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Additive model applications for the fault detection of actuators

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Abstract

The early detection of faults is critical if one wants to avoid the performance degradation and damage to the machinery or the loss of human life. Therefore, accurate diagnosis helps us to make a right decision on emerging actions and repairs [1, 2, 3]. In this paper, a new way of additive models and knowledge discovery data application for designing actuator has been presented. The planned aim is the fault detection of the control valve with a servomotor and a positioner (Fig. 2) based on the received model. Used additive models (1) overcome the curse of dimensionality and allow us to examine the predictor effects separately, in the absence of interactions [8, 9]. The backfitting algorithm with nonparametric smoothing techniques has been used for the estimation of the additive model [8, 9, 10]. The results of the modelling and the fault detection procedures have been presented. All research has been carried out based on the example of a control valve for measurement tracks in the boiler laboratory setup. Received results are satisfactory because the tests detected all simulated faults. Therefore, it is an useful method for the multivariate industrial process fitting and fault detection in the analyzed structures.

Keywords: actuator, fault detection, additive model, data mining.

Zastosowanie addytywnego modelu regresji dla potrzeb detekcji uszkodzeń zaworów regulacyjnych

Streszczenie

W pracy przedstawiono wykorzystanie addytywnego modelu regresji oraz statystycznych technik eksploracji danych do stworzenia modelu zaworu regulacyjnego. Pozyskana wiedza posłużyła do konstrukcji algorytmów detekcji uszkodzeń, a następnie do oceny wrażliwości na występowanie poszczególnych uszkodzeń. Badania przeprowadzono dla przykładowego zaworu regulacyjnego na podstawie danych laboratoryjnych próbkowanych na stanowisku regulacji poziomu wody w zbiorniku walczakowym. Otrzymane wyniki są zadowalające, gdyż zaprezentowane metody pozwoliły na wykrycie wszystkich zasymulowanych uszkodzeń.

Słowa kluczowe: urządzenie wykonawcze, detekcja uszkodzeń, model addytywny, eksploracja danych.

1. Introduction

The detection of faults in engineering systems is of great practical significance. In order to meet reliability requirements of safety-critical processes, the modern control systems should be equipped with mechanisms of fault detection, that is the indicators of prohibited deviations from the normal behaviour in the plant or its instrumentation like sensors and actuators [1, 2, 3]. For this reason, the diagnostics and protection of processes are crucial. Of equal importance are computer systems that aid operators in diagnostics, or even automatically create a diagnosis.

In the automatic control industrial control systems, the possibility of signals values acquisition exists. It allows us to create models based on measured data and expert's knowledge about the object. With the growth of computer technology, new possibilities have arisen in terms of storing data acquisition and speed of their processing. The science of extracting useful information from large data sets or databases is known as data mining [4]. The key task of this discipline for diagnostic purposes is the analysis of observational data sets, and how to find the relevant information quicker and more accurately, which aids the decision making about the recognition of changes of the state of the process during its operation.

Control valves are an increasingly vital components of modern actuator equipment [5]. Properly selected and maintained control valves increase efficiency, safety, profitability, and help the ecology. They are often used in very demanding conditions, which makes their durability largely limited. Actuator faults often lead to the process perturbations causing the product deterioration or the performance degradation. Moreover, the process economy requires that the number of breaks switch-offs and the service costs were as low as possible. For this reason, the quick and correct detection of the faulty valve facilitates the proper and optimal decisions on the emergency and corrective actions and on repairs.

The diagnostics of valves was usually based on the analytical models or models based on fuzzy logic, artificial neural networks and fuzzy neural networks [3, 6, 7]. For many systems, the model study based on differential and algebraic physical equations was either very difficult or almost impossible, and model parameters identification yields further difficulties. Moreover, an increasing number of input signals rapidly increases the computational costs and number of rules, in neural network and fuzzy logic modelling, appropriately.

2. Additive model

In this paper, an alternative technique which overcomes the limitation of multivariate nonparametric modeling, has been presented. This important class of flexible models arises in form of additive models [8, 9]. Let us call the physical measurable quantities influencing the process and resulting from the process operation, the input and output signal, respectively. Considering the structure with $p > 1$ input signals $X_1, X_2, ..., X_p$, and one output signal Y, the additive model is defined by

$$Y = \alpha + \sum_{j=1}^{p} \varphi_j(X_j) + \varepsilon, \quad (1)$$

where error ε is a sequence of independent and identically distributed random variables (iid) with the mean $E(\varepsilon)$ =0 and the finite variance $Var(\varepsilon) = \sigma^2$. The φ_j s are unknown, arbitrary univariate functions one for each predictor X_j. Because all of the unknown functions are one-dimensional, the difficulty associated with the so-called "curse of dimensionality" is substantially reduced. Functions φ_j s can be, for example, roots, logarithms or trigonometric functions. Let us point that we do not assume that the signals X_j are independent [8, 10]. The additive model can be nonlinear in relation to signals X_j but it still is linear in relation to signals $\varphi_j(X_j)$. Hence, since each variable is represented separately, model (1) summarizes the contribution of each predictor with a single coefficient, and provides a simple method for predicting new observations. In practice, this means that once the additive model is fitted to data, we can plot the p-coordinate functions separately to examine the variables in predicting the response. However, the above simplification leads to the fact that the additive model is almost always an approximation of the true regression surface, but with the hope of its usefulness.

Let's notice that without making an additional assumption about the constant in the model (1), there will be free constants in each of the functions. In order to avoid the above nonuniqueness, we need to impose the following conditions for all functions:

$$E[\varphi_j(X_j)] = 0\,, \qquad (2)$$

or equivalently

$$E(Y) = \alpha\,. \qquad (3)$$

Suppose we have a pair $\{(x_{ij}, y_i)_{i=1}^{n}\}_{j=1}^{p}$ of a random sample, where y_i represent measurements of the variable Y and x_{ij} are the n observed values of the variable X_j. Formally, the additive model can be estimated by minimization of the residual sum of squares, such as

$$\arg\min_{\{\alpha,\varphi_j\}} \sum_{i=1}^{n} (y_i - \alpha - \sum_{j=1}^{p} \varphi_j(x_{ij}))^2\,, \qquad (4)$$

which is the discrepancy between the data and our estimation model. Thus, we avoid the necessity of estimation in the multidimensional space. For more flexibility, relations between output signal and input signals are fitted by the use of nonparametric smoothing techniques like locally polynomial smoothers or natural cubic splines [8, 9]. This smoothers are linear smoothers based on n data points and have a single smoothing parameter. In choosing the smoothing parameter, an automatic selection was used by the generalized cross-validation or a graphical method helping us to choose the appropriate value [8].

We want the functions to be fitted simultaneously so we need the unconventional estimation methods of the additive model. One of them is the iterative backfitting algorithm for which the convergence to uniqness and independent of the starting value solution was proved [8, 9]. In order to avoid the lack of symmetry between estimators in a given step of iteration, the symmetrical version of backfitting algorithm was constructed, and convergence to the same uniqness solution, as in the case of the usual algorithm, was proved [9].

3. Fault detection algorithms

Model-based methods of fault detection use the analytical relations in the form of process model equations. Figure 1 shows a general diagram for the process model-based fault detection. The relations between the measured input signals and output signal are represented by a additive model of the process. Fault detection methods then generate quantities called residuals r, which are the comparisons of the actual behavior of the monitored output y to the behavior y_m predicted on the basis of the additive model. The residuals are normally equal to zero. They become nonzero as a result of faults. The residuals are then analyzed to arrive at the diagnostic decision - symptoms of faults S are or are not present.

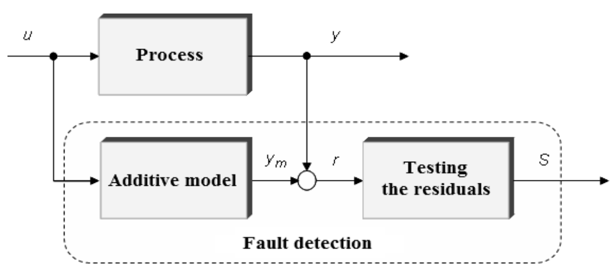

Fig. 1. The diagram of fault detection
Rys. 1. Schemat detekcji uszkodzeń

The detection performance of the diagnostic technique is characterized by important and quantifiable benchmarks, like the fault sensitivity and the reaction speed, that is, the ability of the technique to detect faults of a reasonably small size, and with a reasonably small delay after their arrival. Also its robustness, i.e., the ability of the technique to operate in the presence of noise, disturbances and modelling errors, is affected by the design of detection algorithm [1].

The simplest possible detection algorithm is to compare each observation of the scalar residual individually with the threshold values. Symptom of fault is detected if diagnostic signal $s(r_i)$ is equal to 1, i.e. when the threshold value K_1 or K_2 was exceeded by the i-th residual:

$$s(r_i) = \begin{cases} 0 & \text{when} \quad K_1 \le r_i \le K_2 \\ 1 & \text{when} \quad r_i < K_1 \ \vee \ r_i > K_2 \end{cases}. \qquad (5)$$

Alternatively, in an aim to make detection robust against impulsive disturbances, a fault is declared based on the average of the absolute residual computed over the sliding window. Value of N decides how many samples are in the sliding window, and value of k decides how far shift that window.

$$s(r_i) = \begin{cases} 0 & \text{when} \quad K_1 \le \frac{1}{N}\sum_{l=0}^{N-1} |r_{i,k+l}| \le K_2 \\ 1 & \text{when} \quad \frac{1}{N}\sum_{l=0}^{N-1} |r_{i,k+l}| < K_1 \vee \frac{1}{N}\sum_{l=0}^{N-1} |r_{i,k+l}| > K_2 \end{cases}. \qquad (6)$$

Let us notice that the choice of values N and k in the algorithm (6) determines how the smoothing the trajectory of the process will follow. For optimally fixed N, we chose the appropriate value k for maximizing the test sensitivity of faults.

The possibility of false symptoms generation also depends on the selected thresholds size as the acceptance region of the residual values. The threshold values for test (5) are obtained based on the learning sample, i.e., on residuals from the normal behaviour of process, as following:

$$\begin{aligned} K_1 &= \min\{r_i\} - \hat{\sigma}\{r_i\} \\ K_2 &= \max\{r_i\} + \hat{\sigma}\{r_i\} \end{aligned}, \qquad (7)$$

where

$$\hat{\sigma}\{r_i\} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})^2} \qquad (8)$$

for

$$\bar{r} = \frac{1}{n}\sum_{i=1}^{n} r_i\,, \qquad (9)$$

is sample standard deviation of residuals r_i.

In the case of test (6), the above threshold values are obtained from the average of the absolute residual calculated over the sliding window.

4. Actuator fault detection

The most common final control element in the industrial process control is the control valve with a diaphragm-spring pneumatic servo-motor and the positioner assembly [5]. The diagram of the actuator with measurement signals is showed in Figure 2.

This valve is an air-operated device which controls the flow through an orifice by positioning appropriately a plug. When the air pressure (the output signal from a pneumatic controller) above the diaphragm increases, the diaphragm deflects and the stem moves downwards thus restricting by the plug flow of the fluid through the orifice. When the air pressure goes down, under the action of a spring the stem moves upwards, thus opening the orifice.

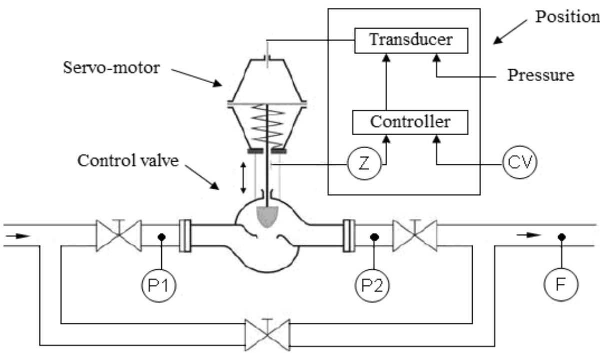

Fig. 2. The diagram of the control valve assembly with measurement signals
Rys. 2. Schemat zespołu wykonawczego wraz z opomiarowaniem

Let Z be the valve plug stem position, CV be the signal of the control valve, $P1$ and $P2$ are water pressures in front of and beyond the valve, respectively, and F is the flow of the fluid beyond the valve.

4.1. Exploratory data analysis

All research has been carried out based on the example of a control valve for measurement tracks in a boiler laboratory setup, controlled by industrial IT control systems, with the use of the R-project [12] designed to advanced statistical calculations.

To be useful for data mining purposes, the databases need to undergo a preprocessing, in the form of data cleaning, data transformation and identifying outliers [4, 9]. Moreover, the monitored plant is usually subjected to random noise. Practical experience shows that the residuals result with relatively large variance due to noise and deviations between the process and its model. Therefore, the signals must be filtered. In order to do it, the finite impulse response of 2nd order FIR filter was applied [11].

In this paper we determined the actuator by the following additive model:

$$F_t = \alpha + \varphi_1(CV_{t-1}) + \varphi_2(CV_{t-2}) + \varphi_3(P1_{t-1}) + \varphi_4(P1_{t-2}) + \varphi_5(P2_{t-1}) + \varphi_6(P2_{t-2}) + \varepsilon_t, \tag{10}$$

where ε_t, for $t = 3,...,n$, are iid random errors.

Table 1 shows variables used in model.

Tab. 1. Variables used in the modeling
Tab. 1. Zmienne użyte w modelowaniu

Variable symbol	Variable Description	Range	Units
F	Water flow beyond the valve	0-5	m³/h
CV	Control value (controller output)	0-100	%
$P1$	Water pressure (valve inlet)	0-400	kPa
$P2$	Water pressure (valve outlet)	0-200	kPa

Basing on model (10), the residuals can be obtained as

$$r_t = F_t - \{\alpha + \varphi_1(CV_{t-1}) + \varphi_2(CV_{t-2}) + \varphi_3(P1_{t-1}) + \varphi_4(P1_{t-2}) + \varphi_5(P2_{t-1}) + \varphi_6(P2_{t-2})\}, \tag{11}$$

which are the approximation of the errors ε_t.

4.2. The modelling results

The additive model (10) was fitted by the backfitting algorithm and a natural cubic spline with degrees of freedom *df*=4, used as a smoothing parameter [8, 11]. Based on the learning sample, we obtained estimated flow values (predicted *F*), and real flow values from the process (*F*), which graph was showed in Figure 3.

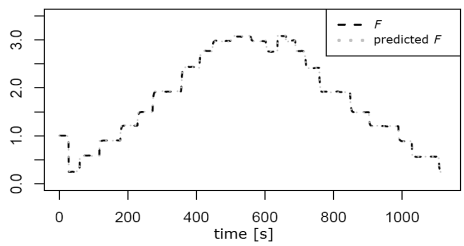

Fig. 3. The process of signals measured and modelled for the learning sample
Rys. 3. Przebieg sygnałów pomierzonego i modelowanego dla próby uczącej

4.3. The quality detection results

In order to examine detection algorithms basing on the received model, a training sample consisting of data from the normal process behaviour and data with simulated faults were applied.

Model (10) can be designed for detecting of the actuator faults. Therefore, we can expect that residuals will be affected by the faults showed in Table 2.

Tab. 2. Simulated faults
Tab. 2. Zasymulowane uszkodzenia

Nr	Fault	Description
1	f_1	Second control valve is opened in 10%
2	f_2	Opened bypass flow-meter
3	f_3	Valve clogging
4	f_4	Applying antipressure on the servo-motor chamber

Figure 4 shows graphs of signals measured and modelled, as well as residuals for samples including the individual faults. On their basis we can clearly see the deviation from the normal process behaviour. Thus, the model (10) is sensitive to the occurrence of individual faults.

Model checking is a procedure which leads to evaluation of the model delivered in the modelling phase for quality and effectiveness. In practice we have to determine measures of variability which will describe how the measurements data in relation to the prediction data are spread out.

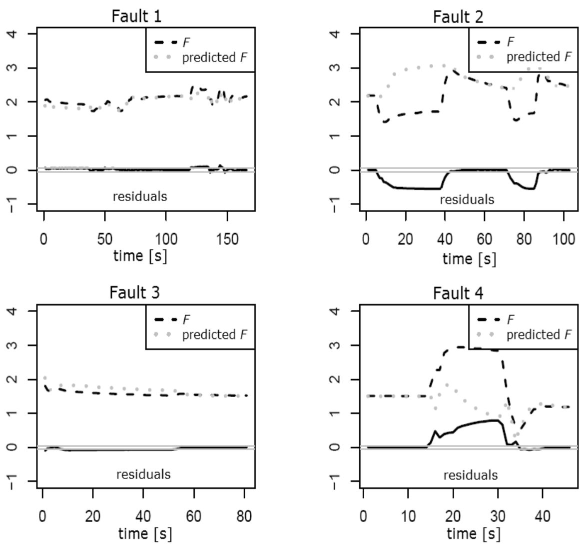

Fig. 4. The process of signals measured and modeled, as well as residuals for samples including the individual faults
Rys. 4. Przebiegi sygnałów, pomierzonego i modelowanego oraz residuum dla prób zawierających poszczególne uszkodzenia

For this purpose, for the learning sample, samples with individual faults f_1, f_2, f_3 and f_4, a sample from the normal process behaviour (N), and also for the whole training sample (T), the mean squared error (MSE), mean absolute deviation error (MADE), mean absolute percentage error in relation to range of measured output signal (MAPE) and variance of errors (VAR) were obtained. The results were showed in Table 3. On the grounds of this measures it is possible to conclude, that the approach based on the additive model performs very well.

Then the test 1 (5) with $(K_1, K_2) = (-0.0467, 0.0437)$ and test 2 (6) with $(K_1, K_2) = (0.2352, 0.0006), N = 10, k = 5$, were applied to the obtained residuals to evaluate model sensitivity to individual faults [11]. The results in Table 3 are satisfactory because on the basis of the mean percentage number of deviation from the normal behaviour process, both tests detected all symptoms of simulated faults, and at the same time any incorrectness in the learning sample were noticed. These results indicate the effectiveness of the fault detection in the analyzed structures.

Tab. 3. Criteria of the additive model fitting and results of detection
Tab. 3. Wskaźniki jakości dopasowania modelu addytywnego i wyniki detekcji

Measures	Learnin sample	Training sample					
		f_1	f_2	f_3	f_4	N	T
MSE	3e-04	0.042	0.657	0.017	0.836	2e-04	0.17
MADE	0.099	0.076	0.567	0.108	0.565	0.011	0.168
MAPE[%]	0.32	9.46	26.98	37.5	23.35	0.879	6.95
WAR	3e-04	0.007	0.349	0.008	0.568	1e-04	0.167
Test 1 [%]	0	33.73	54.37	56.8	50	0	28.06
Test 2 [%]	0	50	73.68	73.3	87.5	0	39.8

5. Conclusions

In this paper, an effective method of modelling and predicting the behaviour of fluid flow through the valve has been presented for detecting purposes. This is a new way in the industrial process diagnosis for which the difficulty associated with the problem of dimensionality is substantially reduced. The main advantage of the additive model is the possibility to examine the roles of variables in predicting the response. Moreover, additive nonparametric regression allows researchers to evaluate data without the necessity to postulate for the relationship between the response variable and inputs, and to combine flexible nonparametric modelling of multidimensional inputs with a statistical precision that is typical of one-dimensional explanatory variable. Because the single variable might be nonparametric in its effects, one can model the process with nonlinearities that are difficult to be specified. Applied backfitting algorithm converges to uniqueness and is independent from the starting value solution, and is also easy to be comprehended and does not require large computational costs. Therefore, it's a useful method for a multivariate industrial process fitting and the fault detection in the analyzed structures.

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