A Deep Learning Approach for Freeway Vehicle Speed and Flow Prediction

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Abstract

This paper presents an innovative approach to estimate short-term future traffic conditions based on historical data received from freeway sensors. These models can be used to provide road operators with predictive intelligence tools to help them optimise freeway operations and avoid traffic breakdowns. The proof-of-concepts presented in this paper apply deep learning Artificial Intelligence techniques using Backpropagation and Recurrent Neural Network architectures. These systems were trained, calibrated and validated using field data collected from a section of the Pacific Highway between Brisbane and the Gold Coast in Queensland. The input included historical individual driving speed and flow data at time (t) and the output represented short term prediction at (t+n) intervals where n ranges from 20 second to 60 minutes into the future. The results showed that Backpropagation deep learning predicted speeds up to 5 minutes into the future with a high degree of accuracy exceeding 90%. Their performance for longer time horizons and for flow predictions were not as reliable. The Recurrent Neural Network models, however, provided a high degree of accuracy for both speed (greater than 90%) and flow prediction (greater than 80%) up to 60 minutes into the future.

1 Introduction

New technologies and data analytics techniques are also increasingly allowing for innovative ways to 'sense' freeway networks. The fast pace of breakthroughs in these technologies, including artificial intelligence and machine learning solutions (Agatonovic-Kustrin and Beresford, 2000), is relentless and continues to unfold on many fronts. By determining when and how to take advantage of these technologies, Transport Authorities have unique opportunities to realise rapid improvements in reducing congestion, improving travel time reliability for its road users and customers, and enhancing the economic and infrastructure productivity of its vital assets.

This research will demonstrate the feasibility of using advanced AI-techniques based on deep learning neural networks to predict speed (km/h) and flow (veh/h) up to 60 minutes into the future. It will provide predictive capability in traffic management, rather

than relying on existing reactive traffic management systems which don't have any predictive capability. The system is developed using historical data extracted from sensors attached on a section of the Pacific Highway between Brisbane and Gold Coast in Queensland. These data are used as input to machine learning and AI algorithms for short-term predictions of speed and flow ranging from 20-second to 60-minute intervals using a commercially available tool NeuralWorks Professional.

This paper is organized as follows: Section 2 provides previous research work. Section 3, 4 and 5 highlight the modelling details of prediction algorithms. Section 6 evaluates the prediction results. Finally, the conclusion is presented in Section 7.

2 Previous Research

Different AI models have been proposed to use the traffic data collected by inductive loop detectors, CCTV, Probe Vehicles and incident reports. These data are used for short term prediction of traffic attributes ranging from 20 seconds to few hours into the future. Most of these studies showed good results during experiments in different locations as stated by Nguyen et al. (2018). They provide a comprehensive review of Deep learning techniques application in transport. Also, Abduljabbar et al. (2019) provide an overview of the AI techniques applied worldwide to address transportation problems mainly in traffic management, traffic safety, public transportation, and urban mobility. The overview concludes by addressing the challenges and limitations of AI applications in transport. Similar to that, Liyanage et al. (2019) address the importance of AI methods in Transport. In 1997, Ledoux (1997) predicted traffic flow up to 1 minute by using simulated data. Dia (2001) Develops object-oriented neural network model with Time-Lag Recurrent Network (TLRN) to predict speed for a freeway up to 15 minutes in the future. (Park et al., 2014) develop an intelligent Artificial Neural Network (ANN) System to predict spot speed along a selected route and trip speed profiles from an origin to destination of that route. However, Cheng et al. (2017) address driver's behaviour, weather condition and route type while predicting speed using deep learning algorithm and Adaptive Neuro-Fuzzy Inference System (ANFIS). According to Chen et al. (2018), a combination of two models is used to provide more accuracy in predicting traffic flow and minimise uncertainties within big data. The two models are: Fuzzy network and Deep learning Convolutional network (FDCN). Also, Multi-Long-Short Term Memory Models (MLSTMs) are presented to forecast traffic flow up to 20 minutes into the future (Xue and Xue, 2018). Polson and Sokolov (2017) state that deep learning provide a precise prediction of flow as they tested the technique on a road sensor data collected in a recurrent and non-recurrent congestion pattern roads in USA. In addition, Huang et al. (2014) implement a deep architecture that requires little prior knowledge of features by using deep belief network (DBN) to predict traffic flow. Lv et al. (2014) use unsupervised artificial neural network for the traffic flow prediction up to 60 minutes which is a stack of autoencoders named (SAE) model. Also, Wu et al. (2018) develop a deep learning model to predict traffic flow in the future state considering the tempo-spatial road characteristics. On the other hand, Yan et al. (2018) predict speed using deep learning neural network. Zhang et al. (2019) present a deep learning based Multitask Learning (MTL) model with Gated Recurrent Units (GRU) to address this issue during speed prediction. According to Jin and Sun (2008), MTL models are also effective in predicting traffic flow when trained using BP algorithm. Whereas, Nguyen et al. (2019) predict travel speed up to 30 minutes in advance using Non-parametric deep learning methods in arterial road networks which is more challenging. Moreover, Mozaffari et al. (2015) develop a hybrid system called

evolutionary least learning machine (E-LLM) and mutable smart bee algorithm (MSBA) to forecast the vehicle time series speed data. (Wang et al., 2019) predict traffic speed using stacked layers of bidirectional long short-term memory neural network (Bi-LSTM NN). More et al. (2016) predict traffic flow with a maximum accuracy using Jordan's neural network. Held et al. (2018) use demographic and Geographic data to predict future mobility demand in Switzerland. Van Lint et al. (2005) Predict travel time using state-space neural network (SSNN).

3   Data for Model Development

The data used for the development of AI models are based on field data collected from a section of the Pacific Highway between Brisbane and Gold Coast in Queensland (Dia 2001). These data were collected for a period of 5 hours (2 hours peak and 3 hours off-peak) conditions. 5,000 observations were gathered and for this research they were divided into 60% training (3,000) sets and 40% testing and validation sets (2,000). See figure 1.

Figure 1: Section of the Pacific Highway between Brisbane and Gold Coast (Dia 2001)
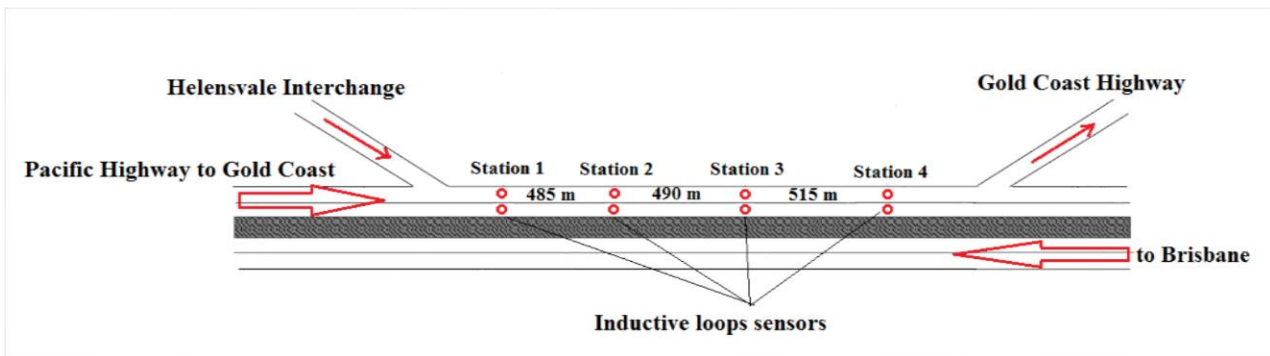
4   Deep Learning Backpropagation system

The model is developed using NeuralWorks Professional Software. Backpropagation is an algorithm used for the training purposes of Artificial Neural Networks' models. The network will use speed (km/h) and flow (veh/h) individually to test the model. First speed is used as the input for the prediction purposes. For this model. There are four layers to be specified: one input layer with 1 PEs, first hidden layer with 6 Pes, second hidden layer with 4 Pes, Third hidden layer with 2 Pes and an output layer with 1 Pes as shown in Figure 2. It should be mentioned here that any neural network architecture with more than one hidden layer is classified as a Deep Learning System.

Figure 2: Predictive Deep learning system representation for speed and flow (source: authors)
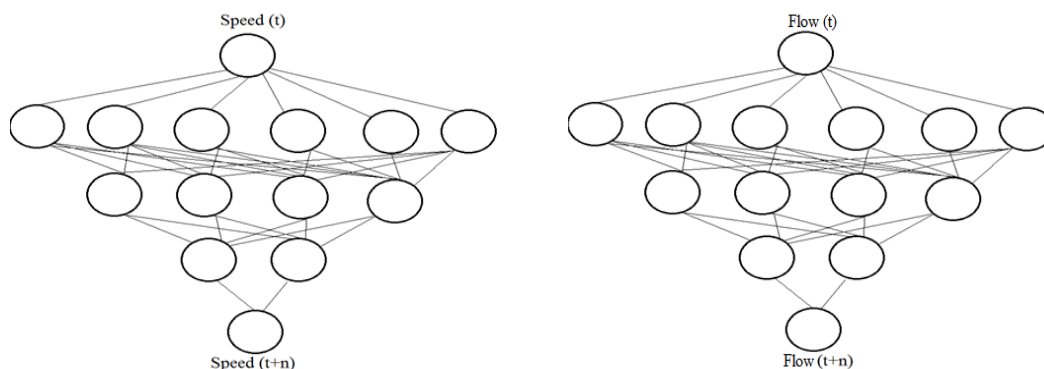
As can be noted above, Deep Learning Neural Network System is able to predict speed with good accuracy. However, the results for flow were poor and needed to be further investigated and tested. To improve the flow results, Exponential Smoothing Method is applied on the original time series data of flow.The results are shown in Table 1.

Table 1: Speed performance for different prediction horizons.

| Prediction Horizon	Average Error %	average Accuracy %	Average Error %	average Accuracy%	Average Error %	average Accuracy%
	Speed	Speed	Flow(without smoothing)	Flow (without Smoothing)	Flow(with smoothing)	Flow(with smoothing)
20 Second	6.6	93.4	41.5	58.5	14.8	85.2
40 Second	7.1	92.9	39.2	60.8	18.4	81.6
60 Second	7.6	92.4	37.1	62.9	19.6	80.4
2 Minutes	8.4	91.6	37.0	63.0	20.4	79.6
3 Minutes	8.7	91.3	37.3	62.7	21.6	78.4
4 Minutes	9.2	90.8	37.4	62.6	21.4	78.7
5 Minutes	10.0	90.0	34.1	65.9	21.3	78.8
10 Minutes	12.6	87.4	40.5	59.5	22.2	77.8
15 Minutes	14.2	85.9	38.6	61.4	22.7	77.3
30 Minutes	15.5	84.5	39.6	60.4	24.9	75.1
45 Minutes	15.8	84.2	40.3	59.7	26.5	73.6
60 Minutes	15.8	84.2	41.4	58.6	29.0	71.0

5   Recurrent Neural Network Systems (RNNs)

RNNs are feedforward neural networks that performs well with time series forecasting dataSpeed / Flow Prediction.The network will use speed (km/h) and flow (afrer smoothing) (veh/h) individually to test the model as shown in Figure 3.

Figure 3: Predictive Recurrent system representation for speed and flow (source: authors).
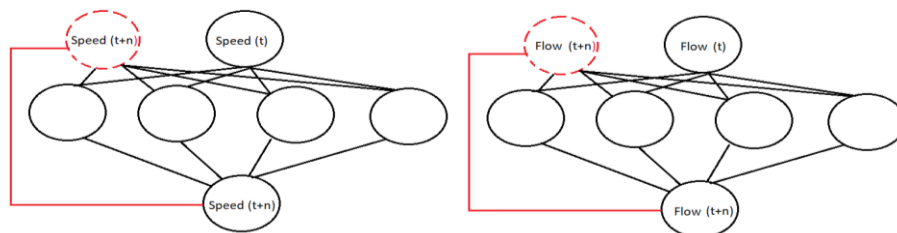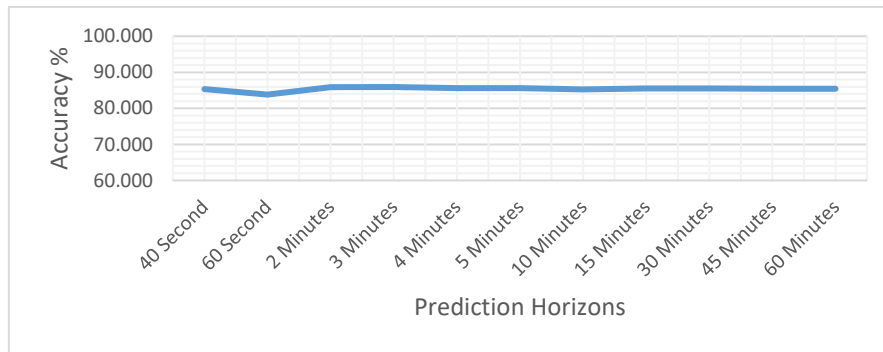

The results of the model are shown in figures below.

Figure 4: Prediction Results for Speed (km/h) (source: authors).
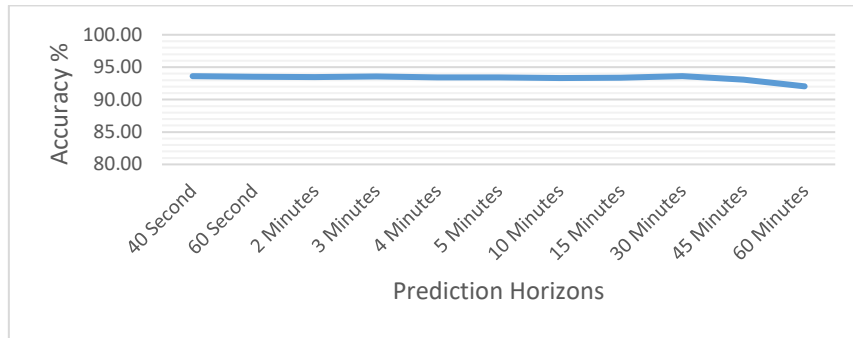
Figure 5: Prediction Results for flow (veh/h) after smoothing (source: authors).

6 Evaluation of Results

The results show that BP neural network is able to predict the speed up to 5 minutes with a level of accuracy of 90%. The use of RNN further improved the results for speed up to 60 minutes with an accuracy of 92%. On the other hand, the results don't look promising when the model trained to predict flow (veh/h) using BP network. For this reason, Exponential smoothing method applied to flow data to enhance the performance of BP. The results improved to predict with 85% of accuracy for 20 second interval to 70% for 1 hour interval. In addition. Flow was tested on RNNs and the results shows that RNNs outperformed BP when predicting speed and flow.

7 Closing Remarks

In this paper, Deep learning BP and Recurrent Neural Network systems are developed to predict speed and flow profiles on a section of the Pacific Highway between Brisbane and Gold Coast. The models were evaluated based on historical field data collected from inductive loop sensors. The results demonstrate the feasibility of applying deep Neural BP Network for speed prediction purposes. The same procedure was repeated to predict flow but the model wasn't capable of providing good prediction. However, Exponential smoothing method was used on flow data which improved the accuracy. The results remarkably improved further for both speed and flow following RNN models. The system was able to predict up to 60 minutes into the future with a higher accuracy than BP for both speed and flow. Future directions in this research include investigating more architectures to improve the accuracy for both speed and flow. Also, collection of more updated data from other real-life freeways in Melbourne and other cities to demonstrate the feasibility of applying predictive Neural Network systems using larger amounts of data for model training, and validation of model performance.

8 Acknowledgment

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