Neural Network Predictive Tool of Ground Settlement

Due to Dewatering Activities

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Abstract

The present paper reports the implementation of a neural network technique to predict ground settlement as occasioned by dewatering activities of a long-term large-scale drainage project. The objective of the project is to lower and maintain the level of the ground water table in urban areas through a system of a non-stop pumping wells whose layout and operation rate are determined and implemented in a pilot project at a district level. To make use of the wealth of data collected and to aid in the decision making regarding extending the project to other areas, a neural network predictive tool is developed to estimate ground settlement induced by the drainage activities near and further away from the pumping wells. The backpropagation architecture is employed to design two networks for drawdown-settlement relationship and attenuation of settlements further away from the pumping wells. Incorporating relevant soil properties in the input nodes considerably improved the performance of both networks.

Introduction

A pilot drainage project (Mossaad, Sadek, and Ghoneim 1997) has been constructed to lower the water table in a 1 km^2 residential urban area in Kuwait City. The drainage system consists of six 50 m deep pumping wells with the objective of lowering the water table to about 4 m below ground surface without adversely affecting the existing buildings, Fig. 1.

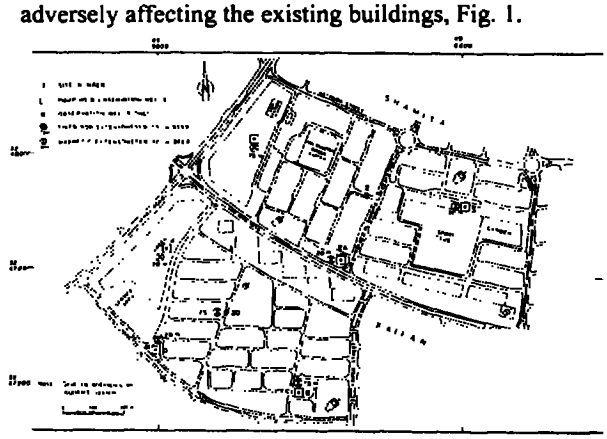

Fig. 1. Layout of drainage and monitoring system

The pilot project is mainly aimed at evaluating the effectiveness of the drainage scheme and assessing the impact of the drainage process on the structural integrity of existing buildings. Monitoring of the impact of the drainage process was carried out through periodic surveying (precise leveling) of roads and buildings settlements and measurement of the change in widths of existing cracks.

The water levels at different depths are monitored through 56 observation wells of depths varying between 6 m and 75 m. The deformations taking place in different soil layers due to the effect of the drainage process have been monitored by means of seven multi-point borehole extensometers 20 to 75 m deep. The impact on buildings structural integrity due to these settlements is a primary concern in the present pilot drainage project and the outcome of the impact assessment will form the basis of decision making to proceed with the full-scale long-term dewatering project.

To make use of the wealth of measurements and to help aid in the decision making for extending the drainage process, it was decided to develop, based on the collected data, a predictive tool which can be used in the future to estimate expected settlements and their differentials induced due to long-term drainage activities. Within this context and due to the complex nature of the problem, which reduces the potential for resorting to analytical approaches, the neural network technique provides an excellent platform. For this purpose, the present paper describes a two-step neural network approach to estimate settlement values near and further away from pumping, or production, wells. First, to estimate settlement in the vicinity of any production well, appropriate and causative drawdown values are fed to the first network and an estimate of the near field settlement is obtained. To predict settlement values further away from the well location, the obtained near field settlement is then attenuated using the second network to give settlement values within 100m zone.

Drawdown-Settlement Network

The drawdown values are measured in observation wells of depths 6m, 15m, 25m, 45m and 75m, and denoted as types A, B, C, D and G respectively. Analysis of the drainage pattern indicates that A and

B-type wells may be generally considered as being located in the same drawdown horizon, which is distinctly different from another horizon encompassing the C and D-type wells. Therefore, it can be reasonably assumed that the drawdown values measured in A-type wells (6m), DDA, and in C-type wells (25m), DDC, adequately describe the general drawdown pattern in the present project and hence they are considered in the input parameters of the drawdown-settlement network.

Training cases of drawdown-settlement pairs are obtained by screening the wealth of measurements through the following criteria:

1. Pairs of drawdowns (DDA and DDC) as inputs and the induced settlement as the output should be spatially and chronologically associated to satisfy cause-effect paradigm. For spatial association, it is required that location of settlement measurement should be reasonably close to the observation wells from which drawdown values are recorded. As for the chronological association, it is simply stipulated that the date of measuring drawdown values should be few days prior to the date of settlement measurement.
2. Measurements corresponding to special events such as heavy rainfalls or pumping stoppage are excluded and only those resulting from normal operations are considered.

The first attempt to develop network relating drawdown and settlement at a site, referred to as DDS, is to use the drawdown values measured in wells A and C as the input nodes and the settlement measured at stations 5m from the well as the output node. After attempting several topologies with different number of the hidden nodes for the DDS network, one hidden layer with five nodes is employed. The topology of the network is shown in Fig 2.

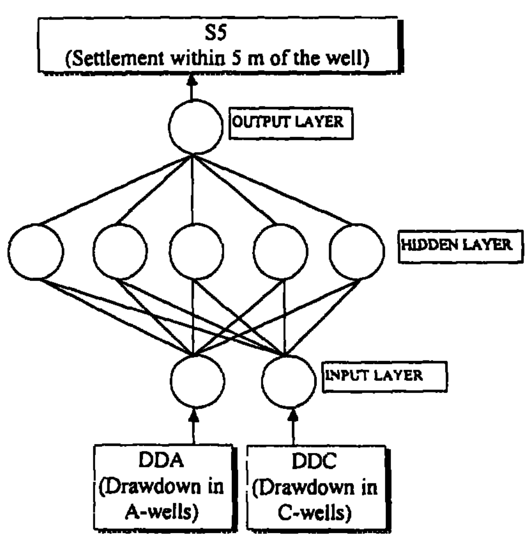

Fig. 2. Topology of DDS network

Transfer functions of the nonlinear sigmoid expression are adopted. Weight factors are initialized at the beginning of the training.

Out of the available 26 qualified cases satisfying the above two requirements, 22 cases are used for training as a minimum and the remaining 4 cases are used for testing. The control panel of the WinNN software employed in the present study allows the user to provide initial values for learning rate η and momentum α, monitor the progress of error function and introduce temporal changes in learning parameters to improve convergence. Tolerable error is set as 0.001 and iterations are performed to reduce the error associated with each training pattern and once this is achieved for any pattern it is declared as a "good pattern". The program terminates iterations when a 100% good patterns situation is reached.

In the second network DDSP, in addition to the drawdown values DDA and DDC, the standard penetration test number (SPTN) at the site is used as the third input node. The SPTN gives a clear indication of the rigidity of the soil, a higher SPTN value indicates a stiffer soil and vice versa. In other words under the same effective load, a soil layer with a higher SPTN will settle less than the one with a lower SPTN. Hence, adding SPTN as one of the input nodes is physically justified. The topology of the DDSP network is shown in Fig 3.

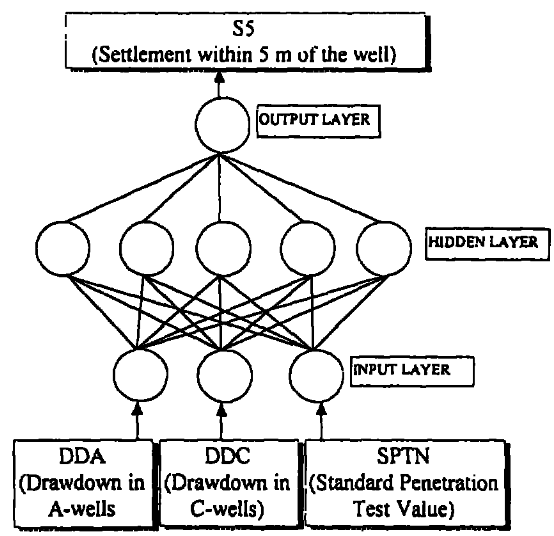

Fig. 3. Topology of DDSP network

The two developed networks DDS and DDSP are tested using the four test cases and the comparison of the target settlement values with the two network estimates is shown in Fig 4. It can be seen that the DDSP with the SPTN is used as one of the input nodes, is far superior to the other network in which only drawdown values are used as inputs.

A sensitivity analysis is performed on the DDSP network by varying the number of nodes in the hidden layer and monitoring the changes in number of iterations required to reach a 100% good pattern and the accuracy of the network. Figure 5 shows the average percentage of error in estimating the test cases, versus the number of hidden nodes. It can be seen the 5-node network can be used satisfactorily.

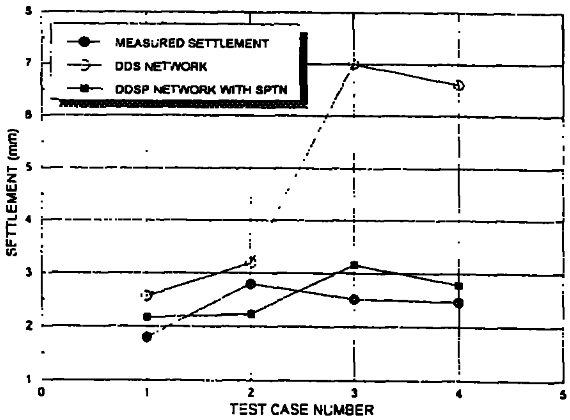

Fig. 4. Measured settlement and estimates of DDS and DDSP networks

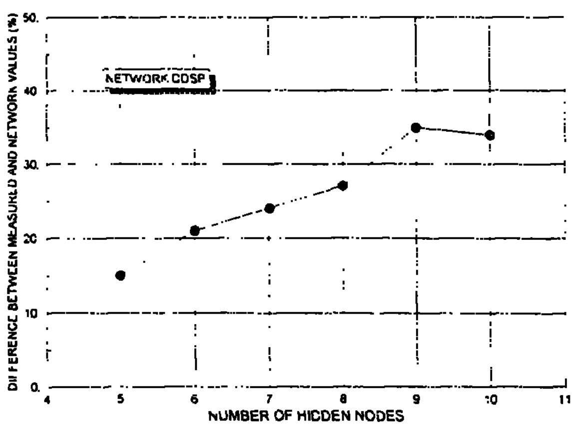

Fig. 5. Sensitivity analysis on hidden nodes

Settlement Attenuation Network

The above drawdown-settlement networks, DDS and DDSP, predict the settlement values in the close neighborhood of observation and production wells. It is of practical interest, however, to estimate settlement further away from the wells where existing structures may be located. In other words it is required to develop a network that attenuates the settlement away from the wells. Reviewing available settlement data, it is found that only road monuments stationed in sites 1, 2A, 3, 4, 5 and 6 can be used as they are positioned at regular distances of 5, 10, 20, 40 and 100 m from the well and hence spatially related settlement groups can be established for the purpose of training the intended attenuation network.

In the first attempt, the network ATEN has one input node of the settlement at 5m from the well (S5), and four output nodes corresponding to settlement values S10, S20, S40 and S100 at 10, 20, 40 and 100m, respectively, away from the well. Number of hidden nodes is taken as nine after testing several networks. Topology of the ATEN network is shown in Fig 6. A total of 30 cases are used for training and testing the network. Testing ATEN network using seven cases and presenting the ratio of the network estimate of the four settlement values to their target values indicated relatively poor approximation with differences reaching ±90%.

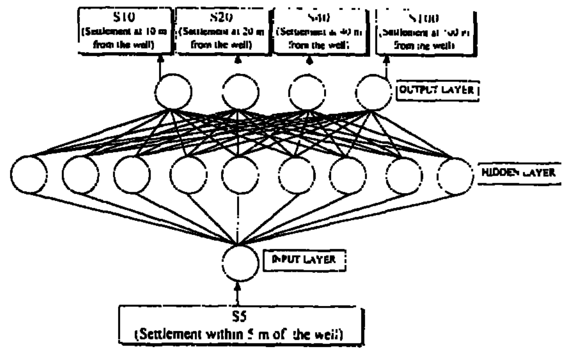

Fig. 6. Topology of ATEN network

The second attempt of attenuation network is to include the SPTN value in the input nodes and to assess its effect on the result. The network ATENP is designed with two input nodes (S5, SPTN), four output nodes (S10, S20, S40 and S100), and 10 hidden nodes (Fig 7).

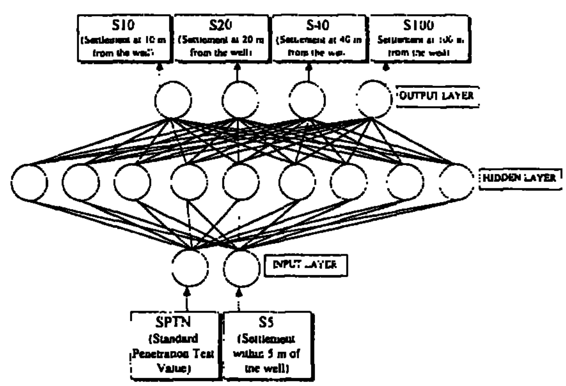

Fig. 7. Topology of ATENP network

The results of the training session are shown in Fig 8. Testing ATENP and presenting the settlement ratios (network to target) as shown in Fig 9, indicate that the inclusion of SPTN as input favorably improve the performance of the network and hence it is recommended to resort to the ATENP network in attenuating settlement. It should be mentioned that, just like human estimates, it is not possible to get a

100% match and the success of the network is generally measured by the percentage of how many cases a good estimate is obtained. Within this framework, it can be stated that the performance of the attenuation network ATENP is satisfactory.

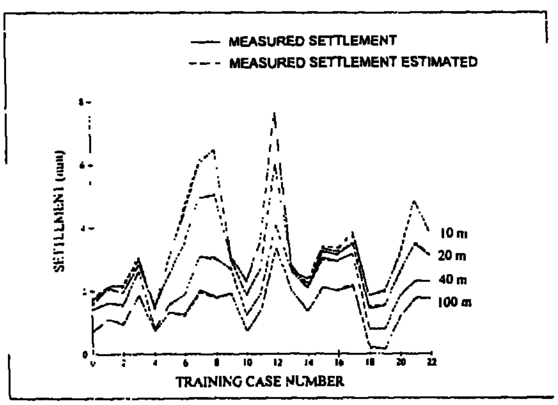

Fig. 8. Net and target values after training Of ATENP network

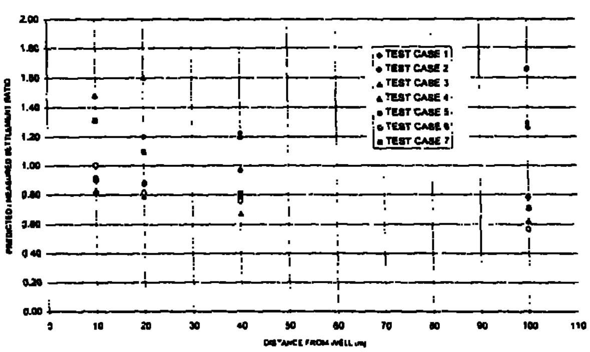

Fig. 9. Test results of ATENP network

Conclusions

The present paper describes a neural network approach for estimating the ground settlement occasioned by drainage activities. Due to the complex nature of the problem, a strategy of implementing two consecutive networks for finding the near and far field settlement values with respect to the production wells has been adopted. Although a limited number of training cases were available, the backpropagation networks have been found satisfactory. Accounting for the soil properties in designing the networks considerably improved the drawdown-settlement and attenuation networks.

Acknowledgements

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References

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