristic of each cluster in order to make region prediction for further input. In conclusion, our study is based on applying a clustering geolocation technique to the obtained region of delivery and making the model learn (knowledge-based) and adapt to the changed routing condition, and further transfer the knowledge to construct a new route. As a result, it can better optimize the traveling distance and cost. The data obtained in this study was from a leading logistics company in Thailand. The results of our survey of this company show that most of their work focuses on solving problems about conditions such as changing travel time, customer demands, and energy consumption by formulating a new route plan every time each of these conditions change; it does not use past knowledge to construct a new route for a new problem.

2. Clustering Method

Previous research used competitive neural network to cluster data using the X and Y-coordinates as input, which represent the customer location. It also considers distance between two point when make clustering. The model then makes predictions of the cluster labels of each unlabeled coordinate pair [6]. Another approach is to use a density-based method for clustering the data from the nearest neighbor, which has minimum distance between two points in the same group [8].

3. Transfer Learning (Learning Algorithm)

Traditional machine learning uses a set of training data to train the system and make predictions on unknown data. However, in the real-world scenario of logistics operations, many conditions undergo changes and sometimes the training data can be outdated. Therefore a lot of new data is needed to feed into the model at all times for keeping the data up to date. However, if a machine is aware of its past experiences similar to a human being, then more accurate and efficient predictions can be achieved while reducing the data required from the training stage in case of a newly changed condition. This technique is called transfer learning, which is adapted from reinforcement learning for knowledge transfer. As an example, in the method developed by Barı ̧s Koc ̧er and Ahmet Arslan [3], they studied the changes in travelling costs, i.e., changing travelling times between two customers by virtue of traffic density. Their models can adapt to rapid changes in routing conditions by transferring knowledge of past experiences to the learner.

Methodology

The design of our proposed method is illustrated in Figure 1. It contains a coordinate agent and a route agent. The coordinate agent builds a knowledge base to predict the new coordinate's region and transfers it to the route agent. All routes are determined within their known region and combined for the final solution. In future development, we expect to use a multi-agent to transfer knowledge to the route agent, as illustrated in Figure 2.

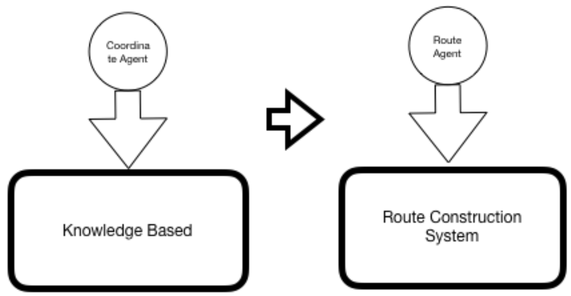

Figure 1: Construction of a single transfer knowledge-based model

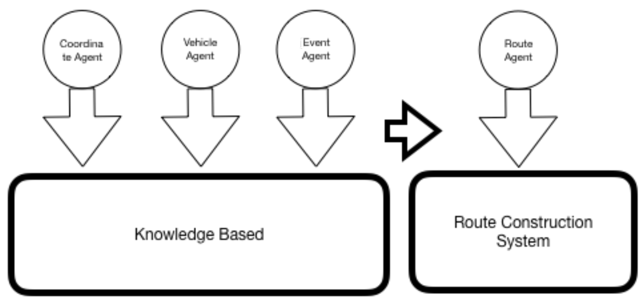

Figure 2: Construction of multi-agent transfer knowledge-based model

The data for input into the model is collected from May 1, 2018 until May 31, 2018 from GPS probe which installed on 10 vehicles. It shown number of origin and destination where each vehicle drives to delivered goods to customer.

The stepwise procedure of routing knowledge-based transfer algorithm is as follows:

1. Obtain fleet routine delivery coordinates and region clustering

In this step, we used k-mean clustering algorithm to cluster customer coordinates into different type of location region. It also depends on road network distance and travel time. In previous works, neural networks were used for clustering; however, in our study, we used unsupervised leaning to cluster the group of coordinates. In this experiment, we used more than 500 coordinates for the training process. The K value is evaluated by the elbow method. The elbow method is a method which looks at the percentage of variance explained as a function of the number of clusters [7]. It can be described as following steps:

1. Initialize k value
2. Start
3. Increment the value of K
4. Measure the cost of the optimal solution
5. If the cost solution drops dramatically set that value to K
6. End

Further, we obtained a result from the described method, which returned the value of K as 4. After that, we obtained the location of the customer cluster in the different region by using this K value in the k-mean algorithm. The results will be discussed in the next section.

2. Setup neural network for model training and prediction of future customer region

After obtaining the result of coordinate clustering to a different type of region, we input the data into a neural network. An agent called "Coordinate Agent" trains the model and makes prediction of future coordinate input. The benefit of predicted the customer region is to minimize the search step and make the system learn and adapt similar to human being. The new coordinates occur so often, and they are depended on customer orders. If we used predefined region then its take time to complied for decision making stage. So, we need past knowledge to supported and make the model more adaptive and extendable for future development.

The neural network architecture that we used in this study contained one input layer, five hidden layers and one output layer. For the number of neurons, we have two neurons for the input layer which is X-Coordinate and Y-Coordinate. Then three neurons for each hidden layer. The main institution behind this is the number of neurons in hidden layer must be between the number of neurons in the input and output layer. We also proved this method by using $\sqrt{n * m}$ where n is the number of neurons in the input layer and m is the number of neurons in the output layer [5] and Finally, we have four neurons for output layer for support four type of clusters. The activation function in the hidden layer is a Rectified Linear Unit (ReLU), and finally the output layer has four neurons with "softmax" activation function, which ensures that the output value is in a range of 0 or 1. Finally, the network uses the Adam gradient descent optimization algorithm with a logarithmic loss function, which is called "categorical cross entropy" in Keras. Keras is an interface built on top of the tensor flow and provides APIs for creating a model. Keras is not only operates on TensorFlow, it also supports other core deep learning framework, such as Theano. We used the K-Fold cross-validation for the model evaluation by setting the number of fold (K) to ten and to random data before partitioning it. Finally, we performed model evaluation and returned ten constructed models in each split of the dataset. We tested up to 5 times before coming up with the final result, which will be discussed in the next section.

3. Construct routing optimization based on customer delivery coordinate region

We would like to divide the explanation of this procedure into three sub categories: the procedure of normal routine route planning from the company, the genetic algorithm, and our proposed method. The results obtained in this section are of the performance comparison in terms of distance and cost optimization.

3.1 Routine operation routing planning of the company

For daily business operation, the company used an experienced operations manager to devise a plan for each vehicle on a daily basis. First, the current locations of the available vehicles are reported. Further, the manager estimates the distance from the vehicle's current location to the depot and from the depot or factory to the delivery site (shortest path algorithm is considered here) in order to determine which vehicle is suitable to receive an order from the customers. The manager manually applies this technique until each driver and vehicle has been assigned to every requested job. The benefit of this technique is that the company can obtain a workable routing plan from few experienced officers; however, it has a drawback that that the determined routes cannot be guaranteed to be optimal or error free. Nevertheless, we used their route planning result in our method validation and assessed the improvement.

3.2 Routing optimization by using classical genetic algorithm

For applying the genetic algorithm to formulate problem hypotheses. It can be summarized [6] as follows: first, we need to encode the solution of the problem to chromosomes. Further we evaluate the fitness and quality of each chromosome then select population for mutation. Repeat these steps until the population with less cost is selected. The distance of each point is evaluated by Euclidean distance.

3.3 Our proposed method

In our proposed method, we used the result obtained from section 2 as input of our modified genetic algorithm. At this step, we discover the customer delivery region; further, we calculate the routing distance by using google direction API and routing cost based on equation in section 4. Subsequently, we divide the coordinates into sub-groups and perform the routing calculation. We combine the coordinates after all calculations are completed. Then we repeat these steps until every region has routing and all customers have been served their demand. This is unlike previous methods which calculate by searching the solution from the overall search space, which may impact the computational time and route efficiency. As illustrated in Figure 3, we have a set of indices. The following is the explanation of the steps of our proposed algorithm.

Step 1: Import the vehicle coordinates, demand, capacity, and service time windows into the algorithm.

Step 2: Make a prediction of the customer region using our prediction model in section 2. After that, group the coordinates with the same label in the region list.

Step 3: Pick the first region and then remove it from the region list. Then, generate an initial random solution.

Step 4: Evaluate solution fitness between two pairs and then select the highest fitness value.

Step 5: Generate two offspring from two parent chromosomes in the population list.

Step 6: Apply random mutation to each offspring. In this study, we set probability to 1:15.

Step 7: Check each array index for violation of vehicle capacity constraint or service time window constraint. If it violates the constraints, then delete the node from solution list.

Step 8: Check whether the number of offspring is equal to number of chromosomes. If yes, then evaluate the result, else repeat the sequence of Step 4 to 7.

Step 9: Compare current solution with the solution in the population list. If the new population appears to have less cost, then set current population to the new. Repeat this step until all solutions have been compared.

Step 10: Return the optimal solution and store it in a list.

Step 11: Check whether all regions have been calculated. If yes, then terminate, else repeat Step 3 to 10 by choosing a new region in the region list.

4. Cost formula to calculate routing cost

We define a set of indices for the vehicle depot or starting point, delivery location, and the truck which is allocated to the company fleet as illustrate in Figure 3.

i : Depot index i	i ϵ I
j : Delivery index j	j ϵ J
tr : Truck index tr	tr ϵ TR

Figure 3: Set of indices for route construction

Further, the calculation of parameters is defined as illustrated in Figure 4. The decision variable for route is as illustrated in Figure 5.

Parameters

DS_{ij}	The travelling distance starts from i to j
T_{ij}	The travelling time starts from i to j
IN_{ij}	Insurance cost from i to j
DC_{tr}	Depreciation cost of truck tr
VDC_{tr}	Tire depreciation cost of truck tr
MC	Maintenance cost
ST_j	Service time at j
T_{max}	Maximum time
LaborC	Labor cost
$Order_{tr}$	Order of truck tr

Figure 4: Description of features for each route

Decision variables

$$X_{trij} \begin{cases} 1, \text{ if truck tr is transported from i to j.} \\ 0, \text{ otherwise} \end{cases}$$

$$Y_{tr} \begin{cases} 1, \text{ if truck tr is selected.} \\ 0, \text{ otherwise} \end{cases}$$

Figure 5: Decision variables for the selected truck and route construction

The objective function can be set as illustrated in Figure 6. The main objective is to minimize the routing cost by optimizing the routing distance of the modified genetic algorithm.

$$OptimalRouteCost = \quad \min\,(RouteCost)$$

Figure 6: Objective function for route optimization

For each trip, the cost can be calculated using the following formula which is the summation of the involved parameters arranged in the following order. The summation operates on labor, insurance, depreciation, and tire depreciation cost in that order, as illustrated in Figure 7.

$$RouteCost = \sum_{tr}^{TR}\sum_{i}^{I}\sum_{j}^{J}(LaborC\ T_{ij})X_{trij} + \sum_{tr}^{TR}\sum_{i}^{I}\sum_{j}^{J} IN_{ij}\, X_{trij} + \sum_{tr}^{TR}\sum_{i}^{I}\sum_{j}^{J}(DC_{tr}\ DS_{ij})X_{trij} + \sum_{tr}^{TR}\sum_{i}^{I}\sum_{j}^{J}(VDC_{tr}\ DS_{ij})X_{trij}$$

Figure 7: Formula for calculating route cost in this study

Result and Discussion

In this section, we state our findings and results starting from region clustering, customer region prediction, and performance comparison of the proposed optimization model with other methods.

1. Customer Region Clustering

After running the k-mean clustering model, we obtained four clusters from 500 points of customer coordinates as illustrated in Figure 8.

Test No.	1	2	3
1	2,501	2,144	1,946
2	2,501	2,143	1,959
3	2,501	2,110	1,946
4	2,501	2,118	1,962
5	2,501	2,123	1,962

Table 1: Performance comparison of routing distance (Km.)

In Table 1, the meaning of each column is described as follows: 1 denotes company route planning, 2 denotes classical genetic algorithm, and 3 denotes our proposed method. Routes which we used in distance and cost calculation are the examples of routing in one week from the company routing plan (14 destinations).

2. Customer region prediction model

The suggested region clustering from the previous step is used as input in this step, and we make a prediction of the customer region for evaluating the model and the knowledge-based input (delivery region) for route construction agent. The result of the prediction is illustrated in Figure 9.

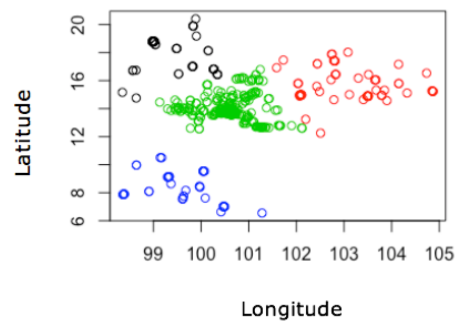

Figure 8: Coordinate clustering into regions by using k-mean algorithm

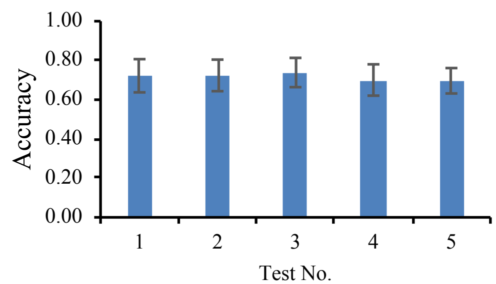

Figure 9: Prediction of the customer region

The average result yield prediction accuracy is up to 0.72 for each test run.

3. Performance comparison of our proposed model with other methods.

As mentioned in the methodology section, we ran the algorithm according to our proposed method. Results show that the proposed method has improvement over routine company route planning (25.68% on average) and the classical genetic algorithm (8.10% on average). The results in Table 1 and 2 are shown in terms of distance and routing cost, respectively.

Test No.	Company route planning (THB)	Classical genetic algorithm (THB)	Our Proposed Method (THB)	Improvement over Company routing	Improvement over genetic algorithm
1	35,458	30,722	28,086	26.24%	9.39%
2	35,458	30,720	28,266	25.44%	8.69%
3	35,458	30,257	28,086	26.24%	7.73%
4	35,458	30,360	28,308	25.26%	7.25%
5	35,458	30,437	28,318	25.21%	7.48%

Table 2: Performance comparison of routing cost calculation methods

Conclusion and Future Work

In this study, we developed a method that applies machine learning in combination with a well-known optimization heuristic algorithm such as GA for solving the VRP. Furthermore, we developed a knowledge-based algorithm to construct a learning system for route planning. As a result, we divided routing calculations into regions (clusters), which provided many benefits over traditional methods. This technique can optimize the routing cost over the traditional company method (25.68% on average) and over the classical GA (8.10% on average) as shown in Table 2. Table 1 shows that our proposed method can reduce the traveling distance compared to other methods. Moreover, the prediction of future customer regions yielded an accuracy of 0.72 on average from the predicted delivery regions of the customers as shown in Figure 9. In future work, we plan to develop a multi-agent learning system for solving the VRP to allow the routing construction system to learn and obtain experiences from various incidents and event condition changes such as the delay in unloading goods or the changing demands during routing at the customer site, as well as increase the accuracy of the prediction model. The final goal of this study is to establish an efficient and environmentally friendly urban freight transport system.

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References
1. Çağrı Koç and Ismail Karaoglan. 2016. The green vehicle routing problem: A heuristic based exact solution approach. *Applied Soft Computing* 39: 154–164.

2. Nathalie Helal, Frédéric Pichon, Daniel Porumbel, David Mercier, and Éric Lefèvre. 2018. The capacitated vehicle routing problem with loading constraints. *International Journal of Approximate Reasoning* 95: 124–151.

3. Baris Kocer and Ahmet Arslan. 2012. Transfer learning in vehicle routing problem for rapid adaptation. *International Journal of Innovative Computing, Information and Control* 8, 10: 6799–6809.

4. Canhong Lin, K.L. Choy, G.T.S. Ho, S.H. Chung, and H.Y. Lam. 2014. Survey of Green Vehicle Routing Problem: Past and future trends. *Expert Systems with Applications* 41, 4: 1118–1138.

5. Timothy Masters. 1993. *Practical Neural Networks Recipes in C++*. .

6. Jean-Yves Potvin, Danny Dubé, and Christian Robillard. 1996. A hybrid approach to vehicle routing using neural networks and genetic algorithms. *Applied Intelligence*, 241–252.

7. Purnima Bholowalia and Arvind Kumar. 2014. EBK-Means: A Clustering Technique based on Elbow Method and K-Means in WSN. *International Journal of Computer Applications* 105, 9: 17–24.

8. Sevgi Erdogan and Elise Miller-Hooks. 2012. A Green Vehicle Routing Problem. *Transportation Research Part E* 48: 100–114.

9. Yiyong Xiao and Abdullah Konak. 2017. A genetic algorithm with exact dynamic programming for the green vehicle routing & scheduling problem. *Journal of Cleaner Production* 167: 1450–1463.