

Deep Learning Based Proactive Multi-Objective Eco-Routing Strategies for Connected & Automated Vehicles

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SUPPLEMENTARY MATERIAL

APPENDIX A DATA COLLECTION

This step was essential for the development of the predictive models of GHG ER and speed. The quality of the collected data contributes to how reflective the predictive models are. The data points were extracted from an agent-based traffic model developed by Djavadian and Farooq (2018).

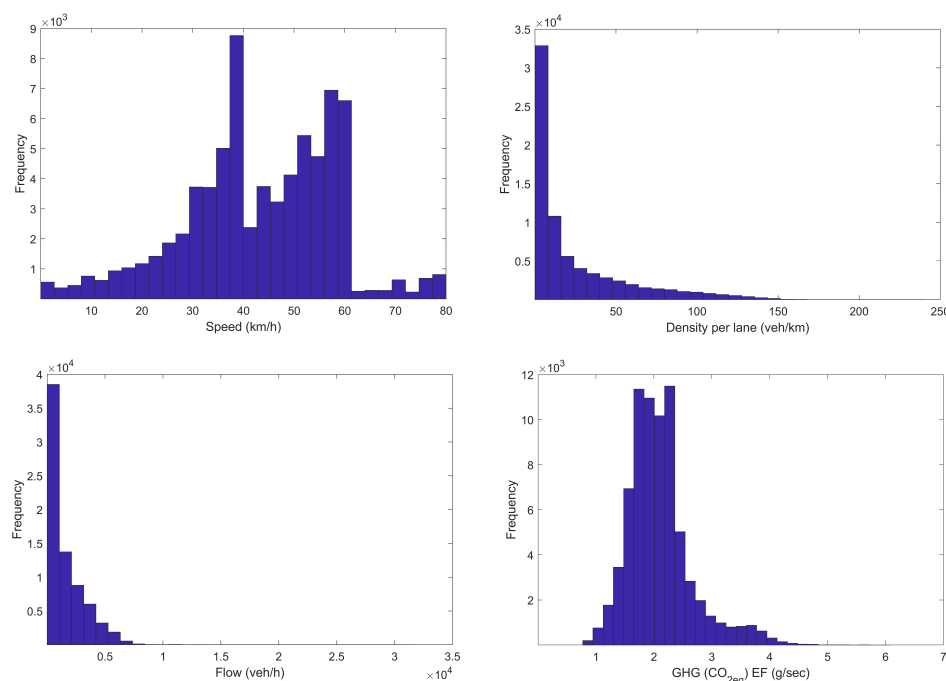


Figure A.1. Histogram of (A) speed, (B) density per lane, (C) flow, and (D) GHG ERs (in CO_{2eq} g/sec)

The demand was synthesized based on actual data from the Transportation Tomorrow Survey (TTS). To train the LSTM networks, 80% of the data was employed, while 20% was used for testing. The training and testing sets consist of 48,652 and 12,159 data points, respectively, for the LSTM predictive models. The

high level of heterogeneity of the traffic and environmental variables contributes to more generic predictive models.

A wide variety of traffic and environmental conditions were captured and used for training the predictive models. To produce different traffic conditions, different demand levels and different departure time distributions were adopted. The number of vehicles varied from 2,437 to 6,988, representing 0.7 to 2 times the actual demand in the year 2014. The employed departure time distributions, to generate the data, were exponential, uniform, and normal. Figure A.1 illustrates the statistical analysis of the three profound traffic variables, speed, flow, and density in addition to the GHG ER in the employed data set for training the LSTM network. Figure A.1A shows that the mode and average are 40 km/h and 56.16 km/h, respectively. Speed range is from 0 to 80 km/h. Density (veh/km.lane) as in Figure A.1B and flow (veh/h) as in Figure A.1C represent different traffic conditions due to the wide range of their values. Finally, GHG ER (in $\text{CO}_{2\text{eq}}$) starts from less than 1 g/sec to more than 5 g/sec as in Figure A.1D.

APPENDIX B CORRELATION ANALYSIS OF PREDICTIVE VARIABLES

In this section, the correlation analysis of GHG ER and speed is presented in order. This analysis was an essential step for reliably selecting the predictors and number of sequences of the developed LSTM model of GHG ER and speed prediction.



Figure B.1. Correlation between the proposed variables at every minute from 1 to 5 (top to bottom) with GHG ER at the 6th minute

A comprehensive list of variables has been assessed to develop reliable predictive models. Not only the link characteristics (speed, density, flow, delay (difference between free flow travel time and actual travel time), and GHG ER, but also the in-links characteristics (speed, density, and flow) were included for the correlation analysis. The in-links characteristics were included to enhance the spatial dimension. The traffic state at the current time step on upstream links implies how traffic condition would be on downstream

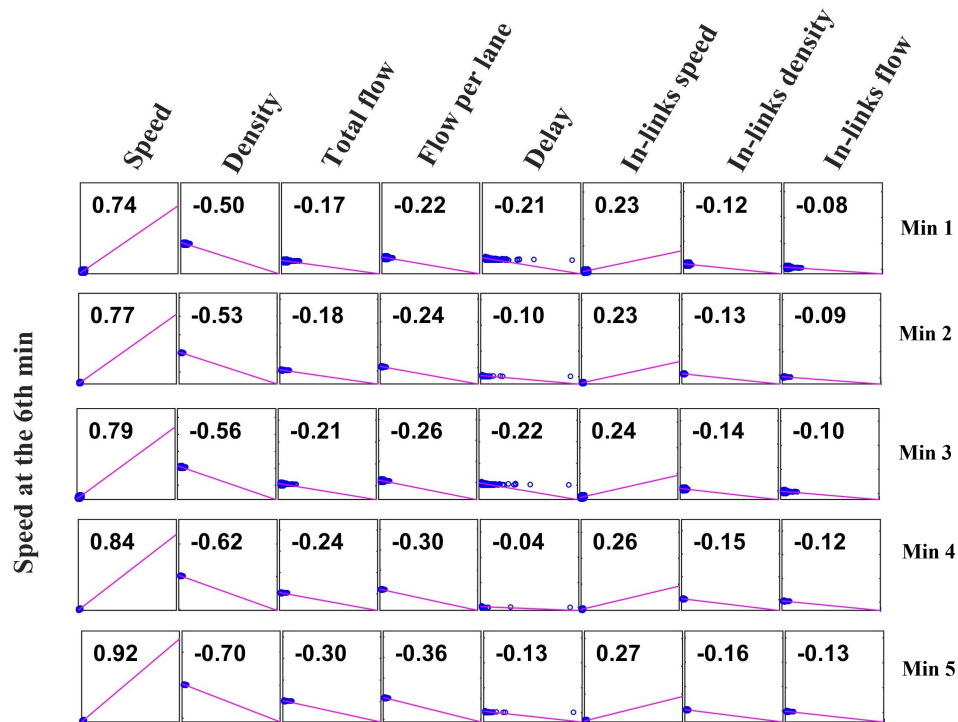


Figure B.2. Correlation between the proposed variables at every minute from 1 to 5 (top to bottom) with speed at the 6th minute

links at the future time step. Five time steps (minutes) were considered for this analysis as within the aforementioned period modifications in the traffic state were detected. The maximum link length in the network is around 450 meters. The speed range is from 0 to 80 km/h. Under the free flow traffic condition, the maximum travel time required to traverse a link is around 0.8 minute. While when the network is congested travel time increases on links. This explains why five minutes were chosen for the correlation analysis.

B.1 Correlation analysis of GHG ER

For this analysis, speed, density, flow, delay (difference between free flow travel time and actual travel time), in-links speed, in-links density, in-links flow, and GHG ER (in $\text{CO}_{2\text{eq}}$ g/sec) were the examined variables.

Figure B.1 shows that the absolute value of the correlation coefficient increases between all of the variables except for the delay from minute 1 to minute 5 (top to bottom) and the GHG ER (in $\text{CO}_{2\text{eq}}$ g/sec) at the sixth minute.

Speed is the most correlated variable with the GHG ER at the sixth minute, followed by GHG ER (in $\text{CO}_{2\text{eq}}$ g/sec), density, in-links speed, and the rest of the variables. GHG emissions estimation depends mainly on speed, which justifies the high correlation between GHG ER and speed. The high correlation between GHG ER and density is due to the relationship between speed and density, which is monotonically decreasing. Among the in-links variables, speed is the mostly correlated with GHG ER on the downstream links. Speed on in-links at the current time step implies what the speed at the future time step would be on a studied link. To obtain the best outcome, different sets of predictors and number of sequences (minutes)

have been assessed.

B.2 Correlation analysis of speed

For this correlation analysis, speed, density, flow, and delay (difference between free flow travel time and actual travel time)), in-links speed, in-links density, and in-links flow were included. Figure B.2 shows the linear correlation between speed at the sixth minute and both the traffic and environmental indicators of the previous five minutes. Figure B.2 shows an increase in the correlation factor of all the variables and minutes, except for delay. The top four highly correlated variables with speed at the sixth minute are speed, density, flow per lane, and in-links speed. The high correlation coefficient with density and flow of 0.70 and 0.36, respectively, is based on the correlation between the three variables shown in the transportation fundamental diagrams, speed, density, and flow. Speed and density are associated with a monotonically decreasing relationship.

REFERENCES

Djavadian, S. and Farooq, B. (2018). Distributed dynamic routing using network of intelligent intersections. In *ITS Canada ACGM (2018)* (Niagara Falls, Canada)