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Applications of Predictive Maintenance Techniques in Industrial Systems

Aleksandra Marjanović[1], Goran Kvaščev[1], Predrag Tadić[1], Željko Đurović[1]

Abstract: Prognostic methods represent a new methodology for system maintenance which offers significant time and cost savings. The paper offers a short overview of the available prognosis techniques and proposes the implementation of one model-based and one data-driven method. As a representative of the model-based methods the autoregressive moving average (ARMA) modeling approach is chosen. The estimated model parameters are further used for implementing the early change detector which is realized as a Neyman-Pearson hypothesis test. On the other hand, hidden Markov model (HMM) based prognosis illustrates the use of data-driven techniques. Using the cross-correlation input-output functions, HMM prognosis algorithm is proposed, as a suitable way of timely detection. Both techniques were implemented to detect performance changes of the water level sensor in a steam separator system in thermal power plants.

Keywords: Condition-based maintenance, Prognosis, Remaining useful life, Data-driven methods, Model-based methods, Steam separators.

1 Introduction

System reliability is one of the main issues in the nowadays industry, thus the development of advanced system maintenance techniques is a very important task. Such techniques can be grouped into two categories. The first one is corrective maintenance and it consists of replacing the component and repairing the damage after some major failure. The second one is preventive maintenance and it refers to avoiding the potential problem by timely replacing the source of failure. In other words, this approach deals with the fault before it actually happens. Preventive maintenance is time-based, meaning that the components are replaced based on a predefined schedule which relies on the working hours of the component. Obviously, this approach is not optimal, since the components are being replaced before the end of their lives, therefore increasing the costs. One possible solution is to use condition-based predictive

[1] School of Electrical Engineering, University of Belgrade, Bulevar kralja Aleksandra 73, Belgrade, Serbia; E-mails: amarjanovic@etf.bg.ac.rs, kvascev@etf.bg.ac.rs, tadicp@etf.bg.ac.rs, zdjurovic@etf.bg.ac.rs

maintenance [22], which uses fault diagnosis and prognosis to describe system future behavior. While fault diagnostics includes detection of abnormal behavior in the system, as well as revealing their causes and locations, fault prognosis refers to predicting the fault evolution over time and thus accurately estimating the remaining useful life (RUL) and the end of life (EOL) of the affected component or subsystem.

Prognosis techniques are usually categorized as model-based or data-driven [6, 22]. Model-based methods use the knowledge about the system and failure models in order to provide RUL estimate [17, 19]. They can use either the physical model of the process [1] or some statistical estimation methods based on state observers, such as Kalman filters [7], particle filters [12, 18], etc. However, the system model is not always easy to obtain. On the other hand, data-driven methods utilize only the available data which are used to train the learning algorithms to estimate RUL. Therefore these methods are used when system monitoring data is available. The illustrative representatives of this approach are neural networks [15, 24] and hidden Markov models [21]. Both data-driven and model-based approaches have their advantages and disadvantages. While model-based techniques are more reliable when the appropriate model is obtained, their reliability is decreased when system complexity increases. On the other hand, although the data-driven techniques use only the data from a limited number of sensors, interpreting the system itself as a black box, they usually demand a large amount of training data. Depending on the system severity, beside the system model and/or observation data, historical information should be used to obtain correct RUL prediction. Therefore, the combination of different approaches into a hybrid method is very popular and provides very good prognosis results.

The paper gives an overview of the popular predictive maintenance methods, considering both model-based and data-driven approaches. Firstly, the ARMA model-based approach is proposed for system identification. The obtained model parameters are additionally processed in order to make an adequate prognosis using the Neyman-Pearson test as a tool for statistical hypothesis testing. Secondly, the HMM data-driven approach is proposed as another option for prognosis. It relies on the cross-correlation functions between available input and output measurements. Additionally, a case study is provided illustrating the benefits and downsides of different approaches. The system that was used in testing purposes is a steam separator system in thermal power plants. Keeping in mind that this is a very important subsystem in thermal power plant boilers, timely fault prediction is of great importance. The organization of the paper is as follows. The Section 2 gives theoretical background of several approaches to predictive maintenance, emphasizing those for which the experimental results are provided. Section 3 introduces the steam separator system of a thermal power plant boiler and describes in details its most important features. Section 4 contains the application of the selected approaches, and shows the obtained results as well as the comparison of the used methods. Conclusion summarizes the obtained experimental results.

2. Prognostic Algorithms

2.1. Model-based fault prognosis

Model-based prognostic techniques rely on a dynamic model of the predicted process. This approach uses a mathematical model of the process in order to implement the physical understanding of the system into the diagnostic problem. Such models should describe both nominal and faulty behavior of the system. As a result, it is possible to explain the fault progress in time, and to make EOL and RUL predictions. These methods involve the estimation of residuals as a deviation between the real system measurements and proposed model outputs. In the ideal case the residuals are zero, but this is not the case because of the permanent noise and modeling errors. It is, therefore, expected that the residuals are small in the nominal working mode and larger in the presence of a failure. Once the residuals are obtained, it is possible to use some statistic representation to estimate the distribution of RUL as a function of present uncertainties and to calculate possible damage.

One of the advantages of these techniques is the employment of the physical understanding in the diagnostic algorithm. Furthermore, component failures are usually closely related to the model parameters. In that way, by monitoring the behavior of the process and gathering new information, it is possible to adapt the model in order to get better performance. This means that new measurements are not obligatory for model-based methods, but when available, they can provide a full prognostic ability during time. Model-based methods include physical-based model, autoregressive moving-average techniques and Kalman/particle filtering. The choice of the method depends on the available knowledge of a specific system.

Physics-based prognosis considers models of the system which are derived by using some physics laws and principles. Since the correct modeling is essential to a good fault prognosis, a great deal of attention is paid to exploring the microstructural material characteristics. A disadvantage of these models is usually a high level of complexity. This is a reason for introducing the so-called metamodels, which represent a reduced-order microstrusural model with the ability to estimate crack initiation and propagation in real-time. Crack initiation models must include all the available information the about component and its environment. The crack propagation models can be divided into two main groups: deterministic and stochastic. Deterministic crack propagation models which usually describe the growth of the crack α, are based on Paris' law [14]:

$$\frac{\mathrm{d}\alpha}{\mathrm{d}N} = C_0(\Delta K)^n ,$$

where $\Delta K = Y(\alpha)(\Delta s)\sqrt{\pi\alpha}$ is a stress intensity factor, $Y(\alpha)$ is related to crack geometry, Δs is the stress range, N represents the number of running cycles, C_0 and n are material dependent constants. Stochastic crack propagation involves models with random parameters which can be estimated using Monte Carlo simulations. The resulting equation which describes the crack growth is of stochastic differential nature.

Parameter estimation prognosis presents another possibility of obtaining the adequate model. Namely, sometimes the physics-based process model is unavailable or too complicated for implementation, thus some of the system identification procedures must be used. Based on the knowledge about the system, a model structure and complexity can be proposed. System identification reduces to estimating the unknown model parameters vector using the observed input and output sequences [10]. Let us consider an autoregressive moving-average (ARMA) model:

$$y(i) = -\sum_{k=1}^{n} a_k y(i-k) + \sum_{k=1}^{m} b_k u(i-k) + e(i) , \tag{1}$$

where $u(i)$, $y(i)$ and $e(i)$ are system input, output and noise respectively. The model can be represented as a linear regression form:

$$y(i) = \boldsymbol{Z}^T(i)\boldsymbol{\Theta}(i) + e(i) , \tag{2}$$

where $\boldsymbol{Z}^T(i) = \begin{bmatrix} -y(i-1) & \cdots & -y(i-n) u(i-1) & \cdots & u(i-m) \end{bmatrix}$ is the regression vector and $\boldsymbol{\Theta}(i) = \begin{bmatrix} a_1 & \cdots & a_n b_1 & \cdots & b_m \end{bmatrix}$ is the unknown parameters vector. There are many well-known techniques which deal with estimating the unknown parameters vector. ARMA models as well as their variations (ARMAX, ARIMA) are very often used as predictors, it terms of using the model and the historical data to predict the expected system behavior. Therefore, parameter identification methods have found a wide use in prognosis.

State observer prognosis is a very popular approach to system maintenance. For linear systems with additive Gaussian noise terms, Kalman filters can be used for prognosis. However, when dealing with systems that are nonlinear with additive Gaussian noise terms extended Kalman filters are useful. For systems that are nonlinear with non-Gaussian noise terms, the particle filters also referred to as sequential Monte Carlo method, which are based on the sequential importance sampling (SIS) and the Bayesian theory, lead to a suboptimal solution to state estimation problem. Particle filters are nonlinear state observers which approximate the posterior state distribution using the swarm of weighted points, called particles. The particles consist of samples from the states-space and a set of weights which represent discrete probability masses. Increasing the number of particles the estimation is better. Particle filtering has a wide applicability in fault prognosis due to the ease of implementation. The algorithm consists of two steps: the first one is state estimation, and the second one is long-term prediction. The state estimation involves estimating the current fault dimensions and changing parameters in the environment. The next step is the state prediction, which uses the current fault dimension estimate and the fault growth model, to generate state prediction from $(\tau+1)$ to $(\tau+p)$. Once the long-term prediction is estimated, given the lower and upper bounds of a failure zone (H_{lb} and H_{ub}), the prognosis confidence interval can be estimated.

2.2. Data-driven fault prognosis

Although model-based methods can provide better results given the use of fault progression model, sometimes the only available data is time plots of monitored signals which are describing the behavior of the system. In such cases it is very difficult or impossible to obtain the process model, thus the prognosis algorithm turns to data-driven techniques. These techniques use measurement signals and their statistics to create nonlinear structures which can provide desirable outcomes given the input data. Such structures include a wide range of methods, from statistical classifiers such as principal component analysis (PCA), partial least squares (PLS), to artificial neural networks, fuzzy-logic systems and graphical models such as Bayesian networks and hidden Markov models (HMM). When compared to model-based approach, data-driven methods are usually easier and cheaper to implement. Also, they cover a large span of systems, unlike the model-based techniques which can have very narrow application. On the other hand, one of the disadvantages of data-driven methods is a large number of training data, as well as potentially wide confidence interval. A very important step in the data-driven algorithm is the selection of the monitoring signals which are relevant to system health. These signals are related to the current health of the system, thus the classification can be done. Data-driven techniques rely on the assumption that the obtained data statistics stay nearly the same during the nominal system behavior, meaning that the bigger changes in the statistics are related only to the malfunctions in the system.

Artificial neural networks prognosis propose methodologies similar to those in the biological nervous system. For a set of available monitoring data which are used as inputs and predefined, known outputs it is possible to use some of the training algorithms, such as backpropagation algorithm, to map the connection between the input and output. Namely, neural networks are self-adaptive structures whose weights between neurons are adjusted by minimizing the criteria to match a model to desired outputs. The training procedure allows the network to learn the relationship among the data without engaging the model of the system. This is why ANNs are very popular in fault diagnostics and prognosis. Once the weights are set, the ANN is ready to generate the desired output as a fault evolution prediction. One of the disadvantages of ANNs is the inability to directly apply standard statistical methods for confidence estimation. Some major steps in solving this problem were done by using nonlinear regression for estimation of confidence intervals [23]. Many other approaches have been proposed, including the enforcement of the probabilistic and generalized regression neural networks [20].

Fuzzy-logic prognosis is generally similar to the ANN. Fuzzy-logic systems also provide mapping between the input and output signals. Unlike neural networks, they are based on linguistic and reasoning human capabilities. By defining the appropriate if-then rules and adjusting membership functions, fuzzy systems can give very accurate prognosis [3]. Being very intuitive, they are widely used in fault diagnosis and prognosis.

Hidden Markov model (HMM) is a statistical model which can be used to describe system transitions between states. It represents an extension of a regular Markov chain with unobservable or partially observable states. The general structure of a discrete-time HMM with N states, $S=(s_1,s_2,\ldots,s_N)$ and M observation symbols, $V=(v_1,v_2,\ldots,v_N)$, is shown in Fig. 1. The states are interconnected so that a transition between any two states is possible. The hidden state at time t is denoted as q_t and the state-transition rule follows the Markov property, meaning that the state q_t depends only on the state q_{t-1}.

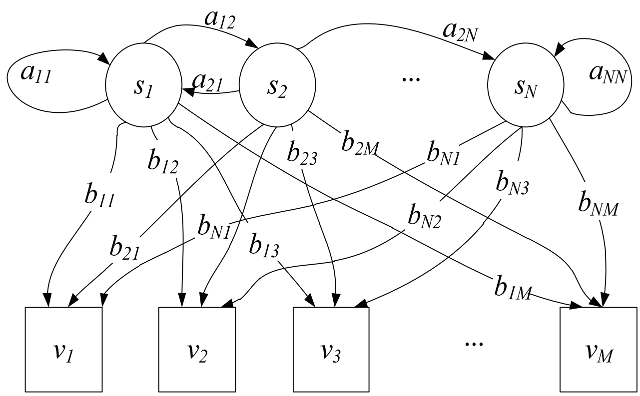

Fig. 1 – *Hidden Markov model.*

Beside the size of state and observation alphabet, N and M, it is necessary to define some other features of HMM. The transition matrix $\boldsymbol{A} = \{a_{ij}\}$ stores the probability of state j following state i. The coefficients a_{ij} are non-negative in general case, and equal zero when there is not a direct connection between two states. The observation matrix, also called emission matrix, $\boldsymbol{B} = \{b_j(k)\}$ shows the probability of observation k being produced from the j-th state. The initial state array $\boldsymbol{\pi} = \{\pi_i\}$ holds the information about initial probabilities, which indicate how likely it is for a new input sequence to start at a given state. Finally, the definition of HMM is given as:

$$\lambda = (\boldsymbol{A}, \boldsymbol{B}, \pi) \tag{1}$$

There are three fundamental problems that can be solved using HMMs. The first problem, the so-called evaluation, is to determine the likelihood of the observed sequence O given the model (1) and the sequence O. The solution of this problem is offered in a form of Forward algorithm, summing all the paths in the model. In that way, the probability of the given sequence $P(O|\lambda)$ is calculated. The second problem is to determine the most likely state sequence given the model (1) and the sequence O. The Viterbi algorithm [16] is proposed as a solution to this problem. The third problem is a problem of training the HMM. In other words, given an observation sequence O and the dimensions of the model N and M, find the model (1) that maximizes the probability of O. The Baum-Welch or the so-called Forward-Backward procedure can be used in order to re-estimate the model parameters. The combination of these problems can help solving many other complicated formulations, and that is one of the reasons why HMMs are so popular. HMMs can also be very effectively used to estimate the occurrence of a failure, before it happens. Using the Baum-Welch algorithm, HMM can be trained in order to give desired outputs related to system health, for the monitored data inputs. Having done that, it is possible to use HMM for fault detection and prognosis. HMM offer a reasonable estimation of the RUL time, meaning the time when the system will be in the specified, faulty state. Also, it is possible to estimate the probability of system being in specified state after n iterations.

$$\hat{\boldsymbol{P}}(n) = \pi_t \boldsymbol{A}^n, \quad RUL = n \quad \leftrightarrow \quad \hat{\boldsymbol{P}}(s = s_N \mid n) = \varepsilon, \tag{4}$$

where ε is a predefined limit for the predicted probability, $\boldsymbol{\pi}$ and $\boldsymbol{A}$ are initial state and the state transition probability distribution, respectively.

Bayesian networks represent a data-based methodology which uses additional knowledge information, and it can also be classified as a knowledge-based approach. Knowledge-based techniques also include such graphical approaches as multi-signal flow graphs and Petri nets [11]. Bayesian or belief networks (BN) provide knowledge representation in structured domain with inherent uncertainty. They represent the state-of-art approach to reliability modeling [9]. One of the advantages of BNs is their flexibility in modeling framework. BN represents a directed acyclic graph (DAG) with nodes representing random variables and arcs representing probabilistic dependencies between variables. This contains a great amount of information about the system. A complete BN requires a conditional probability tables for each node. Unlike HMM which represent a static model of the system, BN incorporates the dynamic of the system.

3 Case Study: Steam-Separator System

Thermal power plants are the largest generators of electricity in Serbia, contributing more than 65% to the overall power supply. As such, their operational efficiency and stability needs to be maximized. Therefore, the condition-based maintenance is of special importance, in terms of longevity and reliability of the facility. It is, therefore, extremely important to monitor vital subsystems and their individual components, such that early detection of any change in characteristics, or faults, will prevent accidents, down time, and substantial financial loss.

The paper addresses steam drums in thermal power plant boilers [2, 4, 13]. A boiler is a unit in which the chemical energy of fossil fuel is converted into heat energy of steam. Fig. 2 shows the basic structure of a steam boiler. An even number of mills (usually 6 or 8) break up and grind coal and then a mixture of coal and preheated air is routed to a furnace via a system of ducts. In parallel, the oxygen needed for combustion is provided by an air supply fan. On the way to the furnace, the air is additionally heated to enhance combustion. Temperatures inside the furnace are as high as 1400°C, such that all its parts need to be resistant to such temperatures. Feedwater pumps deliver partially heated water to the steam drum via an economizer, and then additional pumps discharge the water into a system of pipes where multi-stage heating takes place inside the boiler and the water is converted into steam. The steam drum also removes remaining drops of water from the steam. The steam is then delivered to a multi-stage superheater where it is heated to about 540°C at a nominal pressure (usually 165-175 bars) before it leaves the boiler, and the superheated steam continues on to the turbine.

Specifically, at the TEKO B1 Unit of the Kostolac Thermal Power Plant, the diameter of the steam drum is 0.9 m and its height is about 24 m. Even a small water level variation inside the steam drum results in noticeable steam pressure fluctuations and affects the technical conditions of the process. If the water level is too high, emergency relief valves open to remove excess water and this improves the operational efficiency of the unit. However, if the water level is too low, after a certain time a boiler shutdown procedure is initiated automatically, to protect the piping from overheating. As a result, maintenance of the required water level is a very important control requirement.

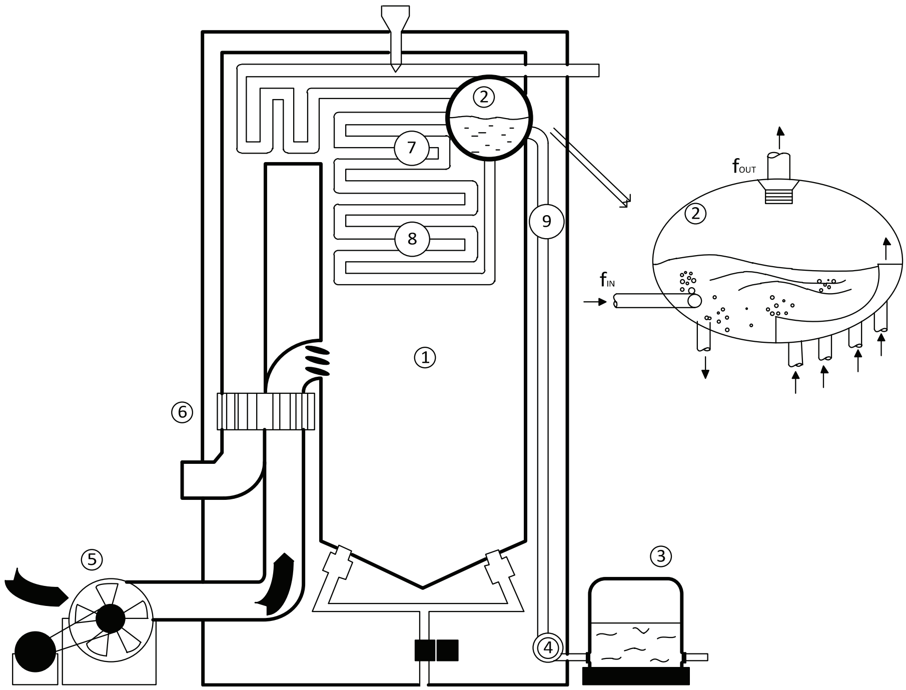

Fig. 2. – *Schematic of a typical boiler*: 1. *furnace,* 2. *Steam drum,* 3. *Feedwater tank,*4. *Feedwater pumps,* 5. *Air supply fan,* 6. *Air preheater,* 7. *Primary preheater,* 8. *Secondary preheater,* 9. *Economizer.*

In this subsystem, one of the most important measurements is that of water levels. Sensor failure due to ageing is rather frequent but this must not affect operational stability. Such situations can be prevented by timely replacement, provided that any change in characteristics is detected on time. That is why the predictive maintenance plays a very important role in managing this system.

Given that the water level in the steam drum depends on the water flow to the drum and the steam flow from the drum, the following can be assumed:

$$\Delta h(z) = f(f_{IN}, f_{OUT}), \tag{5}$$

where Δh is the steam-drum water level increment, f_{IN} is the water flow to the steam drum, and f_{OUT} is the steam flow at the outlet.

4 Experimental Results

The paper discusses timely detection of a water level sensor failure. The failure is reflected as a gradual degradation of sensor performance, from 100% to 94% in approximately 15 hours. Two different analyses are conducted and their comparison is provided. The first one uses the ARMA model-based approach in order to obtain the system model. The next step is to predict the failure by detecting minor changes in the model parameters. This was done using the statistical hypothesis testing technique. The Neyman-Pearson hypothesis test [5] was used to draw the line between nominal mode and the transition mode which leads to the fault. The second analysis is based on the hidden Markov model which represents a data-driven technique. Instead of using the raw data, the data cross-correlation functions were used as inputs to the HMM. Both methods managed to detect changes in the system, long before the complete sensor malfunction happened. On the other hand, we came across certain downsides of these methods, which could be resolved using a slightly advanced or some hybrid approach.

4.1. Combined method of model-based ARMA prognosis and hypothesis testing

First, let us consider the system identification procedure based on ARMA model parameter estimation. As indicated in (5) the steam separator system can be adequately represented with a model with two inputs and one output, thus the following ARMA form is proposed:

$$\Delta h[k] = -\sum_{i=1}^{3} a_i \Delta h[k-i] + \sum_{i=1}^{3} b_{1i} f_{IN}[k-i] + \sum_{i=1}^{3} b_{2i} f_{OUT}[k-i]\,. \tag{6}$$

After a series of experiments, it was shown that the model order of $n = 3$ represents a good compromise between complexity and accuracy. This means that the number of unknown parameters is nine. Therefore, it is necessary to estimate all nine parameters of the model at each time in order to obtain the full representation of the system. Keeping in mind that the nature of the water level measurement is characterized by a sporadic presence of high-intensity measurement noise it is necessary to use a robust adaptive parameter estimation procedure which could deal with such circumstances. The paper proposes the use of M-robust parameter estimation procedure [8]. Fig. 3 shows the estimation results for the water level increment. It is evident that the described parameter estimation procedure showed very good performance in steam separator system identification. Thus, the parameters managed to capture the process dynamic and to provide satisfactory model of the system. Since the proposed method for robust estimation is adaptive, it is expected that the parameters change in time together with the changes in process behavior. Fig. 4 depicts the parameters movement over time, illustrating the degradation in water level sensor performance. The degradation starts at 40,000 s and lasts until 100,000 s. This is visible in Fig. 4, in parameters a_1, a_2 and a_3 where a slight change in parameter behavior present. This means that the changes which present in the system, although very small, are visible in the model parameters.

This encourages the further implementation of an adequate hypothesis test. Firstly, parameters behavior for three separate cases is recorded: nominal (system is in regular working mode), transition (sensor starts to fail) and failure class (sensor performance is degraded to 94%). Thus, the goal is to construct such a classifier which could separate the nominal class from the transient class. Knowing that the system working mode is described with nine parameters at each time instance, it is possible to use some dimension reduction technique in order to obtain a two dimension representation of the system mode. We propose the dimension reduction based on the scattering matrices, which enables easier implementation of a classifier.

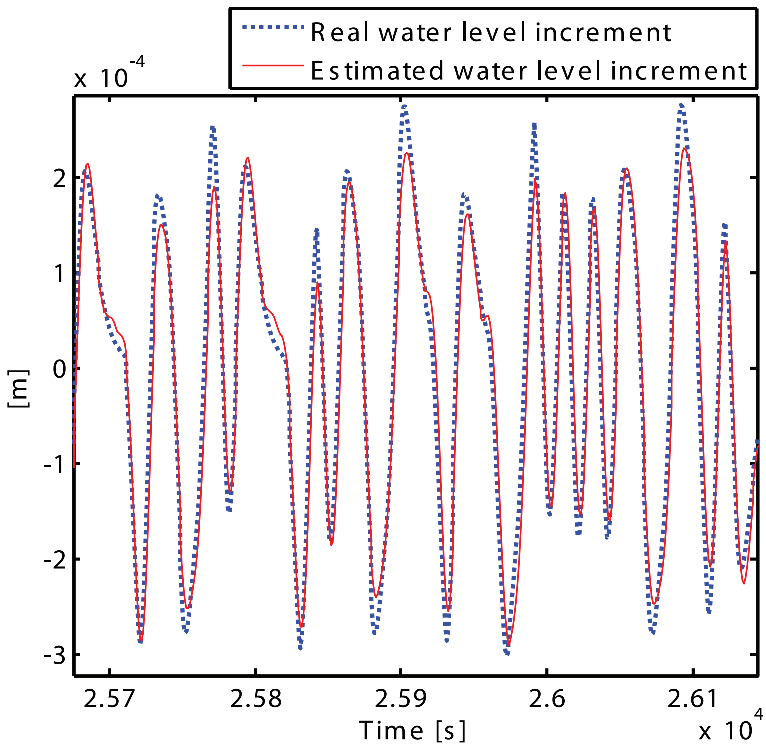

Fig. 3 – *Water level increment estimation.*

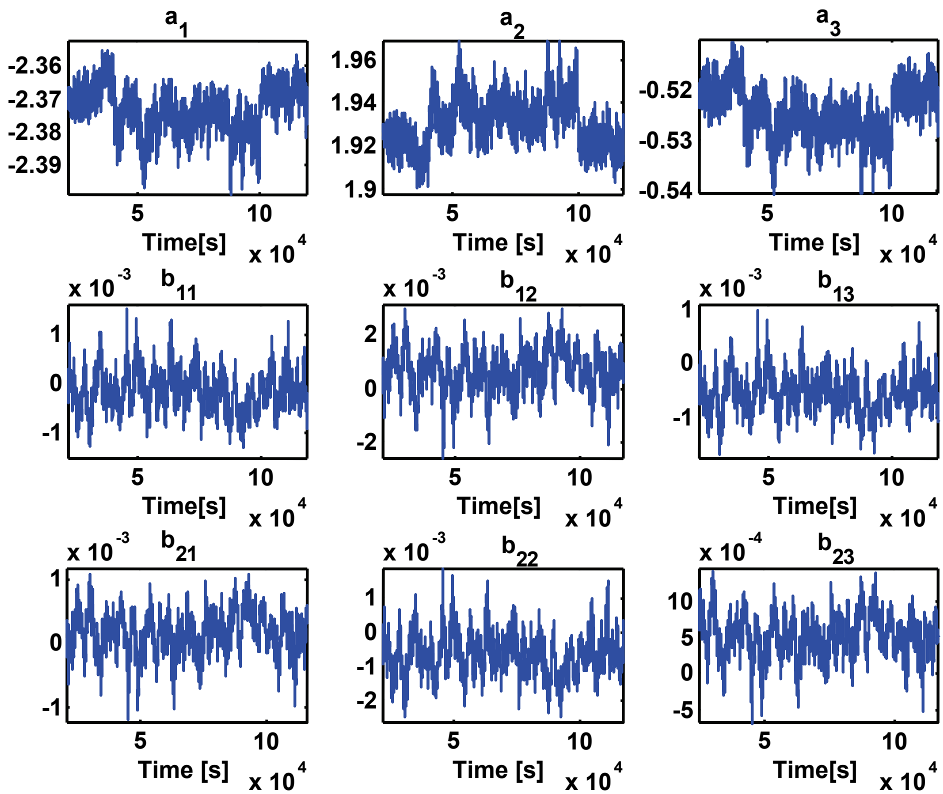

Fig. 5 – *Estimated parameters movement, water level sensor performance decreases from* $t = 40{,}000$ s *to* $t = 100{,}000$ s.

Fig. 5 illustrates the two dimensional representation of each of the three health modes after using the dimension reduction technique. As expected, the second, transient, class overlaps with both nominal and faulty class. Therefore, a compromise must be made, between the error probability and a change detection time. When talking about classification in terms of fault detection two error probabilities are defined: the misclassification (type one) and the false alarm (type two) probability. Neyman-Pearson (NP) classifier allows us to define one error probability and keep it constant, while minimizing the other one. This is very useful in our case, because the probability of misclassification is much more important than the probability of false alarm. The NP decision rule can be reduced to:

$$\frac{f_1(\boldsymbol{X})}{f_2(\boldsymbol{X})} \underset{\omega_1}{\overset{\omega_2}{\lessgtr}} \mu , \tag{7}$$

where f_1 and f_2 are the probability density functions of the first and second class, $\boldsymbol{X}$ is the vector of the data to be classified into one of the two classes ω_1 and ω_2. The parameter μ is selected to minimize the criteria (8) and depends on the probability of error of the first or second type:

$$r = \varepsilon_1 + \mu(\varepsilon_2 - \varepsilon_0) = (1 - \mu\varepsilon_0) + \int_{L_1} [\mu f_2(\boldsymbol{X}) - f_1(\boldsymbol{X})] \mathrm{d}\boldsymbol{X} , \tag{8}$$

where L_1 is a subset of the vector space $\boldsymbol{X}$ corresponding to the first class.

The goal is to design a classifier which will separate the nominal class from the transient one in a reasonable time period. Namely, depending on the chosen error probability, a delay in detection is present. Thus, a compromise should be made between the two, and we chose $\varepsilon_2 = 5\%$ which ensures a delay of around 80 s. Fig. 5 shows a 2D representation of the system health modes together with the chosen classifier. It is evident that the prognosis efficiency is correlated with the error probability, meaning that the more accurate prognosis needs more time.

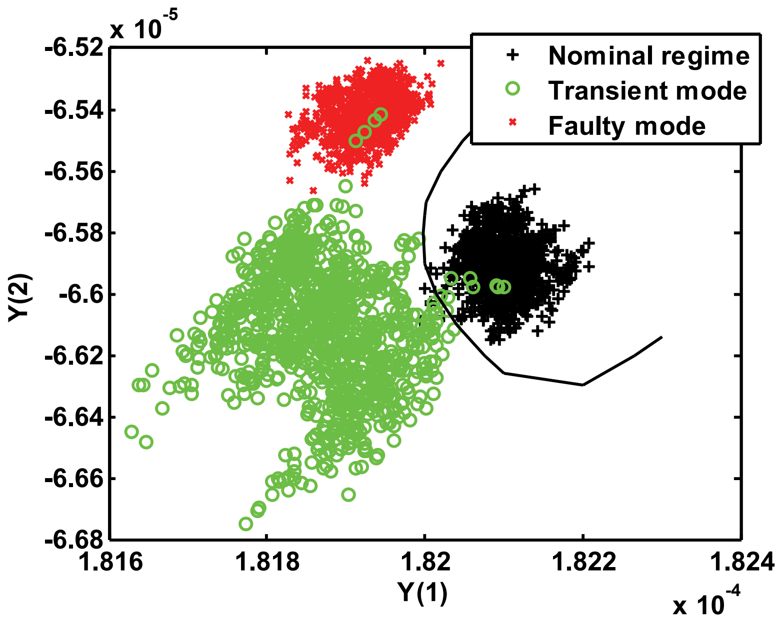

Fig. 5 – *Neyman-Pearson classifier.*

4.2 Data-driven HMM prognosis

Let us now consider the use of HMMs in fault prognosis for the steam separator system. Before proposing the structure of the HMM, it is necessary to decide which system features should be used as appropriate inputs to the HMM. This paper presents the use of the cross-correlation functions between the inputs and the output, as a possible way of extracting the information about the system behavior. The unbiased estimation of a cross-correlation function is used (9):

$$r(m) = \frac{1}{N-m} \sum_{k=1}^{N-m} f_i[k] \Delta Y[k+m] . \quad (9)$$

Three different pairs of input-output cross-correlation functions are obtained. The first one describes the relation between each of the inputs and output in the nominal health state. The second one explains the transition period, of sensor slow degradation. And the last one relates to the sensor failure state, when the degradation epoch is over. For each mode, two cross-correlation functions are recorded. The first one gives the cross-correlation between the water flow and water level, while the other one is the cross-correlation between the steam flow and water level. Consequently, each mode is represented by a single sequence, which is obtained by merging the two cross-correlation functions. Additionally, instead of using these continuous vectors, vector quantizer (VQ) is involved in order to map these observations in a discrete codebook. A 32 level codebook is used in this application. Once the codebook is obtained, it is possible to perform mapping using the simple nearest neighbor computation. Finally, every observation is assigned with a single number, as an index of the nearest codebook vector. The procedure is repeated for $n = 500$ different measurement sequences for every class.

After the pre-processing of signals is done it is possible to use the HMM model in order to predict the changes in the system. A three state hidden Markov model is proposed, where each of the states represents one of the health classes of the system. It is important to point out that in this application terms class and state have the same meaning. As expressed before, HMM is defined by three probability distributions. Having in mind the nature of the system and the failure, we proposed several rules concerning the structure of the three matrices. The first one is that the initial state of the system is the nominal state. Others consider the transitions between classes, such as: the most probable path from nominal (class one) to faulty state (class three) is over the transition state (state two) and the return from faulty state to nominal state is not likely to happen. The early detection consists of two stages. First, it is necessary to train the HMM, using the Baum-Welch procedure for re-estimation of the parameters. Once the optimal parameters are obtained, testing is done using the Viterbi algorithm.

Fig. 6 shows the performance of the described system. A change in the system is detected with a delay of an iteration, which corresponds to 40 s. This is depicted as a change in the classifier decision from one to two. Later, when the degradation stops at 94%, meaning that the sensor shows 94% of the real value, classifier changes the decision to three which corresponds to the faulty mode. The estimation of the useful remaining life time as proposed in (4) does not provide good results. This is to be expected because this estimation takes into consideration only the static probability matrices, and does not have the information about the current state of the system. This problem can be partially solved by using the semi-hidden Markov models, which provide better RUL estimation.

Comparing these results to those obtained by ARMA based prognosis, which are presented earlier in the paper, we can see that the HMM approach shows better performance in terms of shorter delay time and error probability. The delay time of ARMA algorithm can be reduced by allowing greater error probability. When it comes to RUL estimation, both techniques provide inaccurate result, because of the fact that they don't take into consideration the current system state. RUL estimations can be improved by implementing the information about the changes in the system into RUL calculation algorithm.

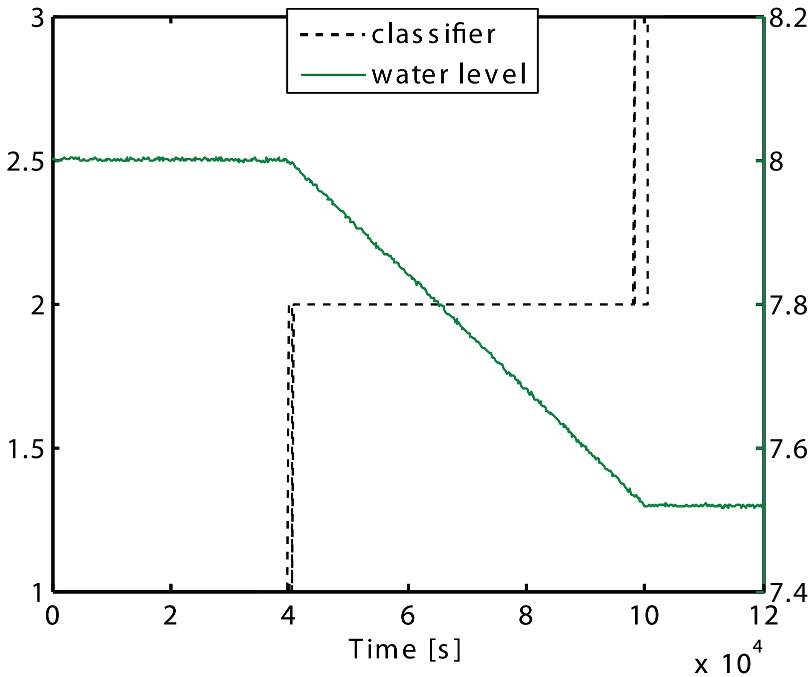

Fig. 6 – HMM *classifier*.

5 Conclusion

Unlike conventional maintenance methodologies, the prognosis methods estimate the system degradation rate based on the observed system condition. The condition-based maintenance based on the model knowledge or available measurements is preferable because of the possibility of predicting the system conditions. The paper proposes different approaches to fault prognosis in the steam separator system in thermal power plants. Two techniques were separately implemented as a prognostic algorithm. First, ARMA based prognosis method showed very good results in model parameter estimation. Using the statistical hypothesis testing, timely detection of the water level sensor operation mode changes is done, emphasizing the need of a compromise between the error probability and the detection time. On the other hand, the HMM approach, which implied the use of cross-correlation functions between the available water level, water and steam flow measurements showed slightly better performance in terms of delay time and error probability. Nevertheless, both methods detected a change shortly after it happened. The obtained results show the possibility of their application in increasing the system reliability and maintenance performance.

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