Modular Neural Networks for Predicting Settlements during Tunneling

By Jingsheng Shi,[1] J. A. R. Ortigao,[2] and Junli Bai[3]

Abstract: This paper discusses back-propagation neural networks (NN) for predicting the settlement during tunneling. Three settlement parameters and 11 major affecting factors have been identified from analyzing the general tunneling operations. A general neural network model is trained and tested using the actual collected data from the 6.5 km Brasilia Tunnel in Brazil. The general model generates an average error of 70 mm for the predicted settlements compared with the actual values. To improve the prediction accuracy, modular NN models are studied based on the concept of integrating multiple NN modules in one system with each module being constrained to operate at one specific situation of a complicated real world problem. The modular concept can make better use of neural computation algorithms to improve the convergence in the training process. It has been studied on modeling multiple output variables and discrete input variables. After applying modular models to the same Brasilia Tunnel, the average prediction error is reduced to 33.4 mm, which shows a significant improvement over the general NN model.

BACKGROUND

Shallow soft ground tunneling in dense populated areas requires several measures to reduce risks and effects to nearby structures. One important step is the prediction of the tunneling effect by evaluating settlements imposed by the excavation. The expected amount of ground deformation will lead to important design decisions related to the tunnel construction and support method and to measurements on nearby structures to reduce the detrimental effect of ground movements. Therefore, settlement prediction in tunneling is important and needs to be studied.

In the early stage of design the designer bases his predictions on previous experience and may use simple empirical methods, such as those described by Peck (1969), Attewell (1977), Attewell and Woodman (1982), O'Reilly and New (1982), and Mair et al. (1993). Alternatively, simple equations based on the theory of elasticity (Uriel and Sagaseta 1989) may also be employed.

The final design generally requires more accurate stress and deformation analyses and finite-difference or finite-element methods may be used, as discussed by Rowe and Lee (1992).

During construction it is important to observe ground displacements and ground water as the tunnel advances. The daily analyses of these data and comparison with previous experience (Peck 1969; Cording and Hansmire, 1975) can lead to predictions of the damage to nearby structures and to modification in the construction method. This is particularly important when work is started on a new tunnel. At the beginning of the excavation even the most trained crew lacks experience at that particular site and/or with new construction equipment. This is reflected in more deformation at the beginning of a new tunnel. After some time, the crew becomes more experienced, construction methods are adjusted, and the quality and pace of the work improves. This will be reflected in the measured deformation, which may decrease. Therefore, the importance of ground movement observations cannot be overemphasized, because it is a gauge indicating change in the quality of the work and a warning of the level of damage to nearby structures.

A neural network-based approach for analyzing and predicting behavior during tunneling was studied in this research. It was tested at a 6.5 km shallow soft ground tunnel in Brazil (Ortigao et al. 1996b). Several network architectures were attempted and the modular neural network (NN) concept was studied for improving the predicting accuracy.

NN MODEL

Neural technology is an emerging field of artificial intelligence (AI), which originated from the biological structure of the human brain. Among various network architectures, back-propagation (BP) networks learn from correct patterns (e.g., past experience), and have gained wide application in engineering. A typical BP network has an input layer, an output layer, and hidden layers. A mapping relationship between the input variables and the output variables will be explored during the training process (Shi, in press, 1998). A detailed description of a BP network can be found in Rumelhart and McClelland (1986).

To apply a NN to solving a real world problem, four basic steps are involved: (1) analyze the real world problem and select a proper network architecture; (2) collect and preprocess data for training and testing; (3) design, train, and test the network model; and (4) deploy the network to the end user.

Designing a BP network architecture includes determining the number of input and output variables (i.e., neurons in input and output layers) and selecting the number of hidden layers and neurons in each hidden layer. The number of hidden layers and number of neurons in each hidden layer in a BP network may affect the training efficiency and the precision of prediction. It is impossible to prove how many hidden layers and how many neurons in each hidden layer can result in the most effective training and the most accurate prediction, although many applications have shown the satisfaction with one hidden layer. The common practice is to experiment with different numbers of hidden layers and different numbers of neurons in each hidden layer. The network that can provide the most accurate prediction will be selected. The number of neurons in the input and output layers corresponds to the expected input and output variables of the problem. Output variables are the expected answers to the problem, and the input variables are factors that affect the answers.

BRASILIA TUNNEL OBSERVATIONS

The Brasilia tunnel consisted of a 6.5 km long, 9.6 m in diameter excavation in shallow soft ground, as described in

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detail by Ortigao et al. (1996b). The tunneling method went through following stages: excavation, placement of lattice girders, shotcreting the primary layer of the lining, closing the invert, and finally placing the final or secondary layer of the lining. In all cases a clay core (not shown) was always left to improve the stability of the face.

Excavation encompassed the three construction methods listed in Table 1 and Fig. 1. Method A is the least expensive and is employed in favorable conditions of face stability and negligible damage to nearby structures. On the other hand, if excavation conditions deteriorate, such as with decreasing thickness of soil cover, poor soils are encountered, sensitive nearby structures exist, or deformation observation indicates that stability may be decreasing, methods B or C could be selected. An additional construction method, D, consisting of side drift with temporary invert, was not included in the analyses, because it was only used for a very short extension of 20 m.

TABLE 1. Construction Methods

Method (1)	Construction method (2)	Distance to close invert behind excavation face (X) (m) (3)
A	Full face	4.8–7.2
B	Heading excavation with temporary invert; bench excavated afterwards in 3 m steps	2.4–5.4
C	Side-drift employing side wall; enlargement to final section, with demolition of side wall	2.4–5.4

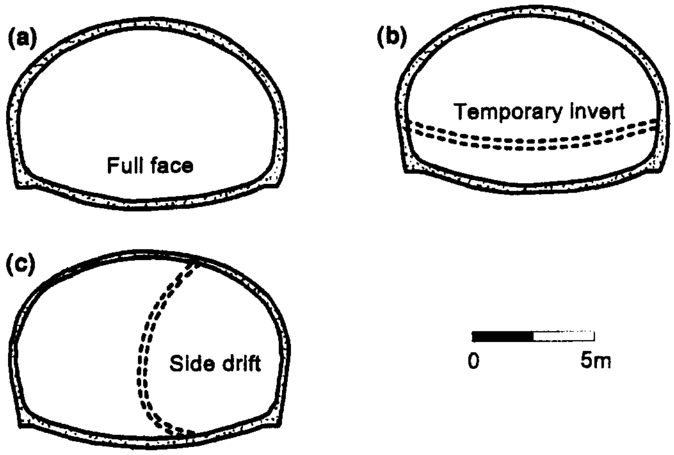

FIG. 1. Construction Methods: (a) Full Face; (b) Temporary Invert; (c) Side-Drift

SETTLEMENT OBSERVATIONS AND ANALYSIS

Surface settlement observations took place at 50-m intervals along the tunnel length at three different excavation stages: (1) at the face passage; (2) at the closing of the inverted arch; and (3) the final value after stabilization (Ortigao et al. 1996b).

Settlement observations can be compared in terms of maximum settlement (S_{max}), the standard deviation i of the fitted Gaussian curve (see Fig. 3), given by the following equation:

$$S = S_{max} \exp\left(\frac{-x^2}{2i^2}\right) \qquad (1)$$

where S = settlement; x = horizontal distance to the axis of symmetry; S_{max} = maximum settlement; and i is the standard deviation of the fitted Gaussian curve.

The settlement trough was obtained as indicated in Fig. 2. In addition, single settlement marks were deployed at 10-m intervals among the fully instrumented stations.

SOIL CONDITIONS

The local soil consists of a soft reddish-brown lateritic clay called porous clay, which is unsaturated for most parts of the tunnel, collapsible, and presents high permeability owing to the high amount of pores in the soil matrix.

The porous clay overlies residual soil from slate or metasiltstones and quartzites, also called metarhythmites, as described in detail by Ortigao et al. (1996a) and summarized in Fig. 3(a). This clay was investigated by means of a Ménard pressuremeter, a Marchetti dilatometer, and a piezocone, as well as laboratory tests. The tests were concentrated in three locations only in order to investigate properties for the most typical soil layers, correspondent to different geological units. However, along the tunnel chainage at 50-m intervals, the site investigation was rather crude, consisting of boreholes with standard penetration tests (SPTs) at each meter of depth. Typical N values from SPT were between 1 and 8 blows per 30 cm in the porous clay and over 50 blows per 30 cm when the metarhythmites were encountered.

Most of the excavation took place well above the water table, except at the south end (Fig. 3a), where the water level was above the tunnel crown.

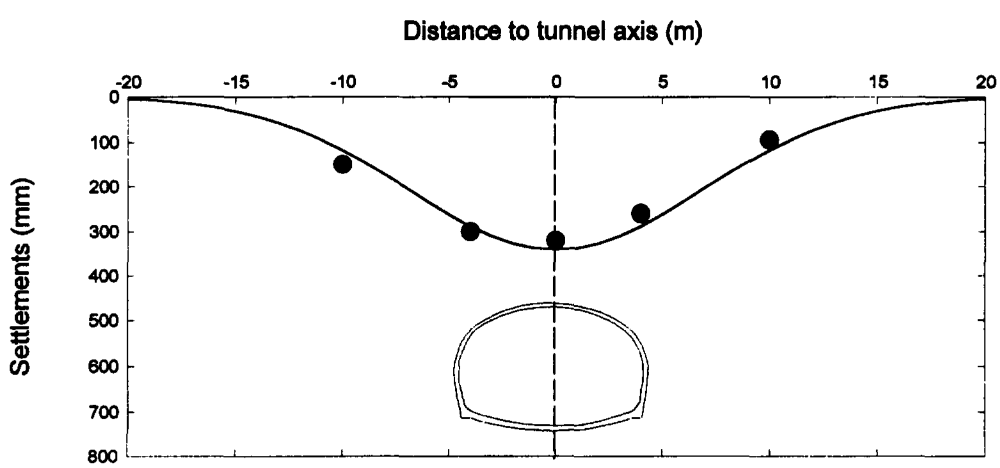

FIG. 2. Settlement Trough

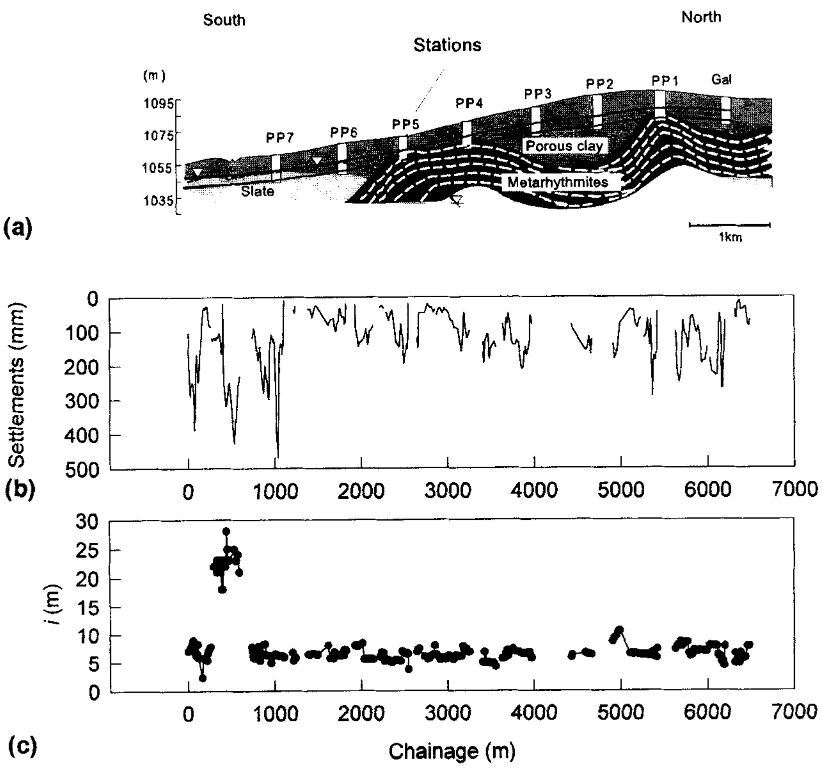

FIG. 3. (a) Soil Profile; (b) Settlements; (c) Parameter *i*

OBSERVED SETTLEMENTS AND *i* PARAMETER

Observed values of settlements and *i* parameter are presented in Figs. 3(b) and (c). Values of *i* are fairly constant, except around chainage 500 m, where the measurements were affected by existing pavement.

Settlements between chainages 0 and 1,000 m were the largest observed in the Brasilia Tunnel. The reasons were discussed by Ortigao et al. (1996b) and Negro and Kochen (1996). The settlements were due to poor construction quality in this drive, such as excessive delay for the closing of the invert, inefficient link between the invert, and the temporary lining and inefficient dewatering. In addition, the soft and collapsible nature of the porous clay also contributed to the large settlement values.

GENERAL NN MODEL FOR BRASILIA TUNNEL

The measured factors that may affect settlements are indicated in Table 2 and Fig. 4. The depth of soil cover and the area of tunnel section will jointly affect the settlements, and a jointed factor, ratio of soil cover/tunnel equivalent diameter (H/D) will be used.

TABLE 2. Measured Factors that Affect Settlements

Symbol (1)	Description (2)
D_r	Length of excavation from drive start
H	Depth of soil cover above tunnel crown
A	Area of tunnel section
X	Delay for closing invert
WL	Water level depth
Rate of advance	Rate of advance of excavation of face for each tunnel drive, taken as average value for each tunnel drive
CM	Construction method
N_c	Mean SPT N value at tunnel crown level
N_s	Mean SPT N value at tunnel springline level
N_i	Mean SPT N value at tunnel inverted arch level

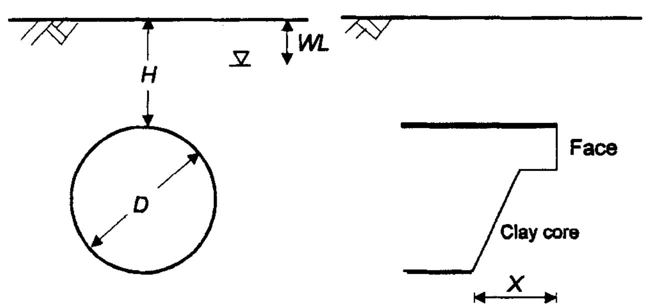

FIG. 4. NN Input Data

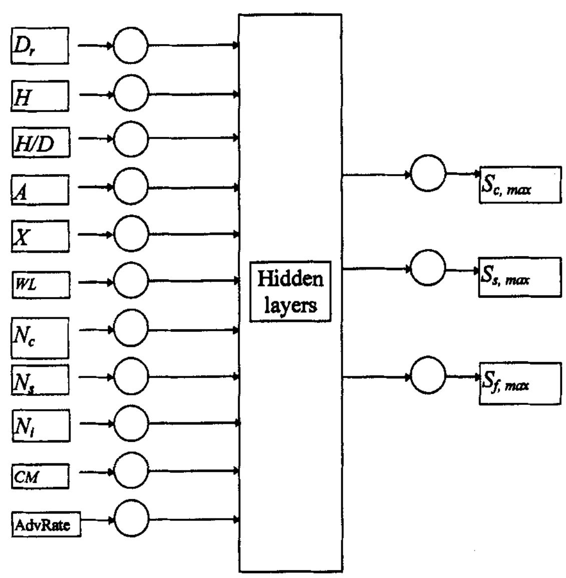

FIG. 5. General NN Model

The same shotcreted lining (220 mm thick) was used throughout the tunnel. Therefore, the effect of the support was modeled by the value of the delay in closing the inverted arch X (Fig. 4).

TABLE 3. Example of Tabulated Data from Field Observations

Chainage (m) (1)	Drive (m) (2)	H (m) (3)	H/D (4)	Area (m²) (5)	X (m) (6)	WL (m) (7)	N_c (8)	N_s (9)	N_l (10)	Rate of advance (m/day) (11)	Construction method (12)	$S_{c,max}$ (mm) (13)	$S_{i,max}$ (mm) (14)	$S_{f,max}$ (mm) (15)
4	0	8.5	1.17	41.38	6.52	3.40	2	5	50	2.10	3	30	40	105
9	5	8.15	1.12	41.38	6.06	3.60	2	5	50	2.10	3	55	80	185
14	10	8.25	1.14	41.38	3.96	3.70	2	5	50	2.10	3	68	92	222
19	15	8.4	1.16	41.38	3.96	3.90	2	5	50	2.10	3	75	103	260
24	20	8.50	1.17	41.38	5.51	4.00	2	5	50	2.10	3	70	150	290
29	25	8.60	1.18	41.38	3.81	3.81	2	5	50	2.10	3	95	160	265
35	31	8.90	1.23	41.38	3.76	3.76	2	5	50	2.10	3	108	160	260
48	44	9.6	1.32	41.38	3.53	3.53	2	5	50	2.10	3	93	110	250
60	56	10.3	1.42	41.38	3.72	3.72	2	6	43	2.10	3	85	120	260
69	65	10.7	1.47	41.38	4.26	5.40	2	5	43	2.10	3	100	180	360
77	73	11.1	1.53	41.38	3.9	5.60	2	5	43	2.10	3	128	230	390
84	80	10.1	1.39	41.38	4.15	5.80	2	4	43	2.10	3	120	190	300
91	87	8.2	1.13	41.38	3.23	5.90	2	4	50	2.10	3	70	115	200
103	99	8.8	1.21	41.38	5.63	6.10	2	4	50	2.10	3	28	86	168
114	110	11.6	1.60	41.38	5.63	6.30	2	4	50	2.10	3	63	125	248
122	118	12.2	1.68	41.38	5.36	6.00	2	4	50	2.10	3	83	160	243
162	158	9.4	1.30	41.38	6.23	5.80	2	4	21	2.10	3	25	52	75
177	173	8.3	1.14	41.38	6.23	6.20	4	4	50	2.10	3	9	25	35
187	183	8.4	1.16	41.38	5.63	6.40	4	6	50	2.10	3	6	15	30
198	194	8.8	1.21	41.38	5.63	6.80	4	6	50	2.10	3	4	17	36
207	203	8	1.10	41.38	5.82	7.10	4	6	50	2.10	3	7	18	28
220	216	7.5	1.03	41.38	5.46	7.50	4	6	34	2.10	3	3	14	27
230	226	10.3	1.42	41.38	6.08	7.70	4	5	34	2.10	3	5	23	48
240	236	11.6	1.60	41.38	5.52	7.70	4	5	34	2.10	3	18	35	78
250	246	11.7	1.46	50.75	7.95	7.60	4	5	34	2.10	2	22	55	85
260	256	8.4	1.04	50.75	3.15	7.50	3	4	13	2.10	2	30	47	85

Note: see Table 2 for explanation of abbreviations; $S_{c,max}$, maximum settlement at tunnel crown level; $S_{i,c}$, maximum settlement at tunnel inverted arch level; $S_{f,max}$, maximum final settlement after tunnel excavation.

The relationships between the affecting factors and three expected maximum settlements can be mapped as in Fig. 5, where $S_{c,\max}$ is the settlement at the face passage; $S_{i,\max}$ is the settlement at the invert closing; and $S_{f,\max}$, is the final settlement after stabilization. These values refer to the maximum values obtained from the Gaussian curve fitting.

TRAINING AND TESTING OF GENERAL NN MODEL

All measured data, as presented in Table 2, were tabulated for each instrumented station along the tunnel, as shown in Table 3. In Table 3, construction methods A, B, and C are correspondently represented by numbers 1, 2, and 3 as required by the neural network program.

A total of 356 valid data patterns were extracted from site observations. Among them, 328 patterns were used for training, and 28 patterns from the northernmost tunnel drive, named Gal (short for Gallery) in Fig. 3, were used for testing.

The NN program used was NeuroShell 2 (Ward Systems Group, Inc.). We have experimented with various BP networks with one or two hidden layers and different numbers of neurons in each hidden layer using the above collected data patterns. The net-perfect function of NeuroShell was used to train the networks.

The network with one hidden layer and 24 hidden neurons has shown good agreement to the training patterns. However, when it was applied to the test patterns, the agreement was poor, as shown in Fig. 6. The statistical accuracy parameters are tabulated in Table 4 for both the training data and the test data, respectively. The results in Table 4 show much smaller errors when the network is applied to the training data than to the test data. Moreover, very high correlation coefficients (>0.8) are obtained when the network is applied to the training data, but poor correlation coefficients are obtained for the test data. The good agreement for the training data sets could be due to overtraining, an error that may occur in the training

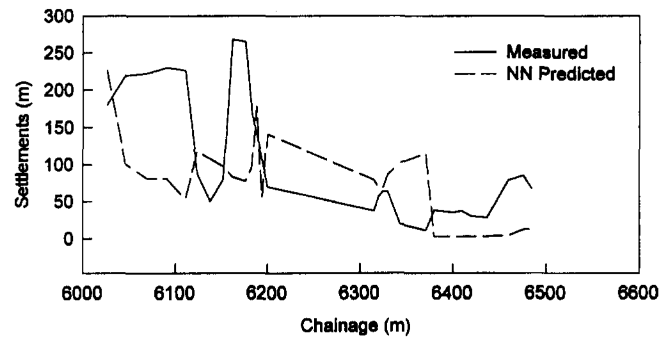

FIG. 6. Results of Test Patterns for Maximum Settlements after Stabilization (Poor Agreement)

process when training patterns are excessively used. This would force the network to memorize the training patterns, but it will not be able to predict new situations, such as test patterns. In conclusion, the general network model is expected to generate an average error of 70 mm compared with the actual values (Table 4) for the predicted maximum settlements for the Brasilia Tunnel, which is very poor. Many other network models have been experimented on with the intention to improve predicting performance, but have failed. New approaches have to be explored.

MODULAR NN

In real life situations, specific expertise is usually required to solve a specific problem. An expert is always domain specific although he/she has certain general knowledge. It should not be surprising if a general NN model cannot provide an accurate prediction for a complicated problem. The modular NN concept naturally comes into existence. A modular network consists of multiple NN modules, each of which only models one specific category of expertise. Each module is

TABLE 4. Accuracy of General NN Computation

Output (1)	Training Patterns $S_{c,max}$ (2)	$S_{s,max}$ (3)	$S_{f,max}$ (4)	Test Patterns $S_{c,max}$ (5)	$S_{s,max}$ (6)	$S_{f,max}$ (7)
R squared	0.6428	0.6661	0.7596	0.0356	0.0227	0.000
Mean squared error	340.0	874.3	1506	1264	3717	7664
Mean absolute error	12.02	19.05	24.70	26.50	48.40	70.03
Minimum absolute error	0.000	0.101	0.323	2.926	0.467	4.989
Maximum absolute error	149.8	194.2	226.5	114.1	156.2	187.6
Correlation coefficient	0.810	0.818	0.872	0.358	0.401	0.320

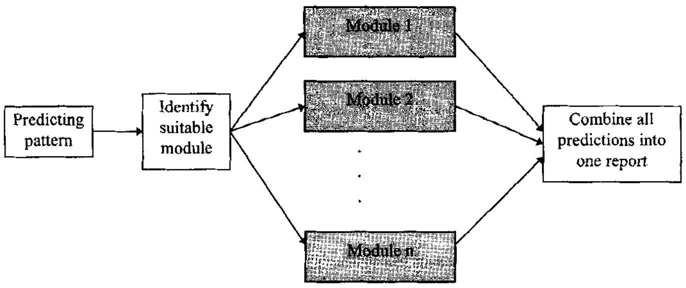

FIG. 7. Modular NN

TABLE 5. Accuracy of Modular NN Computation

Accuracy (1)	Training data (2)	Test data (3)
Minimum error	0.62 mm	5 mm
Mean error	21 mm	64 mm
Maximum error	148 mm	156 mm
Correlation coefficient	0.832	0.575

trained and tested separately using the data patterns in its category. All the trained modules are then integrated into one complete system before it is deployed to the end user as illustrated in Fig. 7. The predicting patterns are at once presented to the system, and proper modules are then identified and employed for predicting corresponding outputs, and all predicted results are combined into one report.

The classification of modules should start by analyzing the real world problem depending on its complexity and expected accuracy for prediction. Investigating expected output and input variables is an effective approach for determining required modules and is detailed as follows.

Modular Network for Multiple Outputs

During the training process of a BP network, the errors between the actual and predicted values for all outputs are combined into one, which is propagated back to update the connection weights. If different outputs need to modify the same connection weight in the same direction or a compromise can be reached, the training will converge; otherwise the training may not converge or the level of accuracy may not be acceptable. Therefore, a BP network usually performs better when it is used to predict one single output.

Modular concept can be applied to substantiate this requirement with one module corresponding to one output. This modular approach converts an original single input-output mapping relationship to multiple input-output mapping relationships. In the single input-output mapping, the input variable set is mapped to the entire output variable set. In the multiple input-output mappings, the input variable set is mathematically mapped separately to each of the output variables.

A single input-output mapping is as follows:

$$(x_1, x_2, \ldots, x_n) \Leftrightarrow (z_1, z_2, \ldots, z_m) \tag{2}$$

where $(x_1, x_2, \ldots, x_n)$ is the input variable set; and $(z_1, z_2, \ldots, z_m)$ is the output variable set.

A multiple input-output mappings is as follows:

$$(x_1, x_2, \ldots, x_n) \Leftrightarrow \begin{matrix} (z_1) \\ (z_2) \\ \\ (z_m) \end{matrix} \tag{3}$$

To facilitate this conversion, the original training data file should be split into multiple training files corresponding to output variables. Each training file will be presented to train each neural module accordingly. The testing can be conducted in the same way. A conversion function can be programmed to manipulate the whole process including splitting the original data file and controlling the training process.

In this tunneling project, three settlement values are expected to be predicted: at the face passage, at the invert closing, and after stabilization. Therefore, three corresponding modules have been trained and tested separately. Applying the trained modular network to the training and test patterns, the statistical accuracy parameters for the maximum settlements are summarized in Table 5, which shows a little improvement over the general NN. The average prediction error is reduced to 64 mm, and correlation coefficient is increased to 0.575. Moreover, the training process converged faster than in training the general NN.

Modular Network for Modeling Input Variables

Some input variables define discrete states corresponding to different situations that the system may be running. Conventionally, they could be identified by labels, symbols, or discrete numeric values. For example, gender can be either M or F; construction methods can be labeled by A, B, C, or D; and the salary scale of an employee can be identified by 1, 2, 3, 4, or 5. It is a common requirement for neural computation to represent these variables in numeric values. For example, construction methods A, B, C, and D can be correspondingly represented with 1, 2, 3, and 4. In a BP network, the input to a neuron in the first hidden layer is fully determined by the inputs to the input layer and the connection weights as illustrated in (4).

$$y_j = \sum_{i=1}^{m} w_{ij} x_i \tag{4}$$

where y_j is the input of neuron j in the first hidden layer; x_i is the input to neuron i in the input layer; and w_{ij} is the connection weight between neurons i and j. y_j determines the output of neuron j, which jointly determines the input to its following neurons in the following layer (next hidden layer or output layer) with the connection weights. Therefore, the outputs from neurons in the output layer are fully determined by the inputs to the input layer and the connection weights cross the entire network. During training, inputs take values from training patterns, and the training process identifies a set of connection weights to minimize the differences between actual outputs and calculated outputs.

Let x_l represent the input variable of the construction method. From (4) the contribution to y_j from x_l is $w_{lj}x_l$. Therefore, the assumed values 1, 2, 3, and 4 for construction methods A, B, C, and D bring an indication that method A ($x_l = 1$) is closer to method B ($x_l = 2$) than to methods C ($x_l = 3$) and D ($x_l = 4$), although there may be no relationships among these different methods.

There are many other cases like these construction methods in which a simple numerating of different situations will bring the misleading indication to neural computation, and therefore they should be avoided.

Modular concepts can be studied to model a discrete input variable. Let x_l represent a discrete input variable; its possible values are $S_1, S_2, \ldots, S_n$; n is the number of states that x_l can take

$$X_l = \begin{cases} S_1 \\ S_2 \\ \vdots \\ S_n \end{cases} \quad (5)$$

n modules are then created to correspond to the n states and x_l is removed from the input variable set. The original collected data patterns are classified into n categories corresponding to the n states, and each of the n modules is trained/tested separately by applying the relevant category of data patterns. Each module will only operate at its corresponding situation. All trained modules will be integrated into one complete system before being deployed to the end user.

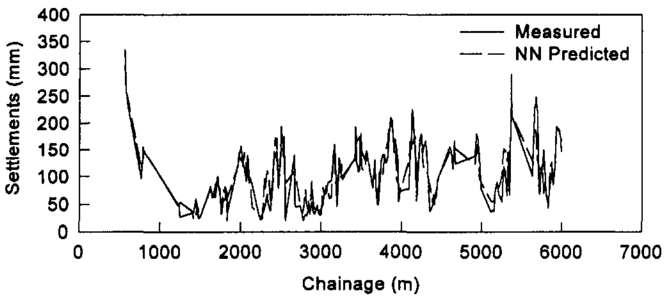

FIG. 8. Results of Modular NN Training Data (Maximum Settlements after Stabilization)

If N discrete input variables are required to be modeled by the modular approach, the total number of modules will be

$$M = n_1 \cdot n_2 \cdot \ldots \cdot n_N \quad (6)$$

where n_i = number of states of input variable x_i. Obviously, M tends to be very large if either number of discrete variables or number of states of variables is large. The resulting problem would be the time requirement for training/testing a large number of modules. Moreover, more training/testing patterns may be needed because each module requires sufficient data patterns for independent training/testing purposes. Therefore, it should be avoided using the modular approach for modeling unimportant discrete input variables.

The tunneling project uses three excavation methods as illustrated previously. Three modules were created corresponding to the three construction methods. The original training file was divided into three files associated with the three construction methods and the construction method was removed from the input variables. The three modules were trained/tested separately using corresponding files. The results are plotted in Fig. 8 for the training patterns and Fig. 9 for the testing patterns. An obvious improvement can be observed from comparing Figs. 9 and 6. However, between chainage 6100 and 6200 m in Fig. 9, the observed settlements were much less than the predicted values. The reasons are an existing underground structure just above the tunnel, which decreased observed settlements. If the three exceptional measured points are excluded from the test patterns, the average prediction error is reduced to 33.4 mm, a significant improvement over the general network.

CONCLUSION

This paper has presented a study of back-propagation neural networks for predicting settlements during tunneling by using the actual collected data from the Brasilia Tunnel in Brazil. Results show that a general NN model cannot achieve a high level of accuracy with an average error of 70 mm for the maximum stabilized settlements; instead, a modular concept, which consists of multiple modules with each one representing one specific aspect of a complicated real world problem, has been studied. The concept has been developed to model mul-

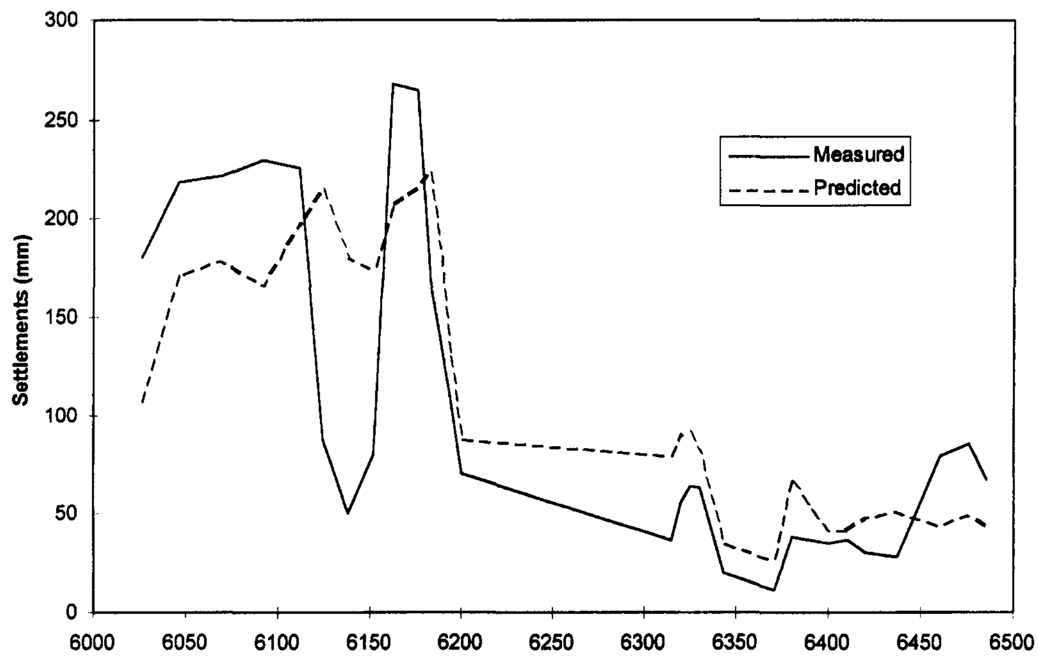

FIG. 9. Test Results from Modular NN Approach (Maximum Settlements after Stabilization)

tiple output variables and discrete input variables. The average prediction error for the same Brasilia Tunnel is reduced to 33.4 mm, which shows a significant improvement over the performance of the general network model.

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