Adapting Traffic Simulation for Traffic Management: A Neural Network Approach

Benjamin N. Passow, David Elizondo, Francisco Chiclana, Simon Witheridge and Eric Goodyer

***Abstract*— Static models and simulations are commonly used in urban traffic management but none feature a dynamic element for near real-time traffic control. This work presents an artificial neural network forecaster methodology applied to traffic flow condition prediction. The spatially distributed architecture uses life-long learning with a novel adaptive Artificial Neural Network based filter to detect and remove outliers from training data. The system has been designed to support traffic engineers in their decision making to react to traffic conditions before they get out of control.**

We performed experiments using feed-forward backpropagation, cascade-forward back-propagation, radial basis, and generalized regression Artificial Neural Networks for this purpose. Test results on actual data collected from the city of Leicester, UK, confirm our approach to deliver suitable forecasts.

I. INTRODUCTION

It is well known that the rapid growth of road traffic places a heavy burden on the existing road networks. Traffic forecasting can provide early warnings of potential bottlenecks before they become a problem [1], [2], [3]. The forecasts can be used to warn and inform drivers [4] and in Urban Traffic Management and Control to influence traffic before congestion builds up [5], [6], [7]. Static traffic macro-simulations are commonly used for planning traffic signalling strategies and long-term transport plans. However, urban traffic, as most live transport systems, is dynamic and evolves over time. Therefore, a static simulation does not provide the appropriate means to test and adapt traffic light signalling strategies in near real-time.

This paper presents novel methodologies for near real-time traffic simulation and management using a spatially distributed adaptive predictor network with life-long learning and an ANN based adaptive data filter technique. The system has been designed to support traffic engineers in their decision making to react to changing network conditions before gridlock and other adverse effects can form.

The rest of the paper is organised as follows: Section II presents background information on traffic simulation and management and reviews related research. Section III provides an overview of the research objectives. Section IV introduces the proposed techniques. Section V presents results from experiments testing the proposed methodology. Conclusions are drawn in Section VI, while Section VII suggests future research work.

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II. BACKGROUND

This section presents background information and related relevant literature on urban traffic management and control, traffic simulation and forecasting as well as data filtering.

A. Urban Traffic Management and Control

A first approach to controlling the traffic in an urban environment involves the analysis of the environment and its implementation in a model for specific times such as the AM and PM peaks. These static models are then used to plan traffic light signalling scenarios [8]. An advanced version of such a based static model is often put together in the form of a macro-simulation and is commonly used in large-scale transport planning [9], [10].

The Urban Traffic Management and Control (UTMC) system collects information about the current situation in the urban environment, such as traffic flow (defined as passenger car units per hour, PCU/h for this paper) and delay via inductive street loops, car park information, and CCTV feeds. This information is made available to traffic engineers monitoring and managing the network.

Although in theory the collected information enables the traffic engineers to react to a variety of situations, most often, only few standard traffic light configurations are used. This is because traffic light signalling in a large urban network is an extremely difficult and complex task where a small change can have a big impact on the whole network [8]. Standard traffic light signalling configurations are carefully designed using a variety of techniques such as modelling, simulation and "green wave" offset adaptation [11]. Such static models are then manually revised. Systems such as SCOOT further adapt some aspects of the traffic light signalling [12].

A vast amount of research has been done on ANNs for traffic forecasting. Ishak and Alecsandru [14] provided a comparison of ANN methods in a study aimed at optimising their performance in forecasting vehicle speed. A useful contribution of this work is the incorporation of a long-term memory component into the input data patterns to help the ANN recognise recurrent patterns that emerge on a day-to-day basis.

An architecture for making real-time traffic information available over the Internet is illustrated in [16]. Part of their work includes using ANNs to interpolate the data from real-time traffic detectors in order to arrive at a global picture of the traffic on a network.

B. Micro versus Macro Simulation

Micro-simulations usually model a small area in great detail, allowing the study of individual motorist and pedestrian behaviors for various scenarios, such as adapting traffic light signalling. Much research has been done on such simulations as they provide the required level of detail, and can be adapted to fit actual conditions in near real-time [17].

Macro-simulations on the other hand are commonly used in large-scale transport planning [18] and contain the information to model the whole urban environment at once [9], [10]. As such these models are carefully built from detailed city plans, historic traffic data, comprehensive driver surveys, and thorough analysis of the combination of all that data. Such macro-simulations are then validated for the required time periods (AM and PM peaks, and sometimes inter-peak (IP)) and built for a number of estimated future scenarios. Macro-simulations are driven by demand definitions such as an Origin-Destination matrix, which is usually static. This means that each day of the week will have one set of demand profiles for the peak and inter-peak periods.

In this paper, the macro-simulator SATURN has been used [19]. It is a combined traffic simulation and assignment model that can handle very large networks whilst being suitable for the analysis of very minor network changes e.g. to adapt traffic light signalling strategies. SATURN was selected as a highly detailed and accurate model of Leicester and the surrounding area already exists.

C. Traffic Condition Forecasting

Forecasting of traffic conditions, such as travel time, queueing time and number of stops, is important for better management and planning of existing infrastructure. These rough predictions are very useful for transport planning but lack accuracy for more detailed traffic management.

Short term traffic condition forecasting can be very useful to react to imminent problems before they happen. Such forecasting is usually more accurate than long term predictions. Nevertheless, incidents such as accidents may cause delay and congestion and may therefore have a severe negative effect on the accuracy of the forecasts.

A hybrid system for predicting travel time using ANNs is established in [20]. It employs a clustering algorithm to select an appropriate ANN according to the state of the input data. A hybrid system comprising principal component analysis and a Back-Projection ANN for predicting traffic accidents is reported in [21]. It is based on a number of criteria such as vehicle populations and road conditions.

A support vector machine is compared with an ANN for predicting highway incidents using a simulated wireless inter-vehicle communication system [22].

A Fuzzy Neural methodology for vehicle classification and prediction of speed, flow and density is proposed in [23]. Their approach demonstrates an ability to extract fuzzy rules from the training data and to apply them appropriately to new data, with a higher degree of predictive capability than conventional feed-forward back-propagation ANNs.

A comparison of two different ANNs (Generalised Regression and Feed-Forward Back Projection) along with an autoregressive model for predicting daily traffic flow is conducted in [24]. It concludes that the Generalised Regression network is the most accurate and robust. A similar work comparing two ANNs is described in [25]. A Feed-Forward Back Projection and a Radial Basis Function with an autoregressive model was used for the purpose of predicting traffic flow. Their conclusion was that the Radial-Basis Function ANN performed best.

D. Outlier Data Filtering

The data collected from street loops is noisy and often corrupted, e.g., due to equipment malfunction. The level of performance achieved with an ANN model is directly linked with the quality of the data. Data errors are referred to as outliers[26]. Several methods exist for handling outliers, including statistical and ANN based ones. Some statistical tools available include box plot, trimmed means, extreme studentised deviate, Dixon-type tests and regression [27].

Some ANN based approaches for filtering outliers are based on self organising models. An example of this is the COADM method developed by Seng, Chong and Lian [28]. Once the data clusters are identified, a search is performed to identify outliers from the rest of the data points within the same cluster. Other techniques are based on Principal Components Analysis to identify outliers based on the minimum volume ellipsoid that is a multivariate extension of the least median of squares is proposed in [29]. The method is based on estimating means and covariance for multivariate data.

III. OBJECTIVES

It is common practice in traffic control rooms to react to congestion or manage incidents using predefined traffic light signalling scenarios. Individual changes can be made to fit the current solution. In most cases this requires the engineer to hand-select settings of traffic light signalling and adapt the system accordingly. Usually the decision making is only supported by a traffic condition nowcast available on the UTMC common database.

Forecasts play a vital role for a traffic engineer to be able to react to changing conditions, such as an increase in delay and congestion, before they build up.

In this work, a novel methodology is proposed combining a static macro-simulation with forecasts to support traffic engineers in their decision making. The forecasters are based on a novel spatially distributed ANN architecture that use iterative learning to adapt to the ever-changing urban environment and an ANN based adaptive filter to delete outliers in training data for more accurate forecasts.

The proposed system uses traffic information from the SCOOT system, a UTMC component that collects data from various sources such as inductive street loops, provides an interface to traffic signalling strategies, and optimises traffic light offsets. The region of interest consists of 20 roads around the A6 London Road in the city of Leicester, UK. The A6 is a major arterial road for the city that regularly

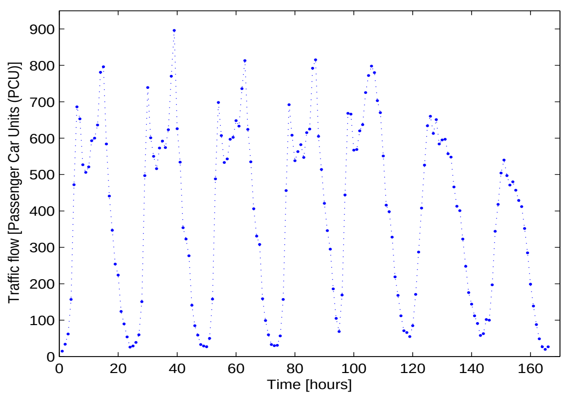

Fig. 1. Hourly traffic flow over one week (Mon-Sun), on the A6 London Road in the city of Leicester, UK

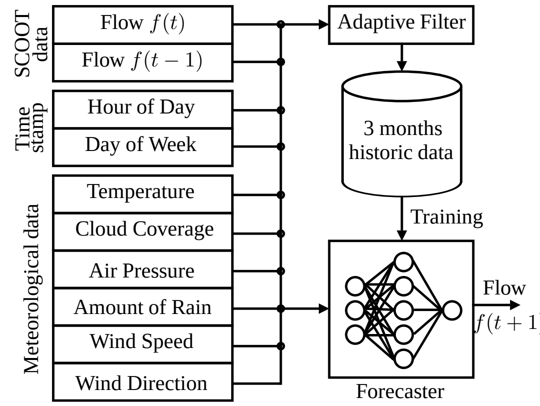

Fig. 2. Proposed system architecture showing all inputs, the iterative learning approach, and the adaptive training data filter.

experiences large amounts of traffic, reduction of flow, increase in delay, and congestion. Figure 1 shows a plot for one week of uncorrupted data from an inductive loop, measuring PCUs/Hour for that section of the A6. Morning and evening peaks are clearly visible for all days from Monday to Friday.

IV. ADAPTIVE DYNAMIC TRAFFIC MODEL

Traffic most often follows a specific pattern that highly depends on a number of parameters. Urban traffic flow and delay are specific to a road, the time of day, day of the week, meteorological conditions, and other variables. Also, certain weather conditions such as heavy rain can slow down the traffic [31]. In order to forecast the traffic flow, all these different parameters need to be considered, which makes this a challenging problem, suitable for ANNs.

As each link possesses its own ANN it is crucial that they be modelled accurately, as even a small discrepancy in the maximum possible number of PCUs passing through in a given time frame can have wide ranging consequences on the predicted behaviour of the rest of the network. Ideally a micro-simulation would provide the level of detail necessary for these purposes, however one is not currently available with similar accuracy to the SATURN model in the region of interest. SATURN is being employed by Leicester City Council for the purposes of network condition prediction and was therefore chosen for the purposes of this paper.

A. Iterative Learning

Urban environments are dynamic and constantly evolving in terms of infrastructure and inhabitants, as such the behaviour of traffic within the network also evolves. Cities employing macro-simulations for transport planning have to remodel the network infrastructure and behaviour every few years to account for these changes.

The proposed system adapts to this dynamic and evolving environment using an iterative learning technique. Incremental learning can potentially adapt to changing conditions while keeping previously learned structures [32], [33]. Although this technique could be used in this work, it could potentially cause problems where the urban environment changes too drastically, such as by reducing a roads throughput by replacing one lane with a bus lane. Keeping previously learned knowledge can have a negative impact in such a case. For this reason, and because it would be beyond the scope of this paper, this work does not use incremental learning but uses an iterative learning approach. This technique retrains the set of ANNs every new month, with 3 months of previous historic data. This introduces new data gradually, enabling the system to adapt to new knowledge.

Figure 2 shows the iterative learning approach with all inputs to the spatially distributed ANNs. The system is trained on the most recent 3 months of filtered data. The data is filtered for outliers using an adaptive ANN based methodology explained in more detail in the next subsection. Once trained, the ANNs are applied to forecast the immediate future traffic flow conditions within the region of interest.

B. Adaptive filter

Traffic information from street loops is prone to a number of faults and false data. In theory, every time a vehicle passes a street level induction loop it is registered by the system. But often, this data is corrupted. Tests on street loops in the City of Leicester, UK, showed an average fault and false data rate of over 10%. In this work an adaptive filter is proposed for filtering such erroneous detector data.

Every time the spatially distributed set of ANNs is to be retrained, the filter is applied to filter out outliers from the training set. Historic data is used to train a simple feed-forward back-propagation neural network with a single hidden layer and neuron. Traffic conditions roughly follow a specific daily pattern (as shown in Figure 1) while the details depend on a variety of more complex relationships.

The trained network is then tested on the same training data. The network can model the reoccurring pattern in the traffic flow well, but fails to follow the false data peaks. Figure 3 shows a sample of data with faulty readings. While a fixed boundary could be used to mark false data in such a way, this method would not allow for the road network to evolve in time. The ANN based filter detects outliers by selecting those readings that are larger twice the maximum

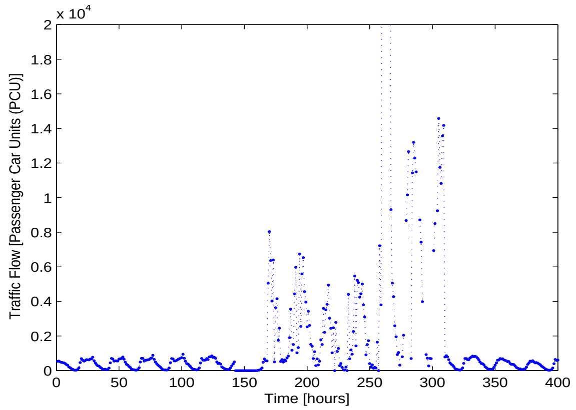

Fig. 3. Sample of loop data from the A6 London Road in the city of Leicester, UK. False data can be observed from hours 143 to 309. Note the points outside the graph at about 260 hours.

TABLE I

COMBINATIONS OF EXPERIMENTAL TESTS AND THEIR TOTAL NUMBER

ANN	Parameters	Test Months	Roads	Repeats	Sum
FF-BP	9	6.75	20	10	= 12,150
CF-BP	9	6.75	20	10	= 12,150
RB	13	6.75	20	1	= 1,755
GR	19	6.75	20	1	= 2,565
				Total	28,620

of the filter ANNs output. Furthermore, if there are more than two false readings within a 48 hour period, all that data is filtered out (such as the false data in Figure 3).

After the filtering process, the most recent three months of filtered data are used to retrain the ANNs. Once retrained, the ANNs are used to forecast the traffic conditions to adapt the static macro-simulation's output.

C. Overall System Architecture

Ultimately, the implementation of the spatially distributed and adaptive predictor network is used together with the static macro-simulation to assist traffic engineers in their decision making. This is achieved by taking the forecasts and applying the simulated changes of traffic flow conditions.

The proposed methodology has been tested on 13 months of data for 20 links in the City of Leicester. The system has been tested with a variety of ANNs, with and without the adaptive historic training data filter. Four different ANNs have been tested: feed-forward back-propagation (FF-BP), cascade forward back-propagation (CF-BP), radial basis (RB), and generalised regression (GR) ANNs.

The RB ANN exhibited very small inter-test variance but very long training times and thus a single test run but for multiple roads and months was decided to be sufficient. The GR ANN does not use random initial weights and therefore provides the same results for different random seeds. Table I gives an overview of the various experimental set-ups.

V. EXPERIMENTAL RESULTS

A total of 47 forecaster techniques were tested using four classes of ANNs (FF-BP, CF-BP, RB and GR) with various

TABLE II

RESULTS FROM EXPERIMENTS TESTING THE PROPOSED ADAPTIVE FILTER AND ANN TECHNIQUES FOR FORECASTING TRAFFIC CONDITIONS USING 13 MONTHS OF ACTUAL DATA.

	Non-filtered		Filtered			
Method	R^2	mean	R^2	mean	ΔR^2 %	Δ mean %
FF-BP-2HN	0.902	148.34	0.917	52.38	1.63	-64.69
FF-BP-4HN	0.934	83.61	0.931	47.25	-0.34	-43.48
FF-BP-6HN	0.908	99.84	0.918	47.67	1.10	-52.25
FF-BP-8HN	0.934	87.81	0.940	50.01	0.66	-43.04
FF-BP-10HN	0.941	89.42	0.938	48.78	-0.32	-45.45
CF-BP-2HN	0.918	75.71	0.898	56.38	-2.17	-25.53
CF-BP-4HN	0.939	89.56	0.925	54.29	-1.59	-39.39
CF-BP-6HN	0.942	85.25	0.937	48.06	-0.59	-43.63
CF-BP-8HN	0.923	84.72	0.947	46.89	2.64	-44.65
CF-BP-10HN	0.922	88.98	0.937	49.36	1.60	-44.53
RB-Spr40	0.622	89.96	0.622	87.32	0	-2.94
RB-Spr50	0.759	73.45	0.759	71.18	0	-3.08
RB-Spr60	0.835	64.84	0.835	62.43	0	-3.71
RB-Spr70	0.878	60.22	0.878	57.82	0	-3.99
RB-Spr80	0.761	57.67	0.792	55.14	4.00	-4.38
GR-Spr15	0.879	50.87	0.879	50.42	0	-0.89
GR-Spr20	0.892	49.09	0.892	48.65	0	-0.90
GR-Spr25	0.901	48.38	0.901	47.98	0	-0.83
GR-Spr30	0.907	48.34	0.907	48.03	0	-0.65
GR-Spr35	0.911	48.78	0.911	48.45	0	-0.67

parameters. The techniques were tested with and without the introduced adaptive training data filter. Each technique was applied to over a year's worth of data collected from 20 individual roads in the city of Leicester, UK. Over 11% of the 13 months of historic data used in this work were already marked as faulty by the system, such as caused by the loop being permanently triggered by a parked vehicle or due to a technical fault. Over all 28,620 experiments (Table I), for various roads, months, repeats, tested methods and their parameters, on average the adaptive filter deleted 135.79 data points per 2,880 readings (about 4.7% of the data). This relatively high rate is to be expected as real inductive-loop based data is frequently disrupted.

The mean and R^2 results from all experimental tests for specific ANN methods are shown in Table II. All four different types of ANNs can forecast the traffic flow conditions with relatively high R^2 and mean values.

The interpretation of the difference on R^2 for filtered versus non-filtered training data based forecasters is not straightforward. However, the mean error on filtered training data based forecasters is always better than the non-filtered training data based forecasters. In some cases there are extreme differences between both techniques, with a reduction of mean error of up to -64.69% using the adaptive filter.

Figure 4 shows the experimental results in terms of mean error for all four ANN types, with varying parameters, and with versus without adaptive training data filter. The number of hidden neurons is important for both FF-BP and CF-BP ANNs trained on the original data set. But when the adaptive ANN based training data filter is applied, the number of hidden neurons becomes less important. This may suggest that the filter provides a more consistent data set for the ANN to train on.

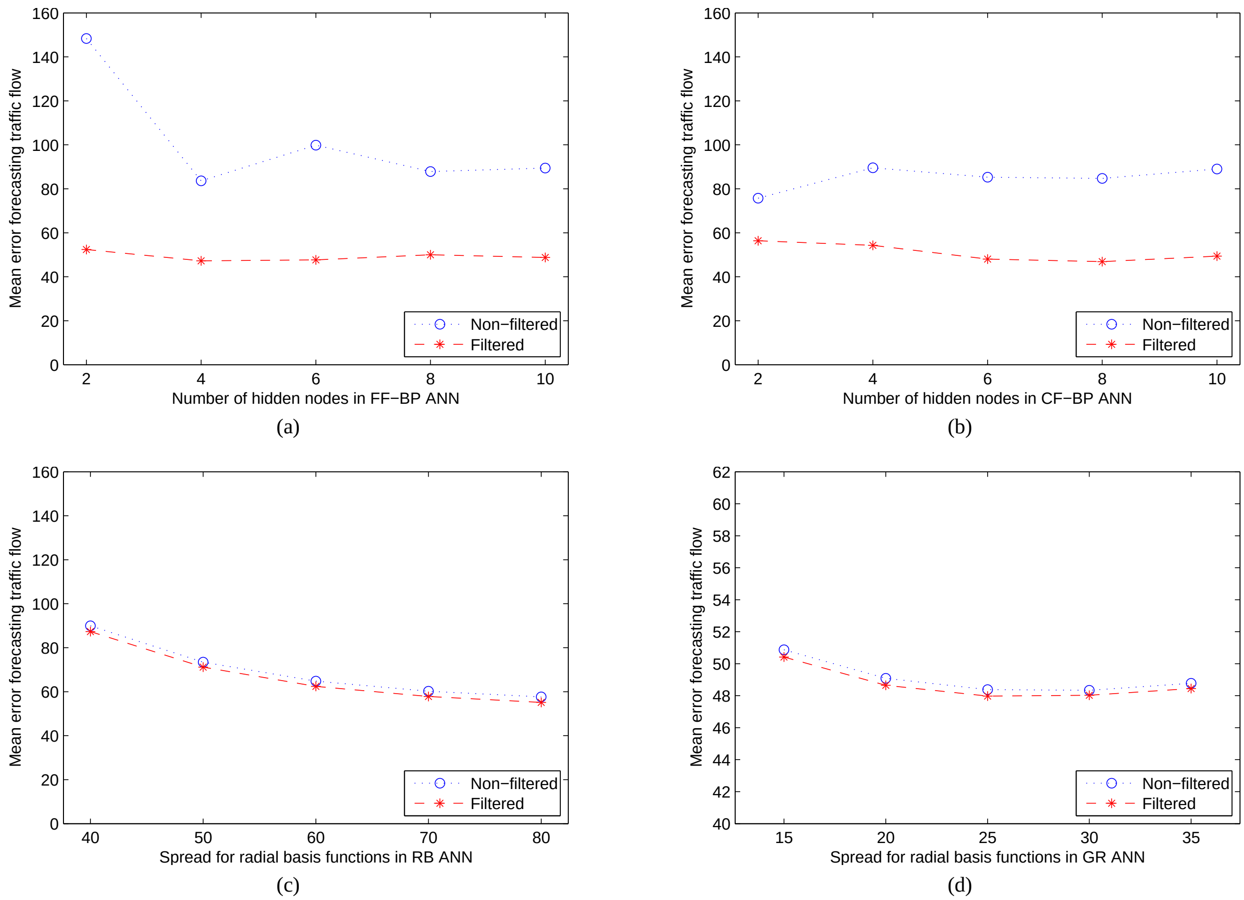

Fig. 4. Results from experiments testing a) FF-BP , b) CF-BP, c) RB, and d) GR networks on original and filtered data in terms of mean error. Please note the different scale in figure d).

VI. CONCLUSION

In this work, methodologies have been proposed and tested for the purpose of near real-time traffic forecasting, simulation and management. The forecasters are based on a novel spatially distributed ANN architecture that use iterative learning to adapt to the ever-changing urban environment and an adaptive ANN based filter to delete outliers in training data for more accurate forecasts.

Four ANN techniques have been implemented and studied for the purpose of forecasting traffic flow: feed-forward back-propagation, cascade forward back-propagation, radial basis, and generalised regression ANNs. Furthermore, an adaptive ANN based training data filter has been introduced and tested. All methods have been tested over 13 months of real data from 20 roads in the city of Leicester, UK.

A large number of experiments have been conducted to test the suitability of four distinct ANN techniques to forecast traffic flow conditions. The feed-forward back-propagation ANN obtained the best results closely followed by the cascade forward back-propagation ANN. The generalised regression ANN on the other hand obtained more consistently very good results. The radial basis ANN also provided good and consistent forecasters, but have not achieved the same level of forecasting as the other methods.

The general regression ANN showed to be an excellent technique to build forecasters, given the right spread was chosen. However, the feed-forward back-propagation ANN in combination with the adaptive ANN based filter showed to be performing best while being relatively independent of the number of hidden nodes. This methodology is the authors' recommendation in the application of traffic flow forecasting.

The introduced adaptive ANN based filter is capable of detecting outliers. The feed-forward back-propagation ANN as well as the cascade forward back-propagation ANN benefit heavily from using the adaptive training data filter. When applying the adaptive training data filter, the mean error of the feed-forward back-propagation ANN reduced on average by more than 48% and the cascade forward back-propagation ANN by more than 43%. The filter also consistently improved the radial basis and generalised regression ANNs performance although not to the same level. The statistical analysis of a large number of experimental tests confirmed the adaptive ANN based filter methodology to provide significantly better forecasters for all tested ANNs.

The proposed spatially distributed ANN architecture, the iterative learning, and the adaptive ANN based filter make this static macro-simulator adapt to the ever-changing urban environment. The test results on actual collected data confirm our approach to deliver accurate forecasts. The adaptive ANN based training data filter shows to deliver better forecasters than without the filter. With these methodologies in place, the forecasts are augmented with the static simulation results to directly explore sensible changes and optimisation possibilities in the traffic light signalling strategies. The next section will discuss some future research into this direction.

VII. FUTURE RESEARCH

As a direct result of the research presented, the following future research is suggested: Full tests of the spatially distributed and adaptive predictor network enhanced traffic simulation for near real-time traffic management and control, the exploration of other life-long learning techniques, a comparative study of various fault detection and outlier filtering techniques and the integration of additional information such as traffic delay and vehicle stops. This research will be further explored within an ESA funded collaborative project.

ACKNOWLEDGMENT

The authors would like to thank the European Space Agency (ESA) for funding the Intelligent Transport Project iTRAQ, on which this research is based, and Leicester City Council for providing the data and for working closely together to create this novel traffic management tool.

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