A Comparison of Ambulance Travel Time Approximation: Using Google Maps and Machine Learning

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ABSTRACT

Accurately estimating ambulance travel time is critical for emergency medical services (EMS) to ensure timely response and efficient resource allocation. This study explores machine learning-based approaches for predicting ambulance travel time, comparing three artificial neural networks (ANN), Google Maps, and the traditional KWH constant speed model. Using real-world data from Nova Scotia's EMS system, we develop and evaluate these models based on prediction accuracy, computational efficiency, and applicability in both real-time and modeling contexts. Our results show that ANN model aligns closely with historical data, making it more suitable for EMS simulation and decision-making, despite requiring more complex feature inputs. This study highlights the strengths and limitations of each method and offers insights into selecting the most appropriate approach based on EMS application requirements.

Keywords

Machine learning, Emergency medical service, ambulance travel

INTRODUCTION

Emergency medical service (EMS) is an important component of the healthcare system. The performance of EMS can affect patient's outcome and the overall performance of the healthcare system. In general, a typical individual EMS response consists of four key time periods: ambulance assignment, ambulance travel, on-scene treatment, and transfer of care to the emergency department (ED). The accuracy of ambulance travel time approximations has significant impacts on EMS studies since the majority of response time is the ambulance travel time and response time is one of the most important metrics for EMS performance evaluation (Togher et al., 2014). Ambulance travel time approximation is also crucial to many other practical EMS problems, including ambulance dispatch and hospital selection.

Traditional methods for estimating ambulance travel times often rely on static speed assumptions or Google Maps (Mohammadi et al., 2023). While these methods are widely used, they may lack the flexibility to incorporate real-time EMS-specific data, such as priority levels and ambulance characteristics, potentially leading to suboptimal predictions in critical situations.

Recent advancements in machine learning (ML) offer promising alternatives for improving ambulance travel time estimation. ML models, particularly artificial neural networks (ANNs), have demonstrated superior ability in capturing complex relationships between features like location data, time of day, and patient acuity, thus enhancing the accuracy of predictions (Xu et al. 2019). By integrating both spatial and temporal factors, as well as EMS-specific patient information, these models may provide more personalized and accurate predictions than traditional prediction methods.

Multiple approaches have been widely used by researchers, but to the best of our knowledge, they have not been formally compared. This paper aims to address this by evaluating and comparing approaches for ambulance travel time approximation, focusing on ANNs, Google Maps, and the constant speed approach. The study also introduces a novel hybrid model: ANN-KWH. This model combines ANN and KWH, a constant speed approach proposed by Kolesar et al. (1975), to utilize the strengths of both ANN and KWH. Through a comprehensive analysis of real-world EMS data, we assess the performance of these models in terms of prediction accuracy, computational efficiency, and applicability in EMS modeling contexts.

The rest of this paper is organized as follows. Section of Related Works provides works related to the context of this research. Section of Machine Learning-Based Ambulance Travel Time Approximation explains the proposed ML-based methodology. Section of Experiment presents the experimental results, followed by sections of Discussion and Conclusions.

RELATED WORKS

Poongodi et al. (2022) predicted the travel time for taxi trips using ANN. The dataset for this study includes the pickup time, pickup location, and dropoff location, a unique code assigned to different taxi companies, and number of passengers. Ejabati (2023) applied ANN to predict travel time and incorporated the predicted travel time to a time-dependent vehicle routing problem with time window. Qiu et al. (2021) applied ANN to short-term travel time prediction for vehicle routing and congestion mitigation problems. In addition to using features of temporal data (e, g. time of the day and month), this work also incorporated the temporal-spatial data related to road segments, including the travel time of the nearest downstream and upstream road segment 15 min before.

Methodologies for approximating ambulance travel time can be broadly classified as three categories: Google Maps Application Programming Interface (API), constant speed, and ML. Google Maps API is an online API that can predict travel time based on the user's input, including the GPS coordinates of departure and destination and departure time. Zhukovskaya et al. (2022) built a simulation model to plan locations of emergency medical stations. In this simulation, the ambulance travel time is approximated using Google Maps. Similarly, Ridler et al. (2022) also incorporate Google Maps into their simulation model of the EMS system.

The constant speed approach assumes that ambulances travel at a constant speed for simplicity purpose. But this approach ignores the heterogenicity between short distance travel and long distance travel. To tackle this problem, Kolesar et al. (1975) proposes a KWH model. The KWH model is defined as follows:

$$P = \begin{cases} 2\sqrt{(L/a)}\,, & L \leq 2d_a \\ v_c/a + L/v_c\,, & D > 2d_a \end{cases}$$

where P is the predicted travel time, a is the acceleration rate, L is the travel distance, v_c is the cruising velocity and $d_a = {v_c}^2/2a$.

KWH has been validated by Budge et al. (2020) and reported to be a reasonable approximation of the median travel time of ambulances. Furthermore, it can distinguish between short and long distances. Li et al. (2021) apply KWH to their Markov decision process model to find the optimal ambulance destination policy to reduce offload delays.

Boutilier et al. (2020) compared four ML models on travel time approximation: AdaBoost, random forest (RF), linear regression with L1-reiglarization (LASSO), and K-nearest neighbors (KNN). Results show that RF makes the most accurate travel time prediction. Tedesco et al. (2023) also used RF to predict the travel time. Abid et al. (2024) compared ANN and decision trees and ANN achieves the best performance. They also conduct data analysis on how different features impact the travel time approximation. This data analysis suggests that the hour of the day have significant impacts on the estimation of the travel time. Oliver et al. (2023) used a Bayesian neural network to predict the ambulance travel time with the inputs of locations of origin and destination, day of the week, hour of the day, and the minute. Mahdiraji et al. (2024) proposed an ANN to predict the ambulance travel time to be incorporated into an EMS simulation model. This ANN uses five features of the patient's priority level of patients, hour of the day, day of the week, and the distance.

MACHINE LEARNING-BASED AMBULANCE TRAVEL TIME APPROXIMATION

In this section, we first introduce the dataset used in this study. Then we explain the features selected for our ML models. Finaly, we propose three models for ambulance travel time approximation using ANNs.

Dataset

The data used in this real-world application is provided by Emergency Medical Care Inc. (EMCi), which is contracted by the Department of Health and Wellness (DHW) of Nova Scotia. EMCi manages and operates the EMS system, including ground ambulance, medical communications, air medical transport operations, and the medical communications centre in Nova Scotia (Emergency Medical Care Inc, 2021). The dataset contains 20,766 call records of ambulance response in Nova Scotia from January 1st, 2021, to December 31st, 2021. Each call record in this dataset includes information about the patient's acuity and timestamps, such as call time and arrival at scene time. The average travel time is 14.41 minutes. The median travel time is 11.15 minutes. 41.1% of the EMS requests from the dataset were from rural areas. It should also be pointed out that Nova Scotia was still under the governmental restrictions for covid-19 in 2021.

Features Selection

ML is a feature-sensitive approach and feature selection plays an important role in model development. As suggested by the works of Boutilier et al. (2020), Oliver et al. (2023), Tedesco et al. (2023), Abid et al. (2024). and Mahdiraji et al. (2024), commonly used features are locations, distance between the patient and ambulance, time, and patient related data. Therefore, we decide to further verify these features on the dataset used in this study.

We categorized features into three types: spatial, temporal, and patient-related. Spatial candidate features include: 1) the GPS coordinates where the ambulance starts travel, named ambulance's location, 2) the GPS coordinates where the patient is waiting for the ambulance, named patient's location, 3) the distance between the ambulance and patient is named distance. Figure 1 shows the distribution of travel time over the distance, which demonstrates the correlation between travel time and distance.

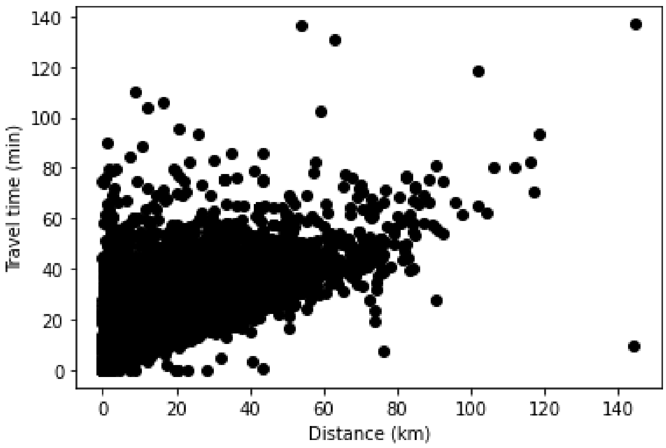

Figure 1. Historical ambulance travel time over the distance between the ambulance and the patient in 2021

Temporal candidate features include: 1) month of the year, 2) weekday, and 3) hour of the day. To decide which of these three temporal candidates features to be included, we conduct a data analysis on the impacts of these three temporal candidates features on the ambulance travel time. Figures 2-4 shows the data analysis results with average travel time and 95% confidence intervals. It can be seen that both month and hour have impacts on the travel time. However, Figures 3 presents overlaps of 95% confidence intervals of average travel time over weekdays. This suggests that there is no correlation between weekday and travel time. This observation may be attributed to reduced traffic resulting from Nova Scotia's COVID-19 regulations in 2021. In summary, we decide to only include month and hour as our temporal input features.

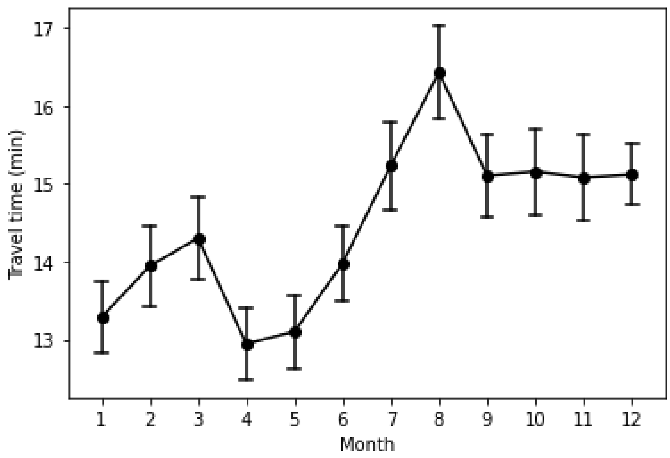

Figure 2. Historical average ambulance travel time over months in 2021 with 95% confidence intervals

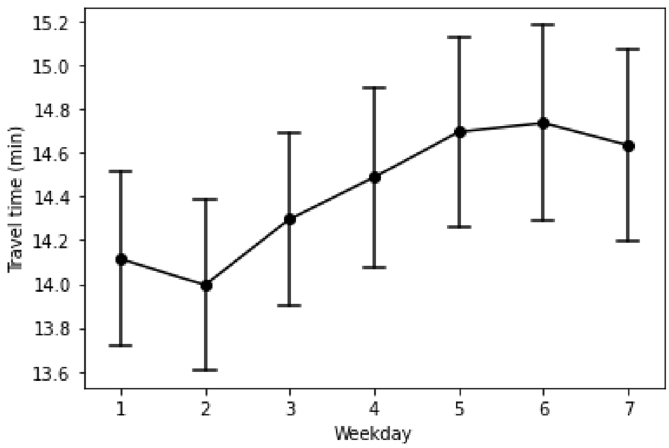

Figure 3. Historical average ambulance travel time over weekdays in 2021 with 95% confidence intervals

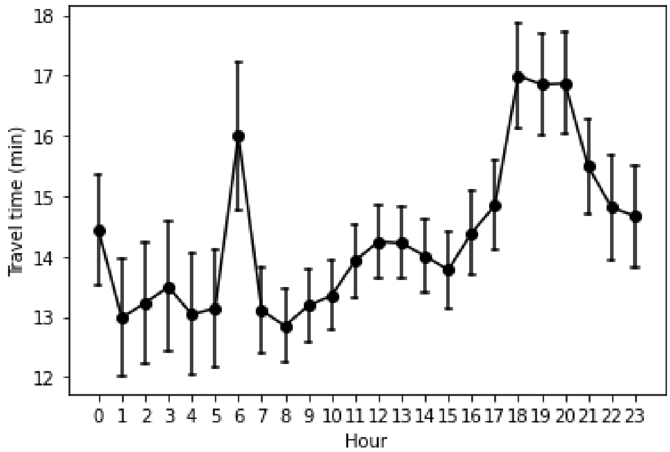

Figure 4. Historical average ambulance travel time over hours in 2021 with 95% confidence intervals

The Patient-related feature in the dataset is patient acuity level, measured by Canadian triage and acuity scale (CTAS) (Bullard et al, 2017). CTAS has a value ranging from 1 to 5: 1 is most acute and 5 is least acute. It can be seen from Figure 5 that travels with CTAS of 1 are significantly faster than travels with higher CTAS. Therefore, we decided to include CTAS.

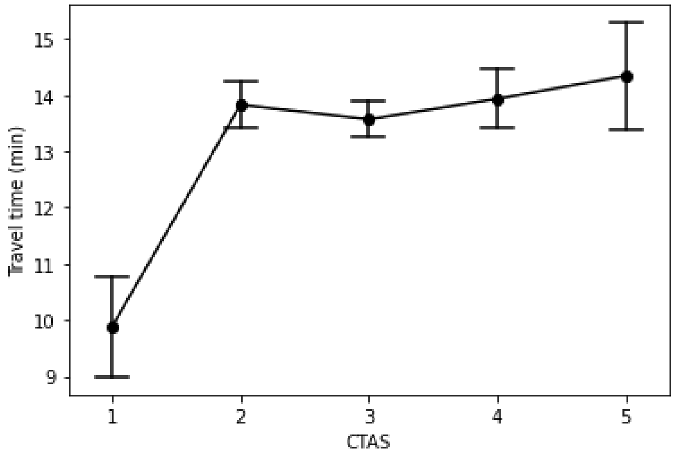

Figure 5. Historical ambulance travel time over CTAS in 2021

In summary, we decide to include the following features in the input: 1) ambulance's location, 2) patient's location, 3) distance (km), 4) month, 5) hour, and 6) CTAS.

Artificial Neural Network Models for Ambulance Travel Time Approximation

We propose three ANN-based models: ANN-Basic, ANN-Google, and ANN-KWH. Each model has been specifically designed to predict ambulance travel time by leveraging key features and by adapting their architecture and input structure to enhance predictive performance.

The architecture of ANN-Basic is shown in Figure 6. It consists of one input layer, two hidden layers with 16 and 8 neurons, and one output layer. It is a common practice is to use a power of two for the number of neurons for each layer and reduce the number in subsequent layers to creates a bottleneck that forces the network to compress and abstract these features, which can improve generalization and reduce overfitting (Kurt, 1991). Meanwhile, the number of neurons of a layer should not be greater than the twice of the number of neurons from its previous layer (Hinton et al., 2006) In this study, the input layer size is eight (i.e. eight features). Therefore, the first hidden layer should have 16 neurons. We further reduced the number of neurons of the second hidden layer to 8 neurons to create a bottleneck.

The input layer receives the features described in the previous subsection. Hidden layer 1 extracts information stored in the features from the input layer. Hidden layer 2 further exploits the extracted information from hidden layer 1. The output layer makes final prediction of the travel time by processing the information from hidden layer 2. Two hidden layers are also connected to Rectified Linear Unit (ReLU) activation functions, defined as $ReLu\ (x) = \max\ (0, x)$, where x is the output of neurons from the hidden layers. This activation function was selected for its ability to introduce non-linearity while mitigating the vanishing gradient problem that can occur with other functions like sigmoid or tanh (Mohammadi et al.,2023). In hidden layer 1, the model begins by identifying complex patterns within these features through ReLU activation, capturing critical interactions that could influence ambulance travel time. This processed information is then passed to the hidden layer 2, which further refines and combines these learned patterns, deepening the model's understanding of intricate relationships among input features. The final output layer, a layer without an activation function, processes the information from the hidden layer 2 and generates a single continuous output representing the predicted ambulance travel time for a given trip.

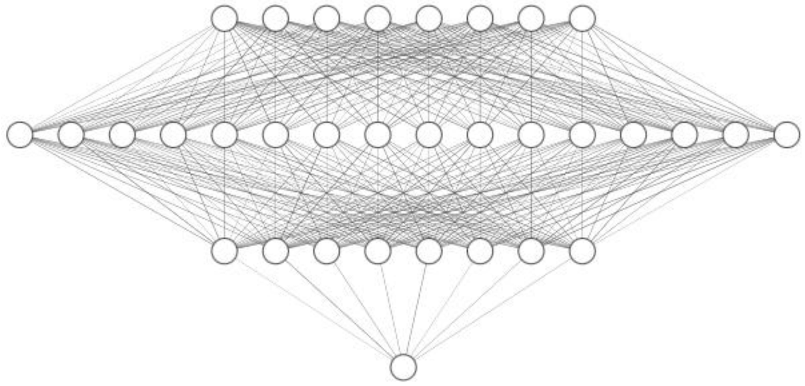

Figure 6. Architecture of ANN-Basic

ANN-Google shares the same fundamental architecture as ANN-Basic, with two hidden layers of 16 and 8 neurons, each activated by the ReLU function, and a single output layer. However, the input layer is modified to incorporate additional information by incorporating the travel time prediction from Google Maps as an extra input into the features. This modification aims to adjust Google Maps' travel time estimated by incorporating additional information that might not be considered by Google Maps, such as the patient's CTAS score and the priority level of the call. By leveraging both Google Maps predictions and patient's information, ANN-Google can potentially enhance the travel time estimation.

In ANN-KWH, we allow the parameters a and v_c in the KWH model to be dynamically adjusted for each ambulance trip to minimize the error between predicted and actual travel times, rather than using constant values as in the original KWH model. Therefore, we propose the ANN-KWH model by combining ANN and KWH. It has the same input layer and two hidden layers as ANN-Basic. However, unlike the other models, the output layer of ANN-KWH produces two outputs: a and v_c, as described in the section of Related Works. Then the travel time is predicted using the KWH model with the predicted a and v_c. ANN-KWH utilizes ANN's ability of data mining to optimize the two parameters of KWH, which are further applied to the KWH model to make prediction on the travel time. This hybrid approach allows the ANN-KWH model to adapt to the variability inherent in ambulance travel, potentially providing more precise and context-sensitive predictions compared to models with static parameters.

EXPERIMENT

We compared the three ANN-based models on the dataset with the KWH approach and Google Maps. We split the dataset into training data and test data with a ratio of 7:3. All computation in this section is conducted on an Apple M1 Pro chip with 16 GB of unified memory for CPU and GPU.

Table 1 presents the average (and 95% CI) travel time for each approach. Google Maps achieves the largest deviation from the historical data with an average travel time of 11.80 minutes. ANN-KWH has the average travel time of 14.42 minutes, which is closest to the historical average travel time among these five approaches.

Table 1. Statistics summary of the historical and predicted travel time over the test data

Method	Average with 95% confidence interval (min)	Standard deviation
Google Maps	11.80 (±0.24)	9.66
KWH	12.66 (±0.20)	8.03
ANN-Basic	12.59 (±0.20)	8.04
ANN-Google	12.49 (±0.20)	7.97
ANN-KWH	14.42 (±0.22)	9.02
Historical	14.41(±0.28)	11.31

Figure 7 shows the historical and predicted hourly travel time over the test data by hour of the day. It can be seen that all five approaches can capture the hour of the day trend well. ANN-KWH yields the closest hourly predicted average travel time when compared to the historical data. Both Table 1 and Figure 7 demonstrates that Google Maps tend to underestimate the travel time.

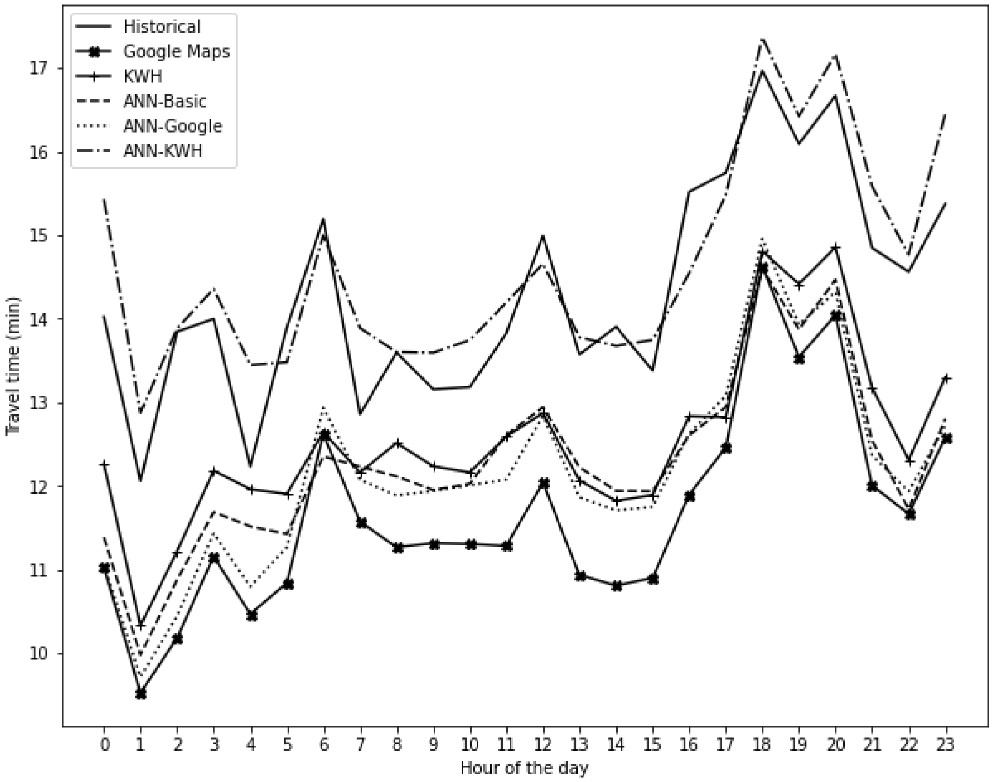

Figure 7. Hourly average travel time over the test data

We also compared the models based on their computation time, as this is a critical factor when time predictions must be computed repeatedly, as is common in many EMS modelling applications. Consequently, a model with high computation time for travel time prediction will significantly increase the overall computation time required for the model. This is particularly important in simulation modelling where multiple replications are needed—for instance, during model validation, scenario testing, or simulation-based optimization. Excessive computation time in such cases could hinder the efficiency and practicality of the simulation. Table 2 listed the average computation time per prediction and total computation time needed to determine the travel time over the test data for each approach. It can be seen that Google Maps is the second slowest approach with an average computation time of 125.455 ms. KWH is the fastest approach with an average computation time of 0.002ms. ANN-Basic and ANN-KWH models share similar computation speed while ANN-Google is the slowest model. The computation time of ANN-Google includes the computation time consumed by both the ANN and Google Maps API querying.

Table 2. Results of computation time needed to determine the travel time over the test data with five approaches

Method	Average Computation Time (ms)	Total Computation Time (minutes)
Google Maps	125.455	13.0264
KWH	0.002	0.0002
ANN-Basic	29.815	3.0958
ANN-Google	154.777	16.071
ANN-KWH	29.696	3.0834

DISCUSSION

In this section, we discuss and compare the five approaches based on practical consideration for application and methodological development requirement, as summarized in Table 3.

Table 3. Comparison of five approaches

Method	EMS modeling	Methodological development requirement
Google Maps	• Computationally expensive • Worst performance on average travel time	• Dataset not required • Hyperparameters tuning not required
KWH	• Computationally cheap • Medium performance on the average travel time	• Dataset required • Hyperparameters tuning required
ANN-Basic	• Medium Computation time • Medium performance on the average travel time	• Dataset required • Hyperparameters tuning required
ANN-Google	• Computationally expensive • Medium performance on the average travel time	• Dataset required • Hyperparameters tuning required
ANN-KWH	• Medium Computation time • Best performance on the average travel time	• Dataset required • Hyperparameters tuning required

We evaluated the five approaches using statistics and computation time. To explain these results, we propose interpreting the metrics in the context of EMS modeling. EMS modeling involves the development of an offline mathematical representation of the EMS system for optimization, scenario testing and decision-making purposes. This process typically incorporates various statistical analysis of system's properties such as call volume, functional and operational considerations such as resource allocation. Furthermore, models can be adapted to simulate and evaluate the system's performance under different scenarios.

For EMS modeling, the ambulance travel time is a critical component of EMS models, as it directly affects response times, one of the most widely used performance indicators in EMS evaluation. However, as shown in Table 2 and Figure 7, Google Maps demonstrates the largest deviation from historical data. Specifically, Google Maps tends to underestimate ambulance travel times, which could lead to the underestimation of response times if used in EMS models. This could undermine the credibility of EMS models and lead to inaccurate decision-making. Conversely, the ANN-KWH approach provides prediction that are the closest to the historical data.

Another consideration is computational efficiency. Google Maps is the second slowest approach, which may present challenges in studies involving simulation modeling. Since simulation often requires multiple replications, using Google Maps can lead to increased computational time. This issue can get worse in simulation-based optimization studies, where multiple simulation runs are necessary to identify optimal solutions. The additional computational demands could make Google Maps impractical for such applications. Considering these factors, the ANN-KWH approach appears more suitable for EMS modeling because its closer alignment with historical data, combined with its computational efficiency and accessibility of required features, make it a more reliable option for EMS decision-making models.

Additionally, these five approaches differ in terms of the methodological development required. Google Maps does not require any hyperparameter tuning nor dataset, making it straightforward to implement. In contrast, both the KWH approach and the three ANN-based models require data collection for training purpose and hyperparameter tuning. Particularly, the KWH approach requires effort to optimize parameters of a and v_c. Similarly, the three ANN-based models require hyperparameter tuning for the number of hidden layers and neurons, which can significantly affect performance. In other words, Google Maps is more generic and easier to apply across different regions without the need for extensive model-specific adjustments, whereas KWH and the ANN-related models demand more customization and parameter optimization.

CONCLUSION

This study evaluated and compared three common approaches for approximating ambulance travel time: Google Maps, constant speed (KWH), and machine learning models (ANN-Basic, ANN-Google, and ANN-KWH). Our results showed that Google Maps tended to underestimate ambulance travel times. This limitation poses risks for EMS modeling, where accurate travel time predictions are critical for decision-making.

Among the machine learning models, the novel approach ANN-KWH demonstrated the best alignment with historical data, making it the most suitable for EMS modeling. However, all machine learning models require detailed feature inputs, such as the patient's CTAS, which are not always available in real-time prediction settings. In contrast, Google Maps, though more computationally expensive, provides a real-time prediction solution without the need for extensive data collection or parameter tuning.

In conclusion, the choice of travel time approximation method should be guided by the specific application context. Google Maps is ideal for real-time prediction due to its ease of use and availability of real-time data, but its limitations make it less suitable for EMS modeling. On the other hand, ANN-KWH is more appropriate for EMS modeling, offering greater accuracy and efficiency despite its higher development and feature requirements. Future work should explore further optimization of machine learning models to enhance both real-time prediction capabilities and accuracy for EMS modeling applications.

This study has certain limitations. Firstly, while we employed ANNs for ambulance travel time prediction, other machine learning approaches, such as support vector machines, decision tree-based models, and ensemble methods like XGBoost, have shown promise in similar contexts. Additionally, variants of neural networks, including convolutional neural networks and long short-term memory networks, warrant exploration. Future research should involve a comparative analysis of these models to identify the most effective approach for ambulance travel time prediction. Secondly, this study did not conduct feature importance analysis. Implementing techniques like SHAP could provide valuable insights into the model's decision-making process, which could be a focus of future work. Lastly, the results presented an interesting observation where techniques such as KWH and Google Maps tended to underestimate the ambulance travel time. This could be attributed to the nature of the EMS system in Nova Scotia where 41.1% of the EMS requests were from rural areas. However, it is still an interesting topic to be further explored in regards of the fundamental difference between rural ambulance travel and urban ambulance travel.

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