

**MACHINE LEARNING BASED TRAVEL TIME
PREDICTION OF URBAN BUS TRANSIT USING
GPS DATA**

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Master of Science (Major Component Research)

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DECLARATION

I declare that this is my own work and this Thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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The supervisors should certify the Thesis with the following declaration.

The above candidate has carried out research for the Master of Science (Major Component Research) Thesis under our supervision. We confirm that the declaration made above by the student is true and correct.

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ABSTRACT

An accurate and reliable arrival time prediction of buses to the next bus stops is a valuable tool for both passengers and operators. Existing studies have some limitations in bus travel time prediction. They focus little on three aspects such as heterogeneous traffic flow conditions, dwell time prediction and interpretation of explanatory variables. Consequently, we break down the prediction problem into sub-models for running times and dwell time prediction and incorporate a feature engineering framework that generates features related to the running bus, the prediction day, and immediate and long historical time variations to capture heterogeneous traffic conditions. We propose a multi-model stacked generalisation ensemble model by leveraging the advantages of best-performing models in homogeneous conditions such as Extreme Gradient Boosting (XGBoost) and convolutional long short-term memory (ConvLSTM) models. It outperformed the state-of-the-art models by 11% in mean absolute error (MAE) on average. It can predict extreme conditions in bus journeys more accurately.

Nevertheless, the input data for the machine learning model should be the historical travel times of the route. We proposed two simple novel algorithms to extract bus trips and match bus stop sequences towards extracting dwell times and running times from the raw crude GPS data generated at a medium sampling frequency of 15 seconds. Those algorithms incorporate various challenges like non-uniformity, poor network coverage, discontinuities in streaming and skipping of bus stops. In addition, we attempted to interpret the feature importance of the generated features. We found insights like driver behaviour and the immediately preceding dwell time influence the stopping pattern and the prediction model, which pave the way for strategic management by authorities.

Keywords: Bus travel time prediction, Machine learning, Multi-model ensemble, Ensemble Learning, GPS data processing, Heterogeneous traffic

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LIST OF ABBREVIATIONS

Abbreviation	Description
AFC	Automatic Fare Collection
ANN	artificial neural network
APC	Automated Passenger Counts
ATIS	Advanced Travel time Information System
AVL	Automatic Vehicle Location
DNN	deep neural network
ES	exponential smoothing
ETL	Extract Transform Load
GPS	Global Positioning Systems
GTFS	General Transit Feed Specifications
ITS	Intelligent Transportation Systems
KF	Kalman filter
kNN	k-nearest neighbor
LSTM	long short-term memory
MAE	Mean absolute error
MAPE	Mean absolute percentage error
ML	Machine Learning
MSE	Mean squared error
OSM	Open Street Map
ReLU	Rectified Linear Unit
RF	Random forest
RMSE	Root mean square error
RMSProp	Root Mean Square Propagation
RNN	Recurrent neural network
SVM	support vector machines
XGBoost	Extreme Gradient Boosting