

URBAN TRAFFIC MANAGEMENT: THE VIABILITY OF SHORT TERM CONGESTION FORECASTING USING ARTIFICIAL NEURAL NETWORKS

Glenn D. Lyons

Mike McDonald

Nick B. Hounsell

Transportation Research Group, University of Southampton, U.K.

Brian Williams

John Cheese

Smith System Engineering Limited, U.K.

Bipin Radia

Department of Transport, U.K.

1. INTRODUCTION

Artificial neural networks (ANNs) are now widely recognised as a facet of artificial intelligence. ANNs represent a set of modelling techniques which are distinctly different from more conventional approaches. This consideration, in conjunction with some notable ANN modelling successes, has prompted researchers in a broad and diverse range of fields (including transportation) to assess the potential of ANNs as an alternative to existing techniques or, indeed, as a solution to problems formerly lacking an appropriate modelling technique.

Rising traffic levels and consequently an increase in the frequency and severity of congestion have prompted considerable investment in the development of traffic management techniques. Traffic management, particularly of an urban road network, relies increasingly on knowledge of the road network traffic status obtained from a growing infrastructure of network monitoring equipment. Consequently a progressively data rich environment has evolved to support traffic management system(s). Traffic flows in an urban network reflect a series of underlying highly non-linear relationships. ANN techniques are notable for their use in addressing non-linear problems in data rich environments.

Set against this background, the Department of Transport commissioned the Transportation Research Group at the University of Southampton, together with Smith System Engineering Limited, to assess the potential application of ANN techniques to urban traffic control (UTC) and in particular to assess the viability of using an ANN technique to forecast the onset of urban congestion.

This paper describes this initial study which was conducted over a six month period. A comprehensive review of key issues considered ANN techniques, their applications in transportation and traffic control, potential data sources and congestion definition and management. Based on the findings of the review, a demonstrator application was defined with the intention of exemplifying the potential of a UTC application of ANNs. The demonstrator application, in fact, performed a much broader role, providing a focus to the study and thereby acting as a catalyst for generation of further

understanding of the relevant issues and implications. The paper provides an elementary level of technical detail and places emphasis on consideration of the issues and implications that emerged from the research.

2. OVERVIEW OF ARTIFICIAL NEURAL NETWORKS

The background, functionality and application of an increasing selection of ANN paradigms (models) is now well documented in a number of informative texts (e.g. Carling, 1992). ANNs match the functionality of the brain in a very fundamental manner. ANN architecture constitutes a distributed representation of data. An ANN consists of a number of interconnecting layers of processing elements (units analogous to the brain's neurons) as illustrated in Figure 1. An ANN is essentially a transfer function relating one or more input(s) to one or more output(s). Internally an ANN evolves a configuration that relates the input(s) and output(s). This configuration develops through the process of training during which the ANN is presented with a large number of representative input examples and corresponding desired output responses. During training the error in the model's response to input examples is measured and the internal configuration is adjusted accordingly (weightings of connections between processing elements are changed) to reduce the error in overall response. Training is analogous to model calibration (Lyons, 1995). Validation consists of assessing the ANN's success in interpreting unseen test examples thereby demonstrating the ability to generalise.

Used in appropriate situations, ANNs represent a powerful form of information processing allowing integration and interpretation of a diverse range of data. The distributed nature of data representation can enable an ANN model to interpret noisy or incomplete data. However this attribute is highly dependant on the data used to train the model. Since an ANN 'learns' from example, its capabilities rely on the data set used in training. An ANN is not able to draw inferences or exhibit common sense. It should be noted that ANNs do not represent truly self-evolving model forms. Although input-output relationships are elicited autonomously during training, the network architecture (i.e. the configuration of the processing elements and connections) and the training schedule must be provided and optimised by the model developer (state-of-the-art software can now, however, assist this process). A pertinent limitation of ANN models is that the input-output relationships are not revealed to the developer but remain in a distributed form, represented by the connection weights resulting from training.

3. A REVIEW OF KEY ISSUES

To assess the potential for developing a neural network model to forecast the onset of urban congestion, four key issues were identified and reviewed. The findings are summarised below.

3.1 ANN Techniques

Most applications of ANNs are within the areas of pattern/image recognition, classification and forecasting. In addressing these application areas, there are an increasing number of neural network techniques available, each with their own

strengths and weaknesses. However, without doubt the most widely applied technique in all these areas is that of the backpropagation learning algorithm (used in conjunction with a Multi-Layer Perceptron (MLP) architecture (Rumelhart et al, 1986)). Backpropagation derives its name from the way it handles the errors in its responses during training - the response error is propagated from the output layer back to the input layer with adjustment of connection weights to bring the predicted output closer to the desired output. Measured success with its use in the financial sector (Diamond et al, 1993) (Yoon et al, 1993) illustrates the generally accepted opinion that the technique is typically the most appropriate for forecasting applications. However, the extensive use of this technique has the potential to overshadow viable alternatives to the extent that the implication in some articles is that the backpropagation technique is synonymous with ANNs. A wider range of options are available for pattern/image recognition and indeed classification applications.

3.2 ANN Applications in Transportation and Traffic Control

Neural computing is now considered a mature technology and indeed its uptake, particularly in exploratory work has been rapid. Yet the most popular technique described above has only been available for 10 years. Set against this background, the use of neural computing for transportation applications began much more recently and work to date has largely been of an exploratory nature. Applications which have been addressed using artificial neural networks include forecasting/classification of traffic flow parameters/traffic states (Dougherty et al, 1993), incident detection (Ritchie and Cheu, 1993) (Ritchie et al, 1995), driver behaviour/vehicle control (Hunt and Lyons, 1994) (Pant and Balakrishnan, 1994) (Pomerleau, 1992), traffic control (Nakatsuji et al, 1994) and traffic monitoring (Wan and Dickinson, 1992). In nearly all of the applications reviewed the backpropagation learning algorithm was used. The success of applications is difficult to establish from the available documentation and it is reasonable to assume that the potential of neural networks in transportation applications has yet to be realised. Despite some encouraging results, the frequent use of simulated data and/or manually prepared real data sets has precluded a definitive assessment of the applicability of neural networks in real scenarios. For artificial neural networks to be viable for on-line applications in transportation they will need to be able to function in real time, processing real data. As a result, training data must ultimately consist of real data which are automatically collected and processed.

3.3 Data Sources

Following from the preceding comments, the availability of appropriate data sources is limited. Without doubt the most viable source of data for urban areas is currently SCOOT (Hunt et al, 1981) and its network of detector sites. Other forms of detection are being used increasingly in UTC and are likely to represent additional sources of data in the future. Buses with Automatic Vehicle Location (AVL) and vehicles equipped for Dynamic Route Guidance (DRG) also offer future possibilities. SCOOT provides, through the now built in ASTRID database system (Hounsell et al, 1990), a range of traffic parameters including estimates of flow, delay, stops, degree of saturation and queue length. Values are typically link based and aggregated into five minute intervals. A number of archives of SCOOT data are available of varying duration.

3.4 Congestion Definition and Management

The majority of available references consider the management of congestion (traffic signal control, ramp metering, congestion pricing etc.). Relatively few references attempt to provide a quantifiable definition of congestion, testament to the fact that congestion is essentially a subjective, qualitative term. To forecast the onset of congestion, it is first necessary to define congestion. Foresight suggests that ideally the definition should be selected such that it best suits the congestion management strategy for which the forecast will be used. The 'congestion indicators' which are identified by a review serve to highlight the broad range of interpretations.

3.5 Summary

The review of key issues lead to the following summarising comments which formed a platform for developing a demonstrator application:

- the backpropagation learning algorithm with a MLP appears to be the most appropriate technique for the forecasting of the onset of congestion
- model development must use real data to effectively assess the viability of ANNs
- implementation of a successfully developed model will ultimately require automated collection of data if ANN models are to have a place in real time traffic control
- the number of suitable data sources is likely to increase although currently data from SCOOT detectors remains the most viable option
- a precursor to forecasting congestion is the continuing problem of understanding and defining congestion

4. DEMONSTRATOR APPLICATION

Development of a demonstrator application was essential to assess ANN potential to forecast congestion and to act as a catalyst for furthering the awareness and understanding of relevant issues and implications.

4.1 Data Source

Archives of SCOOT data (predominantly consisting of aggregated 5 minute data) were available for Southampton and London (Kingston). A particular region of Southampton's SCOOT network was selected for the demonstrator application and software utilities were developed to allow data sets suitable for ANN model development to be prepared from the archived SCOOT message data. Southampton has clearly defined peak periods during which the range of congestion levels is typically highest. Data for the weekday morning peak (0730-0900) were therefore collected (113 useable days were available). Data for Kingston were collected for weekdays between 1000 and 1900 (50 days were available). The morning peak was not used because a congestion mitigation strategy is already operable during this period.

4.2 Model Specification

Figure 2 outlines the model specification considered. A range of options were available, however the following specific model form was used.

Congestion in this study was defined using the Congestion Index (CI) (Van Vuren and Leonard, 1994):

$$CI = \frac{\text{mean travel time}}{\text{free - flow travel time}} \approx \frac{\text{delay} + \text{cruise time}}{\text{cruise time}}$$

This definition was used, in part, because its meaning is easy to interpret and it can be readily calculated from available SCOOT data.

Output from the congestion forecasting model was the value of CI for a particular link at time $t+5$ minutes. Potentially appropriate input information to the model was considered to consist of CI values for the chosen link and for upstream and downstream links at times t , $t-5$, $t-10$ and $t-15$ minutes. The use of such temporal data concurs with previous traffic parameter forecasting applications (Dougherty et al, 1993) (Dougherty and Cobbett) (Taylor and Meldrum, 1995). Corresponding values of flow (veh/h) were also considered as potentially appropriate. With data for a number of upstream and downstream links available, the number of potential inputs to a model was typically about 90. A key stage in ANN model development (or indeed any model) is to identify a sub-set of useful inputs from such a set of available inputs.

4.3 Model Development Software

ANN models are generally developed using simulation software which allows the user to select an ANN paradigm, specify the architecture size and identify training and test data sets. The software will then 'build' and train the ANN model. Until recently however, model development involved a substantial element of trial and error in determining the appropriate sub-set of inputs and an optimum architecture size.

Next generation model development software used in this project, attempts to automate the process of input parameter selection and architecture size optimisation thereby achieving substantial time savings in model development. *Predict* (NeuralWare, 1995) uses a genetic algorithm to select a synergistic sub-set of input parameters and subsequently builds and trains an ANN model using a constructive method called Cascade Learning (which determines a suitable number of hidden-layer processing elements) in conjunction with a backpropagation learning rule.

4.4 Results

Models were developed for 4 forecast links (2 in Southampton and 2 in Kingston). Model performance can be interpreted in a number of ways. The percent average absolute error (PAAE) for each model was calculated initially to obtain a measure of overall performance:

$$PAAE = (1/N) \sum_i |Y_i - O_i| / Y_i \times 100$$

where N is the number of examples
 Y_i is the desired model output
and O_i is the actual model output

The results appeared initially encouraging. Figure 3 plots actual and predicted CI values at time $t+5$ minutes for one of the Southampton links. The model achieves a PAAE value of 15.9 for the test data with a corresponding correlation coefficient, R , value of 0.75 (comparable results were achieved by Dougherty et al (1993) in a very similar approach to urban flow forecasting). However, comparison was then made against a simple benchmark - a model which forecasts the value at $t+5$ minutes as being the value at t minutes. Such a model was, for the same test data, able to achieve a PAAE value of 17.7 and an R value of 0.73. Although performance of the ANN model is marginally better, this indicated that the ANN predictions were closely correlated with the preceding CI value (indeed this commonly occurs when time series data are used in forecasting). Figure 4 confirms this with a comparison of CI values during a particular morning peak period. Indeed, the only clear observation from *Predict*'s selection of a sub-set of input parameters is that all preceding CI values on the forecast link are selected.

An alternative assessment of performance was achieved by treating the model as a tool for predicting the occurrence of a pre-specified traffic condition. For example, for a particular threshold of CI it can be assumed that above the threshold congestion is critical (i.e. it must be detected for some remedial action to be taken). Below the threshold, congestion is considered acceptable with no action required. Figure 5 shows the performance results for such an approach. The rapid decline in detection rate (proportion of examples above the threshold correctly identified by the model) beyond CI threshold values of approximately 3.5 corresponds to the sparse amount of training data available for CI values greater than this. The results suggest that for thresholds of CI of between 2 and 3.5 the detection rate is reasonable while the false alarm rate (proportion of examples below the threshold wrongly predicted as above the threshold) is low. It should be noted however that displaying results as percentages masks the fact that there are typically far more examples below the threshold than above. Consequently the actual number of false alarms, while appearing encouragingly low in percentage terms, can be quite high.

The results were, in general, not as encouraging as had been initially anticipated but a number of issues and implications were identified as a consequence.

5. ISSUES AND IMPLICATIONS

The issues and implications which have arisen from this project can be addressed under three headings.

5.1 Defining the Problem

To forecast (the onset of) congestion it is first necessary to define congestion. A number of definitions exist. For congestion monitoring in SCOOT networks TRL have recently proposed the use of "wasted capacity" which enables the location of the

critical link to be identified and, to some extent, the severity of congestion to be monitored. Wasted capacity is defined as:

$$\text{Wasted Capacity} = \text{Min} [\text{lost capacity, queue at end of green}]$$

where "lost capacity" is the total flow potentially lost on a link, defined as the total time a link is blocked during its green stage multiplied by the link's saturation occupancy.

However, neither CI, wasted capacity or other available definitions provide an entirely comprehensive and pragmatic definition for what is clearly a complex phenomenon. For example, in this study, unrealistically high delay and consequently high CI values were sometimes found to occur as a result of problems in estimating average journey times from flow/delay relationships on links with short time intervals under congested conditions. Contamination of model development data sets by such occurrences is to the detriment of model performance.

Defining the problem also entails determining the model's objective and subsequently identifying a suitable and unambiguous performance measure to assess the model's capabilities. Results presented in 4.4 illustrate the varying interpretations of performance which can result. To isolate an appropriate means of measuring performance, consideration must be given not only to the immediate objective of, in this case forecasting congestion, but to the end-use of the model and any specific demands that are thereby imposed on the model.

5.2 Defining a Solution

Defining the problem determines the model output. It is subsequently necessary to define a solution, i.e. determine appropriate input parameters which will allow the model to deliver the required output.

The set of possible inputs used for the demonstrator application was based on precedents and informed judgement. However, closer consideration highlighted a number of potential flaws in the adopted approach.

Model inputs and output should represent the elements of a cause-effect relationship. For the demonstrator application it was assumed, for example, that the CI value at time $t+5$ minutes on a given link (the effect) was the result, in part, of upstream flows for preceding time intervals (causal factors) which would propagate downstream to the forecast link.

However, capturing the cause-effect relationship for this application is not a trivial matter. The rate of downstream propagation of causal factors (and the subsequent 'arrival time' at the forecast link) is, for example, dependent on traffic conditions. Hence, the importance of particular inputs to the model will vary depending on the traffic conditions in the network.

The data used in the demonstrator application represented 5 minutes intervals. In the context of traffic movement (particularly during relatively uncongested conditions)

this is a long time. Consequently, for example, the effect on a given forecast link at time $t+5$ minutes may be due (in part) to a cause several links upstream at time t minutes, perhaps beyond the extent of the network represented by the model's inputs. This suggests two possible remedial actions. The first is to increase the number of model inputs to cover an increased range of upstream links. There are two points to the detriment of this option. By increasing coverage, the number of inputs to a neural network model will increase. In addition to potentially capturing more causal information, this will introduce an increasing amount of unwanted input information. This is likely to be detrimental to the model's development and performance. Moving progressively further upstream, it becomes increasingly unlikely that traffic on such upstream links is destined for the 'forecast' link. Therefore data from such links is less likely to provide causal information. The second remedial action would be to reduce the level of aggregation of the data. This, however, contravenes the objective of aggregation which is to smooth the SCOOT data which are highly variable on a cyclic basis. An argument could be tentatively put forward that such variability represents useful information and should not be disregarded as noise. However this study's subsequent consideration of a model developed using 2 minutes data showed no noticeable improvement.

There may well be other potential causal parameters that were lacking as inputs to the demonstrator application models. However, to take positive steps towards determining what such parameters might be, it is necessary to further the understanding of congestion itself and its complex process of development (and indeed dissipation).

5.3 Producing an Effective Solution

To produce an effective solution requires good quality data in sufficient quantities to allow an ANN to be fully trained and tested. Typically these two requirements (quality and quantity) are conflicting. If a fixed amount of data is available then the size of a selected sub-set used to train an ANN will decrease as the required quality of the sub-set is increased. Quality can, of course be interpreted in a number of ways. In this study (not unusually) quality related to the ability of the data sets to provide a range of input values representative of the different traffic conditions and congestion levels that can arise. A notable difficulty was the comparative lack of high and sustained levels of congestion and indeed examples representative of the onset of congestion. Although such examples were available, they were outweighed by a predominance of low CI values (particularly for Southampton) reflecting uncongested conditions.

Data quality also concerned the need for provision of complete input examples for ANN training. Inevitably, real data are susceptible to intermittent faults within the system from which the data are derived. If for example, the loop on a particular link providing input data to the ANN was damaged for a short period covered by the archive, then corresponding SCOOT message data will be unavailable. In this study input examples with missing fields were discarded since they were deemed to represent excessively noisy examples. Although such examples should be adequately interpreted by a successfully trained ANN, including such examples in the training data set would be likely to compromise the performance of the model.

Discarding incomplete examples clearly reduces the available quantity of data. The anticipated quantity of data obtainable from the archives was further reduced by the fact that whole days and weeks were unusable or unavailable due, typically, to data recording interruptions due to UTC system maintenance and development work. For the Southampton archive which had 280 potentially useable days of data, only 113 days were retrieved. It should be noted that SCOOT was designed to run on a computer alongside the UTC system. The UTC computer generally performs a number of important tasks and data collection from SCOOT is usually considered to have low priority.

SCOOT currently remains the only source of readily accessible data in the UK which has reasonable network coverage and provides a range of data items. It is however, a misconception to suppose that entire urban areas have SCOOT coverage. Although likely to increase, SCOOT coverage is incomplete. If data from upstream (and downstream) detectors are required to forecast the onset of congestion on a link (and, subsequently, potentially on a route) then the number of 'forecast sites' is limited.

6. CONCLUDING REMARKS

ANN techniques are being increasingly applied for a variety of purposes such as pattern recognition and forecasting in many applications. In transport, specific applications of ANNs such as incident detection on inter-urban roads (Cheu and Ritchie, 1994) and urban journey time estimation from detector data (Cherrett et al, 1996) have delivered impressive results. This in itself substantiates a conclusion that there is a role for ANN techniques in traffic monitoring and control. This study has investigated the potential for ANNs in UTC, concentrating on congestion forecasting. While other studies have looked at forecasting urban congestion, this is believed to be the first study to attempt to build a working model based on a substantial, real database. In so doing, the study has highlighted the extent of ANNs' potential and the problems in its realisation, both through a demonstrator application and through a critical evaluation of issues.

The demonstrator application produced an ANN performance which is only slightly better than a much simpler alternative. It is important, however, in drawing more generalised conclusions about the potential of ANN models to enhance UTC, to set the results of this particular study into context. Addressing any forecasting problem is an order of magnitude more difficult than a corresponding estimation problem. Addressing a problem of forecasting or estimation in an urban context is considerably more complicated than in an inter-urban context. Attempting to forecast the onset of urban congestion is therefore arguably one of the most difficult modelling tasks. The demonstrator application was also limited to a single definition of congestion, for single links only and to particular inputs. Performance results are therefore very specific, limiting any generalisations.

As comprehensive on-line traffic information becomes more readily available it is likely that progress using ANN techniques will be more significant as the quantity of quality data in model development data sets improves. Substantial amounts of data for a large number of data items can already be collected from urban regions under

SCOOT control. However, consistent collection and storing of complete data is currently inhibited by the low priority attributed to data collection in UTC systems.

This study has highlighted the complexity of the urban congestion phenomenon which continues to elude an unambiguous definition and associated understanding. Currently there is no generally accepted definition of the dynamic temporal and spatial queuing variability which characterises congestion. Forecasting congestion then adds a further level of difficulty. Improving the understanding of this phenomenon should enhance understanding of what parameters are most important in representing the underlying cause-effect relationships involved. Subsequently a more rigorous assessment of the viability of short term congestion forecasting using ANNs could be usefully conducted.

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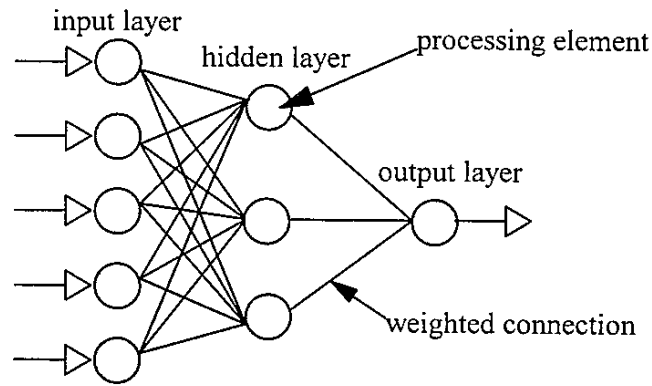


Fig. 1. Example ANN configuration

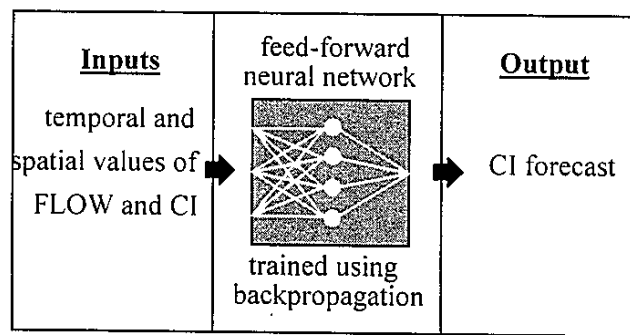


Fig. 2. Demonstrator application - model specification outline

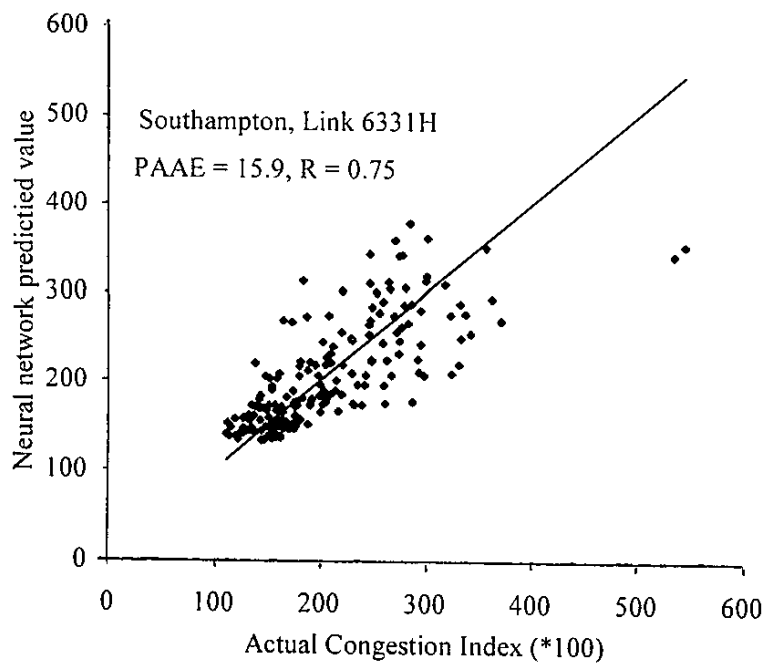


Fig. 3. Comparison of actual and neural network predictions of CI values at time $t+5$ minutes for test data

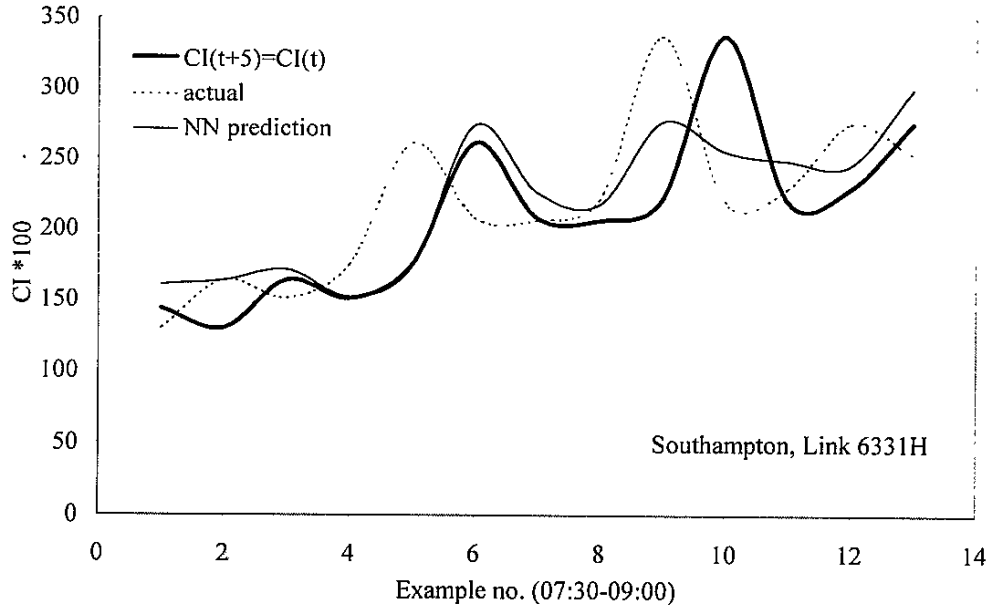


Fig. 4. Comparison of actual and NN predicted values of CI at $t+5$ for a single day with the $CI(t+5)=CI(t)$ forecast superimposed

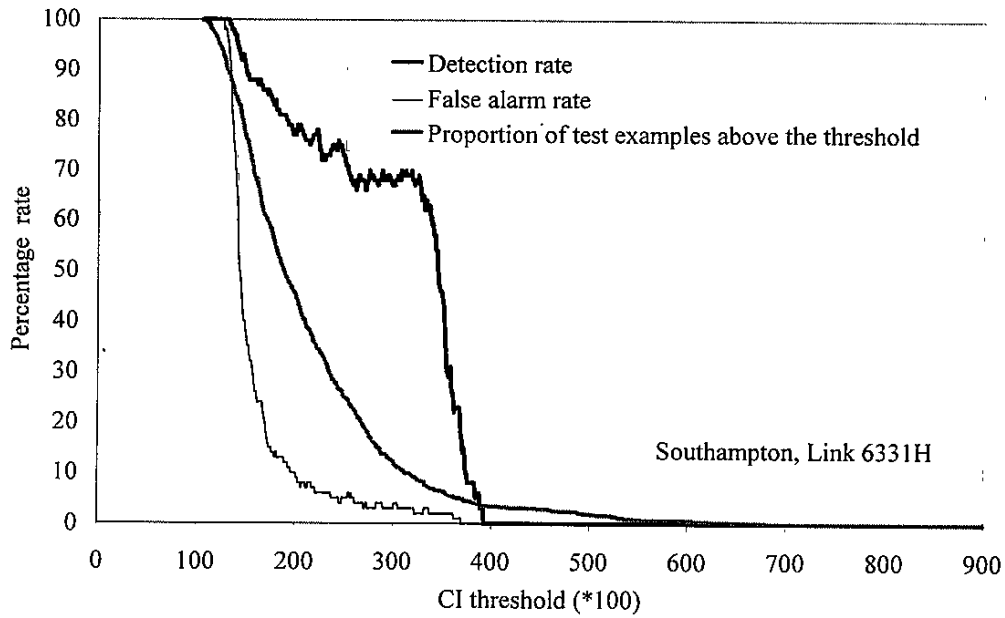


Fig. 5. Neural network model performance in testing considering congestion forecasting as an incident detection problem