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# FUZZY MODEL OF THE OPERATIONAL POTENTIAL CONSUMPTION PROCESS OF A COMPLEX TECHNICAL SYSTEM

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**Abstract**. *During the operation process of a system its technical state is changed. The changes take place because of the wearing factors impact. The impact depends on the flow and intensity of the operation process what is characterized by the time histories of the working parameters. Simultaneously, the changes of the technical state are correlated with the changes of the amount of the operational potential included in a system. In order to avoid the inability state occurrence the amount of this potential should be higher than the boundary value. The amount of the operational potential included in a system is determined by the values of the cardinal features of it but in the case of the real technical system the values cannot always be measured. Therefore, the amount of the operational potential and the technical state of the system cannot always be determined online. To solve this problem the model of the operational potential consumption process was created and presented in the paper. The model uses artificial intelligence techniques to calculate the change of the operational potential amount by determining the changes of the cardinal features of the system on the basis of the time histories of the working parameters. The verification of the model quality was performed using the pulverized boiler OP-650k-040 operating in the power plant. The description of the conducted research and the results of the verification were presented in the end of the paper proving the adequacy of the model implementation in the case of industrial objects.*

**Key Words**: *Fuzzy Model, Operational Potential Consumption, Complex Technical System, Operation, System Feature, Working Parameter*

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## 1. INTRODUCTION

The object under consideration is a crucial technical system of the strategic importance. In the case of such systems the main objective of the operation and maintenance control is to perform the operational tasks and avoiding the failure occurrence [1,2]. This is a very important issue because the consequences of a failure can be very costly or can pose a health risk. In order to avoid failure the operation processes should be stopped and the service activities should be performed. Unfortunately, when the operation processes are stopped the technical system user does not obtain any effect of the system operation. Thus, the service activities should be started at the proper moment. The main question of the research is how to determine that moment.

The failure is defined as a transition of the technical state of the system from the area of the ability states to the area of the inability states [3]. The technical state is determined by the values of the cardinal features of the system [4] and is correlated with the amount of the operational potential included in it. The inability state occurs when the amount of the operational potential included in a system is lower than the amount corresponding to its boundary state [5]. In order to avoid the inability state occurrence it is necessary to know the amount of the operational potential of the system at every moment of the system operation. This amount, similarly to the technical state, is determined by the values of the cardinal features of the system. But not always it is possible to measure the values online. The changes of the values take place during the operation processes because of the forcing factors influence. The forcing factors can be divided into two groups dependent on and independent of the system operation [6]. The first group of the factors acts as a result of the operation process execution while the second characterizes the impact of the environment [7]. Thus, the level of the forcing factors influence is determined by the way of the operation process execution and the intensity of the environment impact. If the intensity of the environment impact is assumed as an independent variable then the forcing factors influence is determined only by the operation process flow which is described by the values of its parameters. In fact, the intensity of the operation process is described by the time histories of the working parameters. So, it was stated that in order to avoid the inability state occurrence it is necessary to apply the model of the operational potential consumption process which can calculate the change of the potential as a function of the time histories of the working parameters. Therefore, the analysis of the existing models of the operation and maintenance processes was performed [8-11] in order to identify their adequateness in the case of crucial, complex technical systems of the strategic importance. As a result it was stated that in the case of complex technical objects changes of operational potential amount could not be given with proper accuracy thanks to analytical models usage. Therefore, in this paper, the system fuzzy model is proposed to model the process under consideration. In Chapter 2 the main idea of fuzzy model application is presented. Its structure and the way of operation are described in details in Chapter 3. Subsequently, in Chapter 4 the industrial research is presented which was performed in order to identify the model parameters values (described in Chapter 5) and to verify prepared model accuracy (described in Chapter 6). Finally, in Chapter 7, some conclusions can be found.

The main contribution and the novelty of the proposed solution are the universal creation method of the system model of the operation potential consumption process. The result of the proposed method is the fuzzy model. Thanks to the fuzzy sets theory implementation the uncertainty of the initial technical state identification and the approximation of the time histories of the operation parameters are taken into consideration.

## 2. THE IDEA OF THE FUZZY MODEL OF THE OPERATIONAL POTENTIAL CONSUMPTION PROCESS

It was decided that the designed model will estimate the levels of the forcing factors influence on the basis of the time histories of the working parameters. Subsequently, on the basis of the levels of the forcing factors influence the changes of the cardinal features values will be identified. Eventually, on the basis of the changes of the cardinal features values the change of the operational potential amount will be determined Eq. (1)

$$\begin{aligned} &M\Delta Pu : \left( po_1(t)\Big|_{t_1}^{t_2},..., po_{aop}(t)\Big|_{t_1}^{t_2} \right) \to \\ &\left( ff_d^{\,1}(t)\Big|_{t_1}^{t_2},..., ff_d^{\,n}(t)\Big|_{t_1}^{t_2}, ff_{id}^{\,1}(t)\Big|_{t_1}^{t_2},..., ff_{id}^{\,r}(t)\Big|_{t_1}^{t_2} \right) \to \\ &(\Delta x_1,..., \Delta x_s) \to \Delta Pu \end{aligned} \tag{1}$$

where: $M\Delta Pu$ - the model of the operational potential consumption process, $po_i$ - $i$-th parameter of the operation process $i = 1,...,aop$, $aop$ - the working parameters amount, $po_i(t)$ - the time dependent value of $i$-th working parameter, $po_i(t)\Big|_{t_1}^{t_2}$ - the time history of $i$-th working parameter in period $[t_1, t_2]$, $ff_d^j$ - $j$-th forcing factor depended on the system operation $j = 1,...,n$, $ff_{id}^k$ - $k$-th forcing factor independent of the system operation $k=1,...,r$, $\Delta x_l$ - the change of the value of $l$-th cardinal feature of the system $l = 1,...,s$, $\Delta Pu$ - the change of the amount of the operational potential of the system.

The application of the constructed model will be used to determine the technical state of the system in $t_2$ moment taking into account the technical state of the system in $t_1$ moment and time histories of the parameters of the operation process in period $[t_1, t_2]$ Eq. (2).

$$\left(s(t_1), po_1(t)\Big|_{t_1}^{t_2},..., po_{aop}(t)\Big|_{t_1}^{t_2}\right) \xrightarrow{M\Delta Pu} s(t_2) \tag{2}$$

where: $s(t)$ - the technical state of the system for time $t$.

The first input value of the model is the technical state of the system in moment $t_1$. It results from the Markov characteristic of the technical state [12]. According to it, the state of the system in moment $t_2$ is unequivocally determined by the state in moment $t_1$ and known input values for $t \subset [t_1,t_2]$ and is independent of the system state and input values before $t_1$ moment.

The operating point of the technical object is expressed by the values of the object features. In the case of complex technical systems operating in the industry the values of the part of the measurable features still can be identified only by destructive testing [13]. Therefore, they cannot be identified at given moment in which the operation processes are performed. Simultaneously, because of immeasurable features presence, it is impossible to accurately determine the technical state of the system. Even though, the moment of the object installation in the operation place is treated as initial moment $t_1$, the technical state depends on conditions during the production phase and pre-operation processes execution. In the course of the technical object designing calculations isotropic structure of the material is assumed. In reality this assumption is fulfilled only approximately. For example, as far as metal is concerned, its non-uniform structure causes up to 20% differences in the mechanical characteristics values. Additionally, during the assembling the designing calculations requirements can be violated. What is more, because of the lack of the equipment required to perform non-destructive testing, the majority of the producers of the machinery, devices and constructions do not support the full quality tests at the end of the production phase [14,15]. Usually, the partial tests are executed (about 5%) and on this basis the decision about the correctness of the whole series of the products is made [16]. As a result, the devices of approximately identified technical state are designated to operation. Subsequently, during the pre-operation processes execution the devices are under the influence of forcing factors. This impact depends on the storage conditions and the intensity of the environment influence, which are tested periodically [17]. Therefore, it was stated that the technical state of the system at the start moment of the operation process can be identified only approximately.

Next group of the input data of $M\Delta Pu$ model are the time histories of the parameters describing performed operation processes. Its values, just like those of the system features, can be measurable or immeasurable. And similarly to the system features, the values can be determined only approximately.

Inaccuracy of the working parameters values and the approximation of the technical condition of the system make it impossible to accurately transform the initial state of the system $s(t_1)$ in resultative state $s(t_2)$. Therefore, the designed $M\Delta Pu$ model has to take into consideration the approximate character of the input data.

This type of inaccuracy consists in the lack of the possibility to categorize the given phenomenon as true or false [18]. To model this type of inaccuracy the fuzzy sets theory is widely used [19,20]. The application of fuzzy logic is especially appropriate in the case when the mathematical model describing the phenomenon does not exist, the existing model is strongly nonlinear, the existing model is irresolvable or the calculation time required to obtain the resolution is too long to fulfill the demands about the model response time [21].

Modeling of the operational potential consumption process can be treated as a case when adequate mathematical model does not exist and tries of the model construction face the problems arising from not clear enough process description and approximate character of the input data. In such cases the fuzzy modeling implementation can be found in industrial application [22-25] as well as in theoretical research papers [26-28]. Thus, on the basis of the research conducted by the author and the literature analyze it was decided that the $M\Delta Pu$ model will be constructed by the fuzzy modeling implementation.

The formulated model of the operational potential consumption is the model of the Multi Input Single Output (MISO) type. The calculation process performed by the model consists of three sequential transformations given in Eq. (1) where the last one is executed according to Eq. (3) [5]:

$$\Delta Pu(\Delta t) = \sqrt{\sum_{i=1}^{n}(x_i(t_1) - x_i(t_2))^2} \tag{3}$$

where: $\Delta Pu(\Delta t)$ - the change of the operational potential amount due to the operation process execution in period $\Delta t = [t_1, t_2]$, $x_i(t_1)$ - the value of $i$-th feature for time $t_1$, $x_i(t_2)$ - the value of $i$-th feature for time $t_2$.

Therefore, the task of creation of the fuzzy $M\Delta Pu$ model was decomposed into creation the *ncf* fuzzy models performing transformation Eq. (4), where *ncf* is the amount of the cardinal features of the system.

$$\begin{gathered} M\Delta x_l : (po_1(t)\Big|_{t_1}^{t_2},..., po_{aop}(t)\Big|_{t_1}^{t_2}) \rightarrow \\ (ff_{d1}(t)\Big|_{t_1}^{t_2},..., ff_{dn}(t)\Big|_{t_1}^{t_2}, ff_{id1}(t)\Big|_{t_1}^{t_2},..., ff_{idr}(t)\Big|_{t_1}^{t_2}) \rightarrow \Delta x_l \end{gathered} \tag{4}$$

where: $M\Delta x_l$ - the model of the change of $l$-th cardinal feature value, $po_i(t)\Big|_{t_1}^{t_2}$ - the time history of the $i$-th working parameter in period $[t_1, t_2]$, $ff_d^j$ - $j$-th forcing factor depended on the system operation $j = 1,...,n$, $ff_{id}^k$ - $k$-th forcing factor independent of the system operation $k = 1,...,r$, $\Delta x_l$ - the change of the value of $l$-th cardinal feature of the system $l = 1,...,s$.

The input data of the models are the time histories of the working parameters in period of the operation process execution while the output is the change of the value of the system cardinal feature.

It was decided that the considered models will be constructed and verified using the measurement collections recorded during the conducted operational test, subsequently analyzed and transformed to the form of Eq. (5) according to the method proposed by the author in the papers [29,30].

$$mmc_j(x_l) : [\delta po_1, \delta po_2, ..., \delta po_{nipo}, \Delta x_l] \tag{5}$$

where: $x_l$ - $l$-th cardinal feature of the system, $po_i$ - $i$-th working parameter $i = 1,...,nipo(x_l)$, $nipo(x_l)$ - the number of the important working parameters for feature $x_l$, $mmc_j$ - $j$-th major measurement collection, $\delta po_i$ - the distance between the time history of $i$-th working parameter and its zero time history (ZTH - the time history of the working parameter for which the difference between the initial and final value of the feature is the minimum one), $\Delta x_l$ - the change of the value of $l$-th feature of the system.

## 3. Structure and the Operation of the Model of the Operational Potential Consumption Process

Each of the models of the system feature value change is of MISO type describing the unknown in shape solution space. Major measurement collections expressed in the form presented above Eq. (5) describe the relation between the models output data (change of the feature value) and the models input data (distances between time histories of the significant working parameters and their zero time histories). So, the collections are the inputs-output samples of the considered models. The inputs-output models are constructed employing the fuzzy sets theory. They can use inference of Mamdani type [31], of Takagi-Sugeno-Kang type [32] or be of relational type [33]. In order to solve the issue under consideration the fuzzy models with use of the Mamdani type inference are chosen because thanks to their generalized structure the accurate knowledge about the structure of the modeled object is not required [34]. Moreover, the inference rules of the models are not uniformly distributed along the solution space. Regions where the solution space changes its shape are modeled by a bigger number of the rules than the regions where the space is of fixed shape. Owing to this, in the Mamdani models the amount of the inference rules can be decreased. The structure and the general scheme of the worked out models operation are presented in Fig. 1.

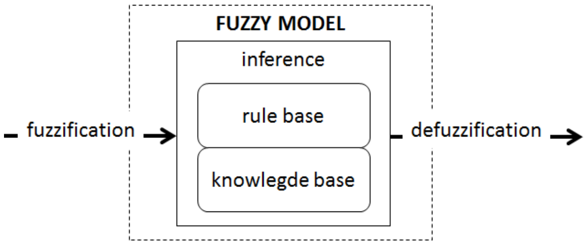


**Fig. 1** The general scheme of the fuzzy model operation

The input data of the models are crisp values of the distance between the working parameters time histories and their zero time histories:

$$\delta po_{FM} = [\delta po_1 \quad \delta po_2 \quad \dots \quad \delta po_{nip}] \tag{6}$$

where: $\delta po_{FM}$ - the input data of the fuzzy model, $\delta po_i$ - the crisp value of $i$-th input parameter, $nip$ - the number of the input parameters of the fuzzy model.

The first step of the fuzzy model operation is the fuzzification process. It is transformation of the crisp values to the fuzzy ones. Fuzzification is accomplished using knowledge base of the model [35]. The knowledge base consists of groups of the fuzzy sets defined for each input and output parameter of the model. These fuzzy sets cover the domain of the parameter in a way presented in Fig. 2.

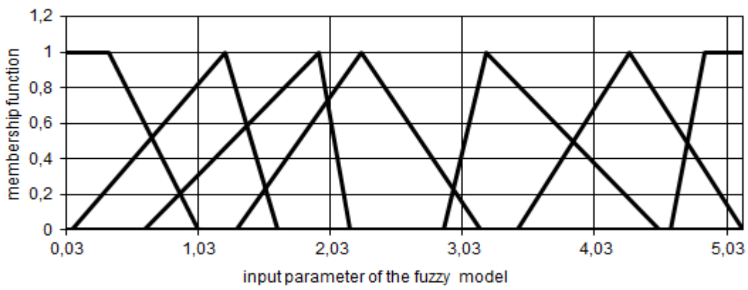


**Fig. 2** The exemplary group of the fuzzy sets for the input parameter of the fuzzy model

The fuzzy sets which cover the domain of the parameter are their linguistic values. First of the sets is of $L$ type, Eq. (7) while the last one is of $\Gamma$ type, Eq. (8). The remaining sets are of $\Lambda$ type, Eq. (9).

$$FS_L(x) = \begin{cases} 1 & \Leftrightarrow x \le rrk \\ \dfrac{rrs - x}{rrs - rrk} & \Leftrightarrow rrk \le x \le rrs \\ 0 & \Leftrightarrow x > rrs \end{cases} \tag{7}$$

where: $FS_L(x)$ - the membership function of the $L$ type fuzzy set, $x$ - the argument of the fuzzy set, $rrk$ - the right range (the maximum value) of the kernel of the fuzzy set, $rrs$ - the right range (the maximum value) of the support of the fuzzy set.

$$FS_\Gamma(x) = \begin{cases} 0 & \Leftrightarrow x \le lrs \\ \dfrac{x - lrs}{lrk - lrs} & \Leftrightarrow lrs \le x \le lrk \\ 1 & \Leftrightarrow x > lrk \end{cases} \tag{8}$$

where: $FS_\Gamma(x)$ - the membership function of the $\Gamma$ type fuzzy set, $x$ - the argument of the fuzzy set, $lrs$ - the left range (the minimum value) of the support of the fuzzy set, $lrk$ - the left range (the minimum value) of the kernel of the fuzzy set.

$$FS_\Lambda(x) = \begin{cases} 0 & \Leftrightarrow x \le lrs \vee x \ge rrs \\ \dfrac{x - lrs}{lrk - lrs} & \Leftrightarrow lrs < x \le lrk \\ \dfrac{rrs - x}{rrs - lrk} & \Leftrightarrow lrk < x < rrs \end{cases} \tag{9}$$

where: $FS_\Lambda(x)$ - the membership function of the $\Lambda$ type fuzzy set, $x$ - the argument of the fuzzy set, $lrk$ - the left range (the minimum value) of the kernel of the fuzzy set, $lrs$ - the left range (the minimum value) of the support of the fuzzy set, $rrs$ - the right range (the maximum value) of the support of the fuzzy set.

During the fuzzification process for each crisp value of the considered input parameter the values of the membership functions of each of its linguistic values are determined:

$$z_i = [\mu_{L^1_{\delta po_i}}(\delta po_i) \quad \mu_{L^2_{\delta po_i}}(\delta po_i) \quad \dots \quad \mu_{L^{nlv}_{\delta po_i}}(\delta po_i)] \tag{10}$$

where: $z_i$ - the fuzzy value of $i$-th input parameter of the model, $\delta po_i$ - the crisp value of $i$-th input parameter of the model, $\mu_{L^j_{\delta po_i}}(\delta po_i)$ - the value of the membership function of $j$-th linguistic value of $i$-th input parameter for $\delta po_i$ value, $L^j_{\delta po_i}$ - $j$-th linguistic value of $i$-th input parameter of the model, $nlv$ - the amount of the linguistic values defined for the parameters of the model.

The second step of the models operation is the fuzzy inference. It is performed using the rule bases of the models. The rule base of each model consists of the inference rules described by Eq. (11), which should be read according to the notation from Eq. (12):

$$FMR_i : \delta po_1 = L^j_{\delta po_1} \wedge \delta po_2 = L^k_{\delta po_2} \wedge ... \wedge \delta po_{\delta po_{nip}} = L^m_{\delta po_{nipo}} \Rightarrow y_i = L^n_{\Delta x_{FM}} \tag{11}$$

where: $FMR_i$ - $i$-th inference rule of the fuzzy model, $\delta po_i$ - the crisp value of $i$-th input parameter of the model, $L^j_{\delta po_i}$ - $j$-th linguistic value of $i$-th input parameter of the model, $y_i$ - the fuzzy output value of $i$-th inference rule, $L^n_{\Delta x_{FM}}$ - $n$-th linguistic value of the output parameter of the model, $\Delta x_{FM}$ - the output parameter of the fuzzy model.

$$\begin{aligned} &FMR_i : z_1(j) > 0 \wedge z_2(k) > 0 \wedge ... \wedge z_{nip}(m) > 0 \Rightarrow \\ &y_i = \begin{cases} 1 \Leftrightarrow i_{out} = n \\ 0 \Leftrightarrow i_{out} \neq n \end{cases} \end{aligned} \tag{12}$$

where: $z_i$ - the fuzzy value of $i$-th input parameter of the model, $i_{out}$ - the number of the linguistic value of the output parameter of the model.

The fuzzy inference consists in the premises aggregation, implication and resulting sets accumulation [36]. For each of the rules present in the rule base of the model the premises aggregation is performed according to the formula:

$$AGR(FMR_i) = \min(z_1(j), z_2(k), ..., z_{nip}(m)) \tag{13}$$

Subsequently, the implication is executed according to formula:

$$y_i(i_{out}) = \min(AGR(FMR_i), y_i(i_{out})) \wedge i_{out} = 1,2,..., nvl \tag{14}$$

where: $FMR_i$ - $i$-th inference rule of the fuzzy model, $AGR(FMR_i)$ - the value after premises aggregation of $i$-th inference rule, $y_i(i_{out})$ - the value of the membership function of the linguistic value on position $i_{out}$ for fuzzy value of the output parameter of $i$-th rule, $nvl$ - the amount of the linguistic values defined for the parameters of the model.

The final step of the fuzzy inference process is the resultant sets accumulation. The step consists in determination of the fuzzy value of the output parameter according to formula:

$$y(i_{out}) = \max(y_1(i_{out}), y_2(i_{out}), ..., y_{nrbr}(i_{out})) \wedge i_{out} = 1,2,..., nvl \tag{15}$$

where: $y(i_{out})$ - the value of the membership function of the linguistic value from position $i_{out}$ for fuzzy value of the output parameter, $y_i(i_{out})$ - the value of the membership function of the linguistic value from position $i_{out}$ for fuzzy value of the output parameter of $i$-th rule, $i_{out}$ - the number of the linguistic value of the output parameter of the model, $nrbr$ - the amount of the rules in the rule base of the model.

Thus, the fuzzy value of the output parameter can be expressed in the following form:

$$y = [y_{L^1_{\Delta xl}} \quad y_{L^2_{\Delta xl}} \quad ... \quad y_{L^{nvl}_{\Delta x_{FM}}}] \tag{16}$$

where: $y$ - the fuzzy value of the output parameter of the model, $y_{L^i_{\Delta xl}}$ - the maximum value of the membership function of $i$-th linguistic value of the output parameter, $L^i_{\Delta x_{FM}}$ - $i$-th linguistic value of the output parameter, $nvl$ - the amount of the linguistic values defined for the parameters of the model.

The expression above should be interpreted as a fuzzy set with support equal to the output parameter domain. The value of the membership function of this set ought to be calculated according to the formula:

$$\begin{aligned}\mu(\Delta x_{FM}) = \max(&\min(\mu_{L^1_{\Delta x_{FM}}}, y_{L^1_{\Delta x_{FM}}}),\\ &\min(\mu_{L^2_{\Delta x_{FM}}}, y_{L^2_{\Delta x_{FM}}}),\\ &\ldots\\ &\min(\mu_{L^{nvl}_{\Delta x_{FM}}}, y_{L^{nvl}_{\Delta x_{FM}}}))\end{aligned} \tag{17}$$

where: $\mu(\Delta x_{FM})$ - the membership function of the output parameter, , $\Delta x_{FM}$ - the output parameter of the fuzzy model, $y_{L^i_{\Delta x_{FM}}}$ - the maximum value of the membership function of *i*-th linguistic value of the output parameter, $\mu_{L^i_{\Delta x_{FM}}}$ - the value of the membership function of *i*-th linguistic value of the output parameter, $L^i_{\Delta x_{FM}}$ - *i*-th linguistic value of the output parameter, *nvl* - the amount of the linguistic values defined for the parameters of the model.

The output of the fuzzy model is the crisp value of the output parameter. It is calculated in the defuzzification process. In the process the fuzzy value of the output parameter determined in the inference process is defuzzified by the centre of gravity defuzzification operator application:

$$\Delta x_{FM} = COG(\mu(\Delta x_{FM})) = \frac{\int_{\Delta x_{FM\_min}}^{\Delta x_{FM\_max}} \Delta x_{FM}\,\mu(\Delta x_{FM})\,d\Delta x_{FM}}{\int_{\Delta x_{FM\_min}}^{\Delta x_{FM\_max}} \Delta x_{FM}\,(\Delta x_{FM})\,d\Delta x_{FM}} \tag{18}$$

where: $\Delta x_{FM}$ - the output parameter of the fuzzy model, *COG* - the centre of gravity defuzzification operator, $\mu(\Delta x_{FM})$ - the membership function of the output parameter, $\Delta x_{FM\_min}$ - the minimum value of the output parameter domain, $\Delta x_{FM\_max}$ - the maximum value of the output parameter domain.

## 4. THE PERFORMED INDUSTRIAL RESEARCH

In the described studies it was decided to construct the considered fuzzy model using learning data registered during the industrial research. There are two main groups of the learning techniques which can be used to solve this issue. First of them is the connection of artificial neural networks and fuzzy systems which is widely applied decision-making and data classification problems [37-39]. The second one is connection of genetic algorithms and fuzzy logic which is implemented in automatic fuzzy model generation and data classification problems solutions [40,41].

The task of creating models as described by Eq. (4) was solved using the automatic iterative method of the Mamdani fuzzy model generation [42]. The applied method generates the models using the sample data in input/output form. Exactly, the sample data were prepared in the form depicted by Eq. (5). In order to collect the data the operational tests were carried out on the biggest Polish hard coal fired power plant in Kozienice. The production system of the plant includes 8 - 200MW power units, 2 - 500MW power units and 1 - 1000MW power unit [43]. The tests were limited to 8 - 200MW production units. Main parts of the units were OP-650k-040 pulverized coal fired boilers [44] and 13K215 steam turbosets. The performed operational tests lasted fifteen months and consisted in collecting the working parameters of the units. After the preliminary analysis of the data correctness 23 parameters were selected for further considerations (Table 1). As a result of the collecting process 5440008 values for each parameter were obtained.

The technical state of the OP-650k-040 boiler is described by the values of the system features. These features also describe the quality of the whole system operation. Therefore, to identify the cardinal features of specified element of the system the TKE method was taken into consideration. TKE is a common analysis method of an operation quality of power units' devices. As a result of the completed analysis deviations *q3* (the deviation of the heat consumption caused by the temperature of the reheated steam [kJ/kWh]), *q4* (the deviation of the heat consumption caused by the pressure in the secondary reheater of the reheated steam [kJ/kWh]), *q5* (the deviation of the heat consumption caused by the water injections to the reheated steam [kJ/kWh]) and *q8* (the deviation of the heat consumption caused by the reduced efficiency of the boiler [kJ/kWh]) were chosen as cardinal features determining the technical state of the boiler [1]. On the basis of the measurements sets collected during the operational tests, the momentary values of the deviations were calculated. Applying the polynomial approximation the time functions of each deviation were formulated.

**Table 1** The set of the selected working parameters of the research object (*RAP* - rotary air preheater, *HP* - high pressure, *MP* - medium pressure)

| No | Value | Medium | Side | Unit | Symb. |
|---|---|---|---|---|---|
| 1. | Temperature | Main steam | left | °C | t0l |
| 2. | Temperature | Main steam | right | °C | t0p |
| 3. | Pressure | Main steam | both | MPa | p0 |
| 4. | Pressure | Outgoing steam of *HP* turbine | both | MPa | psahp |
| 5. | Temperature | Outgoing steam of *HP* turbine | left | °C | tahpl |
| 6. | Temperature | Outgoing steam of *HP* turbine | right | °C | tahpr |
| 7. | Temperature | Reheated steam | left | °C | tssl |
| 8. | Temperature | Reheated steam | right | °C | tssr |
| 9. | Pressure | Incoming steam of *MP* turbine | both | MPa | tsbmp |
| 10. | Temperature | Feed water | both | °C | tfw |
| 11. | Temperature | Flue gasses | 1 | °C | teg1 |
| 12. | Temperature | Flue gasses | 2 | °C | teg2 |
| 13. | Contents | $O_2$ in flue gasses before *RAP* | 1 | % | o2bp1 |
| 14. | Contents | $O_2$ in flue gasses before *RAP* | 2 | % | o2bp2 |
| 15. | Contents | $O_2$ in flue gasses after *RAP* | 1 | % | o2ap1 |
| 16. | Contents | $O_2$ in flue gasses after *RAP* | 2 | % | o2ap2 |
| 17. | Amount | Injected water | left | t/h | wsil |
| 18. | Amount | Injected water | right | t/h | wsir |
| 19. | Amount | Burned mazut | both | t/h | ma |
| 20. | Amount | Burned coal | both | t/h | ca |
| 21. | Amount | Active load | both | MW | P |
| 22. | Amount | Main steam | left | t/h | m0l |
| 23. | Amount | Main steam | left | t/h | m0r |

Using the calculated values of the boiler's cardinal features as well as recorded measurements sets 874 intervals of equal time length (24 hours) were obtained for each distinguished deviation. The measurement collection was formulated for each interval. The collection consisted of the time histories of 23 working parameters in range from the start to the end time of the interval and the difference between the values of the specified deviation for the start and the end time of interval.

Among the formulated measurement collections for each deviation one measurement collection was selected. It was the collection corresponding to the smallest change of the deviation value. On this basis, according to the method presented in literature [29] the measurement collections were transformed into the form described by expression Eq. (5) but comprising all 23 parameters.

Subsequently, according to the method proposed by the author [30], the most significant working parameters in term of the operational potential change have been selected. For deviation *q3* parameters 3, 12 and 17 have been selected and so have, for deviation *q4*, parameters 1, 13, 14 and 15; for deviation *q5* parameters 8 and 10 are selected and so are, for deviation q8, parameters 17 and 18. The numbers are used according to Table 1.

Thus, as a result of the performed studies, for each of 4 models of the cardinal feature change as a function of the most significant working parameters time histories, 874 major measurement collections in form described by Eq. (5) were obtained.

## 5. The Identification of the Parameters of the Operational Potential Consumption Process Model

In order to generate the models of the working parameters time histories impact on the system features values, for each deviation the learning and testing data sets were prepared. Each of the sets consisted of the major measurement collections which included input and output data of the model. The form of the learning and testing data for each deviation is presented in tables (Table 2 - Table 5).

**Table 2** The structure of the major measurement collections for *q3* deviation (Names of the fields according to the symbols from Table 1)

| No. | Field name | Symbol | Unit |
|---|---|---|---|
| 1. | The distance from ZTH - p0 | p0db | MPa |
| 2. | The distance from ZTH - teg2 | teg2db | °C |
| 3. | The distance from ZTH – wsil | wsildb | t/h |
| 4. | The change of the deviation value - object | dq3r | kJ/kWh |
| 5. | The change of the deviation value - model | dq3e | kJ/kWh |

**Table 3** The structure of the major measurement collections for *q4* deviation (Names of the fields according to the symbols from table 1)

| No. | Field name | Symbol | Unit |
|---|---|---|---|
| 1. | The distance from ZTH - t0l | t0ldb | °C |
| 2. | The distance from ZTH - o2bpl | o2bp1db | % |
| 3. | The distance from ZTH - o2bp2 | o2bp2db | % |
| 4. | The distance from ZTH - o2apl | o2ap1db | % |
| 5. | The change of the deviation value - object | dq4r | kJ/kWh |
| 6. | The change of the deviation value - model | dq4e | kJ/kWh |

**Table 4** The structure of the major measurement collections for *q5* deviation (Names of the fields according to the symbols from Table 1)

| No. | Field name | Symbol | Unit |
|---|---|---|---|
| 1. | The distance from ZTH – tssr | tssrdb | °C |
| 2. | The distance from ZTH – tfw | tfwdb | °C |
| 3. | The change of the deviation value - object | dq5r | kJ/kWh |
| 4. | The change of the deviation value - model | dq5e | kJ/kWh |

**Table 5** The structure of the major measurement collections for q8 deviation (Names of the fields according to the symbols from Table 1)

| No. | Field name | Symbol | Unit |
|---|---|---|---|
| 1. | The distance from ZTH – wsil | wsildb | t/h |
| 2. | The distance from ZTH – wsir | wsirdb | t/h |
| 3. | The change of the deviation value - object | dq8r | kJ/kWh |
| 4. | The change of the deviation value - model | dq8e | kJ/kWh |

**Table 6** The values of the parameters of the fuzzy model generation process

| No. | Parameter | Value |
|---|---|---|
| 1. | Coverage degree of the measurement collection | 1.0 |
| 2. | Compatibility limit of measurement collection and inference rule - $\omega_z$ | 0.05 |
| 3. | Incompatibility limit of inference rule and learning data set - $k_{icFMR}$ | 0.1 |
| 4. | Threshold value of the compatibility degree - $\tau_{sFM}$ | 0.25 |
| 5. | T-norm used in generation process | MIN |
| 6. | Amount of the genetic algorithm generations in one iteration | 50 |
| 7. | Amount of useless mutations of evolution strategy until the process stop | 25 |
| 8. | Amount of the chromosomes exposed to the evolution strategy | 20% |
| 9. | The parameter of the σ value mutation used in evolution strategy | 0.9 |
| 10. | Amount of generations of simplification step | 500 |
| 11. | Amount of generations of tuning step | 1000 |
| 12. | Population size of simplification step | 61 |
| 13. | Population size of tuning step | 61 |
| 14. | Parameter of non-uniform mutation | 5 |
| 15. | Crossover probability of generation process | 0.6 |
| 16. | Crossover probability of simplification process | 0.6 |
| 17. | Crossover probability of tuning process | 0.6 |
| 18. | Mutation probability of generation process | 0.004 |
| 19. | Mutation probability of simplification process | 0.003 |
| 20. | Mutation probability of tuning process | 0.005 |
| 21. | Coefficient of arithmetic MIN-MAX crossover operator - $\lambda_q$ | 0.35 |
| 22. | Aggregation operator of the fuzzy model | MIN |
| 23. | Implication operator of the fuzzy model | MIN |
| 24. | Accumulation operator of the fuzzy model | MAX |
| 25. | Defuzzification operator of the fuzzy model | COG |

The learning data set comprised 582 measurement collections (first two-thirds of all measurement collections) while the testing data set comprised remaining 292 measurement collections. Subsequently, on the basis of learning data set the automatic generation of the model was performed. The generation procedure consisted of preliminary generation, simplification and tuning steps. The adopted values of the model generation process can be found in Table 6.

As a result of the calculations four models of the working parameters time histories influence on the values of the system features were obtained. Each of the model in the aggregation process used *MIN* operator, in implication process *MIN-MAX* operator, in accumulation process *MAX* operator and in defuzzification process *COG* operator, Eq. (18). The rule bases of the obtained models included the groups of fuzzy sets defined for each input and output parameter of the model. Below, as an example, the group of fuzzy sets defined for *p0db* - the first input parameter of the model for *q3* deviation is presented (Fig. 3), Eqs. (19-25).

The model obtained for *q3* deviation consisted of 63 inference rules, the model obtained for *q4* deviation consisted of 82 inference rules, the model obtained for *q5* deviation consisted of 20 inference rules and the model obtained for *q8* deviation consisted of 40 inference rules. The exemplary form of the obtained inference rule is presented below Eq. (26). In all expressions describing the rule and knowledge bases of the fuzzy models the symbols were used in accordance with tables (Table 2 - Table 5). The linguistic variables of input and output parameters of the models are marked by subscript meaning the parameter and superscript meaning the number of the linguistic variable.

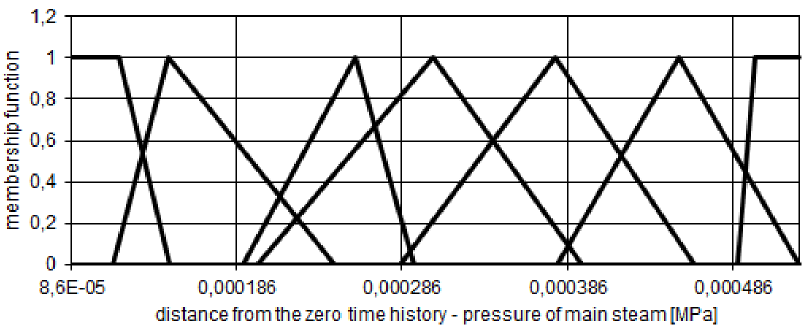


**Fig. 3** The group of the fuzzy sets of first input parameter *p0db* of the model for *q3* deviation

$$L^{1}_{p0db} = \begin{cases} 1 & \Leftrightarrow \text{p0db} \le 0{,}000115 \\ \dfrac{0{,}000146 - p0db}{0{,}000031} & \Leftrightarrow 0{,}000115 < \text{p0db} \le 0{,}000146 \\ 0 & \Leftrightarrow \text{p0db} > 0{,}000146 \end{cases} \tag{19}$$

$$L^{2}_{p0db} = \begin{cases} 0 & \Leftrightarrow \text{p0db} \le 0{,}000111 \vee \text{p0db} \ge 0{,}000245 \\ \dfrac{p0db - 0{,}000111}{0{,}000034} & \Leftrightarrow 0{,}000111 < \text{p0db} \le 0{,}000145 \\ \dfrac{0{,}000245 - p0db}{0{,}0001} & \Leftrightarrow 0{,}000145 < \text{p0db} < 0{,}000245 \end{cases} \tag{20}$$

$$L^{3}_{p0db}=\begin{cases}0 & \Leftrightarrow \text{p0db} \le 0{,}00019 \vee \text{p0db} \ge 0{,}000293\\ \dfrac{p0db-0{,}00019}{0{,}000068} & \Leftrightarrow 0{,}00019 < \text{p0db} \le 0{,}000258\\ \dfrac{0{,}000293-p0db}{0{,}000035} & \Leftrightarrow 0{,}000258 < \text{p0db} < 0{,}000293\end{cases} \tag{21}$$

$$L^{4}_{p0db}=\begin{cases}0 & \Leftrightarrow \text{p0db} \le 0{,}000198 \vee \text{p0db} \ge 0{,}000395\\ \dfrac{p0db-0{,}000198}{0{,}000107} & \Leftrightarrow 0{,}000198 < \text{p0db} \le 0{,}000305\\ \dfrac{0{,}000395-p0db}{0{,}00009} & \Leftrightarrow 0{,}000305 < \text{p0db} < 0{,}000395\end{cases} \tag{22}$$

$$L^{5}_{p0db}=\begin{cases}0 & \Leftrightarrow \text{p0db} \le 0{,}000285 \vee \text{p0db} \ge 0{,}000463\\ \dfrac{p0db-0{,}000258}{0{,}000094} & \Leftrightarrow 0{,}000285 < \text{p0db} \le 0{,}000379\\ \dfrac{0{,}000463-p0db}{0{,}000084} & \Leftrightarrow 0{,}000379 < \text{p0db} < 0{,}000463\end{cases} \tag{23}$$

$$L^{6}_{p0db}=\begin{cases}0 & \Leftrightarrow \text{p0db} \le 0{,}00038 \vee \text{p0db} \ge 0{,}000527\\ \dfrac{p0db-0{,}00038}{0{,}000074} & \Leftrightarrow 0{,}00038 < \text{p0db} \le 0{,}000454\\ \dfrac{0{,}000527-p0db}{0{,}000073} & \Leftrightarrow 0{,}000454 < \text{p0db} < 0{,}000527\end{cases} \tag{24}$$

$$L^{7}_{p0db}=\begin{cases}0 & \Leftrightarrow \text{p0db} \le 0{,}000489\\ \dfrac{p0db-0{,}000489}{0{,}000011} & \Leftrightarrow 0{,}000489 < \text{p0db} \le 0{,}0005\\ 1 & \Leftrightarrow \text{p0db} > 0{,}0005\end{cases} \tag{25}$$

$$p0db=L^{1}_{p0db} \wedge teg2db=L^{1}_{teg2db} \wedge wsildb=L^{1}_{wsildb} => dq3e=L^{1}_{dq3e} \tag{26}$$

## 6. THE ANALYSIS OF THE MODEL ACCURACY AND THE RESULTS OF SIMULATION EXPERIMENTS

Finally, the verification of the generated fuzzy models was performed. To do it, for each model the following measures of the operation quality were determined: the relative minimum error, Eq. (27), the relative maximum error, Eq. (28), the relative mean error, Eq. (29), the relative mean square error, Eq. (30), and the value of the correlation function, Eq. (31). The values of the measures were determined taking into consideration the values calculated using the real collected data and the values calculated by the models for testing data set.

$$\Delta dq_{\min}[\%] = \frac{\min(\left|dq_e(mmc_i) - dq_r(mmc_i)\right|)}{\max(dq_r(mmc_i)) - \min(dq_r(mmc_i))} \cdot 100 \wedge i = 1,2,..., ammc \tag{27}$$

where: $\Delta dq_{min}$ - the relative minimum error [%], $dq_r(mmc_i)$ - the value of the output parameter of the model for *i*-th major measurement collection, $dq_e(mmc_i)$ - the value of the output parameter of the object for *i*-th major measurement collection, $mmc_i$ - *i*-th major measurement collection, *ammc* - the amount of major measurement collections.

$$\Delta dq_{\max}[\%] = \frac{\max(\left|dq_e(mmc_i) - dq_r(mmc_i)\right|)}{\max(dq_r(mmc_i)) - \min(dq_r(mmc_i))} \cdot 100 \wedge i = 1,2,..., ammc \tag{28}$$

where: $\Delta dq_{max}$ - the relative maximum error [%].

$$\Delta dq_{mean}[\%] = \frac{\frac{1}{ammc} \cdot \sum_{i=1}^{ammc} \left|dq_e(mmc_i) - dq_r(mmc_i)\right|}{\max(dq_r(mmc_i)) - \min(dq_r(mmc_i))} \cdot 100 \wedge i = 1,2,..., ammc \tag{29}$$

where: $\Delta dq_{mean}$ - the relative mean error [%].

$$\Delta dq^2_{mean}[\%] = \frac{\sqrt{\frac{\sum_{i=1}^{ammc} (dq_e(rmv_i) - dq_r(rmv_i))^2}{ammc \cdot (ammc + 1)}}}{\max(dq_r(mmc_i)) - \min(dq_r(mmc_i))} \cdot 100 \wedge i = 1,2,..., mmc \tag{30}$$

where: $\Delta dq^2_{mean}$ - the relative mean square error [%].

$$corr(dq) = \frac{\left(\sum_{i=1}^{ammc} dq_e(mmc_i) \cdot dq_r(mmc_i)\right)^2}{\sum_{i=1}^{ammc} dq_r(mmc_i) \cdot dq_r(mmc_i) \cdot \sum_{i=1}^{ammc} dq_e(mmc_i) \cdot dq_e(mmc_i)} \cdot 100 \tag{31}$$

where: $corr(y)$ - the value of the correlation function [%].

The values of the operation quality measures of each model are presented in Table 7.

**Table 7** The values of the operation quality measures of the models

| Measure of the operation quality | model - deviation q3 | model - deviation q4 | model - deviation q5 | model – deviation q8 |
|---|---|---|---|---|
| Relative minimum error [%] | 0.2498 | 1.2772 | 1.2606 | 1.3084 |
| Relative maximum error [%] | 155.3265 | 92.9864 | 92.0827 | 84.574 |
| Relative mean error [%] | 13.8125 | 5.129 | 9.4532 | 11.4643 |
| Relative mean square error [%] | 1.1368 | 0.6205 | 0.8314 | 0.9089 |
| Correlation function value [%] | 63.2596 | 60.7267 | 60.7023 | 82.1394 |

Analyzing the calculated values of the operation quality measures of the models of the working parameters time histories influence on the values of the system features it was decided that the proposed method of the models generation is efficient enough to apply it to the conducted research. It was also stated that the loss of the amount of the operational potential would be calculated as a length of the vector given by Eq. (3) and the estimated changes of the deviations values would be the vector components.

In order to verify the adequacy of the constructed model of the operational potential consumption process in case of the real complex technical system the simulation experiments were carried out. The experiments covered 14 days period of OP-650k-040 steam boiler operation. The calculations were performed for 25 selected initial states spread uniformly in the range of the disposed amount of the operational potential calculated for all initial states.

The time histories of the most significant working parameters for the considered 14 days period and the initial values of the deviations determined on the basis of the data recorded during the operational tests were used as input values of the models of the working parameters time histories influence on the values of the system features. As a result of the models operation the estimated values of the deviations for the end of the simulated operation period were obtained. Having determined real initial values of the deviations and estimated final values of them the estimated change of the disposed amount of the operational potential was calculated according to expression Eq. (3). Similarly, using real initial and real final values of the deviations (obtained as a result of the operational tests) the real change of the disposed amount of the operational potential was calculated.

In Table 8 for each one of the 25 initial states considered during the simulation experiments the initial values of the deviations, the initial value of the disposed amount of the operational potential and real and estimated final values of the disposed amount of the operational potential can be found. Additionally, in the table the values of the relative error of the model operation calculated according to formula Eq. (32) are presented.

$$Err_{rel}(M\Delta Pu) = \frac{\left|\Delta Pu_{est} - \Delta Pu_{real}\right|}{\Delta Pu_{real}} \cdot 100\% \tag{32}$$

where: $Err_{rel}(M\Delta Pu)$ - the relative error of the operation of the $M\Delta Pu$ model [%], $\Delta Pu_{est}$ - the change of the operational potential amount estimated by the model, $\Delta Pu_{real}$ - the real change of the operational potential amount.

Analyzing results of the model operation in case of 25 selected periods of the OP-650k-040 steam boiler operation it was stated that the accuracy of the estimation of the operational potential consumption process by the generated model is very high (up to 99%).

Thus, it was proved that the presented model can be successfully used to estimate the loss of the operational potential in the case of complex technical systems. Therefore, it is planned to apply the proposed solution to the control of the complex technical systems operation in order to decrease the loss of not exploited operational potential and avoid the failure of the system.

**Table 8** Results of the *M∆Pu* model operation ($\delta P$ - disposed amount of the operational potential [kJ/kWh])

| No. | Initial values of the deviations [kJ/kWh] [q3;q4;q5;q8] | Initial $\delta P$ | Final $\delta P$ - estimated value | Final $\delta P$ - real value | Relative error [%] |
|---|---|---|---|---|---|
| 1. | [-19.3074;-5.8577;-8.5227;-405.9765] | 638.8881 | 128.118 | 120.1735 | 6.61 |
| 2. | [-39.0666;4.4073;56.2565;-263.0552] | 490.3015 | 137.7455 | 138.8941 | 0.83 |
| 3. | [-27.5759;8.9035;59.6207;-223.0393] | 449.131 | 103.6373 | 99.0042 | 4.68 |
| 4. | [-36.0886;8.9555;57.9187;-156.9477] | 384.6197 | 111.7565 | 111.1584 | 0.54 |
| 5. | [-17.9859;4.1348;27.6282;-103.3115] | 335.065 | 115.4199 | 115.7112 | 0.25 |
| 6. | [-13.8601;1.3529;42.9267;-90.7771] | 319.9943 | 115.3871 | 114.5998 | 0.69 |
| 7. | [-9.9071;1.5013;44.2801;-79.7246] | 308.6944 | 118.2544 | 116.392 | 1.60 |
| 8. | [-30.7651;11.8714;70.5773;-64.6891] | 291.6223 | 116.3791 | 114.7306 | 1.44 |
| 9. | [-22.9398;-21.7261;36.5607;-18.2813] | 255.517 | 114.4198 | 113.0098 | 1.25 |
| 10. | [-10.7811;-19.3661;36.2806;17.0488] | 220.7192 | 113.5734 | 115.2506 | 1.46 |
| 11. | [-24.7443;-16.0588;62.7121;39.1986] | 195.0298 | 112.5225 | 112.5837 | 0.05 |
| 12. | [-23.6838;-15.0915;63.2691;48.5913] | 185.6962 | 113.0006 | 112.6729 | 0.29 |
| 13. | [-15.2574;25.7487;75.0135;70.5717] | 155.21 | 112.9432 | 112.3101 | 0.56 |
| 14. | [-10.5887;21.7895;42.7999;78.6968] | 154.5821 | 112.3773 | 111.9687 | 0.36 |
| 15. | [-9.8674;24.6442;44.6542;94.1526] | 139.3418 | 99.1767 | 98.7857 | 0.40 |
| 16. | [-9.5275;25.5339;45.6591;101.7391] | 131.903 | 94.7355 | 95.0247 | 0.30 |
| 17. | [-9.2861;25.9666;46.4051;106.8706] | 126.8706 | 87.563 | 87.0652 | 0.57 |
| 18. | [-18.5995;9.2839;46.0432;118.2013] | 120.3831 | 76.1608 | 75.7769 | 0.51 |
| 19. | [-7.7767;26.9908;50.5532;124.9305] | 108.5901 | 76.0057 | 76.0297 | 0.03 |
| 20. | [-28.3647;19.5421;74.9466;130.5547] | 101.4431 | 72.5974 | 72.6728 | 0.10 |
| 21. | [-1.2134;9.3858;70.4222;138.4202 | 91.0723 | 70.2585 | 70.1301 | 0.18 |
| 22. | [-15.15119.2709;67.0263;151.5864] | 82.7258 | 56.9301 | 56.825 | 0.19 |
| 23. | [-0.5087;10.4719;74.4923;157.4561] | 72.1249 | 53.7195 | 53.81 | 0.17 |
| 24. | [-0.3174;10.7947;75.6293;162.7304] | 66.9231 | 50.0816 | 50.0096 | 0.14 |
| 25. | [-0.04222;11.2884;77.2998;170.4669] | 59.3524 | 44.0658 | 43.9252 | 0.32 |

## 7. Summary and Conclusions

In the paper the studies in the field of the complex industrial technical systems operation and maintenance were presented. As a result of the studies the model of the operation process of the power boiler was prepared. Below some conclusions and highlights from the research can be found:

1. The prepared model of the operational potential consumption process should be designed to take into consideration inaccuracy of the working parameters values and approximated knowledge of the technical condition of the considered object,
2. The modeling of the operational potential consumption process is the issue when the adequate mathematical model does not exists and attempts of the development the model come across the problems arising from not enough clearly defined description of the process and the approximate character of the input data,
3. The fuzzy modeling was used to develop the system model M∆Pu of changes of the operational potential included in a technical object,

4. The task of the fuzzy MΔPu model creation was decomposed into creation of ncf fuzzy models of the influence of the working parameters time histories on the changes of the values of the system features, where ncf is the amount of the cardinal features of the system,
5. The set of the working parameters can be very large; thus the set of the parameters of the highest influence on the change of the specified feature value should be defined,
6. During the operational tests of the OP-650k-040 steam boiler the list of the most significant parameters in term of the operational potential changes was specified,
7. The fuzzy models of the influence of the working parameters time histories on the values of the features of the considered boiler were generated using the inputs-output samples according to the iterative method of the automatic generation of the Mamdani models,
8. The quality of the models operation was verified using the set of the major measurement collections recorded during the conducted operational tests,
9. Analyzing the values of the measures of the models operation quality it was decided that the iterative method of the models generation is efficient enough to implement it into the conducted research,
10. Considering the results of the simulation experiments performed it should be stressed that thanks to the implementation of the developed MΔPu model in the case of the selected technical system very high accuracy (mean error about 1%) of the process estimation was obtained.

The major benefit that accrues from the described method application to the complex technical system is the development of a very accurate model of the operational potential consumption process (mean efficiency about 99%) according to the universal manner. Its novelty consists in the universal system approach which can be used in the case of a wide range of the technical systems. Prior to the application of the proposed method the operation parameters time histories should be registered. Additionally, all cardinal features should be identified and their values at the beginning and the end of the operation parameters collecting period have to be accessible for measurement. These two elements are the main limitations of the described solution.

The research on the problems of complex technical system operation and maintenance control will be continued. The first direction of future studies will cover the verification of the proposed method in the case of different technical systems. It is planned to construct the model of the operational potential consumption process for systems where the number of the cardinal features is significantly higher than four and to check the method usefulness in the case of the systems with a limited number of cardinal features (less than 4).

The second issue is the application of the created model to control the complex technical systems operation in order to decrease the loss of not exploited operational potential and avoid the failure of the system. It is supposed to be achieved by using the model described in the paper and the reverse model of the operational potential consumption process.

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