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EMPIRICALLY-BASED MODELLING APPROACHES TO THE TRUCK WEIGH-IN-MOTION PROBLEM

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ABSTRACT

The paper develops and compares a comprehensive range of configurations of empirical modeling techniques for solving the truck classification by weigh-in-motion problem. A review of existing artificial neural network approaches to the problem is followed by an in-depth comparison with support vector machines. Three main model formats are considered: (i) a monolithic structure with a one versus all strategy for selecting truck type; (ii) an array of sub-models each dedicated to one truck type with a one versus all truck type selection strategy; and (iii) an array of sub-models each dedicated to selecting between pairs of trucks. Overall, the SVM approach was found to outperform the ANN based models. The paper concludes with some suggestions for extending the work to a broader scope of problems.

1 INTRODUCTION

Empirical modeling is concerned with the development of a representation of some aspect of a system based on data observed from that system or from an analog of that system, and is widely used in fields such as business, engineering, and science where there is a lack of theory describing the relationship between the system variables (input to output mappings) or computationally too slow to allow results to be generated within a reasonable period of time. A good example of such a problem is truck weigh-in-motion (WIM) where there is a need to estimate the attributes of a fast moving truck (such as, its axle spacings and axle loads) from measurements of the strain response of the structure over which it is traveling. An accurate WIM system has many potential applications including, for example, allowing comprehensive statistics on truck-bridge loading to be obtained for use in highway bridge design or fatigue rating of existing bridges (Moses and Ghosn 1983). However, more fundamentally, WIM is a rich problem exhibiting many of the challenges that empirical modeling techniques have difficulty resolving, such as input vector translation, model extendibility, and an explosion in the number of training patterns with problem extension (Flood and Issa 2010); as such it offers a good base problem for developing new approaches to empirical modeling and in comparing their performance.

This paper reviews and compares the alternative empirical modeling approaches that have been developed for solving this problem, and identifies future directions for model development.

2 ARTIFICIAL NEURAL NETWORK APPROACHES

Preliminary work by Gagarin et al. (1994) demonstrated the viability of using artificial neural networks (ANNs) to estimate truck attributes from bridge strain data. A two stage neural network system was considered, similar to that illustrated in Figure 1. The first of the two stages (that shown to the left of the figure) was designed to classify a given truck loading condition and thus select an appropriate set of networks from the second level of the system. The laterally connected architecture shown at level 1 in the figure is typical of networks used for classification purposes, though conventional feedforward networks were used in the original study. The networks in the second level were designed to operate for a given truck loading class, providing estimates of velocity, axle spacings and axle loads.

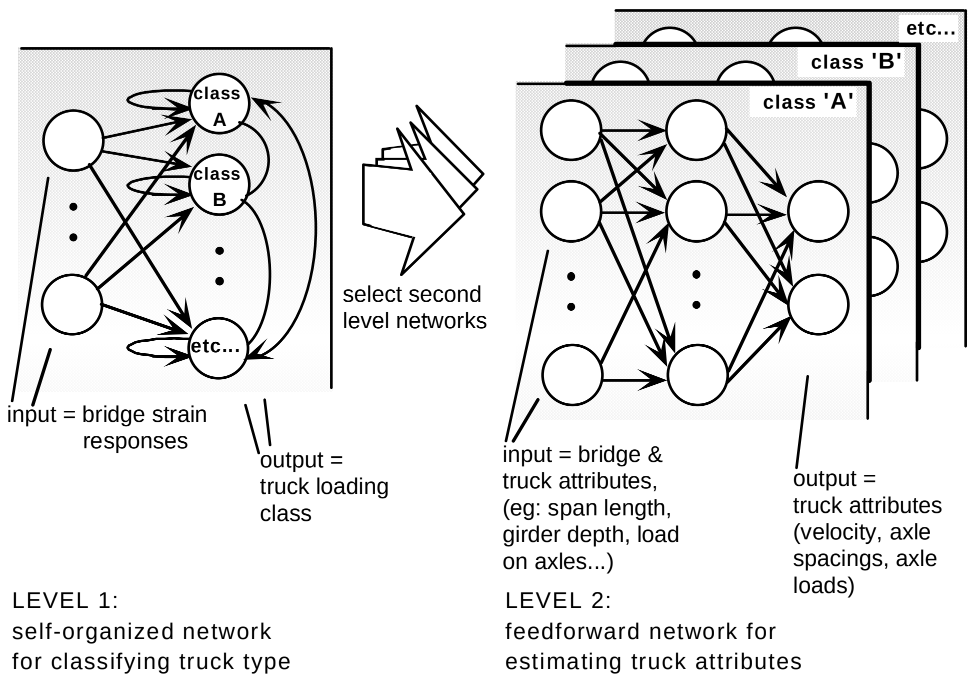

Figure 1: Overall Structure of Modular ANN (adapted from Flood 2000).

This modularized approach was adopted, in preference to a monolithic network, to facilitate the task of training the ANNs (Gagarin et al. 1994). In addition, it enabled individual modules to be retrained, and new modules added, as new training data become available, without the burdensome task of having to retrain the complete network system. However, this system is only as good as its weakest link. In particular, if the first level network misclassified the type of truck crossing the bridge, then the incorrect second level network would be selected and the estimates would be completely invalid. The focus of much subsequent work was, therefore, was to develop alternative more accurate modules for the classification stage of this system (level 1 in Figure 1).

A variety of different types of supervised-training neural network were considered for the first level in the network, the truck type classifier. The first of these was a radial-Gaussian feedforward networking system (RGIN) that uses an incremental training algorithm (Flood 1999). This system uses a supervised training algorithm and so a classification system for trucks must be adopted; the FHWA system of truck classification was used for this purpose, and is illustrated in Figure 2 and summarized in Table 1 (see Gagarin et al. 1994). Input to the RGIN networks was an array of strain readings measured at a fixed location on a girder of the bridge during the passage of a truck, as schematized in Figure 3(a). Each output from the RGIN network represented a different truck loading class. The class to which a given truck loading situation belongs is indicated by the output neuron that generates the value closest to 1.0 (all other outputs should generate a value close to 0.0).

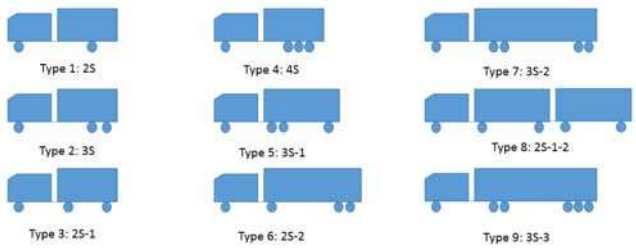

Figure 2: Nine truck types used in this paper adapted from Gagarine et al. (1994).

Table 1: Axle Load and Spacing Range of Nine Truck Types adapted from Gagarin et al. (Gagarin et al. 1994).

Truck Type	Axle Loads (KN)						Axle Spacings (m)				
	1	2	3	4	5	6	1 and 2	2 and 3	3 and 4	4 and 5	5 and 6
1	13.3-53.4	8.8-80.1					2.74-6.10				
2	13.3-53.4	8.8-80.1	8.8-80.1				2.74-6.10	1.22			
3	13.3-53.4	8.8-80.1	8.8-80.1				2.74-4.98	5.49-11.6			
4	13.3-53.4	8.8-80.1	8.8-80.1	8.8-80.1			2.74-5.49	1.22	1.22		
5	13.3-62.3	8.8-71.2	8.8-71.2	8.8-80.1			2.74-6.10	1.22	6.10-11.6		
6	13.3-53.4	8.8-80.1	8.8-80.1	8.8-80.1			2.74-5.49	6.10-11.6	1.22		
7	13.3-53.4	8.8-71.2	8.8-71.2	8.8-80.1	8.8-80.1		2.74-6.10	1.22	6.10-11.6	1.22	
8	13.3-53.4	8.8-71.2	8.8-71.2	8.8-80.1	8.8-80.1	8.8-80.1	2.74-6.10	1.22	6.10-11.6	1.22	1.22
9	13.3-53.4	8.8-80.1	8.8-80.1	8.8-80.1	8.8-80.1		2.74-5.49	5.49	3.05	5.49	

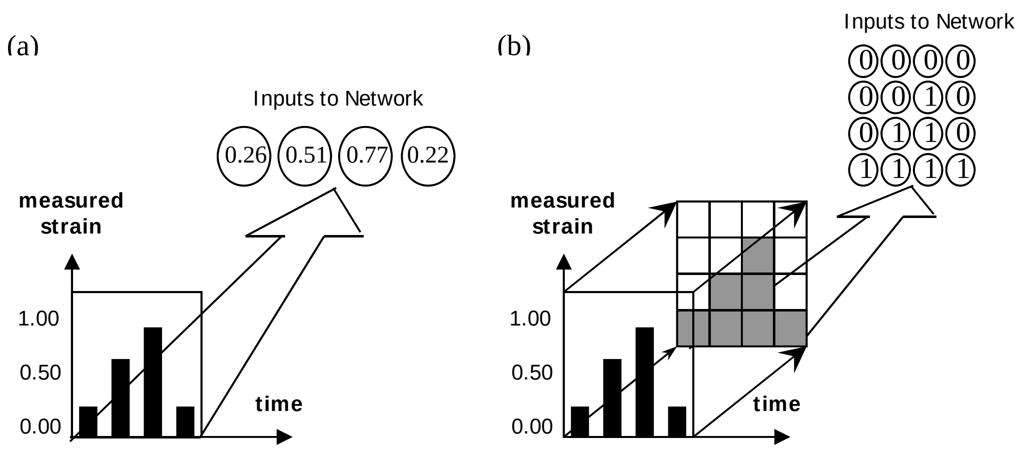

Figure 3: Formatting Strain-Time Curves for Input to a Neural Network: (a) vector of real-values; (b) matrix of binary values (adapted from Flood 2000).

A second type of ANN used for the truck type classification was an extension of the simple Hamming network EHAM, a detailed description of which is provided by Flood and Kartam (1998). Again, this system used a supervised training algorithm, and so the FHWA classification system for trucks was adopted. Input to the EHAM networks was a matrix of binary values representing a projection of the strain readings measured at a fixed location on a girder of the bridge during the passage of a truck. The binary map was a 32 by 32 matrix, with one dimension representing sample strains taken at different points in time during a truck crossing event, and the other dimension indicating the magnitude of the strain readings (see, for example, Figure 3(b)). Each output from the EHAM network represents a different truck loading class. The class to which a given truck loading situation belongs is indicated by the output neuron that generates the binary value 1 (all other outputs should generate a binary value of 0).

A detailed description of the training and relative performances of these classifiers is provided in Flood (2000). However, in summary, they each had an average success rate at truck classification in the 80 to 90% range, except for the truck type 2S-1-2 which was in the high 70% range. The poor performance of the classifiers for the truck type 2S-1-2 can be attributed to the significantly different axle configuration of this type of vehicle compared to the others in the FHWA classification system.

3 SUPPORT VECTOR MACHINE VERSUS ANN APPROACHES

Recently, a series of studies was undertaken to determine whether support vector machines (SVMs) could improve on the truck type classification performance of the ANN approach. New training and testing data were established for this purpose, to facilititate a direct comparison between the techniques. The bridge type considered was 100 meters in length, single span, simply supported, with a single lane. The bridge was treated as a rigid beam and the study assumed no dynamic effects on the structure. Single truck crossing events only were considered.

3.1 Model Structure

A truck crossing event was represented as an array of bending moments induced at mid-span, while the type of truck inducing the bending moments was indicated across an array of outputs. The FHWA system of truck classification was adopted as described in section 2 above.

Three different model formats were considered as illustrated in Figure 4, and described in detail by Wang (2015). The first model format comprised a monolithic model that mapped directly from the input array of bending moments to a set of 9 outputs representing the different truck types. Each output represented a different truck type and was capable of generating a value between 0.0 and 1.0. The output that generated the closest value to 1.0 in response to a set of bending moments was assumed to identify the truck type. This format was only adopted for the ANN model since SVMs cannot include more than one output.

The second model format shown in Figure 4 comprised a set of 9 sub-models, each dedicated to a single truck type. A single array of bending moments was shared as input, and each sub-model had a single output capable of generating a value between 0.0 and 1.0. As for the first model format, the output that generated the closest value to 1.0 was assumed to identify the truck type. This format was adopted for both the ANN and SVM models.

The third model format shown in Figure 4 comprised 36 sub-models, each dedicated to selecting between a pair of truck types (there being 36 permutations of truck pairs in total). A single array of bending moments was shared as input. Each output would select between a pair of trucks. For example, sub-model 1 was dedicated to comparing truck types 1 and 2; an output of 0 would indicate truck type 1 and an output of 1 would indicate truck type 2. The truck type with the most selections across the output array was assumed to be the truck type crossing the bridge.

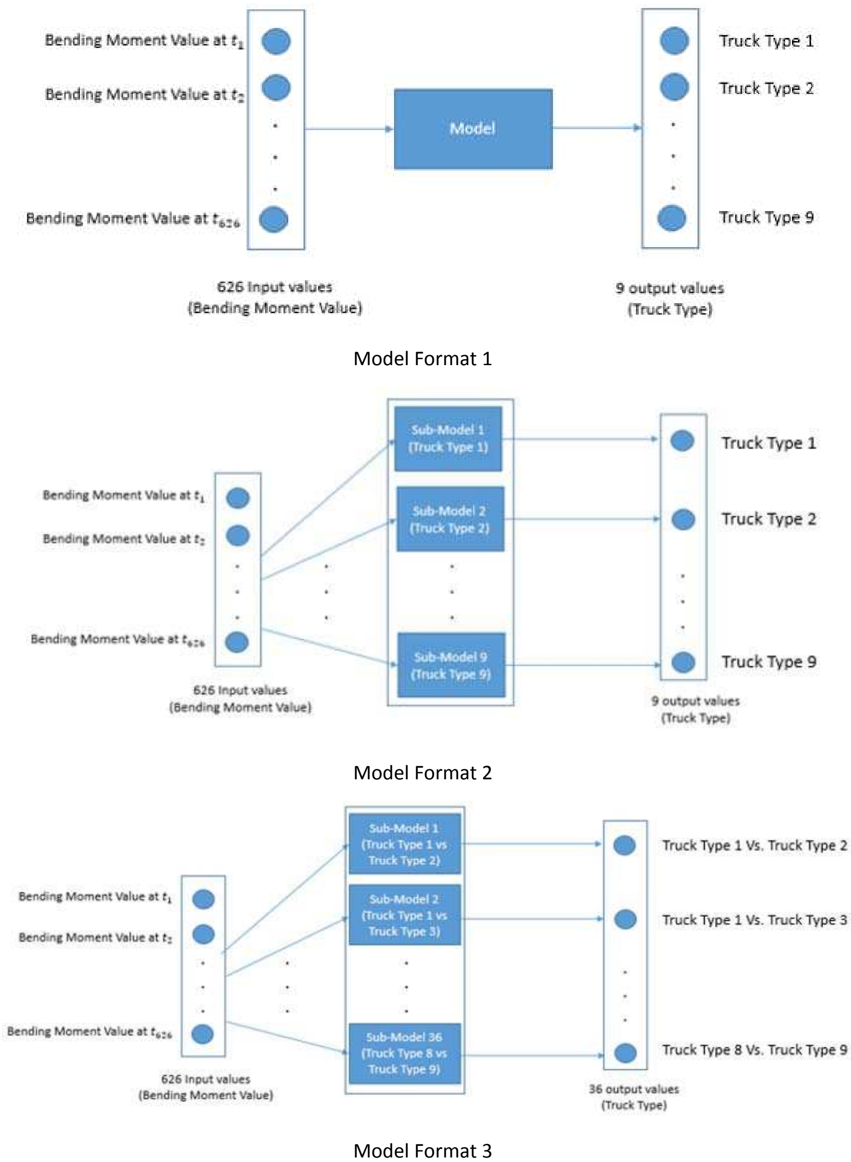

Figure 4: Three model formats adopted for the study.

3.2 Truck Crossing Simulation

The data used for training and validation of the models was based on a random selection of truck configurations within the ranges provided in Table I. Data was generated by simulating the passage of a truck crossing the bridge. The bending moment induced at the mid-span of the bridge, m, was calculated during the truck crossing event using a 50 Hz sample rate. Each simulated truck crossing event was used to generate a single input to output pattern to be used for training or validation of the models. For model formats 2 and 3, each sub-model was trained independently. Each pattern comprised 626 inputs representing the bending moments induced by the truck crossing event, and an array of binary outputs used to indicate truck type. A total of 900 input patterns were generated (100 for each truck type) and the corresponding outputs were tailored to match the operation of each model/sub-model. For each pattern, the axle loads and spacings were selected using a uniformly distributed random variate with values ranged between the limits listed in Table 1.

3.3 Model Development

Training of both the ANN and SVM models requires preselection of certain training parameters, the values of which can significantly affect the performance of the model. In addition, since the initial input arrays have a high dimension (626 values) Principal Component Analysis (PCA) was used to prune this number down to something more manageable.

The architecture of the ANNs adopted for this study was the popular feedforward layout. Two ANN variants were considered, one with a single hidden layer of 600 neurons and a second with two hidden layers of 300 hidden neurons each. This provided a total of four ANNs, two using format 1 (Figure 4) and two using format 2. All ANNs used the sigmoidal activation function. The training algorithm used for the ANN was error backpropagation, a gradient descent technique, and was implemented within the MATLAB R2012a environment.

Since the ANN backpropagation approach requires a careful selection of the step size to ensure convergence and acceptable training quality, this study tested a range of learning rates from 0.01 to 0.1 in intervals of 0.01. For the SVM, the kernel function adopted was the Radial Basis Function due to its popularity. The SVM's kernel function also requires a careful selection of its scaling value, and so a range of values were tested from 3.60 to 3.70 with intervals of 0.01. For pruning the number of input variables, a range in the array size was considered from 10 to 55 in steps of 5, using principal component analysis (PCA) to select the most significant inputs in each case.

3.4 ANN Development, Model Format 1

Training of an ANN was allowed to progress until 300 training epochs had been completed. Training used a random selection of 80% of the 900 pattern data set. The remaining 20% of the patterns were used for validating the resultant ANN. Model development was repeated for the range of learning rates and input vector sizes outlined above, providing 100 training trials. These experiments were repeated 10 times, each occasion using a different set of 900 patterns. The performance of the ANNs was measured as the portion of the validation patterns correctly classified. This was averaged over the 10 repetitions of the experiment. Local scatterplot smoothing (LOESS) was used (with a span value of 0.15) to find the peak performance and thus the optimal values for the number of input variables and the learning rate. Figure 5 shows the results of these experiments, plotting the proportion of correct classifications (from 0.0 to 1.0) against the number of inputs and the learning rate. The optimal values were found to be 32 for the number of inputs and 0.088 for the learning rate. The corresponding R square value was 0.8249, indicating an acceptable description of parameter relationship using the smoothing method.

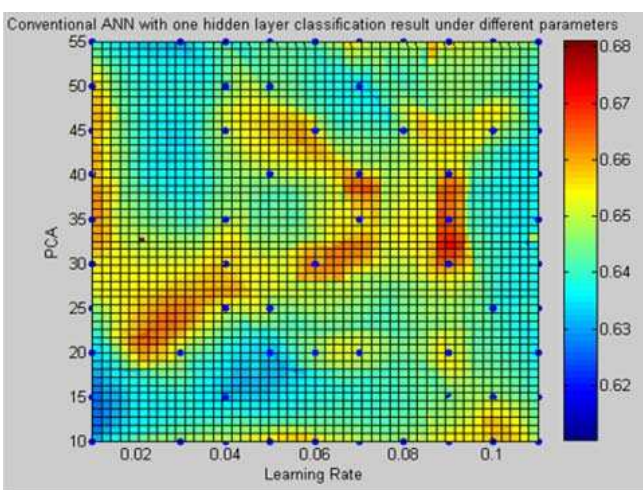

Figure 5: LOESS regression on the performance of ANN Format 1 with one hidden layer.

The experiment was repeated this time using an ANN with two hidden layers. The optimum set-up was found to be 35 inputs with a learning rate of 0.0676. The R squared value was again acceptable at 0.8926.

3.5 Development of ANN, Model Format 2

The set of experiments described in 3.4 above were repeated but this time using the model format 2 shown in Figure 4, that is, the system comprising 9 sub-models. For the one hidden layer ANN, the number of hidden neurons in each sub-model was 67 for the one hidden layer ANN, giving 603 hidden neurons in total. For the two hidden layer ANN, 33 hidden neurons were included in each layer of each sub-model providing a total of 594 hidden neurons.

Figure 6 shows the results of these experiments, as before plotting the proportion of correct classifications against the number of PCA selected inputs and the learning rate.

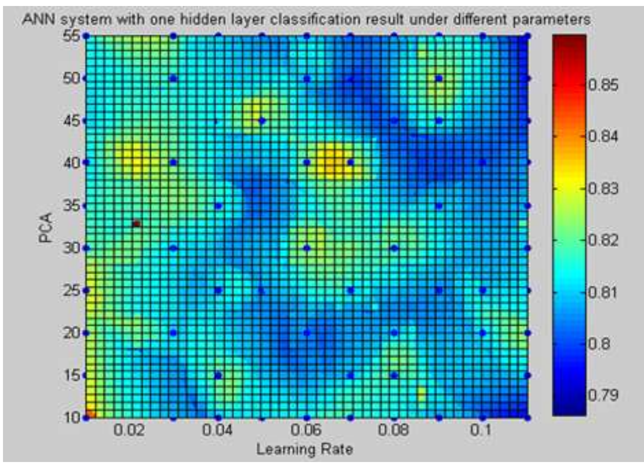

Figure 6: LOESS regression on the performance of ANN Format 2 with one hidden layers.

The optimal values were found to be 39 for the number of inputs and 0.06520.088 for the learning rate. The corresponding R square value was acceptable at 0.8304. Similarly for the two hidden layer ANN based on model format 2, the optimal values were fund to be 40 for the number of PCA selected inputs and 0.0736 for the learning rate, with an R square value of 0.8304.

3.6 Development of SVM, Model Formats 2 and 3

The next set of experiments concerned development of the SVM models, the first using the one versus all strategy (model format 2, Figure 2) and the second using the one versus one strategy (model format 3, Figure 2). Figure 7 shows the LOESS smoothed performance surface for the SVM based on model format 2. This plots the proportion of correctly classified trucks in the validation data set versus the number of PCA selected inputs and the Radial Basis Function kernel scaling value. The optimal values were found to be 19 for the number of inputs and 3.6677 for the kernel scaling value, with an R square equal to 0.9984. Similarly the SVM system based on model format 3 is plotted in Figure 8. The optimal values were 18 for the number of PCA selected inputs and 3.6960 for the kernel scaling value, with an R square value of 0.9999. It can be seen from Figures 8 and 9 that the scaling value did not play an important role in determining the performance of the resultant SVM. However, the number of PCA selected inputs was clearly very important for both SVM modeling approaches.

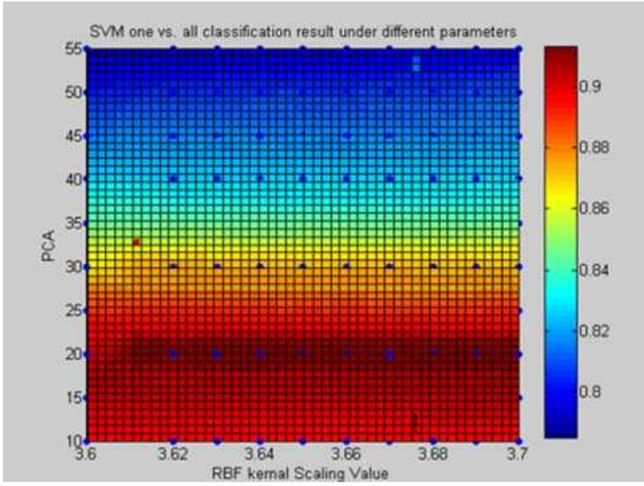

Figure 7: LOESS regression on the performance of SVM Format 2 with a one versus all strategy.

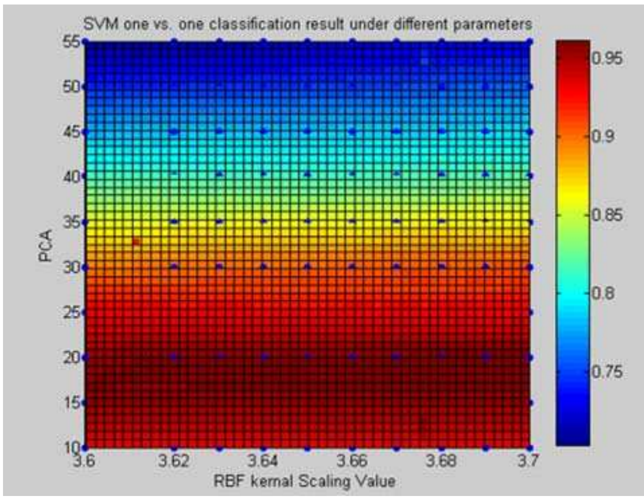

Figure 8: LOESS regression on the performance of SVM Format 2 with a one versus one strategy.

4 MODEL EVALUATION

The optimal values determined for the number of inputs and the learning rate or kernel value were used to develop the final versions of each of the 6 model forms. The performance of each of these models is compared in Figure 10 in terms of their ability to correctly classify the validation patterns. All 1,800 validation patterns generated across the 10 data sets were used for this purpose.

Clearly, the results demonstrate that the SVM models outperform the ANN models. Of the SVM models, the one versus all strategy was found to slightly outperform the one versus one strategy.

For the ANN models, the structure comprising 9 sub-models significantly outperformed the monolithic ANN structure. Having individual sub-models may allow the system more flexibility in learning the pattern of a specific truck type and therefore improve the accuracy of the entire model.

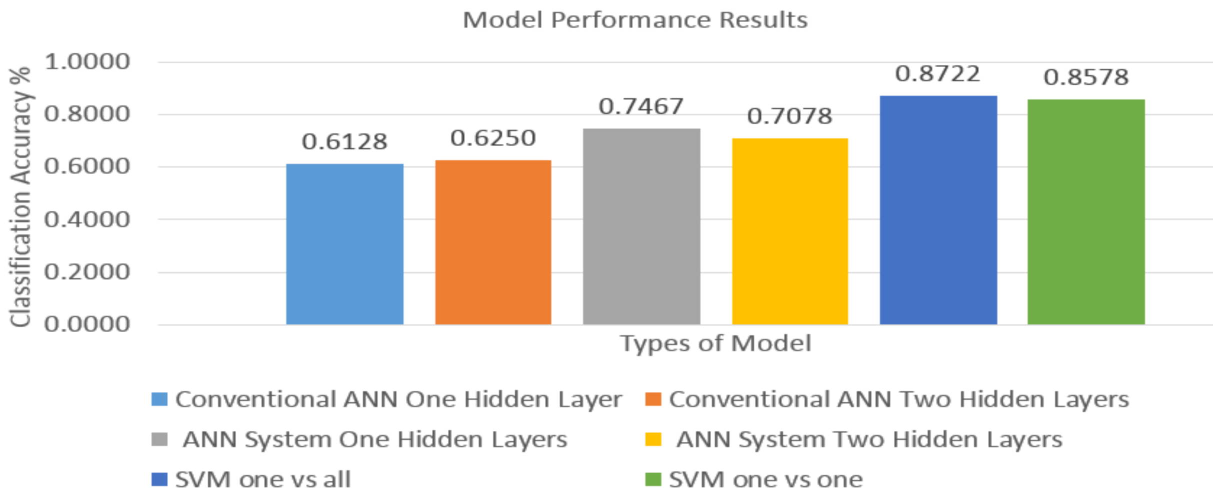

Figure 9: Comparison of optimal model performances for 1,800 validation patterns.

For the ANN models, the number of hidden layers did not appear to have a significant impact on classification performance. Figure 10 provides an analysis of the misclassified truck patterns for the single hidden layer ANN, model format 1, for the validation patterns. The blue arrows indicate the number and direction of the misclassifications. It can be seen from this figure that the misclassifications between truck types 7, 8 and 9 and truck types 1, 2 and truck type 3, 5 and 5, 6 contributed to the majority of the misclassification instances. As might be expected, it is also apparent from this that the misclassifications tended to occur between trucks with similar axle configurations.

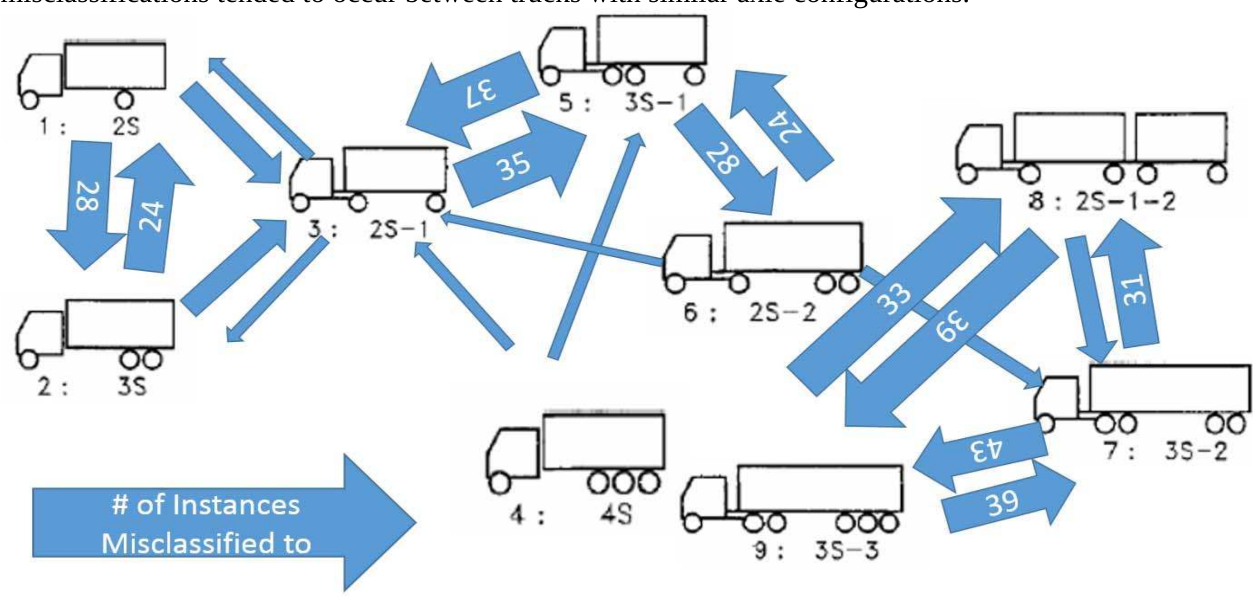

Figure 10: Analysis of truck misclassification for the single hidden layer ANN, model format 1 (*Figure 4*).

5 CONCLUSION AND FUTURE WORK

The study reviewed existing empirical modeling approaches to solving the truck WIM problem, specifically for truck type classification, and proposed the use of SVMs as an alternative potentially more accurate approach. The study developed and compared the performances of six ANN and SVM based truck classifiers using synthetically generated truck weigh-in-motion data. The optimal versions of each model were determined using a LOESS based empirical modelling parameter selection schema. The results indicated that the SVM models significantly outperformed the ANN models in terms of the number of correct truck classifications.

Future work should be concerned with developing models that are extendable to a wider range of problems, including bridges of different lengths, span configurations, and numbers of lanes, as well as situations involving multiple truck crossing events. Such models should also be able to estimate truck parameters such as axle loadings and spacing, the level 2 components of Figure 1. A challenge is to achieve this while circumventing the problem of a geometric increase in the number of training patterns with respect to the number of variables required to describe the problem.

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