Transactions of the VŠB – Technical University of Ostrava, Mechanical Series
No. 2, 2010, vol. LVI
article No. 1796

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ASSESSMENT OF THE ADEQUACY OF POWER PLANT SUPERHEATER DYNAMICAL MODEL

STANOVENÍ ADEKVÁTNOSTI DYNAMICKÉHO MODELU ELEKTRÁRENSKÉHO PŘEHŘÍVÁKU

Abstract

In this contribution we apply a statistical analysis to evaluate prediction ability of the mathematical model of power plant superheater. Model evaluation by comparison of model-based predictions and measured values is used. The mean square error of prediction (MSEP) between model predictions and measured values has been used as a directly relevant measure of predictive success, with MSEP partitioned into three components to gain further insight into model performance. To analyze MSEP this paper applies next decomposition: error due to mean bias, regression bias and unexplained variation respectively. The results of analysis were used to improve the predictive ability of model.

Abstrakt

Příspěvek je věnován aplikaci statistické analýzy pro hodnocení predikční schopnosti matematického modelu elektrárenského přehříváku. Pro evaluaci modelu je použito srovnávání velikostí modelem predikovaných a skutečně naměřených hodnot. Kritériem kvality predikce je střední kvadratická chyba predikce, dekomponovaná do tří komponent pro získání detailnějšího pohledu na vlastnosti modelu. Jednotlivými komponentami jsou podíly chyby, respektující a kvantifikující systematické i náhodné složky chyb. Výsledky statistické analýzy jsou použity pro lineární modifikaci předikovaných hodnot ke zlepšení predikční schopnosti modelu.

1 INTRODUCTION

The interchange of energy from chemical to electrical in power plant is a complex process and its mathematical model enables operator the control of the actual plant. This contribution deals with power plant heat exchangers, particularly with superheaters. Superheaters are parts of the power plant boiler. The heating medium is usually the flue gas generated by combustion of some kind of fuel. The heated medium is usually steam or the mixture of steam and air.

Superheaters are connected to the other parts of the boiler by pipelines and headers. Inertias of heat exchangers and their pipelines are often decisive for the design of the power plant steam temperature control system.

Applying the energy equations, Newton´s equation, and heat transfer equation, and principle of continuity the behavior of five state variables of superheater can be well described by five non-

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linear partial differential equations the mathematical model of the steam exchanger was developed [1].

Technical designs of the superheaters result in construction that are complicated and complex. Accuracy off a three-dimensional dynamic model of a superheater is limited by the accuracy of its parameters.

To verify the mathematical model, the superheater assembly was agitated by the set of long term forced input signals. The dynamic responses were both simulated and measured. The measured and calculated results were compared and performed through a statistical analyze method. The results of analysis were used to improve the predictive ability of model.

2 POWER PLANT SUPERHEATER MODELLING

The mathematical model of the heat exchanger was specified for the parallel flow output superheater of the 200MW block of Detmarovice thermal power station. It is equipped with very modern digital controllers and computer control system.

Fig.1 shows the scheme comprising the superheater, piping, and the basic controllers that stabilize the temperature of steam at the output of superheater assembly. The inlet superheated steam enters the mixer, the outlet superheated steam leaves the last pipeline.

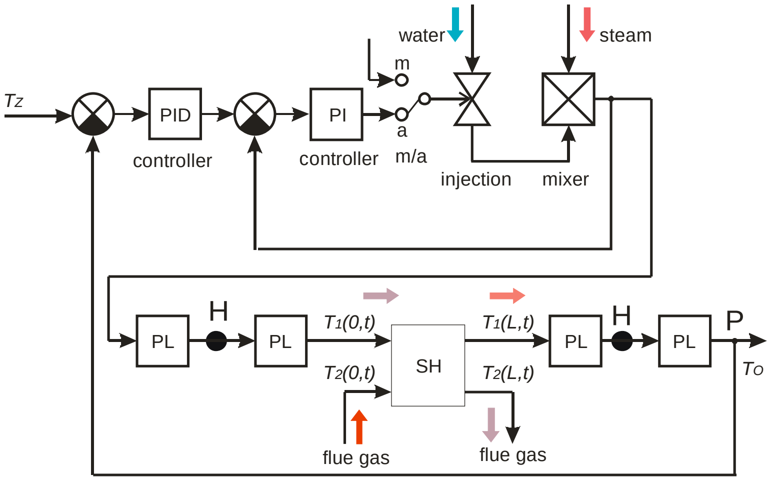

Fig. 1 Scheme of the superheater assembly

The control circuit includes two control loops. The fast loop with PI controller regulates the water flow rate by the valve injection to balance the temperature behind the mixer. The main loop with the PID controller stabilizes superheater assembly outlet steam temperature T_0.

Superheater assembly being controllers consists of the input section, parallel flow superheater SH, and the output section. Both input and output section consists from two pipelines PL separated with a header H. The manual to automatic control switch m/a is set to the automatic control mode, and the assembly outlet steam temperature T_0 measured at point P is stabilized to the set point value T_Z = 540° C.

Applying the energy equations, Newton´s equation, and heat transfer equation, and principle of continuity the behavior of five state variables of superheater can be well described by five non-linear partial differential equations the mathematical model of the steam exchanger was developed [1]. The accuracy of the model would depend on both the accuracy and correctness of coefficients of the model of the superheater.

3 POWER PLANT SUPERHEATER MODEL EVALUATION

The dynamic responses were both measured and simulated. The measured and calculated results were compared and the accuracy of mathematical model was determined using methods of statistical analysis. Comparison of measured and simulated outlet temperatures at the open loop control system experiment is shown in Fig.2.

To evaluate the mathematical model, the concept of its accuracy and precision is reflected [2]. Accuracy measures how closely model-predicted values are to the true values. Precision measures how closely individual model-predicted values are within each other. In the other words, inaccuracy or bias is the systematic deviation from the truth. In contrast, imprecision or uncertainty refers to the magnitude of the scatter about the average mean.

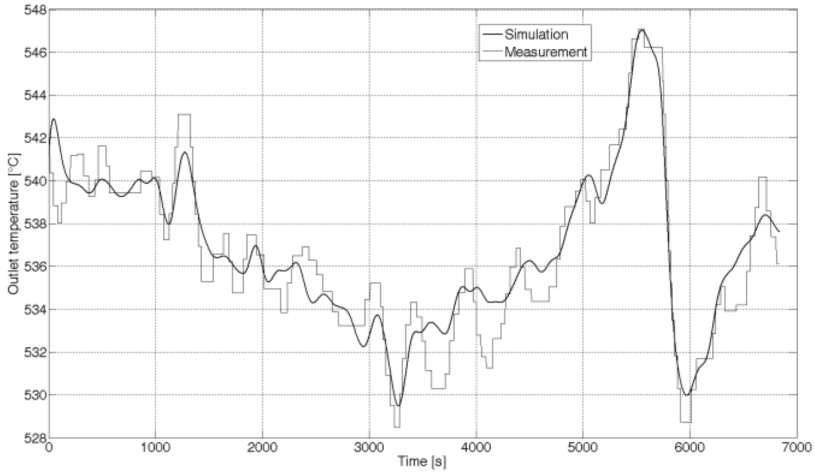

Fig. 2 Comparison of measured and simulated outlet temperatures

The statistical analysis have been used frequently to evaluate model adequacy. A linear regression between measured and predicted values is commonly used. The mean square error of prediction (MSEP) is the most common and reliable estimate to measure the model predictive accuracy in the form

$$MSEP = \frac{1}{n}\sum_{i}(T^{M}{}_{i} - T^{S}{}_{i})^{2} \tag{1}$$

where:

$T^{M}{}_{i}$ - i-th measured outlet temperature value,

$T^{S}{}_{i}$ - i-th model-predicted (simulated) outlet temperature value,

i = *1,2,…,*n - index and number of measured values.

The pair of the data ($T^{M}{}_{i}$, $T^{S}{}_{i}$) is mutually independent (the outcome of the pair does not depend on the outcome of another pair) and the model is independent (the parameters of the model were derived from independent experiments), hence the MSEP estimate is a reliable measure of model accuracy.

To analyze model adequacy the method to decompose the sources of variation of MSEP was introduced in [3]. Eq. (1) can be expanded and solved for known measures of linear regression rather than individual pair of data using relation

$$MSEP = (\overline{T}^{M} - \overline{T}^{S})^{2} + (s_{S} - r s_{M})^{2} + (1 - r^{2}) s_{M} \tag{2}$$

where $\bar{T}^M$ is mean of measured values given by

$$\bar{T}^M = \frac{1}{n}\sum_i T^m{}_i \tag{3}$$

$\bar{T}^S$ is mean of model-predicted (simulated) values given by

$$\bar{T}^S = \frac{1}{n}\sum_i T^S{}_i \tag{4}$$

s_M is standard deviation for $T^M{}_i$ given by

$$s_M = \left[\frac{1}{n}\sum_i (T^M{}_i - \bar{T}^M)^2\right]^{\frac{1}{2}} \tag{5}$$

s_S is standard deviation for $T^S{}_i$ given by

$$s_S = \left[\frac{1}{n}\sum_i (T^S{}_i - \bar{T}^S)^2\right]^{\frac{1}{2}} \tag{6}$$

and r is correlation coefficient given by

$$r = \frac{\frac{1}{n}\sum_i (T^M{}_i - \bar{T}^M)(T^S{}_i - \bar{T}^S)}{s_M s_S} \tag{7}$$

The three addends in (2) represent error in central tendency (mean shift, mean bias), error due to regression (because it deals with the deviation of the regression slope from 1) and error due to disturbances (random error - i.e. unexplained variance that can not be accounted for by the linear regression) respectively.

By dividing each of three terms of (2) by the mean square prediction error we can obtain three inequality proportions, namely

$$UM = \frac{(\bar{T}^M - \bar{T}^S)^2}{\frac{1}{n}\sum_i (T^M{}_i - T^S{}_i)^2} \tag{8}$$

$$UR = \frac{(s_S - r s_M)^2}{\frac{1}{n}\sum_i (T^M{}_i - T^S{}_i)^2} \tag{9}$$

$$UD = \frac{(1 - r^2) s_M{}^2}{\frac{1}{n}\sum_i (T^M{}_i - T^S{}_i)^2} \tag{10}$$

where UM represents the bias proportion, UR represents the regression proportion and UD represents the disturbance proportion respectively. Now we can write

$$UM + UR + UD = 1 \tag{11}$$

The bias proportion UM and regression proportion UR are the proportions of predicted error arising from systematic under-estimation or of the mean of the variable being predicted, and the disturbance proportion UD is the proportion of the prediction error that is random. Therefore, the bias and regression proportions identify sources of systematic error that predictor should be able to remove with time and the disturbance proportion comes from a non-systematic error.

If the prediction is optimal, the systematic components should not differ significantly from zero and the non-systematic component should not be significantly different from 1.

In the actual case, the set of data pair ($T^M{}_i$, $T^S{}_i$) was processed. To obtain sufficiently large values of deviations of state values and output signals, the superheater´s automatic feedback control loops were disconnected during experiments and the control of the controlling water injection was set to the manual model. Data were measured into three second sampling interval. In this way, the number of n = 6841 ($T^M{}_i, T^S{}_i$) pairs were prepared and next processed.

To use the above equations (1) – (10) following results were obtained.

$MSEP = 2{,}4923\text{C}^2$ $\quad UM = 0{,}0838$

$s_M = 4{,}0248\text{C}$ $\quad UD = 0{,}6513$

$s_P = 3{,}005\text{C}$ $\quad UR = 0{,}2653$

$r = 0{,}9486$

4 LINEAR REGRESSION OPTIMIZATION

If the decomposition indicates a systematic error, the predictor could re-specify the model or use additional information to adjust the mean of the prediction. Ref. [3] suggests a linear correction in the form

$$T^{S^*}{}_i = a + bT^S{}_i \tag{12}$$

where $T^{S^*}{}_i$ represents the optimized value of $T^S{}_i$. That is, we multiply each prediction $T^S{}_i$ by some coefficient b and add some constant a. To apply the mean square error criterion [3]

$$\frac{1}{n}\sum_i (a + bT^S{}_i - T^M{}_i)^2 \tag{13}$$

Minimizing with respect to a and b, we can obtain following equations

$$b = \frac{\sum_i (T^S{}_i - \overline{T}^S)(T^M{}_i - \overline{T}^M)}{\sum_i (T^S{}_i - \overline{T}^S)^2} = \frac{rs_A}{s_P} \tag{14}$$

$$a = \overline{T}^M - b\overline{T}^S \tag{15}$$

To apply optimizing procedure the bias proportion UM and the regression proportion UR vanish, disturbance proportion UD remains unaffected (the squared correlation coefficient r² is invariant under linear transformation).

The optimal linear correction reduces the mean square prediction error to its disturbance proportion

$$MSEP^* = \min_{a,b} \frac{1}{n}\sum_i (a + bT^S{}_i - T^M{}_i)^2 = UD\frac{1}{n}\sum_i (T^S{}_i - T^M{}_i)^2 \tag{16}$$

In the real case, the calculated parameters are

$a =$ -145,7339

$b =$ 1,2705

To apply linear optimization procedure (16) the new value of mean square error predictions decreased from original value $MSEP = 2{,}4923C^2$ to

$$MSEP^* = 1{,}6210C^2$$

value and the predictive ability of the mathematical model was improved.

5 CONCLUSIONS

The comparison and results of statistical analysis of measured and simulated values of the superheater outlet steam temperature validates good model description of static regime of the superheater. The mathematical model prediction error decomposition into bias, regression and disturbance proportions respectively and next linear correction procedure can improve the accuracy of a model prediction abilities. Using the linear regression optimization the value of mean square prediction error was decreased from MSEP = $2{,}4923C^2$ to MSEP* = $1{,}6210C^2$ and the differences between measured and simulated values was decreased.

Present results demonstrate that the accuracy and precision of the model is sufficient for power plant operators and boiler designers.

ACKNOWLEDGEMENT

This work was supported by the grant: "Simulation of heat exchangers with the high temperature working media and application of models for optimal control of heat exchangers" GA ČR 102/09/1003 of the Czech Science Foundation

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