COMPUSOFT, An international journal of advanced computer technology, 9(9), September-2020 (Volume-IX, Issue- IX)

Available online at: https://ijact.in

Date of Submission	28/07/2020
Date of Acceptance	20/08/2020
Date of Publication	30/09/2020
Page numbers	3817-3823 (7 Pages)

ISSN:2320-0790

COMPUSOFT
An International Journal of Advanced Computer Technology

TIME PREDICTION ALGORITHM BASED ON DISTANCE AND REAL-WORLD CONDITIONS

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Abstract: Prediction algorithms have seen a rise in popularity in various applications. These algorithms are frequently implemented in applications to assist in making data-driven decisions based on the predicted output. Time prediction algorithms are often used to predict the travel time between two distances that allow better planning and anticipation. However, the non-linear situation of urban traffic has undermined the accuracy of these predictions. With the increased application of such algorithms in urban settings, it is important to conduct research to further improve the accuracy of current algorithms. The factors affecting travel time are researched to develop an algorithm that includes these factors into consideration during calculation.

Keywords: Algorithms, Artificial Neural Networks, data collection, distance, Machine Learning, non-linear, prediction models, time prediction, traffic.

I. INTRODUCTION

Algorithms are sets of defined rules and finite steps that solve computational problems. They take in a finite number of variables and return a set number of outputs by processing the variables according to the set definitions [1]. It simplifies the solution finding process for a set of problems and abstracts the entire process without the need to constantly monitor the problem-solving process [2]. Besides, it can increase efficiency and reduce the need to understand every single process hence allowing users to focus on other aspects and areas [1]. In modern computing, most electronic devices have some sort of algorithm to aid in its operations, ranging from simple algorithms to complex algorithms such as those used in computers that processes anything from simple calculations to more complex predictions and mathematical problems [2].
Prediction algorithms have seen a rise in popularity with its use in many aspects such as the prediction of personal preferences or in more commercial applications such as predictions of market trends. Artificial Neural Networks (ANN) is one of the common models used for prediction. It is defined as a system made up of simple but highly interconnected processing elements, where information is processed by their dynamic state response to external inputs[3]. It consists of algorithms or hardware that is loosely modelled after the neural structure of the mammalian cerebral cortex[3]. ANNs mimics biological neurons where incoming signals would determine if the neuron would fire an impulse onwards [4]. Most ANNs have a ‘learning rule’ where weights are adjusted according to the input patterns, hence allowing it to ‘learn’ [3].
One of the more common usages for prediction algorithm is in predicting travel time. Travel times are important especially in larger cities where they assist in journey planning, displaying arrival times of public transport vehicles etc. in information systems [5]. A time prediction algorithm is especially present in many systems or applications which require live location detection to facilitate the functioning of the system.
To have a time prediction algorithm with a high accuracy, conditional factors such as weather, climate and overall driving habits need to be factored into calculation. This is important as travel habits vary from an area to another where these factors would directly and indirectly play a role in affecting travel times. An example would be people may drive faster on wider

roads compared to smaller roads, or traffic being generally slower when it is raining [6]. This project aims to compare various existing algorithms and develop a solution to improve the prediction performance.

II. RESEARCH BACKGROUND

Ma et al. [7] found that Artificial Neural Networks (ANN) is a popular method towards non-linear problems such as unpredictable urban traffic situations. This is further supported by Abdollahi, Khaleghi and Yang [8] which mentioned that machine learning would be able to pick up on behaviour and trends with data without the need to be explicitly programmed. This is opposed to common linear algorithms used in route guidance systems that has its own limitations, which may result in inaccurate prediction of time due to the unpredictability of modern urban traffic [9].This is further supported by van Lint and van Hinsbergen [10] that concluded linear prediction methods such as using historical travel times, which is widely adopted due to its scalability and low computation effort, would start to show inaccuracies when predicting non-linear traffic data in urban areas, whereas neural networks would demonstrate more accuracy.

A study conducted by Masiero, Casanova and de Carvalho [11] showed that time prediction algorithm has been improving with development in technologies and processes to automate procedures to allow the discovery of patterns, groups and trends. These could be used in finding the factors that affects travelling time in creating algorithms that factor in non-linear situations. This can be further highlighted in a study by van Hinsbergen et al. [12] which mentioned that neural networks are more likely to have a better ability in predicting cases that were not present in the training set by generalizing situations, thus making it more robust and suited to predict travel times in an urban environment.

A. Artificial Neural Network in Prediction

An artificial neural network (ANN) typically consists of 4 parts, being the processing units, weighted interconnections between processing units, an activation function and occasionally a learning rule that specifies the weight adjustments. ANNs can adapt to new environments with adjustments done to the weights [13]. This allows the processing unit to modify its input and outputs behaviour according to the environment. Besides, neural networks are able to associate input and output patterns to make assumptions through generalization. This is particularly useful to achieve human-like performance in areas like recognition and learning.

A study conducted by Raju et al. [14] shows that the simplified mathematical models of ANN gives the ability to learn and offer meaningful solutions to non-linear problems. It can make predictions even with noisy data compared to conventional techniques. A simple feed-forward algorithm is shown to give a high-level overview of a simple neural network.

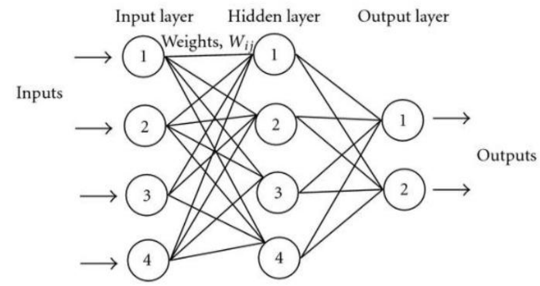

Figure 1: Overview diagram of ANN [14]

A typical neural network consists of 3 to 4 layers, with the number of hidden layers being determined according to the problem. Trial and error method are usually used to determine the best architecture for a problem situation, with weights assigned to each link to represent the connection strength of 2 nodes, usually with the use of an equation.

This is further supported by Yoon [15], which stated in the study that neural networks aim to produce a desired output by modifying the weight of the neurons' analogues of dendritic synapses, supervised or unsupervised. ANN models are commonly identified by their learning architectures, commonly being:

- Correlational where the weights of neurons are adjusted proportionally to the output of both neurons, and inputs that generates an impulse are reinforced.
- Competitive where the output neurons compete for domination where the neurons connected to the dominant output neuron is altered.
- Error correction works by minimising errors with respect to each weight in the system against the calculated mean square errors.
- Stochastic trains the model statistically by adjusting the weights to minimize a statistical quantity that is similar to the thermodynamic entropy function.
- The study conducted by Kolarik and Rudorfer [16] touched on the selection of suitable parameters to construct a suitable topology for the network model. The main parameters mainly consist of:
- Learning Rate. This parameter determines the weight adjustment strength that should be adjusted by the learning algorithm for a given error. Higher adjustments would lead to faster learning but may sometimes affect prediction outcome.
- Momentum. This parameter would affect the gradient descent of the weights which prevents each neuron connection from following every little change.
- Number of Inputs and Hidden Units. The input units are largely equal to the size of the input window in which the neural network looks into during prediction. The hidden units would then be the number of layers in between the input and output layers. The number of layers is not defined and can range anywhere from a single layer depending on the application.

B. Data Collection and Inputs for Prediction Models

Various hurdles posed currently restrict the proper implementation of many time prediction algorithms and models. The difficulties faced in obtaining sufficient accurate data sets seem to be a common challenge in implementing many time prediction methods. It was noted that many prediction models required huge amounts of data sets to yield accurate results, where there is a difficulty obtaining data due to limited coverage of traffic data-collecting sensors [17]. These limitations may affect the quality of the final prediction due to incorrect assumptions from limited data. This was also mentioned in a study by Liang and Wakahara [18], where the non-parametric regression model relied on large amounts of historical data for the training process.

Tiesyte and Jensen [19] acknowledged the difficulties of collecting live data and also understood the expensive computational costs of ANN which makes it unsuitable for real-time updating. The study preferred to rely on historical data which does not require any live data for seamless integration into existing transport management systems. The study established relationships between trajectory data to discover patterns which would then allow the algorithm to predict travel time based on historical data from similar routes. A similar research by Wu et al. [20] aimed to predict the varying speed of each road segment instead to be used with the fastest route recommendation algorithm. Proven assumptions are factored into the calculation to predict the average travelling speed instead. For example, it is known that traffic surrounding a junction would slow down if the junction were to be congested. This method could be extended to areas where information regarding road topology is scarce.

Data collected for a model should be processed accordingly before training to ensure that the data is of quality to train a particular model as well as to avoid skewed performance or overfitting. Some of the observed data pre-processing techniques were data division (also known as train-test split) and the extraction of road data such as intersection tags via 3rd party open source maps such as OpenStreetMap (OSM) [21]. The ANN model for time series prediction called Nonlinear Autoregressive network with Exogenous Input (NARX) was proposed by As and Mine [22] to predict bus arrival times with the following framework as shown in the figure below.

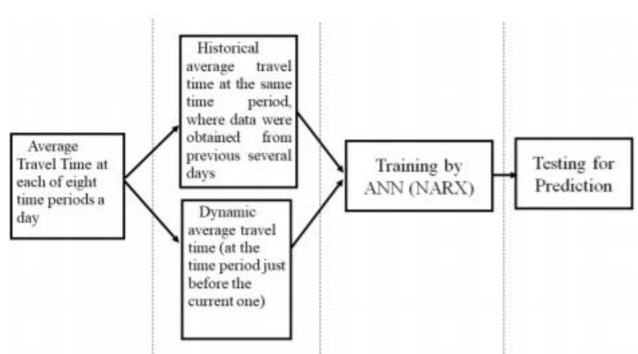

Figure 2: Proposed prediction framework [22]

C. Architecture of Prediction Models

To date, various methods have been conceived to achieve the aim of predicting travel arrival time. Artificial Neural Network (ANN) has been highly favoured due to its ability to make predictions in non-linear cases. Van Hinsbergen et al. [12] found that the most applied traffic prediction models are ARIMA-like time series predictions, Kalman filtering, linear weight regressions, neural networks, simulation models as well as committee approaches. Committee approaches utilises several models and combining their outputs to get a weighted average. These models however do not always yield accurate results. A study by Ma et al. [7] noted that the prediction accuracy would decrease in the presence of various factors such as weather conditions, temporal change in traffic during peak and non-peak hours etc.

In an effort to predict the time spent of a vehicle in between two points, Masiero, Casanova and de Carvalho [11] developed a mechanism to predict time based on historical data of a vehicle such as average driving speed factored in with other semantic variables for accuracy. It was done by processing raw data to discover behavioural trends of vehicles. Several input factors are used for the model, called Support Vector Regression (SVR), such as the latitude and longitude of the segment start and end points, segment distance, type of vehicle etc. The SVR model uses traffic segmentation as it acknowledges that traffic speeds vary throughout a journey. Each stop is divided into segments that create a new entity in the model called the Segment entity.

A study conducted by Vora et al. [23] used multiple independent algorithms rather than the common approach of just a single algorithm. The study acknowledged the limitations of each individual model and found that the using multiple models will ensure a distributed decision-making process. Non-linear Regression, Kalman Filtering and Regression Trees are used where each model will independently make assessments of the traffic. The results by each model would then be assigned a weight and the final prediction will be an average of the combined 3 outputs.

D. Conclusion

Overall, each ANN model developed in general is specific to a particular use case and there has not been a model found to suit multiple use-cases. Various studies have conceived different ANNs, but the limitation found was that the testing of the research was confined to a specific area or situation. Further studies are needed to increase the flexibility of the algorithm to suit various use cases while maintaining the accuracy level.

Most ANNs for prediction have similar fundamentals to receive inputs and generate an output, with the main difference being how the data is handled and the type of input data used. Further studies are needed for hybrid models to overcome the disadvantages of implementing a single model. This achieves higher accuracy as compared to the prediction of a single model only. According to Lin et al. [24], hybrid models are increasingly used as traffic flow is affected by many factors and single-component models is not sufficient for prediction, especially in the era of big data transportation where traffic sensor technologies provide more abundant and detailed data.

III. Results and Discussion

3.1 Questionnaire Results

Data was collected from a total of 50 respondents to further understand the importance of travel time, and the factors affecting it. Section A consists of the demographic profile of the respondents. This is used to determine if there is a relationship with the age group and the travelling experience of a person.

Most of the respondents were from the 18-24 age group totalling up to 47% of respondents. The remaining respondents belonged to the 25-34 age group and 35-54 age group with 28% and 30% respectively. The age groups are said to have an almost equal representation in this study therefore most of the data collected could be applied across all age groups. However, there were more male respondents with up to 68% and the remaining 32% were female respondents. As for employment status, half of the respondents are in full-time employment, where they tend to travel frequently and have a better gauge of their travel experience. The 2nd majority group are students with 37%. They have the need to constantly travel from their place of residence to their education institution. The remaining minority respondents are unemployed, self-employed, part-time employed and retirees. This group of people has a more irregular travelling frequency and their insights would be that of a less frequent traveler.

Section B of the questionnaire focuses on the individual mobility of the respondent. This section is to establish the understanding between the respondent's environment, their ways of mobility and their experience of using map applications in assisting them in their travels. An insight to the current problems is summarized in this section to better understand the factors of travel delay.

Most respondents live in a large urban area, with up to 58% living in urban areas. These groups of people face constant unpredictable traffic as compared to the 24% of respondents in a small town and 2% of respondents in the village. Respondents from small towns and villages are most likely to only experience the occasional heavy traffic such as during festive seasons. The remaining 16% of respondents live in suburbs which may also face a similar situation to urban respondents as people constantly travel into the nearby cities for work.

72% of respondents travelled with a private vehicle. The remaining respondents would commute using public transport such as a trains and buses. Approximately 37% of respondents travelled for less than 5km, with only 13% having to travel 5km-10km, 24.1% having to travel 10km-20km and up to 25.9% having to travel for above 20km. This is more apparent in large urban areas where people would have to travel further to get to their destination.

The most common negative experience of respondents during their daily commute was found to be traffic jams, with 54% of respondents agreeing so. The high volume of people on the road came in at 2nd place with 20% of respondents which relates to the contribution of traffic jams. Among the other reasons that was found to contribute to a negative travelling experience was frequent breakdowns of vehicles, construction, regulations and unexpected delays. The smaller contributing factors were mainly on the poor driving standards and the lack of respect for the law by drivers, which mainly came at 2% each.

All respondents were found to have used navigational applications at some point of their journey. The main reason for using these apps was because they were mainly not familiar with the particular area. 28% of respondents wanted to know the fastest way to get to their destination while 18% of respondents wanted to know the latest traffic conditions. The travel time was found to be very important for users in deciding their route before the journey starts. Several other reasons given were also highly similar relating to the route to take and the traffic conditions.

Most respondents were highly satisfied with their experience with navigational applications with 67.3% of respondents giving 4 out of 5 points for route accuracy and convenience. The remaining respondents were somewhat mildly satisfied to very satisfy with the accuracy. This shows that the accuracy of routes provided contributed to the positive experience of users with navigational applications. However, users would occasionally face inconsistencies and inaccuracies with navigational applications, mainly due to miscalculations or inaccurate data [25]. One of the top reasons for inaccuracies were unexpected road closures and applications that prefer routes through main roads where in some cases smaller streets would be faster despite a lower speed limit. Out-of-date maps are also a great factor especially in cities where roads constantly change. Inaccurate reporting also seems to be a factor of navigational inaccuracy faced by respondents, such as inaccurate reporting of traffic accidents etc. with 28% of respondents agreeing so. The inaccuracies cause travel time to be calculated wrongly and a different route is given instead.

Lastly, respondents' answers regarding their overall travelling experience could be grouped into a few main factors which are shown below.

Unpredictable traffic
Unfamiliar roads
Live traffic information needed.

Section C aims to study user experience with using location-based applications such as e-hailing and food delivery applications and the importance of time prediction in these apps. Majority of respondents were found to have used location-based applications, with only 4% of respondents not having the experience of using it.

The time predictions are commonly susceptible to inaccuracies which are noticeable to the users. Perceived accuracy seemed to vary across the respondents from a range of low accuracy to very high accuracy. Most respondents found that the predicted times were highly accurate with 42% giving 4 out of 5 points, while a minority of 10% felt that the travel time predicted was quite inaccurate. Although navigational features are usually provided in these location-based applications, detours by drivers seem to be prevalent with 72% of respondents gave a score of 3 and above in terms of frequency of detours. The main reason for detours was because drivers were not familiar with the road conditions. The 2nd highest factor was the navigational application was not functioning properly. Other reasons given were mainly out-of-date maps lacking information such as road closures, traffic jams as well as confusing road layouts that may not be accurately depicted on the map. This is also portrayed in the accuracy of wait times shown after a ride is booked or an order is placed which collected mixed reviews. 28.6% think it is inaccurate, 22.4% have mixed reviews in accuracy while the remaining 49% of respondents felt that it was largely accurate.

One of the main factors' respondents felt that their drivers were arriving later or earlier than predicted was due to traffic conditions. Weather conditions would also play a role as drivers tend to be slower and more careful during bad weather. Other reasons given by respondents are poor GPS navigation or external factors such as restaurants that take longer than expected to complete an order which delayed the driver's journey. Most felt that the predicted travel time is important and would affect the overall usage experience of the app. The main factor for this is that it would affect the upcoming plans of the person, with 40.8% agreeing so. The other 34.7% felt that the inaccurate prediction of travel time would reduce the trust towards the application while the remaining 24.5% of respondents felt that it would reduce the reliability of the service.

3.2 Observational Results

Observation in this study involves collecting data to get a more accurate scenario of road conditions as and validate the responses collected by respondents as they may intentionally or unintentionally provide erroneous information. Naturalistic observation was conducted at different periods throughout the day, with notes taken periodically in a non-controlled setting. The advantage of using this method is that it would help ensure the validity of collected data when the study is recorded in a natural setting without any interference [26]. Besides, new possibilities may be opened that have not been previously considered, thus enhancing the value of recorded data and the final product. Limitations of this study is that it is easy to miss some behavioural data [26], which may be overcome by having more than a single independent observer, where recorded data can be compared later on to reduce discrepancy and inconsistencies.

The first section consists of observed predicted travel times collected from various live location-based applications. Accuracy of prediction was seen to be high in clear traffic conditions, but however became more inconsistent with heavy and unpredictable traffic conditions. A sample journey with ride-hailing application Grab was recorded in Singapore. The initial predicted travel time given by the app was approximately 1 hour, with an arrival time of 12.45pm. However, halfway through the journey, the predicted travel time got revised to 12.38pm as the journey was smoother than expected. However, the final arrival time was 12.48pm, which was much later than the predicted times. The inaccuracies of prediction were due to the slowing down of driving speed when the driver was near to the destination as well as traffic conditions such as traffic lights.

In another scenario, the travel time prediction of Google Maps was observed. This observation was conducted during a period where there was no traffic congestion. It was found that the accuracy of predicted travel time in this situation was high. This proves that the prediction was accurate especially when there is no traffic on the road during that period.

Several factors were observed to affect travel time as well. The table below shows factors that would affect travelling time in a journey.

No.	Factor	Explanation
1	Road Type and Conditions	Vehicles would tend to slow down on narrower roads or roads with many speed bumps. Slower traffic can also be observed with roads that are not properly maintained.
2	Weather and Environmental Conditions	Slower traffic can be observed during adverse weather, or at night especially in poorly lit roads.
3	Law Enforcement	Traffic would be significantly slower when there is traffic enforcement. Certain events would also slow traffic around an area especially if there is traffic diversion involved.
4	Personal Factors	Personal factors such as stopping to pick up a call would increase the travel time. This factor is highly unpredictable and travel time prediction algorithms are currently not able to use this factor.
5	Driving habits	The driving habits of users were found to affect travelling time. Constant lane switching was found to slow down traffic as vehicles behind would have to slow down and give way.

Table 1: Factors affecting travelling time

These factors must be taken into consideration by the algorithm depending on the weight of these factors in affecting the total travelling time. A proper assessment needs to be conducted with proper testing to determine the relationship of these factors with the travel time.

IV. CONCLUSIONS

The study has effectively researched on the importance in conceiving a time prediction algorithm with high prediction accuracy while studying its various possible implementations. The questionnaire, the importance and public opinion on this algorithm was highlighted while new insights were gained to create an effective prediction algorithm. The observation done also helped researchers to understand factors that affect traffic conditions and get a real-world understanding of the environment where the algorithm would be implemented in.

The studies of existing similar systems and research projects have been essential in gaining insight to existing implementations. Useful information found in other research could be used in this study where suitable, eliminating the redundancy of research being carried out. The study of existing systems also helped in understanding the field of Artificial Neural Networks (ANN) and travel time prediction, allowing a new solution to be developed that improves on current implementations. With the field of ANNs expanding in the recent years, the number of research conducted has significantly increased. These would be very useful in conceiving an algorithm with high prediction accuracy to be deployed to the mass public.

By understanding the factors that affect travel time, further study of suitable prediction models could be done that would include these factors as input variables to the algorithm. The algorithm could then be used in various applications predicting the travel time in various situations, ideally starting from a small scale for accuracy tests. With the emergence of new prediction models and the increased computing power, more research could also be furthered into studying more complex models such as deep learning that may yield high accuracies with low human intervention.

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