LSTM Approach for Spatial Extension of Traffic Sensor Points in Urban Road Network

Arthur Couto Piazzi[1] and Tamás Tettamanti[1]

Abstract— **In order to have a well-established Intelligent Transportation System, it is essential to have real-time traffic data across the network. The growing adoption of smart mobility technologies led to an even greater need for monitoring all road links in a network. However, placing more sensors could represent a more complete set of information, installing and maintaining them across whole networks is not a cost-effective approach. Consequently, large traffic networks tend to limit the monitoring to only critical road links. In order to address this issue, the paper aims to virtualize the measurements on routes without traffic detectors by implementing machine learning based models. The presented method uses the information from monitored road links as input to the deep learning model and estimates virtual measurements on unmonitored ones. A Long Short Term Memory Neural Network architecture was implemented and the Bayesian optimization was the chosen method to tune the hyperparameters of the models. The prediction techniques were developed and tested taking into consideration the mobility of each individual vehicle, i.e. by using microscopic road traffic simulation.**

Index Terms— **traffic sensors, artificial neural networks, LSTM, spatial extension**

I. INTRODUCTION

The availability of real-time traffic flow data is crucial in the implementation of any control strategy on road networks. Without reliable traffic monitoring system, an Intelligent Transportation System (ITS) cannot operate properly. The monitoring system should gather and transmit data to a centralized information system or a control room, allowing any traffic control strategy to be implemented [1]. Additionally, due to the increasing penetration of connected and automated vehicles into the roads, ITS has been presenting growing importance nowadays [2].

The acquisition of traffic data, such as traffic flow, densities, and speeds, requires different types of sensors. Although new measurement technologies for traffic monitoring systems were developed in the last decades (Floating Car Data (FCD) and Floating Mobile Data (FMD), for example) [3], several systems still depend exclusively or mainly on traditional cross-sectional sensors, e.g. loop detectors and magnetic sensors. One of the reasons is that different measurement systems have problems handling inhomogeneous data, such as a difference in time aggregation and location availability and different semantics [4].

For dense networks, e.g. in urban contexts, the traffic monitoring system based on cross sectional sensors cannot provide an accurate assessment of the whole network. For economic reasons, only a fraction of links will present detection points. In other words, there is a compromise between the budget addressed to install and maintain all sensors and the reliability expected from the monitoring system.

In this paper, an Artificial Intelligence based methodology for spatially extending traffic data and, as a result, improving the quality of the monitoring system is proposed. By using the information from monitored links it is possible to infer the values of unmonitored ones. To the best of our knowledge, there were only three other papers proposing similar approaches, [5], [1], [6]. In the next section, the strength and weakness of those works will be discussed.

II. PRELIMINARIES

Artificial Intelligence (AI) based methods have been widely used to support several activities in the transportation field. One prominent example of AI use in transportation is traffic estimation, and inside the field Neural Networks (NNs) based models stand out as the most researched one, as pointed out in [7].

Traffic estimation can fall into two categories i) Temporal estimation (long or short-term prediction, being the latter more relevant and advanced) and ii) Spatial estimation (extension of traffic data links to links) [8]. The temporal extension is beyond the scope of this paper, therefore, the literature review regarding this category will be omitted. A thorough literature review about this topic can be found in [7], [8], [9]. The research intensity and the results achieved in them, evidence the ability of learn traffic dynamics from data.

On the one hand, leveraging data to predict future values is a very mature and well-established field. On the other hand, spatial extension research is still very embryonic. Even though this subject has been studied for a long time, in the 1980s, [10] proposed a method of updating the Origin-Destination (OD) matrix based on traffic counts and estimating link flows using assignment algorithms. But limitations in the updating proceeding of OD matrices were exposed in [11].

In [12] a spatial extension of sorts was proposed as well. Focusing on mitigating the costs of communication in a wireless sensor network, spatial correlation between sensors was studied allowing temporal shifting among them. The study showed that 20 of the 112 sensors present in the city of Cambridge (U.K.) could be removed and their measurements would be derived from the others with acceptable error margin.

[1]Dept. of Control for Transportation and Vehicle Systems, Budapest University of Technology and Economics, Budapest, Hungary {piazzi.arthur, tettamanti}@mail.bme.hu

However, the use of AI to solve the previously mentioned task was not investigated until recently. By employing shallow Neural Network to perform the extension of traffic flow in a synthetic grid network, [5] was the pioneer in that topic. The feature construction was manually performed based on empirical knowledge of traffic behavior. Further work was depicted in [6], comparing several regression methods, such as Linear Regression, Kernel Regression, Support Vector Machine, Generalized Least Squares, and NN, for the same grid network.

In [1] simulations were carried out in a network representing the city of Benevento in the South of Italy. The monitored links in the network were selected to match the traffic surveys realized during the drafting of the Urban Traffic Plan of Benevento. Again the shallow Neural Network was employed to effectuate the extension, attaining good fitting characteristics with a coefficient of determination $R^2 = 0.978$ in the best link.

III. SIMULATION

The research work was supported by traffic simulations carried out in SUMO (Simulation of Urban Mobility) which is a high fidelity microscopic traffic simulation software [13]. A grid network with 80 road links was used for the simulation. The demand patterns which generated the flows in the network were randomized and varied during the simulation. Moreover, the perimeter edges in the corners of the network were considered as possible origin-destination points. The choice of the traffic network and the origin-destination points was made to match the setup used by [5], providing a baseline for comparison.

To build up the training and testing database, 30 simulations were performed, each one lasting one day. The values were aggregated in 60 seconds interval.

Although short sampling intervals typically produce noisy data [14], monitoring systems are usually set up for aggregation intervals between 5 and 10 minutes [15]. For that reason, the values were aggregated in 10 minutes intervals using a moving average filter (MAF) for less erratic data (in [16] several digital filtering techniques were investigated for smoothing loop detector data, including MAF, similarly, in this work, MAF was chosen due to its simplicity).

IV. PROPOSED APPROACH

In this section, the employed Deep Learning model, the parameter optimization process as well as the feature engineering procedure will be introduced.

A. Deep Learning models

The works depicted previously, consist in the state-of-art for the considered task since they are the only approaches proposed until this date. Regarding the input of these models, the current value of monitored links was used. In this way, the temporal relationship is not leveraged in the inference process.

In the scope of traffic flow short-term forecasting, several approaches based on Long Short Term Memory (LSTM) neural network were proposed, such as [17], [18], and yield promising results. LSTM Neural Networks is a type of Recurrent Neural Network widely used in time series related problems [19].

B. Bayesian hyperparameter optimization

Neural Network based methods performance can be very sensitive to hyperparameter setting (e.g. number of neurons, dropout rate, regularization rate). This parameterization can be performed manually based on empiric knowledge allied with trial and error fine-tuning, even though it is a common and valid practice it does not assure an optimal solution.

In the realm of automated hyperparameter optimization grid search is the most straightforward, realizing an exhaustive search through a manually specified subset of the hyperparameter combination, which can be very time-consuming. Random search takes points randomized instead of evenly spaced like grid search does [20].

Evolutionary optimization can tune up deep learning models thoroughness, achieving new benchmarks in several fields like exposed in [21], but the computational burden still limits this approach.

Bayesian search presents a viable solution in fine-tuning deep learning models, requiring acceptable computing power and great optimization capabilities [22]. In general lines, the performance of the deep learning model is assumed to be a Gaussian process, expressed by the surrogate function $g(.)$ dependent of the hyperparameters θ. The optimization process is defined by:

$$\theta^* = arg \max_{\theta \in \Theta} g(\theta) \tag{1}$$

where Θ corresponds to the domain of the parameters.

The guesses of θ can be made in a more informed manner, choosing the best performing point in the surrogate function $g(.)$, evaluating in the model and updating $g(.)$ iteratively until the maximum iteration or other stop criteria is met.

In the paper, a Bayesian search was applied to find the optimal parameters of the LSTM architecture (i.e. number of neurons, dropout rate). Since, changing the number of layers introduces new parameters to the optimization process, such as a new number of neurons, be optimization of the number of layers together with other parameters is not recommended. In this way, the choice of numbers of hidden layers was made exhaustively, varying from 1 to 3 hidden layers.

Initial results have shown that time window size variation (i.e. number of time steps into the past) of the LSTM input sequence introduces disruptive differences into further parameters (e.g. number of neurons) and model performance. A fact which compromises the optimization process, for this reason, the window size was also searched exhaustively with values varying from 2 to 20.

C. Edge selection

The process of edge selection consists of a crucial step to the overall performance of spatial extension. The grid network focus of this work presents 80 links. Even for this small scale network, the number of possible input/output combinations exceeds 1.2×10^{24} if the ratio of monitored and unmonitored links is not set, and if a fixed ratio the possibilities can surpass 10^{23}.

In a real traffic network sensors are opportunely located to provide maximum information about the network. In [23] a two-stage approach was proposed to maximize OD flow coverage dealing with uncertainty. In the paper, a different approach was adopted.

The link selection was made in a constructive manner, starting from a very small number of monitored links (the eight corner links). The unmonitored link that presented the worse performance in this configuration was considered to be monitored in the next iteration. The process continued until stop criteria were met.

The Bayesian optimization showed similar results between iterations, for that reason it was only performed when a stagnation or loss in performance was noticed.

V. Numerical Results

In this section, the results achieved by the depicted approach of section IV are presented. All the results presented below are regarded to the testing set, which corresponds to 20% of the whole data set. The traffic variable chosen as target of the prediction was average traffic speed of the given road link (i.e. space mean speed). The speed values were normalized in a standard score manner, setting the values to present zero mean and the standard deviation equal to one before the training process.

The results are presented in terms of the coefficient of determination R^2, the maximum value of R^2 is 1 (when the model can perfectly reproduce the observed data) and not bounded inferiorly. For each road link R^2 can be defined by equation (2):

$$R^2 = 1 - \sum_i \frac{(y_i - v_i)^2}{(y_i - \bar{y})^2} \tag{2}$$

where v is the predicted speed in a specific link, i is the index of the value in the test dataset, y and $\bar{y}$ are the observed data in the specific link and the average value respectively. The overall R^2 score can be calculated as the average of all links R^2 across the output links.

A. Edge selection results

Naturally, as well as in traditional monitoring systems, there is a positive correlation between the number of monitored points and the monitoring quality. Firstly, a greater number of monitored links provide more information about the network and therefore enabling better estimations. Secondly, a smaller number of unmonitored links simplifies the task in hand. Fig. 1 shows the evolution of the overall performance and the performance of the best and worst links with respect to the ratio of monitoring links for the LSTM model.

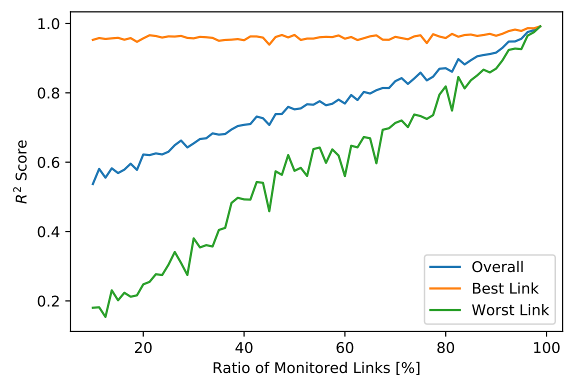

Fig. 1. Evolution of performance according to the ratio of monitored links: LSTM Neural Network

B. Model validation

In order to validate the proposed approach, the method was tested against traditional Artificial Neural Network (ANN) and Time Lagged Neural Network (TLNN). Both approaches were also optimized via Bayesian search. Additionally to the parameters in the LSTM architecture, regularization rate and type, and activation function type were optimized.

The input/output configuration considered to established the comparison between models were the first configuration which yielded overall performance above 0.8. This outcome was achieved with 63.75% of monitored links in the network.

Table I shows the Bayesian optimization parameter results and the numerical results generated by this configuration in terms of best, worst and overall R^2 score.

It can be observed that approaches that take into consideration past values (LSTM and TLNN) outperforms approaches which consider only instant values. The LSTM model presented itself superior among others models, achieving not only better estimations in all links in network, but also more concise results with less dispersion.

For the LSTM model, the optimization process rejected the use of dropout between layers, which corroborates the results found in [24], disfavoring the use of per element dropout in LSTM networks. Both LSTM and TLNN agreed on the time window size, showing 8 time steps as optimal window size for the estimation.

Although the ANN models could effectually achieve acceptable results on the best-performing link, only LSTM could maintain acceptable average results. The results for the worst link in the LSTM model were superior to the average results of the ANN approach, which is up until this date is the benchmark in the application.

VI. Conclusions

In this paper, a spatial extension of monitoring points was realized using Long Short Term Memory Neural Network. Spatial extension of traffic data via Artificial Intelligence configures a great opportunity for monitoring systems. Once

TABLE I

PARAMETERIZATION AND RESULTS BETWEEN APPROACHES

	LSTM			TLNN			ANN		
Number of neurons	[127, 47]			[59, 59, 47]			[25,11]		
Number of hidden layers	2			3			2		
Time Window	8			8			1		
Activation type	Relu			Sigmoid			Tanh		
Regularization type	-			l2			l1		
Regularization rate	-			[0.0, 0.05, 0.0]			[0.0, 0.0]		
Dropout rate	[0.0, 0.0]			[0.0, 0.218, 0.0]			[0.0, 0.0]		
	Worst	Overall	Best	Worst	Overall	Best	Worst	Overall	Best
Result	0.685	0.805	0.953	0.616	0.745	0.952	0.198	0.633	0.943

it is capable of increasing system coverage without aggregating additional costs. This proposed strategy overcome the current alternatives available in the literature.

As future research directions, the authors recommend:

- Perform extension in different traffic networks, including case studies in real networks.
- Investigate different deep learning approaches.
- Include measurement errors and data incompleteness to evaluate the robustness of the model.

VII. ACKNOWLEDGMENT

The project has been supported by the European Union, co-financed by the European Social Fund. EFOP-3.6.2-16-2017-00002

REFERENCES

[1] M. Gallo and G. De Luca, "Spatial extension of road traffic sensor data with artificial neural networks," *Sensors*, vol. 18, no. 8, p. 2640, 2018.

[2] Z. Szalay, . Nyerges, Z. Hamar, and M. Hesz, "Technical specification methodology for an automotive proving ground dedicated to connected and automated vehicles," *Periodica Polytechnica Transportation Engineering*, vol. 45, no. 3, pp. 168–174, 2017. [Online]. Available: https://pp.bme.hu/tr/article/view/10708

[3] E. I. Vlahogianni, M. G. Karlaftis, and J. C. Golias, "Short-term traffic forecasting: Where we are and where were going," *Transportation Research Part C: Emerging Technologies*, vol. 43, pp. 3–19, 2014.

[4] T. Tettamanti, M. Horváth, and I. Varga, "Road traffic measurement and related data fusion methodology for traffic estimation," *Transport and Telecommunication*, vol. 15, no. 4, pp. 269–279, 2014.

[5] M. Gallo, F. Simonelli, G. De Luca, and C. Della Porta, "An artificial neural network approach for spatially extending road traffic monitoring measures," in *Environmental, Energy, and Structural Monitoring Systems (EESMS), 2016 IEEE Workshop on*. IEEE, 2016, pp. 1–5.

[6] R. Iannella, M. Gallo, G. De Luca, and F. Simonelli, "Regression methods for spatially extending traffic data," *INTERNATIONAL JOURNAL OF ENGINEERING, TECHNOLOGY MANAGEMENT & APPLIED SCIENCES*, vol. 5, pp. 5–14, 2017.

[7] L. N. Do, N. Taherifar, and H. L. Vu, "Survey of neural network-based models for short-term traffic state prediction," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 9, no. 1, p. e1285, 2019.

[8] G. De Luca and M. Gallo, "Artificial neural networks for forecasting user flows in transportation networks: Literature review, limits, potentialities and open challenges," in *Models and Technologies for Intelligent Transportation Systems (MT-ITS), 2017 5th IEEE International Conference on*. IEEE, 2017, pp. 919–923.

[9] I. Lana, J. Del Ser, M. Velez, and E. I. Vlahogianni, "Road traffic forecasting: Recent advances and new challenges," *IEEE Intelligent Transportation Systems Magazine*, vol. 10, no. 2, pp. 93–109, 2018.

[10] E. Cascetta, "Estimation of trip matrices from traffic counts and survey data: a generalized least squares estimator," *Transportation Research Part B: Methodological*, vol. 18, no. 4-5, pp. 289–299, 1984.

[11] V. Marzano, A. Papola, and F. Simonelli, "Limits and perspectives of effective o–d matrix correction using traffic counts," *Transportation Research Part C: Emerging Technologies*, vol. 17, no. 2, pp. 120–132, 2009.

[12] A. Skordylis, A. Guitton, and N. Trigoni, "Correlation-based data dissemination in traffic monitoring sensor networks," in *Proceedings of the 2006 ACM CoNEXT conference*. ACM, 2006, p. 42.

[13] P. A. Lopez, M. Behrisch, L. Bieker-Walz, J. Erdmann, Y. Fltterd, R. Hilbrich, L. Lcken, J. Rummel, P. Wagner, and E. WieBner, "Microscopic traffic simulation using sumo," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, Nov 2018, pp. 2575–2582.

[14] P. K. Houpt, M. Athans, D. G. Orlhac, W. J. Mitchell, *et al.*, "Traffic surveillance data processing in urban freeway corridors using kalman filter techniques," United States. Dept. of Transportation. Research and Special Programs , Tech. Rep., 1978.

[15] D. Park, S. You, J. Rho, H. Cho, and K. Lee, "Investigating optimal aggregation interval sizes of loop detector data for freeway travel-time estimation and prediction," *Canadian Journal of Civil Engineering*, vol. 36, no. 4, pp. 580–591, 2009.

[16] B. Coifman, "New methodology for smoothing freeway loop detector data: introduction to digital filtering," *Transportation Research Record: Journal of the Transportation Research Board*, no. 1554, pp. 142–152, 1996.

[17] Y. Wu and H. Tan, "Short-term traffic flow forecasting with spatial-temporal correlation in a hybrid deep learning framework," *arXiv preprint arXiv:1612.01022*, 2016.

[18] Z. Zhao, W. Chen, X. Wu, P. C. Chen, and J. Liu, "Lstm network: a deep learning approach for short-term traffic forecast," *IET Intelligent Transport Systems*, vol. 11, no. 2, pp. 68–75, 2017.

[19] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[20] L. Rastrigin, "The convergence of the random search method in the extremal control of a many parameter system," *Automaton & Remote Control*, vol. 24, pp. 1337–1342, 1963.

[21] R. Miikkulainen, J. Liang, E. Meyerson, A. Rawal, D. Fink, O. Francon, B. Raju, H. Shahrzad, A. Navruzyan, N. Duffy, *et al.*, "Evolving deep neural networks," in *Artificial Intelligence in the Age of Neural Networks and Brain Computing*. Elsevier, 2019, pp. 293–312.

[22] J. Snoek, H. Larochelle, and R. P. Adams, "Practical bayesian optimization of machine learning algorithms," in *Advances in neural information processing systems*, 2012, pp. 2951–2959.

[23] X. Fei, H. S. Mahmassani, and P. Murray-Tuite, "Vehicular network sensor placement optimization under uncertainty," *Transportation Research Part C: Emerging Technologies*, vol. 29, pp. 14–31, 2013.

[24] G. Cheng, V. Peddinti, D. Povey, V. Manohar, S. Khudanpur, and Y. Yan, "An exploration of dropout with lstms," in *Proc. Interspeech*, 2017.