MODELLING AND OPTIMIZATION OF THE FORCE SENSOR NETWORK

Grzegorz Bialic, Marcin Zmarzły, Rafał Stanisławski

Abstract:

The power boiler erection process requires temporary suspending of buckstays (Fig. 1). The aim of buckstays installation is to brace screens of combustion chamber. Suspending of buckstays is performed by means of strand jacks and steel rods. The amount, location and force ranges of each rods are modelled on the basis of static structural strength computations. In the paper the force sensor network incorporated into computer and wireless communication system designed to prevent overloading of the rods resulting from force asymmetry or computational faults is introduced and next subjected to optimization procedure. The operational data delivered by the network and recorded on the system hard drives let the authors perform the correlation analysis and linear regression to reduce the number of sensors. Thus two stage hierarchic algorithm which constructs the set of models for every single sensor and estimates their parameters, and then using genetic procedure minimizes a certain loss function to automate the sensor network optimization process is introduced. As a result, such investigation could significantly reduce cost of the whole system.

Keywords: sensor network optimization, mathematical modeling.

1. Introduction

In 26 on October 2007 on one of the biggest construction site in Europe in Grevenbroich - Neurath in North Rhine-Westphalia in Germany a building accident took place. Three people were killed and another five workers were injured. The accident was caused by faults in structural strength computations. To avoid such terrible results of designers faults in the future the force sensor network [6] for online force monitoring in steel rods was designed and built in cooperation with Remak S.A.
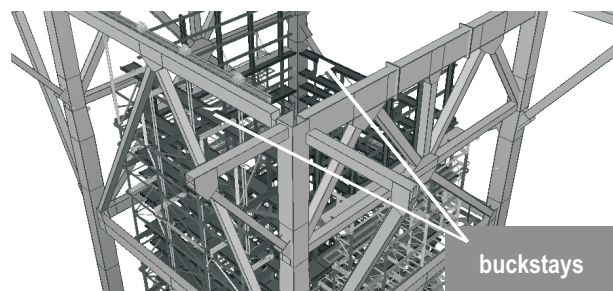

Fig. 1. Support construction of power boiler with temporary suspended buckstays.

The network was applied during temporary suspending of backstays procedure on the block G in Neurath. In the first section the architecture of the measuring system incorporated into force sensor network is introduced. In second and third sections the historical, operational data are investigated using correlation analysis, linear regression and parametric optimization of a certain loss function to reduce the number of required sensor units.

2. Force sensor network measuring system

The force measuring system (Fig. 2) consists of 24 calibrated measuring units (Fig. 3) which make the sensor network. Each of them is based on a measurement foot designed so as to move part of a known force axially to tensometer sensor. The voltage across tensometer bridge is measured in the measuring transducer. The first element of that transducer is measuring amplifier with analog-digital converter with Sigma-Delta modulation performing measurements with an accuracy of 10 bits. Then, the result of measurement is filtered and scaled using the microprocessor unit. Scaling is based on the data from the calibration procedures [1]. The measured force is compared with the threshold values derived from the maximum load for the sensor (150%) and the values of the maximum acceptable load for the rod. The measurement data are available from SLAVE module by means of communication protocol with the physical layer interface based on RS485. The MASTER unit is working in the pulling mode. Each of the 24 measuring units in the network replies with the information about the current value of measured force and short-term exceeded limits.

MASTER module provides further aggregated data *via* the industrial radio modem operating in the 869 MHz band. This enables the remote measurement by the system installed on mobile cross-bar which is raised to a height of 160 m. Visualization software is installed on the operating unit and it has been made in technology JavaSE, where a number of procedures is responsible for: the processes of receiving data, visualization, alarms detection, recording and transmission of the historical data to the Web server [7], generating reports and analysis of historical data trends. The use of the Java platform [2] provides user-friendly tool what is an important advantage in daily operation of the system.

Java platform is characterized by an open architecture. It is a set of standards used by many software companies, which guarantees extensive support for this technology in the future. Detected alarms and warnings are indicated acoustically by an independent microprocessor system.
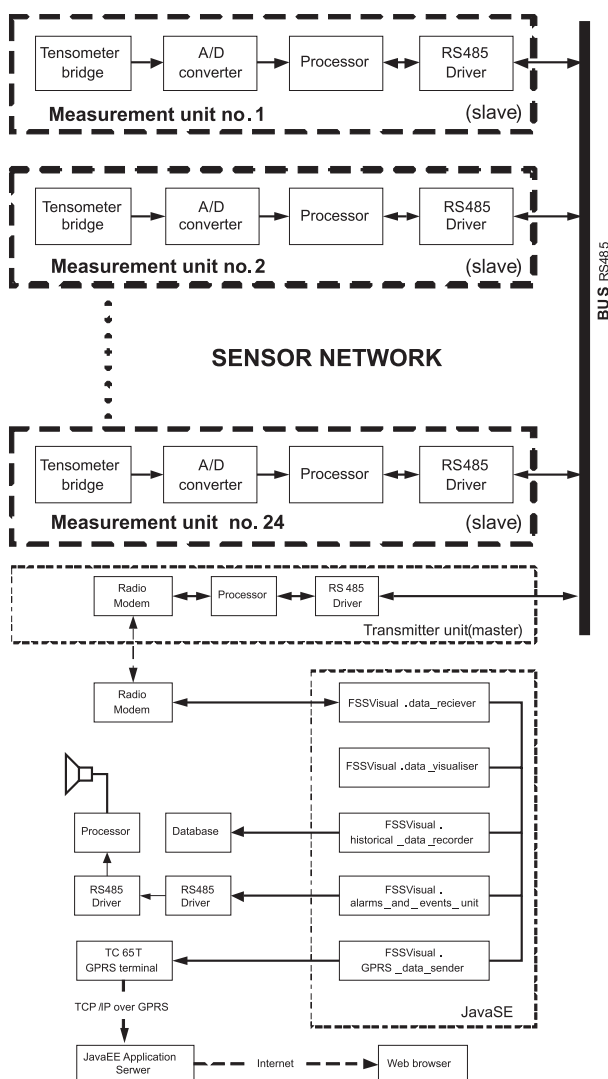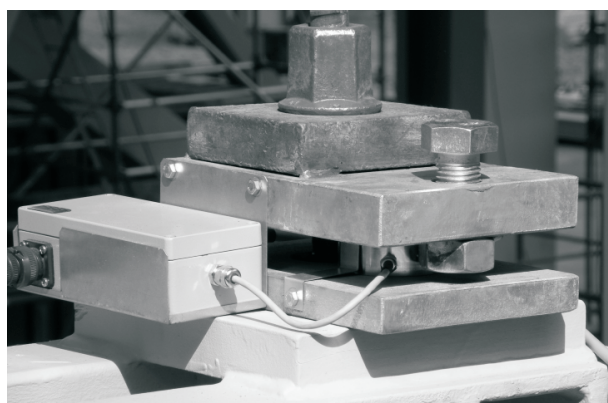
Fig. 2. Block diagram of the system.

Fig. 3. Measurement unit.

Data visualized online allow continuous monitoring and regulation of stress in rods. Fig. 4 presents a fragment of the force decomposition characteristics which describes the suspending process. The technology used in the assembly process allows to correct the load only on currently installed buckstay. Suspending of consecutive buckstay prevents the further load revision at a higher levels.

The number of measurement units has the most significant impact on the cost of the whole force indication system. Therefore it appeared very important the optimization of the network by reducing a certain number of sensors. Reduced sensors have to be replaced by their models based on other measurements. In the next sections the correlation analysis, modelling using linear regression and minimization of a certain objective function in the sense of relative mean square error rate are used in this purpose.
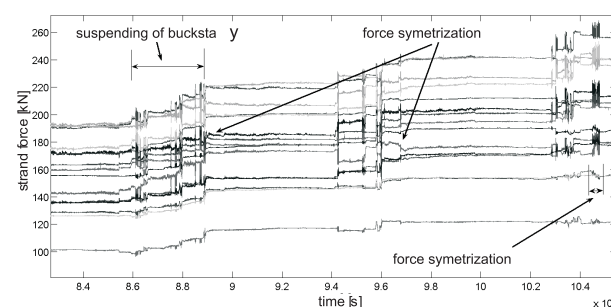

Fig. 4. Historical force values for every single strand.

3. Correlation analysis

The correlation analysis specifies the correlation coefficients among all sensors. Then one can determine whether the particular sensor can be directly replaced with the another one. Table 1 shows the correlation coefficients ρ between the sample sensor (S_2) and remaining sensors.

It is easy to observe that the correlation coefficients are too low to replace the sensor S_2 by the other one. Similar results (on the average) have been obtained for remaining sensors. On the other hand, the results of correlation analysis indicate that signal for the particular sensors are strongly dependent on each other. Therefore using more advanced algorithm to reduce the number of sensors one can obtain satisfactory results.

4. Two stage network modelling and optimization

In this section two stage algorithm (consists of modelling stage and next optimization stage) which mini-

Table 1. The correlation among the measurements for sensor S_2 against the others.

sensor nr	1	3	4	5	6	7	8	89
ρ	0.667	0.580	0.661	0.679	0.672	0.639	0.674	0.109

sensor nr	10	11	12	13	14	15	16	17
ρ	0.629	0.523	0.669	0.631	0.042	-0.17	0.652	0.677

sensor nr	18	19	20	21	22	23	24	25
ρ	0.612	-0.24	0.676	0.071	0.6534	0.567	-0.02	0.641

mizes the number of sensors was employed. The hierarchical block diagram of this method is presented in the Fig. 5.
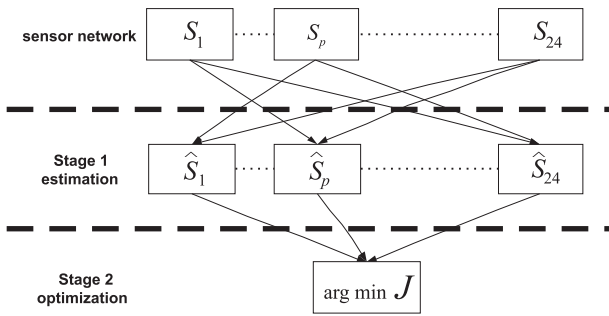

Fig. 5. Block diagram of the two stage algorithm which minimizes the number of sensors.

A. Sensors modelling and estimation

First stage involves modelling of S_p element by means of a linear combination of two others sensors. The equation of model for the S_p element can be written in following form

$$\hat{y}_i^p = a_0^p + \sum_{j=k,l} a_j^p y_i^j \qquad (1)$$

where: a_0^p, a_k^p, a_l^p are the unknown model coefficients and y_i^k, y_i^l are the outpus of the S_k, S_l sensors in i-th sample $(k,l=1,...,24)$. The model equation for the S_p unit can be easily presented in linear regression form

$$\hat{y}_i^p = \hat{\theta}_p^{k,l} \varphi_i^{k,l} \qquad (2)$$

where $\hat{\theta}_p^{k,l}$ estimates of unknown model parameters

$$\theta_p^{k,l} = [a_0^p \ \ a_k^p \ \ a_l^p] \quad \text{and} \quad \varphi_i^{k,l} = [1 \ \ y_i^k \ \ y_i^l]^T \qquad (3)$$

or in alternative vector/matrix form

$$\hat{y}^p = \hat{\theta}_p^{k,l} \Phi_{k,l} \qquad (4)$$

where $\hat{y}^p$ is the model output signal vector of the form

$$\hat{y}^p = [\hat{y}_1^p \ \ \hat{y}_2^p \ \ ... \ \ \hat{y}_N^p] \quad \text{and} \quad \Phi_{k,l} = [\varphi_1^{k,l} \ \ \varphi_2^{k,l} \ \ ... \ \ \varphi_N^{k,l}]$$

where N is the number of measurements. Thus unknown parameters of the model can be estimated by means of the classical least squares method [3, 4]

$$\hat{\theta}_p^{k,l} = (\Phi_{k,l} \Phi_{k,l}^T)^{-1} \Phi_{k,l} y^p \qquad (5)$$

Using this method for each element S_p $(p = 1,..,24)$ the set of models was developed and constructed for each pair y_l, y_k $(k, l = 1,..., 24)$ where $l \neq k$ and $l, k \neq p$. Among all these models for the element S_p best fitted model in terms of relative mean square error value (rMSE) should be chosen. Relative MSE is calculated by means of the following equation

$$rMSE = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{\hat{y}_i - y_i}{y_i} \right)^2 \qquad (6)$$

B. Loss function minimization

Assuming above presented methodology one can obtain the set of models for each element of the network. Every model imitates a certain element of the network with some accuracy. Certainly only the model which produce the lowest value of MSE could be selected to replace the sensor in the network. This in turn means that the replaced before sensor cannot be further used to model remaining elements of the system. As a result, the optimization of the sensor selection process has to be performed. The selection procedure should follow the guidelines: replace as many sensors as possible, simultaneously keeping the lowest MSE rate of the model. Thus, there was required to develop the tool for optimization the sensor selection process. The amount of the sensors n which are supposed to be reduced was defined as the input of the routine. Finally the algorithm returns the indices of the sensors which should be replaced by the model on the basis of minimization of the following loss function

$$J = \left(\sum_{i=1}^{n} rMSE_{p_i}^{k,l} \quad \text{for} \ \ k,l \in \{1,...,24\} \setminus p \right) \qquad (7)$$

where $p = \{p_1, ..., p_n\}$ and n is the number of reduced sensors. The complexity of the above defined loss function (7) (large number of local minimums) decided that the genetic algorithm (GA) was chosen for finding the optimal solution. GA parameters were as follows:
- population size: 20,
- maximum generation: 100,
- selection function: stochastic uniform,
- cross-over function: Heuristic with cross-over probability 0.9 and mutation probability: 0.1.

The stochastic nature of the genetic algorithm caused that the optimization was started from different initial conditions. Then form the set of the solutions the most optimal result was selected.

The properties of models used for sensor replacement for the number of reduced elements $n=4$ are shown in Table 2.

Table 2. The properties of reduced sensors models.

modelled sensor	k	L	ρ	MSE [%]
1	4	17	0.9954	4.74
4	7	13	0.9959	3.72
13	10	16	0.9950	4.58
20	17	22	0.9968	4.38

In the Table 3 values of these models parameters were collected.

Table 3. Values of the models parameters.

modelled sensor	a_0	a_k	a_l
1	-15.6591	0.5202	0.6700
4	3.6157	0.8150	0.302
13	-21.0073	0.3382	0.8331
20	-2.1117	0.4892	0.4652

The assumption that $n=4$ results in the MSE rate below 5% and then keeps total functionality of the considered system. In the Fig. 6 current value of sensor S_4 vs. defined by the model illustrates pretty good performance of the methodology, which has been introduced in the paper.
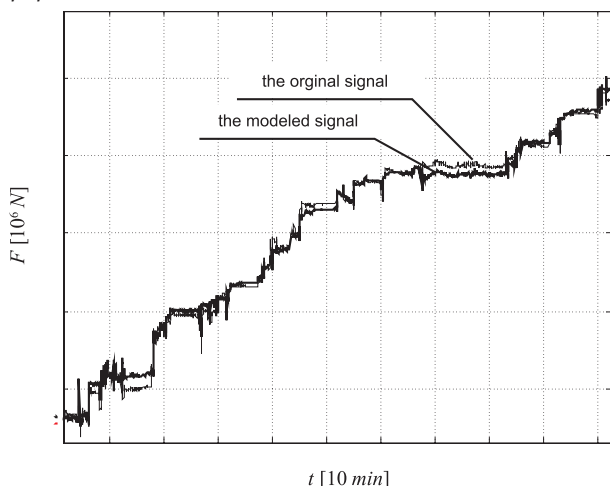

Fig. 6. Plots of actual vs. estimated outputs of the model for the sensor S_4.

In the Fig. 7 the impact of the reduced sensors number n on the quality of estimation was illustrated. Thus the values of the mean square error (J/n), and the maximum value of the MSE (max(MSE)) as a function of n were plotted in this figure. The maximum value of the MSE reflects the estimation error for the sensors with the worst fit model.
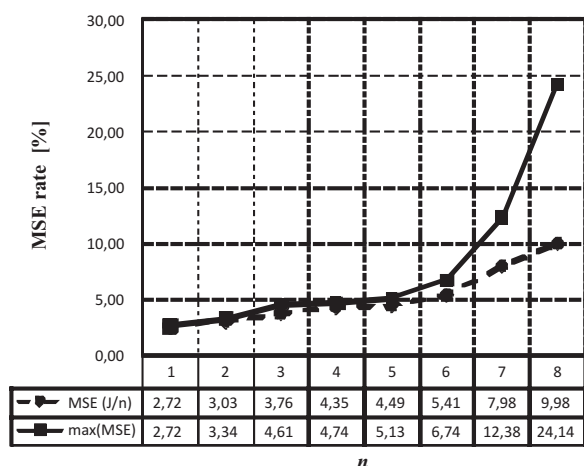

n	1	2	3	4	5	6	7	8
MSE (J/n)	2,72	3,03	3,76	4,35	4,49	5,41	7,98	9,98
max(MSE)	2,72	3,34	4,61	4,74	5,13	6,74	12,38	24,14

Fig. 7. Dependence of MSE and max(MSE) on the reduced sensors number.

Certainly, the number of reduced elements depends on the assumed error rate. The larger acceptable error, the more elements can be reduced. For example, for relative MSE < 7%, 6 sensors may be replaced by its models. In order to preserve the functionality of the designed system the error rate of every single modeled sensor should be kept in range of 10%. From this point of view the reduction of 6 measurement units seems to be the most desired.

5. Conclusion

Application of force sensor network during suspending of buckstays has improved the safety of the whole erection procedure. The electronic measurements in real time and recorded data let engineers symmetrize the force and verify values modelled before. Using presented in the paper two stage algorithm based on correlation analysis, linear regression and parametric minimization of a certain loss function, gives them the opportunity to reduce the number of measurement units in the network which significantly diminishes the costs of the system. It was presented in the paper that some sensors could be replaced with computationally modelled data and then error (in the mean square sense) of the whole force indication system leaves in reasonable range. Moreover, it is worth emphasizing, that the presented above solution discovers new fields for applying modern measurement systems and microprocessor, computer and information technology.

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