The Contribution of Soft Computing Techniques for the Interpretation of Dam Deformation

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Key words: Arch Dam, Structural Safety Monitoring, Multiple Linear Regression, Multi-Layer Perceptron.

SUMMARY

The structural health and reliable functioning of an arch dam requires good understanding of causative factors and the mechanism of deformations. This can be achieved only through proper monitoring and analysis of the investigated dam. To monitor and model the deformations, an interdisciplinary effort is needed to get significant decisions.

The data from the Theme C of the 6th ICOLD Benchmark Workshop on Numerical Analysis of Dams which was dedicated to the interpretation and a subsequent prediction of the crest displacements of Schlegeis arch dam is used (Perner & Obernhuber, 2001). The observed radial crest displacements of the dam are analysed using the time histories of water level and concrete temperatures as input parameters. The response value to be interpreted is horizontal crest displacement of the central cross section. This displacement is measured by pendulums, and the point of reference is 80m below the foundation surface.

According to the analysis, MLR exhibited the best performance with the value of 0.9917, under the criteria of R^2. MLP’s R^2 performance is 0.9916. Furthermore, the best MLP architecture has only one hidden neuron, which shows that Dam Deformation depends on input parameters linearly. It is known that Linear Regression is the most appropriate solution of linear problems. In spite of linearly depending, soft techniques showed acceptable performance according to MLR.

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1. INTRODUCTION

The central task for geodetic application in environmental monitoring is analysis and monitoring of short and long term deformation signals of building such as bridge, dams and natural structures such as regional or local geodynamic process and slopes (Eichhorn, 2007). A comprehensive interpretation of measurement results is an essential part of dam surveillance and indispensable for guaranteeing dam safety. According to this (Perner & Obernhuber, 2001), the two main objectives thereby are:

- To get to know about the performance of the dam and to justify the mathematical model used for the structural analysis,
- To detect, at an early stage, deviations from what is supposed to be the “normal” dam behaviour.

In literature, there are many studies, which are also part of classical statistics and soft computing. According to Silva Gomes et al (1985) various statistical procedures have been proposed for the analysis of monitoring data. A model of quantitative analysis is a functional relationship between observed effects and corresponding actions. Another study of displacement prediction is about the Hydrostatic-Season-Time model (HST). HST is a regression model, which takes into account the hydrostatic level as a fourth degree polynomial the seasonal effect, as a sum of four sin functions (Crépon et al., 1999). ENEL (1980) uses a statistical model to predict the behaviour of dams. The effect of water level, ambient temperature, and creep are considered. A non-linear model issued to describe the effect of reservoir level variation. Blas (1989) describes a methodology used in the analysis of an arch dam that was exhibiting moderate irreversible upstream displacements. A statistical model was developed to estimate these radial components of displacements at the top of three dam blocks. Hulea et al. (2000) describe stochastic (statistical) and deterministic models used for monitoring the Tamita arch dam. Crest displacements were almost 60% larger than predicted displacements. However, the dam structure did not show any significant signs of deterioration. Chouinard et al. (1995) apply Principal Component Analysis (PCA) to estimate the principal modes of deformation of a dam from a historical record of instruments. The PCA was applied independently to two groups of instruments, one for data from stress meters and the second for data from instrumented cylinders. SNCOLD (2003) describes a method "measured-calculated" for modelling dam behaviour and detecting anomalies. The method consists of the following steps, 1) monitor and model dam behaviour through instruments, 2) calculate the same quantities through numerical models, 3) compare the predictions and measure values.

Within the last years, a fundamental change took place in the methodology of geodetic deformation analysis (Eichhorn, 2007). The classical stochastic view is extended to, such as ANN (Artificial Neural Networks), of the soft computing techniques/artificial intelligence approaches. Several studies were performed on learning techniques using artificial neural networks or neuro-fuzzy networks (Heine, 2008; Miima, 2002). This concerns the field of Soft Computing in general – which can be understood as a branch of AI–with emphasis on fuzzy logic and fuzzy control (Haberler-Weber et al., 2007). In dam engineering, these have been developed for the prediction of dam displacement. MLR and MLP models to the prediction of the upstream-downstream displacement of an arch dam recorded by a pendulum are compared in (Mata, 2011). The wavelet neural networks were used for fitting and prediction of dam deformation monitoring by Gao (2003). Back-propagation neural network model was used for fitting analysis and forecasting of dam deformation monitoring data by Deng (Deng 2004). Beside MLP, Fuzzy Inference System (FIS) to describe complicated systems has become very popular and been successfully used in various engineering problems (Demirkaya and Sahin, 2008; Heine, 2008).

In this study, it has been presented the comparison of MLR, MLP and ICOLD Benchmark Workshop competition participant's methods to construct the daily displacement forecasting system to ensure the Schlegeis arch dam structural health safety. In statistical methods such as MLR and MLP, the most important problem in dam displacement problem is to determine how many previous days inputs the data will provide the model. In addition to classical statistical methods, some more sophisticated methods are needed for optimizing how many previous days input data will be used. Validation algorithm, which is the important algorithm of machine learning literature, produced solution.

2. METHODS

MLR and MLP are well known methods in the area of dam deformation analysis literature for dams (Weber, 2001; Liu et al., 2010; Zhang et al., 2010. In this section, simple introduction and basic understanding of related methods and success metrics are presented.

2.1 Multiple Linear Regression

MLR is a multivariate statistical technique for examining the linear correlations between two or more independent variables and a single dependent variable (Montgomery et al., 2001).

If the total number of data to be n and the number of independent variables to be p, then they are shown as $\{x_{i,1}, x_{i,2}, ... x_{i,p}\}_{i=1}^{n}$, dependent variables shown as $\{y_i\}_{i=1}^{p}$. The predicted values of dependent variables are shown as $\{\hat{y}_i\}_{i=1}^{n}$. The predicted values of individual dependent variables belong to the independent variables, by through linear function, which is shown as

$$\hat{y}_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + ... \beta_p x_{i,p} \tag{1}$$

Error function of predicted value is given by

$$J = \frac{1}{2}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 = \frac{1}{2}\sum_{i=1}^{n}\left(\beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \ldots \beta_p x_{i,p} - y_i\right)^2 . \tag{2}$$

Coefficients, which minimize the error function, are the desired β coefficients. According to β partial derivatives of error function must be equal to zero at desired points.

$$\left\{ \frac{\partial J}{\partial \beta_i} = 0 \right\}_{i=1}^{p} \tag{3}$$

Desired β coefficients must yields (3).

2.2 **Multi-Layer Perceptron**

ANN (Artificial Neural Network) is an information-processing system that has certain performance characteristics in common with biological neural networks. ANNs have been developed as generalizations of mathematical models of human cognition or neural biology, based on the assumptions as follows (Fausett, 1994).

- Information processing occurs at many simple elements called neurons
- Signals are passed between neurons over connection links
- Each connection link has an associated weight, which, in a typical neural net, multiplies the signal transmitted
- Each neuron applies an activation function (usually non-linear) to its net input (sum of weighted input signals) to determine its output signal.

ANN is the most widely used model, which finds linear or non-linear relationship between input and output patterns. Finding the relationship between input and output sets, firstly, well-known training set are used to generalize relationship. After generalized, ANN tries to predict the outputs of never seen before the test set. The performance metrics of ANN is measured by quality of test set prediction value. There are many types of ANN in function approximation literature. These are Multi Layer Perceptron (MLP), Radial Basis Functions Networks (RBFN), Generalized Regression Neural Networks (GRNN) and fuzzy logic-based decision-making systems of the incorporation of ANN, ANFIS (Adaptive Neural Fuzzy Inference System).

A MLP is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate output. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is with a nonlinear activation function. MLP utilizes a supervised learning technique called back-propagation for training the network. (Rosenblatt & Frank, 1961; Rumelhart et al., 1986).

According to this method, MLP consists of three different layers as input layer, hidden layer and output layer. Input layer's neuron number and output layer's neuron number are equal to dimension of input variables and output variable, respectively. The number of hidden layers and number of any hidden layer's neurons are determined by the designer. If the number of hidden layers and any hidden layer's neurons increase, then non-linear feature of the model will increase, too. Schematic representation of MLP model shown is Figure 1.

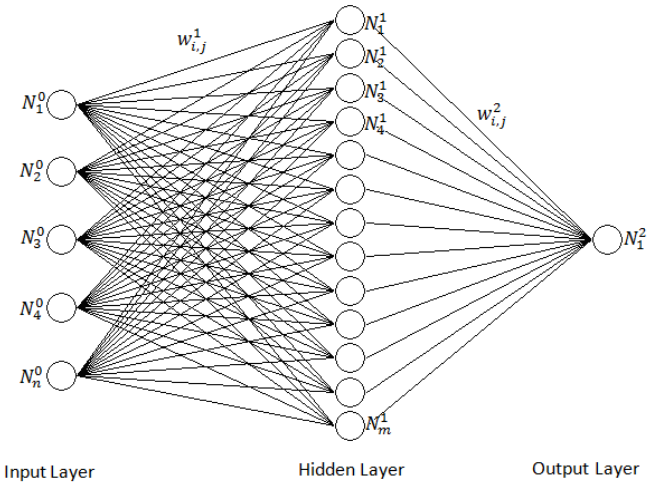

Figure 1: Schematic representation of MLP

N is the number of input parameters used for estimation of displacement, m is neuron number in hidden layer, inputs of MLP (0th layer outputs) shown as $\{N_1^0, N_2^0, \dots N_n^0\}$, output values of hidden layer (1th layer outputs) shown as $\{N_1^1, N_2^1, \dots N_m^1\}$, output value of output layer (2th layer outputs, predicted value) shown as N_1^2, the connection weight of ith neuron of input layer to jth neuron of hidden layer shown as $w_{i,j}^1$, the connection weight of ith neuron of hidden layer to jth neuron of output layer shown as $w_{i,j}^2$, jth neuron of lth layers bias value shown as b_j^l, lth layer transfer function shown as f_l, jth neuron of lth layers output is calculated as

$$N_j^l = f_l\left(b_j^l + \sum_i N_i^{l-1}.w_{i,j}^l\right) \tag{4}$$

In literature, there are many different kinds of transfer functions such as purelin, tansig, logsig, and ...etc. If the train set outputs are shown by D, then the error function of prediction calculated as

$$J = \frac{1}{2}\sum\left(N^{out} - D\right)^2 \tag{5}$$

The optimization method applied to find w and b values, which will provide a minimum value of J in (5), is called MLP learning algorithm. The mean of the training process is to calculate optimal w and b values by through of the train set. Gradient Descent, Gradient Descent with Momentum, Conjugate Gradient, Quasi-Newton, and Levenberg-Marquardt methods are the well-known learning algorithms in literature.

2.3 Validation

Validation must be done to measure how much successful regression is made by algorithms, each of which is supervised learning method data points obtained from experiment. The most well-known validation methods; hold out validation, k-fold cross validation, and leave-one-out cross validation.

According to k-fold cross validation method, n data obtained from experiments is divided randomly k number set in the form of each cluster has equal element, and each set is numbered from1 to k.

$$\upsilon_i \in \{1,2,..k\} \qquad i = 1..n \tag{6}$$

Firstly, data whose υ_i value is equal to 1 are taken to test set and data whose value is different from 1 are taken to train set.
Suggested method is trained with train set and examined with test set. Then data whose υ_i value is 2 are sent to test set, data whose υ_i value is different from 2 are sent to train set. The method is re-trained with new train set and examined with test set. This process continues until all folds are tested (Alpaydin, 2004).

2.4 **Performance Criteria**

To show the success of prediction, five criteria were used for the interpretation of measurement results (Perner & Obernhuber, 2001). They are the mean of errors (μ), the standard deviation of errors (σ), the coefficient of determination (R^2), and the most probable of the values of σ's and R^2's.
If the total number of data to be n, experimental outputs shown as y_i, the mean of experimental outputs shown as $\bar{y}$, and predicted outputs shown as $\hat{y}_i$, then the formulation of all criteria shown as follows:

$$e_i = y_i - \hat{y}_i \qquad \mu = \frac{1}{n}\sum_{i=1}^{n} e_i \qquad \sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(e_i - \mu)^2} \qquad R^2 = 1 - \frac{\sum_{i=1}^{n}(e_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{7}$$

3. APPLICATION TO AN ARC DAM

3.1 **Overview and data provided**

Geodetic methods are presently used throughout the world for the measurement of absolute horizontal displacements of dams. However, it has been universally considered that the fastest, simplest and most precise system is that of the pendulum.

Two kinds of the pendulum (plumb line) are used in controlling the stability of vertical structures. They are direct (suspended) and inverted or reversed (floating) pendulum. Inverted pendulums have an advantage over direct pendulums in the possibility of monitoring absolute displacements of structures with respect to deeply anchored points in the foundation rocks which may be considered as stable. In the case of power dams, the depth of the anchors must be 50m or even more below the foundation in order to obtain absolute displacements of the dam's crest. Several types of recording devices that measure displacements of structural points are mechanical or electromechanical micrometres. With these, the pendulum wire can be positioned with respect to reference lines of a recording (coordinating) table to an accuracy of ±0.1mm or better. Automatic sensing and recording is possible. An automated vision system that has been developed uses CCD video cameras to image the pendulum line. Two sources of error which may sometimes be underestimated by users are: the influence of air currents and the spiral shape of wires. To reduce the influence of the air pressure, the pendulum line should be protected within a PVC tube with openings only at the reading tables. A combination of the direct and inverted pendulum can be replaced geodetic method in the measurement of absolute displacements.

3.2. **Study Area**

Schlegeis arch dam was constructed between 1969 and 1971. It is a double curvature arch dam with a ratio of crest length to dam height of 5.5. The dam height is 131m, crest length 725m and crest thickness 9m. The provided data (input data) for the benchmark are the water level, the air temperature and the concrete temperatures at 6 points – one value per day for the period 1992 to 2000. The air temperatures are the arithmetic mean values from 00:00 until 23:00, the other values are those for 09:00 MET (Mean European Time).

The response value which is to be interpreted is the radial crest displacement of the central cross section. This crest displacement is measured by pendulums, the point of reference is 80 m below the foundation surface. Again, one value per day (at 09:00) is provided for 1992 to 1998. The central cross-section indicating the location of the thermometers and the arrangement of the pendulums are shown in Figure 2.

The dam is monitored with a large number of instruments. The most important surveillance instruments are five shafts with pendulums (see; Figure 2). We considered the pendulums in block 0 only. The radial movement of the crest of the dam relative to the point of reference 80m below foundation has to be analyzed.

Because of the vertical curvature of the dam, it was necessary to install two pendulums (one inverted pendulum fixed 80m below the dam base and one direct pendulum fixed at the dam crest) to obtain the crest displacement. The provided values for this benchmark workshop are the crest displacements for the period 1992 to 1998, one value per day (at 09:00). The concrete temperatures are measured daily in block 0 in two horizons, elevation 1750.65m and 1677. 15m. In each horizon, three thermometers are installed (See; Figure 2 for details). The provided values are those for 09:00 MET, for the period 1992 to 2000.

Air temperatures are measured from the dam crest at each full hour. This 24 values per day (from 00:00 until 23:00) are used to calculate arithmetic mean values, which are provided for the period 1992 to 2000. The water level at 09:00 MET is provided every day for the period 1992 to 2000.

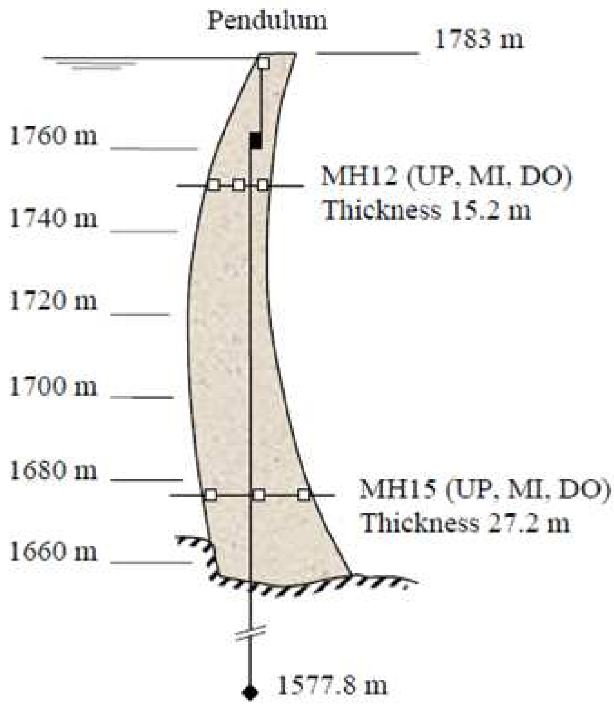

Figure 2: Schlegeis Dam- The arrangement of thermometers and pendulums in the cantilever section

In this workshop, independent variables at time t are 1, 2, 3 and 4th power of water level $\{w_t, w_t^2, w_t^3, w_t^4\}$, air temperature T_t^{air}, temperature of upstream, middle, downstream concrete at H12 location $\{T_{t,up}^{H12}, T_{t,mid}^{H12}, T_{t,down}^{H12}\}$, temperature of upstream, middle, downstream concrete at H15 location $\{T_{t,up}^{H15}, T_{t,mid}^{H15}, T_{t,down}^{H15}\}$, positive effect of time e^t and negative effect of time e^{-t}. Independent variables have 13 dimensions. The only dependent variable is crest displacement value shown as D_t.

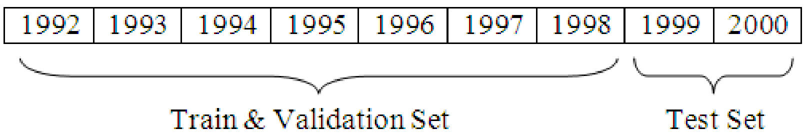

Figure 3: Train, Validation and Test Sets

6th ICOLD Benchmark Workshop organizers divided all 9-year measurement data from 1992 to 2000 two sets as train and test sets. First 7-year data was appointed as training set and last 2-year data was appointed as test set. In the present study, training set was used both train and model validation set according to 4-fold validation method. Figure 3 shows how the data is divided into train validation and test sets.

3.3 Application of Multiple Linear Regression

In this analysis, how many previous days' input data will provide the best regression success with MLR model is investigated. MLR model which used previous m day of input is shown as MLR_m. Independent variables of these models are shown as follows;

$$\left\{w_i, w_i^2, w_i^3, w_i^4, T_i^{air}, T_{i,up}^{H12}, T_{i,mid}^{H12}, T_{i,down}^{H12}, T_{i,up}^{H15}, T_{i,mid}^{H15}, T_{i,down}^{H15}, e^i, e^{-i}\right\}_{i=t-m}^{t}$$

To decide which MLR model is the optimum predict success, all models from MLR_1 to MLR_{40} were tested. 4-fold cross validation process was implemented to decide best MLR model over the 7-years train set. According to cross validation process, each model's mean error, standard deviation, and R^2 values obtained are shown in Figure 4.

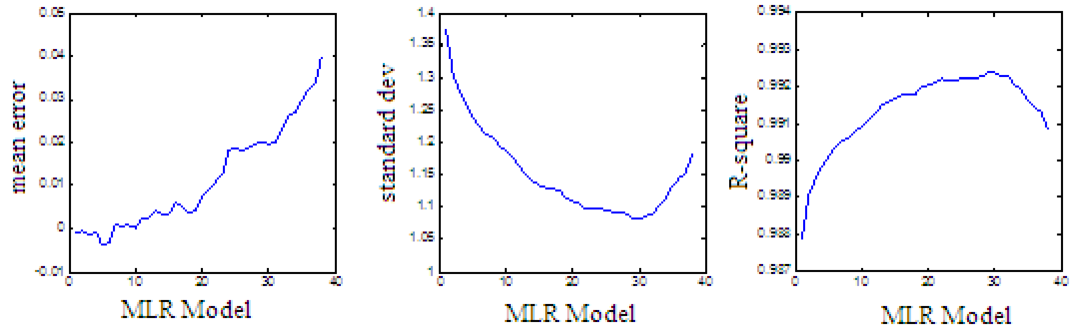

Figure 4: Performance of MLR Model in Validation Set

The result of the validation process shows that MLR_{30} developed has the optimum validation performance. It is shown that MLR_{30} will show the best test set performance, too. The success of MLR_{30} prediction in test set is shown in Figure 5.

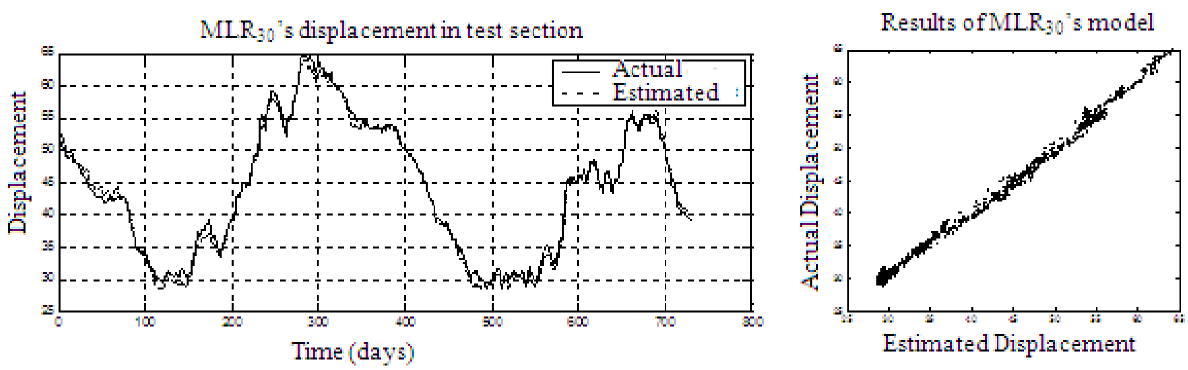

Figure 5: The best MLR Model's Outputs in Test Set

3.4 Application of Multi-Layer Perceptron

In application, selected architecture of MLP has only 1 hidden layer as Figure 1. Back-propagation model with Levenberg-Marquardt methods is used for learning algorithm. Transfer function of 1st and 2nd layers are tansig and purelin respectively shown as (8).

$$f_1(x) = \frac{2}{1+e^{-2x}} - 1 \qquad f_2(x) = x \tag{8}$$

In addition to these parameters, the number of neurons in hidden layer and how many days' input will be given to MLP is not exact. These two parameters are investigated.

MLP model, which used has been previous m day input and has h hidden layer's neuron shown as MLP_m^h. To investigate the optimum MLP model, the performance of all 7-years training data was confirmed by two different 4-fold cross-validations. In the first validation process, the number of previous days input will be used is determined. The results of these validation processes are shown in Figure 6.

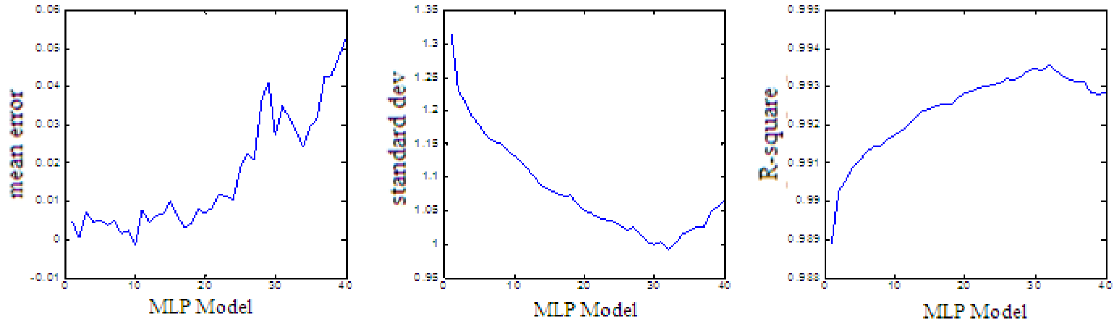

Figure 6: Performance of MLP Model for number of days input in Validation Set

According to the first validation process using 32 days inputs has the best performance. The second validation process is applied to determine the best MLP models hidden layers neuron number. According to this analysis, it shows that when the number neurons in the hidden layer increases, the performance of MLP deteriorates. This information proves that dam displacement prediction problem is nearly linear as chosen independent variables. The result of second validation process is shown in Table 1.

Table 1: Performance of MLP Model for number of neuron in hidden layers in Validation Set

	Model	MLP_{32}^1	MLP_{32}^2	MLP_{32}^3	MLP_{32}^4	MLP_{32}^5	MLP_{32}^6	MLP_{32}^7	MLP_{32}^8	MLP_{32}^9	MLP_{32}^{10}
R-square	Validation	0.9901	0.9900	0.9867	0.9831	0.9864	0.9881	0.9718	0.9817	0.9559	0.9750
	Train	0.9932	0.9953	0.9953	0.9993	0.9992	0.9984	0.9980	0.9974	0.9991	0.9991

Depending to all validation processes, MLP_{32}^1 has the optimum validation performance. It is shown that MLP321 shows the best test set performance. The success of the test set of MLP_{32}^1 prediction of test set is shown in Figure 8.

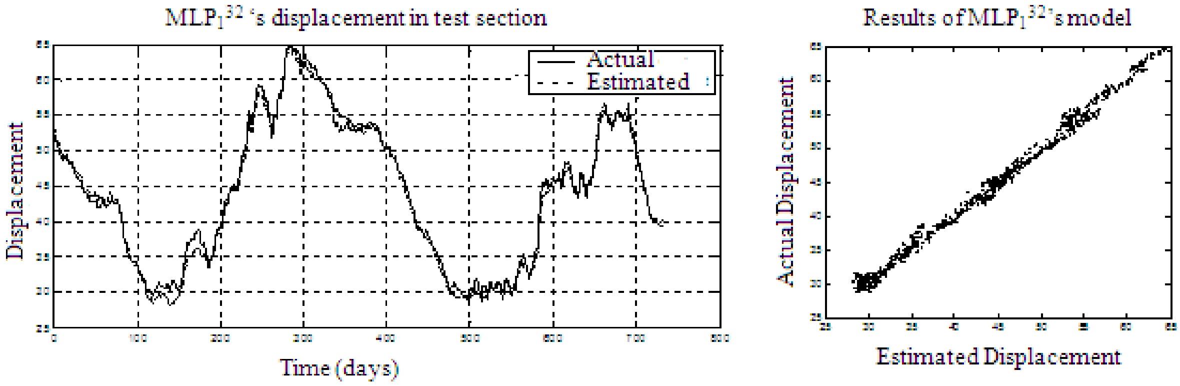

Figure 8: The best MLP Model's Outputs in Test Set

4. RESULTS AND DISCUSSIONS

According to the Synthesis Report of 6th ICOLD Benchmark Workshop on Numerical Analysis of the Dams, nine participants attended. In general, the calculations were carried using various deterministic and statistical models and combinations of them. The used methods are MLR, ARMA (Autoregressive Moving Average), NARX (Non-linear Autoregressive with exogenous input), ANN, NP (Nonparametric polynoms), FE (Finite Elements) and TLM (Trial Load Method). Some participants attended more than one solution. The most optimum results of each participant are compared with our proposed method results. The name of participants and their methods are shown in Table 2.

Table 2: Participants and Methods

Participant	Authors	Methods
1	S. Bonelli and H. Felix	MLR+ARMA
2	A. Carrere and C. Noret-Duchene	MLR
3	M. Fanelli and G.Guiseppetti	MLR+FE
4	P. Palumbo and L. Piroddi	MLR+NARX
5	F. Perner and W.Koehler	FE+MRL+ANN
6	A. Popovici and R.Sarghiuta	MLR+FE
7	R. Promper	MLR+TLM
8	V.Saouma and E. Hansen	NP
9	B. Weber	MLR

The most important difference of our study from other studies is that the number of the previous days as input that will be used in the proposed model is determined by the validation process. Thus, the best optimum model was found. Our models and the workshop's results are shown in Table 3. According to the table, both MLR_{30} and MLP_{32}^{1} model performances are better than all participants' performance. MLR_{30} and MLP_{32}^{1} performances are close to each other, but MLR_{30} is the optimum model. The reason for being the best method of MLR method is explained by the prediction of dam displacements. For the chosen independent variables are nearly linear, so MLR method the most ideal method for linear problems.

Table 3: Test Results

	MLR_{30}	MLP^{1}_{32}	P1	P2	P3	P4	P5	P6	P7	P8	P9

Mean Error	0.3095	0.4073	-0.81	-0.05	-0.71	-0.14	-0.93	-0.79	-0.67	-1.02	-0.73
St.Dev.	0.8056	0.8423	1.30	1.62	1.75	1.20	1.39	1.20	1.77	2.40	1.26
R-square	0.9925	0.9912	0.983	0.974	0.969	0.986	0.980	0.985	0.968	0.942	0.984
(St. Dev.)	0.8056	0.8423	1.01	1.62	1.61	1.19	1.03	0.890	1.64	2.18	1.02
(R-square)	0.9934	0.9929	0.99	0.974	0.974	0.986	0.989	0.992	0.973	0.952	0.989

5. CONCLUSION

In this study, the comparison of MLR, MLP and ICOLD Benchmark Workshop competition participant's methods to construct a daily displacement forecasting system to ensure the Schlegeis arch dam structural health safety has been presented.

In statistical methods, such as MLR and MLP, the most important problem in dam displacement problem is to determine the number of data belonging to the past days. In addition to these methods, some more sophisticated methods are needed to optimize that number.

Validation algorithm, which is the important algorithm of machine learning literature, produced solution.

Implementation of machine learning methods at dam displacement prediction is possible with working civil, surveying and computer science engineer together.

It has been used k-fold cross validation method to determine the optimum number of previous days' inputs over the training set.

Furthermore, it has been applied second validation process to determine neuron numbers at hidden layer in MLP method. The result of optimized MLR and MLP are better than all participants' performance.

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