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Towards Product Robust Quality Control with Sequential D-optimum Inputs Design

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Recently, there is a high demand on companies for high quality, reliable products for a reasonable price in a timely manner. In order to provide such goods novel methods of product quality control are required to be developed and used in industrial practice. For example, it is possible to use methods based on analytical redundancy. In such approaches the effectiveness of the methods depends on the quality of a product model. This paper proposes a new methodology for improving the neural model of the controlled product. For this aim experimental design technique is applied. Furthermore, a method of product quality control robust to neural model uncertainty is developed. All these conceptual approaches find the practical application for the three-screw spindle oil pump.

1. Introduction

Manufacturing organizations apply various quality control techniques to provide customers the products with high quality. Among several quality control methods the approaches based on parameters (Kackar, 1985), support vector machine (Minowa et. al., 2014), statistical quality control (Montgomery, 2001), neural network (Guh, 2002) and statistical process control (Zorriassatine and Tannock, 1998) can be distinguished. However, in the last years a particular attention was paid to methods which refer to mathematical modelling of controlled products. Such methods can be effectively applied for several complex products or systems e.g.,bottle conveyor (Jasiulewicz-Kaczmarek, 2015), brushless DC motor (Mrugalska, 2013b), cylinder head milling machines (Misztal and Bachorz, 2014), oil pump (Mrugalska et. al., 2014) and wind turbine (Hilbert et. al., 2013). They allow early detection and end-to-end product oversight without application of an expensive hardware redundancy. In order to obtain such models the knowledge of physical laws is required or the identification process has to be carried out (Soderstrom and Stoica, 1989) for example by the application of the Artificial Neural Networks (ANNs) such as the Multi-Layer Percetron (MLP) (Haykin, 2009) or the Radial Basis Function (RBF) neural networks (Santos et. al., 2013). Such a technique is especially attractive in modelling of nonlinear and dynamic products. Unfortunately, the effectiveness of the analytical model-based quality control methods mainly depends on the quality of the model. In order to improve the neural model quality in the paper a novel approach, which is based on the Sequentional D-optimum Experimental Design (SDED), is proposed. This method is based on the selection of the appropriate data for training of the neural model what leads to the improvement of its quality. Nevertheless, it should be emphasised that there is no guaranty that the model of the controlled product is certain. Not taking into account the neural model uncertainty (Blanke et. al., 2003), noises and disturbances, (Mrugalska, 2013a) into product quality control method may result in the false alarms or undetected faults in the products. Thus, the robustness against all the above mentioned factors is one of the most desirable features of the efficient quality control method. To be able to deal with such challenges in this field a novel robust product quality control method is developed. Its concept relies on obtaining the neural model uncertainty description in the form which allows to calculate the

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adaptive thresholds containing the product response for the fault-free case. The fault in the product is detected when the system responses cross the adaptive thresholds. It should be underlined that the neural model uncertainty is calculated by the application of the SDED algorithm. The paper contains an illustrative example, involving the application of the developed approach to three-screw spindle oil pump, which proofs the efficiency of the proposed quality control method.

2. MLP in the modelling of the controlled product

The controlled product (Vuchkov and Boyadjieva, 2002) can be generally defined as a set of all possible pairs $\mathbf{u}_k^{\ T} = [u_{k,1}, u_{k,2}, ..., u_{k,n_u}]$ and $\mathbf{y}_k^{\ T} = [y_{k,1}, y_{k,2}, ..., y_{k,n_y}]$ representing the product inputs and responses at the k-th time samples. The range of change of $\mathbf{y}_k$ depends on the changes in the values of $\mathbf{u}_k$ and in the time invariant values of $\mathbf{p} \in R^{n_p}$ which denotes a vector of parameters representing the physical characteristics of the controlled product. The behaviour of the controlled product can be described by (1):

$$\mathbf{y}_k = F(\mathbf{p}, \mathbf{u}_k) + \boldsymbol{\varepsilon}_k \tag{1}$$

where relation $F(\cdot,\cdot)$ represents nonlinear properties of the controlled product, $\boldsymbol{\varepsilon}_k$ is a Gaussian and uncorrelated noise so that $\mathrm{E}(\boldsymbol{\varepsilon}_k) = 0$ and $\mathrm{E}(\boldsymbol{\varepsilon}_i \boldsymbol{\varepsilon}_k^{\ T}) = \delta_{i,k}\mathbf{C}$, where $\mathbf{C} \in \Re^{n_y \times n_y}$ is a known positive-definite matrix of the form $\mathbf{C} \in \sigma^2 \mathbf{I}_{n_y}$, and σ^2 and $\delta_{i,k}$ stand for the variance and Kronecker's delta symbol, respectively. It should be underlined that the noise influence the product quality during both the manufacturing and operational stages should be taken into consideration during developing of the robust control method. For the modelling of the nonlinear properties of the controlled product the MLP presented in Figure 1, can be used

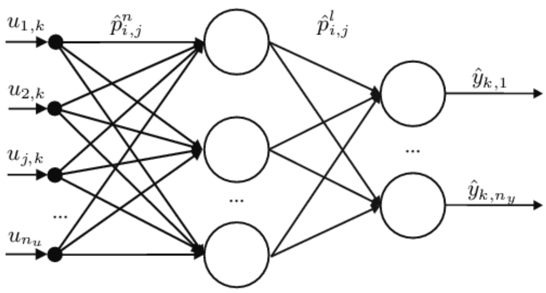


Figure 1: Structure of the MLP applied for modelling of the controlled product

The behaviour of such a neural model can be described by (2):

$$\hat{\mathbf{y}}_k = \mathbf{P}^{(l)} F(\mathbf{P}^{(n)} \mathbf{u}_k) = F(\mathbf{P}, \mathbf{u}_k) \tag{2}$$

where $\mathbf{u}_k \in \Re^{n_u}$ and $\hat{\mathbf{y}}_k \in \Re^{n_y}$ are the vectors of the neural model inputs and outputs, $F(\cdot) = [f_1(\cdot), ..., f_{n_h}(\cdot)]^T$ is the vector of neurons nonlinear activation functions. The matrices $\mathbf{P}^{(l)}$ and $\mathbf{P}^{(n)}$ contain the linear and nonlinear parameters representing the properties of the product and can be written as the vector: $\mathbf{P} = \left[\mathbf{P}^{(l)}, \mathbf{P}^{(n)}\right]^T = \left[p^{(l)}(1)^T, ..., p^{(l)}(n_y)^T, p^{(n)}(1,1)^T, ..., p^{(n)}(n_u, n_h)^T\right]^T \in \Re^{n_p}$ where $n_p = n_y(n_h + 1) + n_u(n_h + 1)$ and n_h denotes the number of neurons in h hidden layer of the neural network and $\mathbf{P} \in \Re^{n_p}$.

3. Quality improvement of neural model with sequential experimental design

The objective of this section is to provide an approach that can settle a problem of improving modelling quality and minimizing uncertainty of a neural model. Let us start with the celebrated Recursive Least Square (RLS) algorithm that is extended in such a way that it can cope with nonlinear model like a neural network:

$$\hat{\mathbf{p}}_{k+1} = \hat{\mathbf{p}}_k + \mathbf{k}_{k+1} \varepsilon_{k+1} \tag{3}$$

$$\mathbf{k}_{k+1} = \mathbf{P}_k \mathbf{r}_{k+1} \left(\lambda_k + \mathbf{r}_{k+1}^T \mathbf{P}_k \mathbf{r}_{k+1} \right)^{-1} \tag{4}$$

$$\varepsilon_{k+1} = y_{k+1} - f\left(\hat{\mathbf{p}}_k, \mathbf{u}_{k+1}\right) \tag{5}$$

$$\mathbf{P}_{k+1} = \frac{1}{\lambda_k} \left[\mathbf{I}_{n_p} - \mathbf{k}_{k+1} \mathbf{r}_{k+1}^T \right] \mathbf{P}_k \tag{6}$$

where $\hat{\mathbf{p}}_k$ is the parameter estimate with the associated covariance matrix $\mathbf{P}_k$, λ_k is the forgetting factor, $\mathbf{r}_k$ is the so-called regressor vector, which is simply a gradient of $f(\cdot)$ with respect to the parameter vector $\mathbf{p}$. The problem is to determine a sequence of $\mathbf{u}_k$ minimizing the determinant of $\mathbf{P}_k$ in the subsequent iterations. It will correspond to the local D-optimality (Fedorov and Hackl, 1997), which is related with the minimization of the volume of the parameter confidence region. This optimization procedure will lead to the models with improved quality, which will provide more reliable results during the application to the product quality control. It can be determined from Eq.(6) that the determinant of $\mathbf{P}_k$ is:

$$\det\left(\mathbf{P}_{k+1}\right) = \det\left(\frac{1}{\lambda_k} \mathbf{P}_k \right) \det\left(\mathbf{I}_{n_p} - \frac{\mathbf{P}_k \mathbf{r}_{k+1} \mathbf{r}_{k+1}^T}{\lambda_k + \mathbf{r}_{k+1}^T \mathbf{P}_k \mathbf{r}_{k+1}} \right) \tag{7}$$

Using the identity that $\det(\mathbf{I} + \mathbf{a}\mathbf{b}^T) = 1 + \mathbf{b}^T\mathbf{a}$ the Eq.(7) can be written as:

$$\det(\mathbf{P}_{k+1}) = \frac{\lambda_k^{-n_p}}{1 + \lambda_k^{-1} \mathbf{r}_{k+1}^T \mathbf{P}_k \mathbf{r}_{k+1}} \det(\mathbf{P}_k) \tag{8}$$

Equation (8) clearly indicates that an adequate input selection (note that $\mathbf{r}_k$ depends on $\mathbf{u}_k$) will minimize the determinants of $\mathbf{P}_k$, and hence, improving the overall model quality. Therefore, $\mathbf{u}_{k+1}$ that minimizes $\det\left(\mathbf{P}_{k+1}\right)$ is obtained by solving the optimization problem:

$$\mathbf{u}_{k+1}^* = \arg \max_{\mathbf{u}_{k+1} \in U} \mathbf{r}_{k+1}^T \mathbf{P}_k \mathbf{r}_{k+1} \tag{9}$$

where *U* denotes the admissible input space that is consistent with the input constraints. To summarize, the proposed algorithm can be written in the following form:

Step 0: Set $k = 0$, determine $\hat{\mathbf{p}}_0$ with the available product input-output data measurements, set $\mathbf{P}_0 = \delta\mathbf{I}$ with δ being a sufficiently large positive constant. Set n_t, a predefined number of input-output measurements.

Step 1: Determine $\mathbf{u}_{k+1}$ by solving Eq.(9) and feed at the inlet of the product in order to get y_{k+1}.

Step 2: Obtain $\hat{\mathbf{p}}_{k+1}$ with Eq.(3)-(6). If $k = n_t$ then STOP else set $k = k + 1$ and proceed to *Step 1*.

It should be pointed out that Step 0 can be realised with any algorithm for training neural networks providing that a suitable modelling quality is attained. In the subsequent part of this paper the Levenberg-Marquard (LM) algorithm (Haykin, 2009) is employed, which is a standard routine in many computational packages like MATLAB. Furthermore, the global optimization problem of Step 1 can be tackled using a large spectrum of global optimization routines e.g. an Adaptive Random Search (Solis and Wets, 1981) which is recommended in this paper. Finally, the proposed algorithm alternates two phases: Step 1 – input determination and system response measurement, Step 2 – parameter estimation and update of $\mathbf{P}_k$. The proposed algorithm enables development of a neural model with possibly small uncertainty that can be efficiently used for robust product quality control. This task constitutes the primary objective of the subsequent part of this paper.

4. Robust product quality control with output adaptive thresholds

The quality of the neural model is crucial for appropriate product quality assessment. It follows from the fact that the neural model is applied for generation of the residual signals which contains the information about the state of the controlled product. The residual signal $\boldsymbol{\rho}_k$ is obtained as a difference of the controlled product $\mathbf{y}_k$

and model $\hat{\mathbf{y}}_k$ responses for the same input signals $\mathbf{u}_k$. During the product quality control the analysis of the residual signal is performed. The most often applied method is based on the application of the so-called constant threshold (Blanke et. al., 2003) for the detection of the fault in the controlled product. In such method it is assumed that the fault is detected when the residual signal $\boldsymbol{\rho}_k$ is distinguishably different from zero. In practice, the fault is detected when the absolute value of the residuum is larger than an arbitrarily assumed threshold value $|\boldsymbol{\rho}_k| > \eta_y$. Unfortunately, the constant threshold based method can be unreliable because the residual signal often is corrupted by the measurement noise or/and the uncertainty of the model obtained during the identification. To order to solve such problem, the quality control method robust against noise and model uncertainty should be developed. The concept of the proposed method is based on the calculation of the output adaptive thresholds which take into account neural model uncertainty is presented in Figure 2.

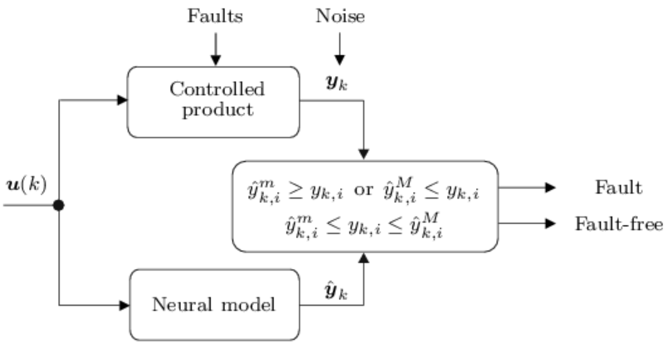


Figure 2: Scheme of robust quality control of the product

The proposed in Section 3 method of the experimental design allows to obtain the neural model uncertainty in the form of the covariance matrix $\mathbf{P}_k$. Such knowledge allows to calculate the neural model uncertainty in the form of the output adaptive threshold described by the Eqs.(11)-(13):

$$\hat{y}^m_{k,i} \leq y_{k,i} \leq \hat{y}^M_{k,i} \tag{11}$$

where:

$$\hat{y}^m_{k,i} = \hat{y}_{k,i} - t^{\alpha/2}_{n_t-n_p}\hat{\sigma}(1 + r_{i,j}P\mathrm{r}^T_{i,j})^{1/2} \tag{12}$$

$$\hat{y}^M_{k,i} = \hat{y}_{k,i} + t^{\alpha/2}_{n_t-n_p}\hat{\sigma}(1 + r_{i,j}P\mathrm{r}^T_{i,j})^{1/2} \tag{13}$$

and $y_{k,i}$ and $\hat{y}_{k,i}$ denote the *i*-th response of the controlled product and its estimate, $t^{\alpha/2}_{n_t-n_p}$ is the t-Student distribution quantile at confidence level $1-\alpha$ for $i = 1,...,n_u$, and $\hat{\sigma}$ is the standard deviation estimate (Walter and Pronzato, 1997). The fault in the controlled product is detected when the product response y_k cross the output adaptive thresholds calculated according Eq.(11). In other words the output adaptive threshold should contain product response when the controlled product is fault-free.

5. Robust quality control of three-screw spindle oil pump

The main purpose of the present section is to show the improvement of the proposed robust product quality control methodology following from the application of the experimental design during product modelling. In order to achieve this goal the three-screw spindle oil pump depicted in Figure 3 is applied. Such a pump is an example of the product which may constitute a part of compound systems or industrial processes. The early detection of the faults in such a product allows to avoid economical losses in the whole compound system or process. The behaviour of the modelled pump can be described by the relation (14):

$$y_k = F(u_{k,1}, u_{k,2}, \mathbf{p}) \tag{14}$$

where inputs $u_{k,1}$ and $u_{k,2}$ represent the motor speed and differential pressure in the inlet of the pump, respectively, and y_k denotes the outlet of the pump.

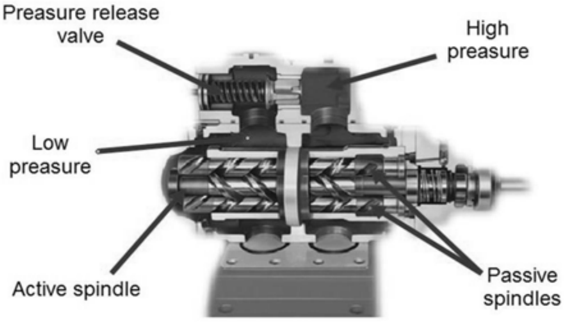
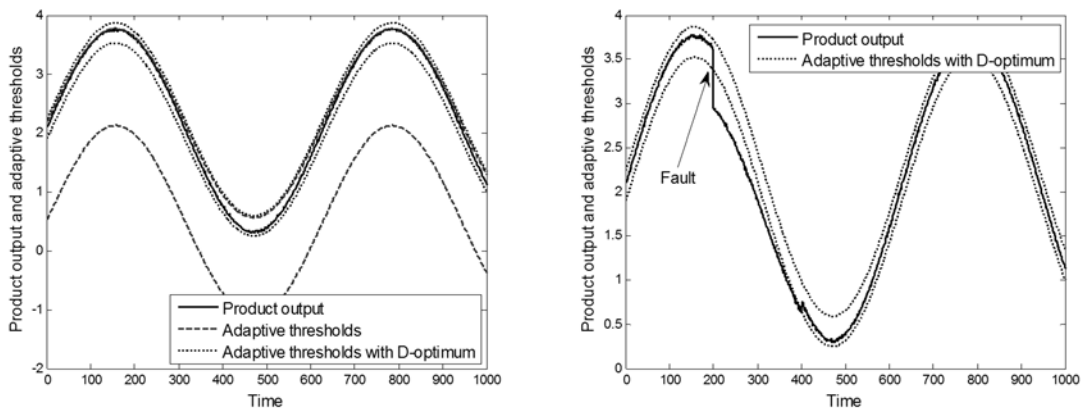


Figure 3: Three-screw spindle oil pump

At the beginning of experiment, a pump simulator developed in MATLAB Simulink, is applied to obtain the data sets required to research. The first data subset was applied to training the neural model of the pump. The second data subset was used to validate the quality of the neural model for the fault-free pump. Moreover, such data set allows to show the improvement of the neural model quality resulting from the application of the proposed experimental design method. The last data set, containing the faults simulated in the pump, was applied to demonstrate the effectiveness of the proposed robust product quality control method. During the experiment the neural network consisting of six neurons with a nonlinear tangensoid activation function in the hidden layer and one neuron with linear activation function in the output layer were chosen. During the training of the neural model the LM algorithm was applied. At this stage the proposed experimental design algorithm was used to select the most value training data samples. The result of application of the proposed method is illustrated in Figure 4. Such figure shows the output of the modelled pump and the corresponding adaptive threshold obtained according to the proposed methodology for the validation data set without faults.



(a) (b)

Figure 4: Controlled product output and the corresponding adaptive thresholds obtained with and without experimental design for the validation data set (a) and for the faulty (b)

From the obtained results it can be seen the output adaptive threshold for the neural model trained with the application of the proposed experimental design approach is tighter than one without it. Such results prove that the neural model obtained with the application of the experimental design is characterised by lower uncertainty. In other words, the selection of the measurements at the support points region during the training of the neural model results in the tighter adaptive threshold and consequently better sensitivity of the robust control method of the product what results in the detection of even small faults in the controlled products. The effectiveness of the proposed robust control design method was tested on the basis of the data subset containing the fault relying on the 20 % performance degradation of an induction motor feeding the pump. The result of the experiment is shown in Figure 4b. Such figure presents the outlet of the pump and corresponding adaptive threshold obtained with neural model obtained on the basis of the proposed experimental design method. As it can be seen the simulated fault appearing for time sample *k=200* is correctly detected. From these results it is evident that the proposed approach can be successively applied in the product quality assessment tasks.

6. Conclusions

In this paper a new robust quality control method based on neural model was developed with the use of MLP and a sequential D-optimum experimental design technique. It allowed to obtain the neural model uncertainty and calculate the adaptive thresholds. However, it should be also underlined that the application of the experimental design technique allows to improve the neural model quality and in the consequence it increases the sensitivity of the robust product control method. The presented approach includes its practical verification and validation with the three-screw spindle oil pump.

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