An Improvement of the Arrival Time Estimation of an EV System Using Hybrid Approach with ANN

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***Abstract*—In this research, an approach for estimating the travelling time used by an electric vehicle and selecting an updating period of such vehicle to a particular location are proposed. The real-time based and historical data based techniques are used with Artificial Neural Network (ANN) as a process for memorizing the offset for estimating the vehicle velocity and updating period in the following round. The route of the vehicle, the time of the day, and the day of the week are taken into account. The proposed approach is analyzed and compared to the conventional approach by testing with the data (time and position of the vehicle) collected from running the vehicle around Naresuan University campus. The data was recorded every 1 second for 3 months using the wireless transmitter installed in the vehicle. From the results, it is found that, using the proposed approach, the bandwidth utilization of the network and the error of the displayed time are improved by 75%. With this significant improvement, if the proposed approach is further developed or utilized, the public vehicle service's reliability could be increased; thus, less number of private vehicles utilized; resulting in a good environment saving.**

***Index Terms*—Electric Vehicle; Arrival Time; Updating Time; Real Time Monitoring System; Artificial Neural Network.**

I. INTRODUCTION

Currently, the information system can be applied in many applications including the transportation. This can improve the quality of service in transportation application in terms of data service to the passengers. The Advance Traveler Information System (ATIS) as a part of the Intelligent Transportation System (ITS) is focused on providing the important travelling data to the passengers so that they can make a proper plan in taking any particular public vehicle. There are many research work related to this aspect [1-3].

To obtain this travelling data, a system for estimating the travelling time of a vehicle has to be conducted. Generally, there are two major types of having such system done depending on the connection between the system and the server. The first type is the offline system. In this system, the algorithms for predicting the arrival time of a vehicle without using the current data are focused. The advantage of such system is that there is no need to access to the network; that is, no cost of internet access. However, the prediction result is not adaptively adjusted according to the real data. For the second type, it is the online system, which has been further developed from the monitoring and tracking system [4-7]. The current vehicle position can be determined and the arrival time to the next stop can then be estimated accurately. The data transferred between the vehicle and the system (or server) has to be done repeatedly.

Considering the travelling estimation system in public vehicle, there are many research work related to this aspect. These works have been studied and tested in variety of areas and traffics. The techniques that have been used can be categorized into 4 main groups. The first group deals with the historical data based approach [8 9], which makes use of the average from the collected data in the past. The second group utilizes the real-time based approach [10,11] based on the concept that the current data can be used to predict the next one. For example, the current velocity of a vehicle and the rest of the distance are used for determining the travelling time; thus, the arrival time can be estimated. For this group, the data transferred between vehicles and the system has to be done again and again. The machine learning technique [12-15] is applied in the third group. In this group, a huge amount of sample data is utilized in order to allow the system to recognize adequate data and able to predict the next one. For the last group, a model based approach is adopted [16-20]. The relationship between parameters is studied and modeled in order to forecast the travelling time or the arrival time of a public vehicle. There also are some hybrids [3,21-22] which make use of some of these four groups in order to improve the estimation system.

In this research, a hybrid technique combining the historical data based approach and the real-time based approach is proposed. Additionally, Artificial Neural Network (ANN) is adopted in order to use as a mechanic for adjusting the vehicle velocity in the calculation. The proposed system has been tested with the electric vehicle (EV) service in Naresuan University campus, Thailand. The bandwidth utilization and the error in terms of the arrival time between the actual and the prediction ones have been collected.

In Section 2, the basic techniques and theories used in this work are given. The proposed technique and system overview are explained in Section 3. The tested results and discussion are shown in Section 4. And, finally in Section 5, the conclusion is given.

II. RELATED TECHNOLOGY OVERVIEW

A. Real-Time Based System Infrastructure

For the electric vehicle system, to have a real-time based approach in order to estimate the arrival time of a particular vehicle, the whole system can be viewed in Figure 1.

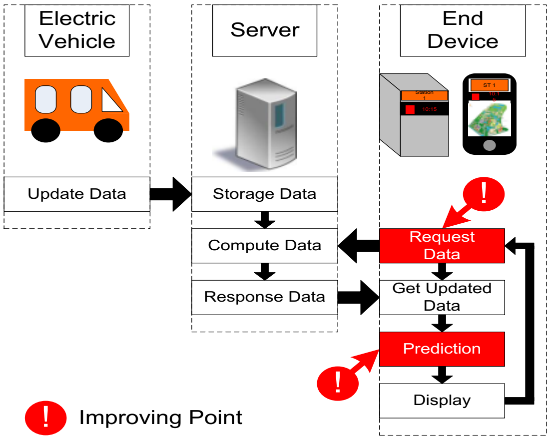

Figure 1: The real-time based system for estimating the arrival time of an electric vehicle.

From Figure 1, it is seen that the system is divided into 3 sections; that is, the electric vehicle, the server, and the end device. For the electric vehicle, there must be a transmitter installed for sending and updating data about its position to the server. For the server, it works as a storage and data analyzer receiving data from the other sections and responding to the end device(s). The last section is the end device, which could be an intelligent display installed at the stop or a smart phone of a passenger. For the end device, it is seen that there are four major tasks; that is, requesting data from the server, receiving data from the server, predicting the arrival time of the electric vehicle, and displaying the prediction to the passenger.

Since this is the real-time based system, data updating process must be taken place all the time between the electric vehicle and the server and between the server and the end device. This updating process will certainly require internet access resulting in the increase of the bandwidth utilization and cost of the internet access. To reduce the access to the internet, the number of requests between the server and the end device has to be considered. If this number can be reduced appropriately, the internet access or bandwidth utilization can then be decreased. However, this can then cause another problem, namely, the error of the estimated arrival time of the electric vehicle. This problem can be solved using the proposed technique.

B. *Cumulative Moving Average (CMA)*

According to determining an average cumulatively [23-25], moving average or running mean is widely adopted. The process of averaging here, shown in Equation (1), behaves like a low-pass filter to the data; thus, the data is smoothed out.

$$CMA = \frac{x_1 + x_2 + \quad + x_n}{n} \tag{1}$$

where CMA = cumulative moving average
x_i = the i^{th} data
x_n = the current data
n = the number of data

Considering Equation (1), it is seen that the result of determining CMA is the average of the whole data considered up to the current one. In this work, such average is adopted.

C. *Artificial Neural Network (ANN)*

The Artificial Neural Network or ANN [26-29] is categorized in the field of Artificial Intelligence (AI). It was developed from the requirement to have a machine or a computer to think (or memorize) like a human.

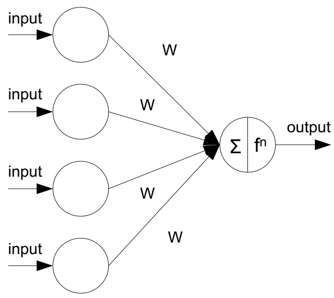

Figure 2: General Model of ANN.

The ANN model is shown in Figure 2. It is seen that there are 5 elements in the model. Each input is passed to a node and multiplied by the weight according to its node. Then all weighted input are summed and passed to an activating function depending on the application to be used. And, the output of the ANN is obtained.

The learning in ANN will be in the form of weight adjustment. The current set of input (new information) will allow ANN to learn more and this affects the weight to be used in the next cycle. The process is done repeatedly; thus, a more precise model of the learning is obtained.

III. Proposed System

In order to estimate the arrival time of the electric vehicle, the vehicle velocity and the distance are two important factors. Different types of velocity are shown in Figure 3.

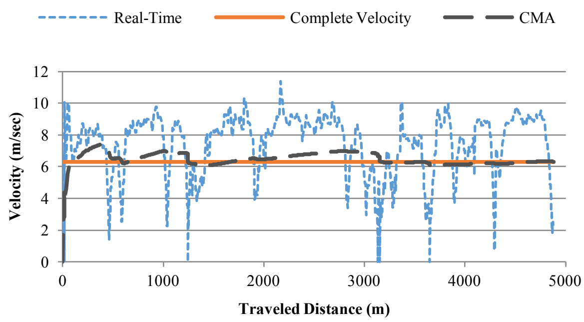

Figure 3: Three types of velocity for the electric vehicle.

After the vehicle running completely for one round around the campus, the average complete velocity, shown by the solid line, can be obtained. Another velocity is the real-time velocity (dotted line). This velocity is the real velocity of the vehicle at a particular position. It is seen that this velocity changes rapidly depending on the distance. It cannot be used in estimating the arrival time of the vehicle since the estimated time will be varied considerably and cannot be used by the passengers. However, if the real-time velocities are averaged out using CMA, another velocity called CMA velocity (dashed line) can be determined. Comparing CMA velocity to the complete velocity, they are slightly different depending on the distance considered.

However, using the difference between these two velocities, an offset can be determined and used as the compensation for the predicted velocity of the electric vehicle as shown in Equation (2). Additionally, the estimated required time for the vehicle to reach a particular stop can be obtained from Equation (3).

$$v_{predict} = v_{CMA} + v_{offset} \tag{2}$$

$$T_{predict} = \frac{D_{rest}}{v_{predict}} \tag{3}$$

where $v_{predict}$ = the predicted velocity of the vehicle
v_{CMA} = the CMA velocity of the vehicle at a particular distance
v_{offset} = the offset velocity
$T_{predict}$ = the estimated required time to reach the station of interest
D_{rest} = the distance between the stop and the current position of the vehicle.

In this work, the offset velocity has to be determined. Considering Figure 3, it is seen that the offset varies as the distance changes. To obtain such non-linear offset, ANN is adopted here.

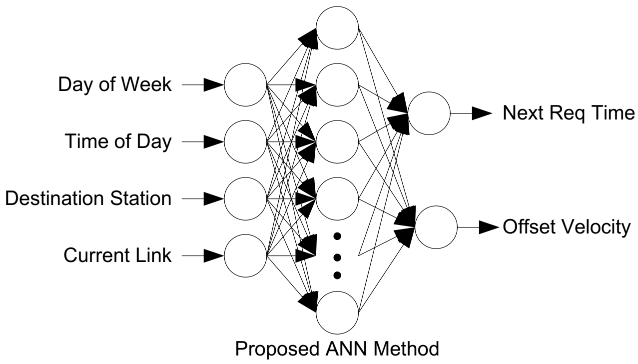

Figure 4: The ANN model used in proposed system.

From Figure 4, it is seen that there are 4 inputs to the ANN; that is, day of the week, time of the day, destination stop, and current link (path) of the vehicle. The outputs are the offset velocity to be used in Equation (2) and the next request time. If the data is passed to this ANN the weights in ANN will then adjusted accordingly so that the proper outputs can be obtained.

The diagram of the proposed system is shown in Figure 5. It is seen that the real-time approach, the historical data based approach, and ANN are utilized in the system. For the real-time approach part, the EV data from the server is obtained depending on the request of the end device. The EV data contains the vehicle latitude, longitude, and velocity. The EV data is sent to the preprocessing unit to determine the CMA velocity; then, sent to the feature extraction unit for extracting the data to be used as the input of ANN.

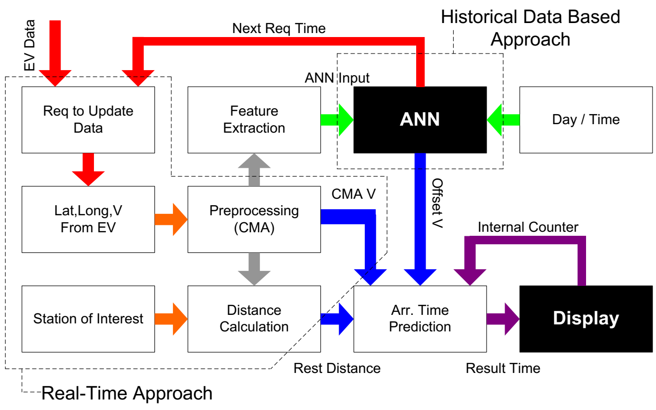

Figure 5: The diagram of the proposed system at the end device.

From Figure 5, the data from the preprocessing unit is sent to the distance calculation unit to determine the rest of the distance that the vehicle needs to travel in order to reach the station of interest. The outputs from ANN, preprocessing, and distance calculation units are passed to the arrival time prediction unit to determine the estimated required time to reach the station of interest. This estimated time is then sent to the display to view by the passengers. The display can be the LED monitor placed at the stop as an intelligent stop or the monitor of the smart device. Another output from the ANN unit is the next request time. This will be used the end device to send out the request for updating the information about the electric vehicle. Using ANN, the next update time can be varied adaptively depending on the current vehicle velocity and other parameters.

IV. Results and Discussion

The data from the campus electric vehicle system in Naresuan University, Thailand has been collected every second for 3 months and is categorized according to day of the week and time of the day. After analyzing the data, 120 sets of data are obtained. These 120 sets of data are then divided into 2 groups; that is, to be used as the training data sets (60 sets) and to be used as the testing data sets (60 sets). For the training data sets, they are appointed for being using in historical based approach as the training data for ANN.

The testing data sets are applied to 3 different types of systems; that is, Type A, Type B, and Type C. For Type A, the proposed system is used. That is, before applying the testing data sets to the system, the training data sets are applied to the ANN unit in order to allow the system to learn and adjust the offset velocity appropriately. For Type B, the testing data is applied and the CMA velocity is determined. And, for Type C, the testing data is fed to the system without any modification. The output performance determined from applying the testing data sets to these 3 systems is the error in terms of the arrival time (in seconds) comparing between the estimated time and the actual time at the station of interest. Additionally, the data-update interval is increased from every 2 seconds to every 4, and 10 seconds, respectively, to reduce the bandwidth utilization of the internet access. The percentage of bandwidth utilization is compared to the case of updating every 1 second. Note that the bandwidth utilization of the proposed system is adaptively changed; however, for 3 values of bandwidth utilization, the next request time of the proposed system is manually modified in order to have the bandwidth utilization as mentioned in the table. The results are shown in Table 1.

Table 1
Arrival Time Error for different types of system and different bandwidth utilization

	Arrival Time Error (in seconds)		
	2-sec Updated (50% BW)	4-sec Updated (25% BW)	10-sec Updated (10% BW)
Type A	34.21	34.26	34.50
Type B	45.31	45.27	46.27
Type C	172.92	162.41	145.09

From Table 1, it is seen that using Type C system in which only the real-time data is utilized, the arrival time error is very large; that is, between 145 to 173 seconds. These are from the fact that the velocity of the vehicle varies significantly from one point to another, as can be viewed from Figure 3. Increasing the updated interval (that is, reduce the bandwidth utilization) seems to reduce the error. However, the error still in the unacceptable range since it is more than 2 minutes.

Considering the results for Type B, it is seen that the arrival time errors are much less than those from Type C. The errors are in the range of 45 to 47 seconds. The reduction in time error for Type B is from the fact that the velocity used in estimating the arrival time is determined from CMA. Increasing the updated time slightly increases the arrival time error; that is, from 45.31 to 46.27 seconds.

For the proposed system, Type A, in which the historical based approach, the real-time based approach, and ANN are combined, it is seen that the best results in terms of the arrival time error are obtained. Changing the updated time from every 2 second to every 10 second, the arrival time error is slightly increased from 34.21 to 34.50 seconds. This further improvement comparing to those from Type B and Type C is the result of an appropriate offset velocity determined by ANN. Note that the amount of arrival time error in the range of 30 to 40 seconds is acceptable since the vehicle velocity in the campus is around 6 m/sec. It means that within 40-second period, the incoming vehicle is approximately 200 meters away from the station of interest, which the passenger there can view the vehicle.

Comparing the arrival time error from these 3 types of system, it is seen that the proposed system can reduce the arrival time error by 25% and 75% from the obtained arrival time error of Type B and Type C, respectively. Additionally, it is seen that instead of fully utilizing the bandwidth (that is, updating every 1 second), applying the proposed system, the arrival time error is still in the range of 35 seconds while the bandwidth utilization can be kept by 90% reduction; that is, updating the data every 10 seconds.

V. CONCLUSIONS

In this work, the arrival time estimation of the electric vehicle is studied. A hybrid system between the historical based approach and the real-time based approach are combined. And, the Artificial Neural Network (ANN) is adopted. The historical data is trained to ANN unit in order to allow the network to adjust its weights accordingly. The outputs of the ANN are the next request time and the offset velocity. The offset velocity is added to the CMA velocity so that the predicted velocity can be determined. This then results in a significant improvement in the arrival time estimation; that is, 75% improvement. The next request time is the proper time to request a new set of data from the server. This request time changes adaptively depending on the current velocity of the vehicle. With this type of adaptiveness in request time, an improvement of bandwidth utilization can be obtained, as well.

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