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IMPROVING THE OPERATIONAL RELIABILITY MODEL OF THE "NIKOLA TESLA - BLOCK A" THERMAL POWER PLANT SYSTEM BY APPLYING AN INTEGRATED MAINTENANCE MODEL

Summary

The evaluation of the reliability status of complex technical systems is of great importance for their uninterrupted operation at full capacity and with a preventive maintenance plan in place. Limited research on the subject indicates that there is need to improve models of reliability simulation. The goal of the paper is to outline an improved operational reliability model of a thermal power plant using the power plant block "TENT A" as an example. The model is based on the failure interaction of the system components and is based on probability theory - the Weibull distribution, the Monte Carlo simulation and the established mathematical models of failure interaction of components using new software solutions.

The results of the simulations show which direction the development of preventive activities should take in the case of failure interaction, which might lead to minimum downtime in power plant operations in the future.

Key words: *failure interaction, Monte Carlo simulation, power plant system, reliability, Weibull distribution, software*

1. Introduction

To date, there is limited research on the evaluation of the reliability status of technical systems in which preventive maintenance is of paramount importance and the number of failures is small, and thus it is difficult to offer valid evaluations of reliability. What is even more difficult to find is the application of these models to thermal power plants where the principal focus is on evaluation by means of technical diagnostics. When we take into account the increasing demand for energy and that fossil fuel reserves are rapidly disappearing, [1] it is even more necessary to raise the reliability of existing power plants to an even higher level. The goal of this paper is to offer concrete possibilities of modelling reliability of a block in a thermal power plant based on the failure interaction of the system components. Relying on the empirical research of the "Nikola Tesla Block A" (TENT A) thermal power plant, the biggest thermal power plant in Serbia, carried out from 1990 to 2017, and the existing database on the operating conditions of the system at that time, it was possible to isolate the components of the system into blocks, and divide each block into 10 sub-components. The database includes records of operating statuses of the system which have been classified and numbered in the following way: a pipe system with feed pipes – 04, steam boiler - 05, turbine - 06, generator - 07, electrical protection - 08, firing - 09, delivery of coal - 10, delivery of fuel oil - 11, remaining devices – 12, power failure - 13 (Figure 1).

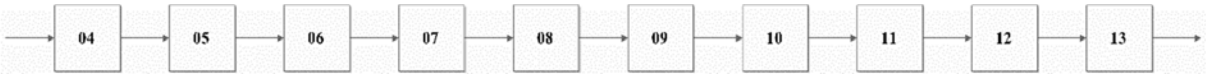

Fig. 1 A block diagram of the reliability of TENT A power plant block

The database contains more than 2,000 operational statuses of the thermal power plant blocks. Since the databases are extensive, Table 1 presents only a portion of the failures occurred in "Block A" based on the classification of changes in the operational status.

Table 1 Number of component failures based on the classification of operating statuses of the system from database

Component	04	05	06	07	08	09	10	11	12	13
Number of failures (Block A)	231	197	135	60	60	2	5	8	41	13
Overall operating time	6,024,904 min.									
Average annual operating time	307,866 min (5,131 hours)									

Even though the components of the system do not react directly, there is failure interaction in the components in the sense of changes in the reliability of one component after another component has failed. These changes occur for a number of reasons, such as each failure being able to reduce component life, or the maintenance crew increasing the level of reliability of the components which have not failed during the failure. The component whose failure initiates changes in the reliability of another component is known as the *affecting component*. The component whose reliability changes under the influence of the *affecting component* is referred to as the *affected component*.

The improved reliability model must be able to predict varying values which might *effectively and more simply* express the influence of the affecting component on the affected one, as well as all the individual cases of failure interaction. Three possible scenarios are included in the improved model of failure interaction of the components:

– the failure of the affecting component decreases the level of reliability of the affected component,
– the failure of the affecting component increases the level of reliability of the affected component,
– the failure of the affecting component does not alter the level of reliability of the affected component.

From the aforementioned, we can conclude that system component failure can be monitored if it is temporary and gradual [2]. In order for a model to represent such exceptionally complex systems, artificial neural networks (ANN) can also be used to replace mathematical approximations [3]. However, a shortcoming of these models is the slow learning process, and so with the occurrence of new, already insufficient data on failures, we now need a new, long-term learning process, i.e. training artificial neural networks. By relying on the experiences of Webber and Jouffe [4], Moazzami et al. [5] as well as papers

[6-8] with modelling reliability, we opted for a model which will hereinafter be presented as an improvement to the Environmental And Social System Assessment (ESSA) model, which had previously been outlined in other papers [9, 10].

2. The improved model of system component interaction

The model which takes component interaction into consideration is based on a combined influence of components, which means that the failure of one component influences another component by altering the level of reliability and hazard by *aging the component* for a certain time interval.

The assumptions behind this model are:

- the system operates continuously without interruption,
- the system is maintained in a combined manner, that is, in a corrective manner following the failure of the system for the given component, and preventively during an overhaul,
- each component of the system is replaced or fixed after failure, so that it again functions at the level of the highest reliability (100%),
- the system is overhauled annually – a large periodic overhaul, after which it is in a state of the highest reliability (100%),
- the model begins with the assumption that all of the components of the system could interact, which enables the prediction of certain interactions.

A model with interactive system component failure will be presented in the following steps.

2.1 Deriving failure time and operational time from the database

For each component of the system it is necessary to determine the duration of its failure and the duration of its operational time. The time interval without failure should be separated based on the number of failure interactions of each of the remaining components so as to determine the influence of each one. For each failure-free interval, the affected components should be separated from the affecting components.

2.2 Square regression analysis of the mean time to failure (MTTF) for the affected component depending on the number of failure interactions of the affecting component

Each component should be considered to be a potentially affecting component compared to other system components, and it should be determined whether there is any interaction between the components.

The analysis of the mean time to failure of an affected component for various numbers of failure interactions of a potentially affecting component clearly indicates the existence and nature of the interaction between the components included in the analysis. The result is a square equation which can be used for trending. The validity criterion of the regression analysis is the coefficient of determination (R^2). The number of combinations to be analyzed depends on the decomposition of the system, and every component needs to be considered to be a potentially affecting component in relation to all other components of the system. Therefore, it is necessary to create a software solution which will automatically resolve this problem (Fig. 4, Fig. 6). An example of the influence of a failure of an affecting component on the mean time to failure is graphically depicted in Fig. 2.

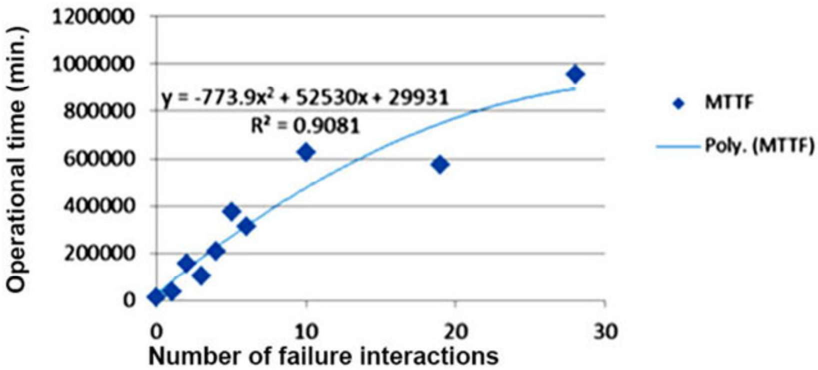

Fig. 2 Influence of the number of failure interactions of affecting component (K2) on the mean time to failure of affected component (K1) and the squared regression equation

The equation is the following:

$$y = ax^2 + bx + c, \; x \geq 0, y \geq 0, x \in \mathrm{N}_0 \tag{1}$$

where:

- y is the dependent variable (mean time to failure of the affected component),
- x is the independent variable (number of failure interactions of the affecting component).

The polynomial coefficients *a* and *b* enable us to identify the influence of maintenance and interaction of components, if it exists.

2.3 Selection of cases in which there is failure interaction of the components

Following a regression analysis, it was determined in which of the individual cases there was failure interaction based on the number of degrees of freedom and values of the determinant coefficient. Since the number of degrees of freedom equals $n - 2$, where n is the number of MTTF points for a certain number of failure interactions. The minimum accepted value was the degree of freedom 4 (6 points). A smaller number of points represents a linear dependence or inability of drawing conclusions on the dependence. The elimination leaves 43 cases for both blocks of the thermal power plant which meet the criteria and can be analyzed further.

The minimum value of the determinant coefficient accepted as the criterion is 0.9 ($R^2 > 0,9$). After elimination, a total of only 3 cases is listed in Table 2.

Table 2 Failure interaction cases for components which meet the criteria of selection (y - dependent variable (MTTF), x - independent variable (number of failure interaction of the affecting component))

Block-affected-affecting K	$y = ax^2 + bx + c$	R^2	Degrees of freedom *(n - 2)*
A-5-8	$y = 1411.7\ x^2 + 10147\ x + 30229$	0.9662	3
A-12-6	$y = -745.07\ x^2 + 66630\ x - 51873$	0.9571	8
A-12-8	$y = -1761\ x^2 + 10856\ x - 14845$	0.9908	5

2.4 Determining an appropriate distribution of the occurrence of failure between the Weibull 3-parameter (hereinafter W3) or 2-parameter (hereinafter W2) distribution

In order for this task to be performed, we must once again rely on a software solution due to a great number of expected calculations. A mathematical solution is complex, and thus an efficient means to numerically solve the problem of finding a suitable distribution, followed by a value of the parameters of distribution with satisfactory accuracy. These calculations should take into consideration only failures of the affected components which have no failure interaction from their affecting components in order to obtain a distribution. Determination of the parameters is an attempt made within the W3 distribution, and if it has no solution which satisfies the parameter of the position of distribution γ, we obtain the value *0* and proceed with determining parameters of the W2 distribution. To solve this problem we can use a method for determining these parameters. The first step is thus the calculation of the parameter of the W3 distribution. The Weibull probability plotting paper is used [12-14].

If a change in parameter γ cannot lead to a linear value of the approximative function for $\gamma > 0$, then the remaining procedure is reduced to determining parameters of the W2 distribution.

For example, component K4 of block A did not have any affecting components. Thus, it is necessary to align all failures, 231 in total, based on their size, and to form cumulative values of the time to failure. After that, further work is carried out in the coordinate system where the coordinates are represented with expressions (2) and (3) with the aim of using Weibull probability plotting paper to determine the existence, that is, the size of the parameters of the distribution of γ.

$$x_i = \ln\left(t_i - \gamma\right) \tag{2}$$

$$y_i = \ln\left[\ln\left(\frac{1}{F\left(t_i\right)}\right)\right] \tag{3}$$

By changing the values of parameter γ we are looking for a linear approximation of the function over the points in the coordinate system of the following form (4):

$$y = ax^2 + bx + c \tag{4}$$

The values of the remaining two parameters are obtained with the following expressions (5):

$$\beta = b\,,\ \ \eta = e^{-\frac{c}{b}} \tag{5}$$

This procedure was carried out using software (Fig. 4, Table 5) and the values of the parameters were analytically determined so that a large number of cases could be solved in the shortest possible period of time. If by changing the parameter γ we do not obtain a linear approximation of the function for $\gamma > 0$, then further procedure is reduced to determining parameters with a W2 distribution.

By solving the equations (6) we obtained the values of parameter β and parameter η.

$$\frac{\mathrm{MTTF}}{\Gamma\left(\frac{1+\beta}{\beta}\right)} = (-t_{\max} / \ln\left(\frac{1}{2\cdot(n-2)}\right)^{\frac{1}{\beta}}, \qquad \eta = \frac{\mathrm{MTTF}}{\Gamma\left(\frac{1+\beta}{\beta}\right)}. \tag{6}$$

The procedure for solving these equations is numeric and for that purpose software solutions were created which allow us to quickly obtain results with a greater number of needed calculations.

The selection of cases where interaction between the components occurs or does not occur is based on criteria. Cases where there is an insufficient amount of data to draw any conclusions regarding the interaction, or where it is clear that there is no interaction (the number of degrees of freedom), are rejected.

The criteria for accepting the existence of interaction coefficients include the following:

- the number of degrees of freedom of the approximation curve, which is determined by the number of points of various numbers of failure interactions (a minimum of 4 degrees of freedom or minimum 6 points),
- the value of the coefficient of determination ($R^2 > 0,9$).

The failure interaction cases for the components which meet the criteria of selection are given in Table 2 in Chapter 2.3 using expressions (2) to (6).

2.5 Designing an interaction matrix

The following matrix should be formed:

$$\mathrm{Y} := \left(y_{k1,k2}\right)_{mxm} \tag{7}$$

where: $y_{k1,k2}$ - the least squares regression function, k_1 - the affected component, k_2 - the affecting component, m - the number of system components, and the following stands [9, 11]:

$$y_{k1,k2} = a_{k1,k2}x^2 + b_{k1,k2}x + c_{k1,k2}\,. \tag{8}$$

If there is no interaction between the components, then $y_{k1,k2} = 0$. The simulation software needs to input the values from the matrix, and at the moment of occurrence of the failure the simulation determines the value of the change in the MTTF of the affected component due to individual failures of the affecting components from the matrix.

After each failure of the affecting component *K2* there is a change in the value of the MTTF of the affected component *K1* in the sense of a reduction, when the component *ages*, or an increase when the component undergoes *rejuvenation*. This time a „*shift*" in the value of the *MTTF* of the affected component *K1* could be formulated by the introduction of a new variable τ_p, which, in the case of negative values ($\tau_p < 0$) denotes the aging of the component, and in the case of positive values ($\tau_p > 0$), it denotes its rejuvenation after failure of the affecting component and preventive maintenance. In order to obtain a general pattern for this variable, it is necessary to consider what is taking place in each of the failure interactions individually (Table 3).

Table 3 Values of MTTF of the affected component and their changes in relation to the number of failure interactions of the affecting component

Number of failure interactions *K2* (*x*)	$MTTF_x$ od *K1* ($y_{k1,k2}$)	Change $MTTF_x$ - $MTTF_{x-1}$
0	$c_{k1,k2}$	/
1	$a_{k1,k2} + b_{k1,k2} + c_{k1,k2}$	$a_{k1,k2} + b_{k1,k2}$
2	$4a_{k1,k2} + 2b_{k1,k2} + c_{k1,k2}$	$3a_{k1,k2} + b_{k1,k2}$
3	$9a_{k1,k2} + 3b_{k1,k2} + c_{k1,k2}$	$5a_{k1,k2} + b_{k1,k2}$
4	$16a_{k1,k2} + 4b_{k1,k2} + c_{k1,k2}$	$7a_{k1,k2} + b_{k1,k2}$
5	$25a_{k1,k2} + 5b_{k1,k2} + c_{k1,k2}$	$9a_{k1,k2} + b_{k1,k2}$

Changes in the values of the MTTF and in the relation to the number of failure interactions can be defined as [6, 8]:

$$MTTF_x - MTTF_{x-1} = (2x-1) \cdot a_{k1,k2} + x \cdot b_{k1,k2} \tag{9}$$

As previously defined, the value of the time shift τ_p defines whether, after the failure interaction, the value of the reliability of the affected component will decrease or increase. Changes take place in a sequential order even in the case of hazard, and so the model is combined since it includes changes of both hazard and reliability.

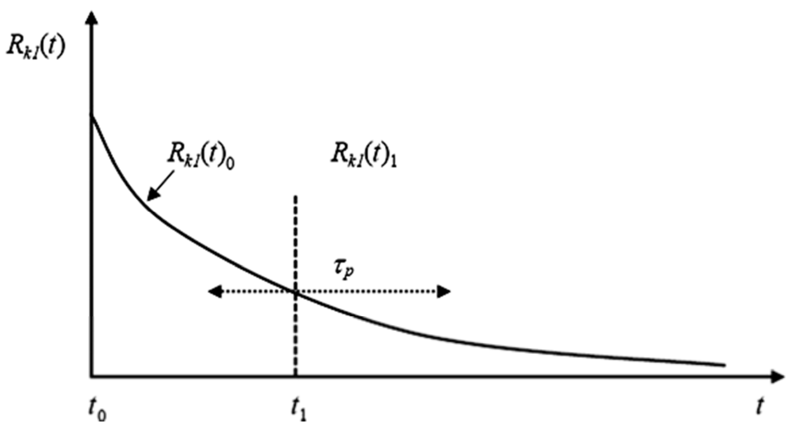

Fig. 3 Changes in the affected component reliability after the first failure interaction of the affecting component [8]

If the value of the MTTF is viewed as a point in time which divides the surface beneath the reliability curve into two equal parts, then we could conclude that the time shift τ_p by changing only the reliability after the failure interaction influences the overall value of the MTTF depending on the relationship between the value of reliability prior to the failure interaction $R_{k1}(t_1)_0$ and the remaining reliability in case the failure interaction did not even occur, that is, the unreliability of the affected component $F_{k1}(t_1)_0 = 1 - R_{k1}(t_1)_0$. Thus, the time shift in the case of the first failure is defined as:

$$\tau_p = \frac{2\cdot\left(MTTF_1 - MTTF_0\right)\cdot\left(1-R_{k1}\left(t_1\right)_0\right)}{R_{k1}\left(t_1\right)_0} = \frac{2\cdot\left(MTTF_1 - MTTF_0\right)\cdot F_{k1}\left(t_1\right)_0}{R_{k1}\left(t_1\right)_0} \tag{10}$$

Representation of changes in general numbers after the *x-th* failure interaction can take the following form:

$$\tau_p = \frac{2\cdot\left(MTTF_x - MTTF_{x-1}\right)\cdot\left(1-R_{k1}\left(t_x\right)_{x-1}\right)}{R_{k1}\left(t_x\right)_{x-1}}. \tag{11}$$

By connecting equations (4) and (5) we obtain the final form of the required time shift of the affected component τ_p after a failure interaction *x* of the affecting component:

$$\tau_p = \frac{2\cdot\left(\left(2x-1\right)\cdot a_{k1,k2} + x\cdot b_{k1,k2}\right)\cdot\left(1-R_{k1}\left(t_x\right)_{x-1}\right)}{R_{k1}\left(t_x\right)_{x-1}}. \tag{12}$$

where: x - the ordinal number of the failure interaction of the affecting component, k_1- the affected component, k_2 - the affecting component, $R_{k1}\left(t_x\right)_{x-1}$- the reliability of the affected component prior to the occurrence of failure interaction [8].

The following interaction matrix is formed $\text{Y}:=\left(y_{k1,k2}\right)_{mxm}$, where

$$y_{k1,k2} = a_{k1,k2}x^2 + b_{k1,k2}x + c_{k1,k2}.$$

2.6 Parameter correction and the simulation of the operational reliability of the power plant block system

Once we have defined the mathematics for creating a model, it is necessary to provide a valid simulation. The number of failures in the simulation needs to represent the number of failures from the database. After that, it is necessary to create a simulation of the reliability of the entire system. This should be done in 3 steps:

- creating software for compiling the necessary data from the database,
- correcting the parameters by means of a simulation (validation),
- simulating the system operations.

The first step means that since there is a multitude of data, it is necessary to perform the procedures for data calculation on the overall operation of the system and the average operating time during the calendar year, as well as the overall and average number of failures of each sub-system.

It is possible to present the most important data which refer to the values of *working time* – the operating time of the system and *NofF* – the number of system failures (components). These data are shown in Table 4.

Table 4 Number of failures of each component and the system and the overall operating time of the system

Component	Average annual operating time (h)	Average annual number of failures	Median	Standard deviation	Measures of shape (skewness)	SW Test W (α=0.05)	p-value
A-K4	5,131	13.28571429	15,238	27,880.76460	1.738777729	0.986293499	0.025617
A-K5	5,131	10.93516484	9,893.5	36,216.01278	3.137013611	0.97910269	0.016954
A-K6	5,131	7.460439560	22,108	56,512.65061	2.013559902	0.994981074	0.921555
A-K7	5,131	3.372527473	41,748	113,043.56300	1.154532263	0.987983495	0.858540
A-K8	5,131	3.474725275	50,583	121,971.40820	2.28582301	0.991323565	0.947381
A-K9	5,131	0.153296703	186,412.5	256,960.48300	/	1	1
A-K10	5,131	0.306593407	442,700	486,140.09190	1.18704459	0.976693956	0.916208
A-K11	5,131	0.715384615	282,604	240,095.3073	0.880196026	0.987544858	0.944738
A-K12	5,131	2.708241758	5,241.5	25,382.61038	1.751270134	0.987129225	0.996203
A-K13	5,131	0.766483516	96,002	264,912.38570	1.303497571	0.991763795	0.999922
Block A total	**5,131**	**43.178571430**					

Once the necessary data were obtained, the second step was the correction of parameters W3 or W2 of the distribution. The initial parameters refer to continuous variables and the transfer to discrete variables is necessary for the simulation of the operating system. It is certain that the number of time points of the calculation influences the values of the corrected parameters of distribution, so it will be necessary for them to be identical for the duration of both simulations, that is, for the duration of parameter correction and reliability simulation of the system. The algorithm for parameter correction is presented in Figure 4, with abbreviations listed below.

NumOfFailures - number of failures of the affected component

G, B, A - parameters of the position, shape and extent of the distribution of the affected component

MaxFailures - duration of the maximum failure of the affected component

CT - final time calculation

Y - interaction matrix

LastChange - duration of the final change/fix of the affected component

X - the variable which determines the failure of the affected component

Sim – the pseudo-accidental number whose value determines the failures of the components (of the sub-system)

Tp - duration of the shift due to failure interaction of affecting components

Tp(*i*) - duration of the shift due to the failure interaction of the affecting component *i*

MSimNumFailures - the average number of failures of the affected component during the simulation

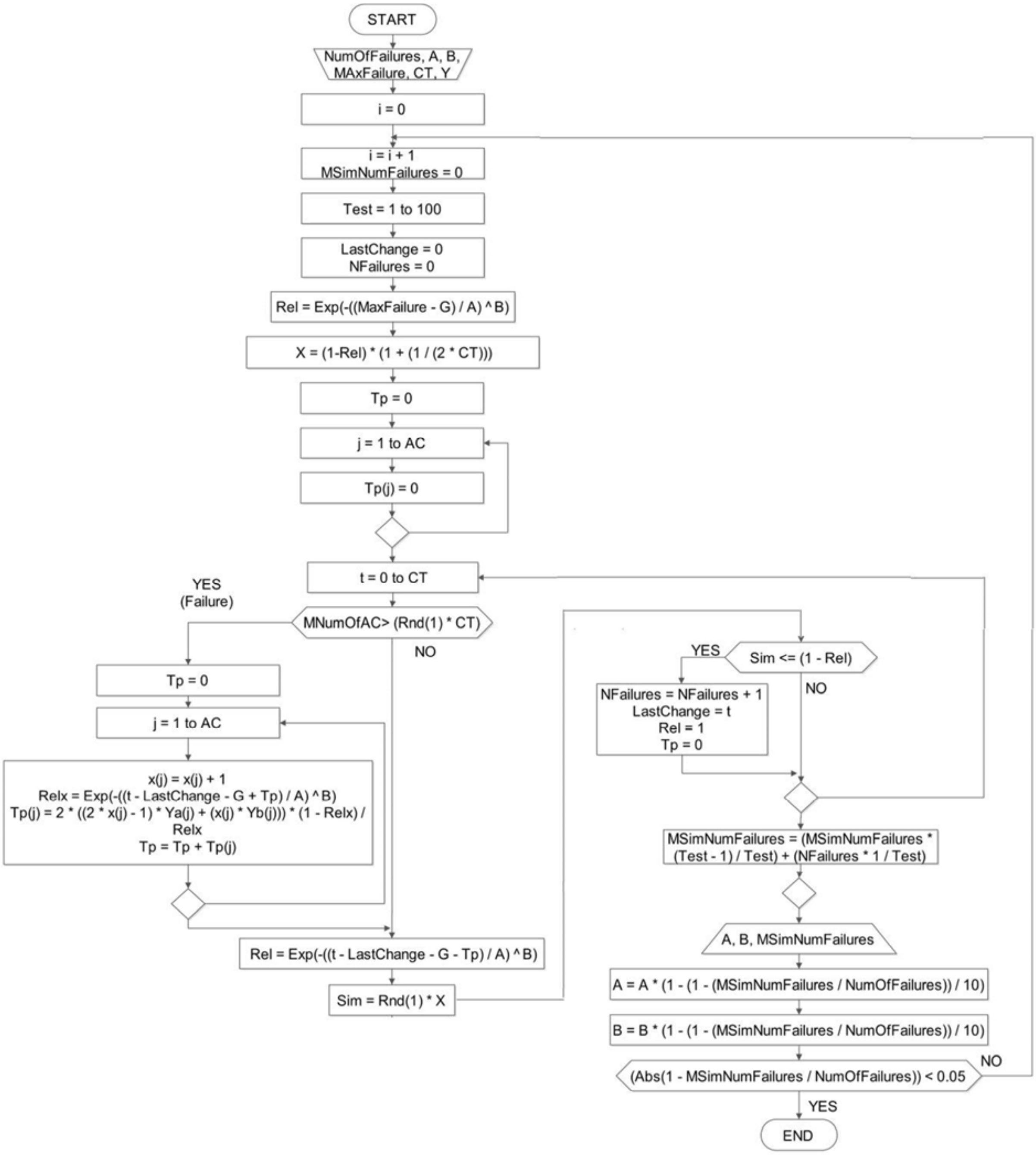

Fig. 4 System parameter correction algorithm with failure interaction of the components [8]

Once the correction of the parameters was completed, the values presented in Table 5 were obtained.

Table 5 Distribution of parameters of each of the components of thermal power plant block A

Block-Component	γ	β	η
A-K4	48.0787597	1.10434268	43093.2339
A-K5	0	1.316000267	29683.3920
A-K6	0	1.296029204	56662.7140
A-K7	0	1.407753248	137122.5009
A-K8	0	1.405367947	132015.6800
A-K9	0	2.256622074	413798.0507

Block-Component	γ	β	η
A-K10	0	1.654387432	911901.4621
A-K11	0	1.689153944	480385.2463
A-K12	0	2.180171632	36597.6443
A-K13	0	1.822532337	299272.1739

The third and last step in this model is the simulation of the reliability of the entire system. In order for the obtained parameters for each component to reflect the real probability of failure, the time points of the calculation of reliability in the simulation of the operation of the system must be the same as in the previous algorithm. The simulation is presented by the algorithm given in Figure 6, with the following abbreviations:

KVK - final duration of the calculation

NoPCS - the number of components of the system

Y - interaction matrix

MaxCanc - duration of the maximum failure of the affected component

N(i) - number of failures of component *i*

G, B, A - the parameters of position, shape and extent of the distribution

GS - the number of iterations of the test, i.e., the simulated number of years of system operation

NoCanc(i) - simulated number of component failures *i*

Rel(i) - reliability of the component *i*

X - the variable which determines the failure of individual components

Sim – a pseudo-accidental number whose value determines the failures of the components (the sub-system)

Last Change - the time of the last change/fix of the affected component *i*

Move(i) - the time shift as a result of the failure interaction of the component *i*

i - the simulated number of failure interactions of the affecting components

The complete system reliability simulation is shown in Fig. 5.

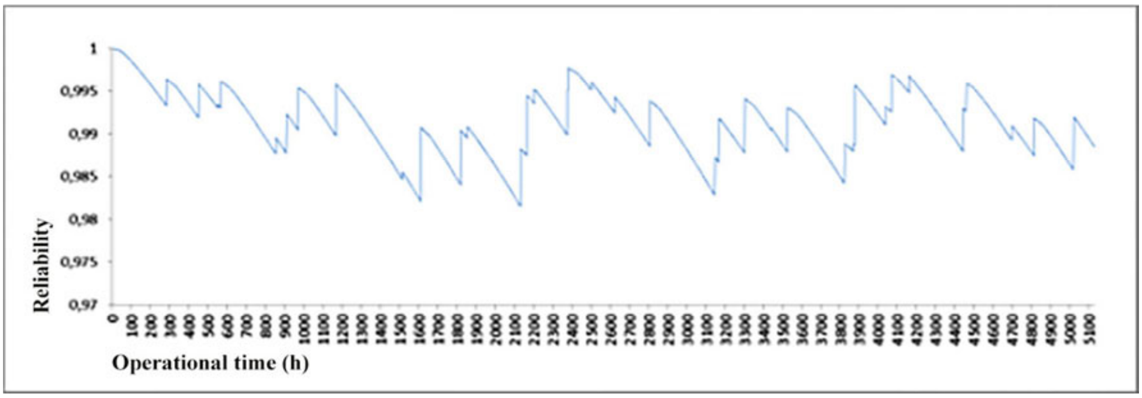

Fig. 5 Simulation of system reliability for a period of one year

The results of the reliability model which was applied to the blocks of the thermal power plant Tent A emerged, as in the previous model, from the iterative repetition of the simulation of the blocks allowing us to obtain a broader picture of the reliability of the power plant. The model also enables us to track isolated cases for analyzing closer preventive activities regarding certain components of the system in a certain percentage by changing the parameters in the interaction matrix, which would be a result in possible preventive maintenance activities.

The first results of the simulation refer to the iterations of the simulation of reliability of the entire power plant, and thus provide average values of reliability of entire blocks of the power plant and its components. The graph presenting changes in the reliability of the components of the block systems of the power plant for a period of one year as an average of 100 iterations is shown in Figure 7. Furthermore, the regression functions for each component are also given.

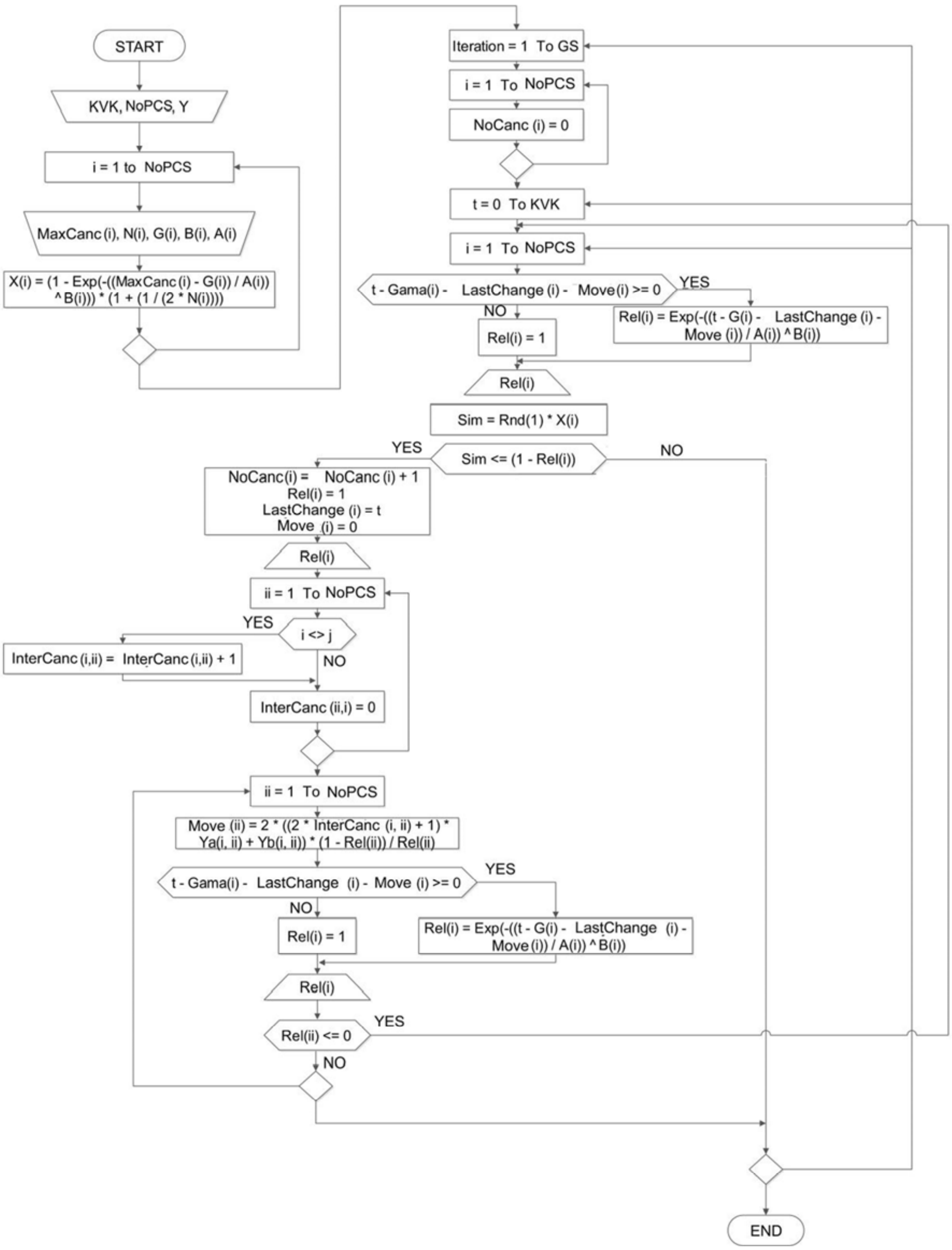

Fig. 6 Software algorithm for the system reliability simulation of the power plant block [6]

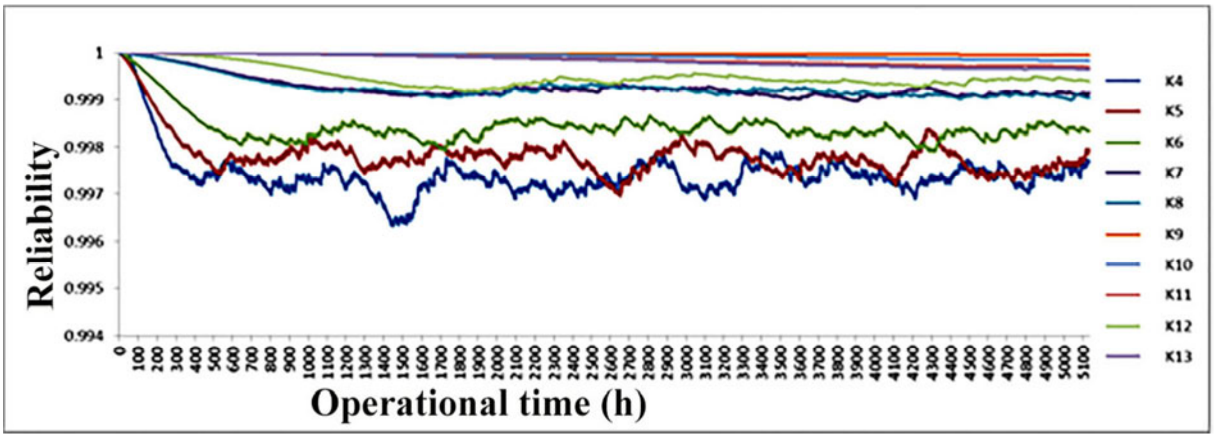

Fig. 7 A comparative view of average values of reliability of components of block A during one year of operation (100 iterations)

By increasing the effects of preventive maintenance activities by 50% each, that is, by increasing the parameters which influence the time shift, i.e., the rejuvenation or aging of the affected components of the system, we might achieve a clearer image of the effects of preventive maintenance activities. The simulation needs to be carried out in iterations of 100.

After each individual series of simulations, we can obtain data on the changes in the reliability of the entire system or relative differences which occur over time. Since we are dealing with a potentially negative influence of the affecting component on the affected component, then it can be said that it is possible to quantify the influences by means of a regression function or cumulative functions of reliability, along with relative differences in reliability. However, the data on the number of failures still remains valid even though in certain situations it may be too few pieces of information to explain the occurrences. After a series of simulations, we obtained the following data on average failures of the system components, as presented in Table 6.

Table 6 Average level of system failures during the simulation for the increase of values in the interaction matrix by 50% (100 iterations)

Block-affected-affecting component	Increased interaction influence	Changes in the average number of block failures
A-K5-K8	$150\% \cdot \tau_{5,8}$	-0.28999999999996
A-K12-K6	$150\% \cdot \tau_{12,6}$	-0.260000000000027
A-K12-K8	$150\% \cdot \tau_{12,8}$	-0.250000000000027

3. CONCLUSION

The available data can indicate the direction of preventive activities during the failure interaction, which might lead to the smallest possible number of failures in the power plant in the future. The results of this series of simulations of the interaction of component A-K8 as the affecting and A-K5 as the affected component are shown in Fig 8.

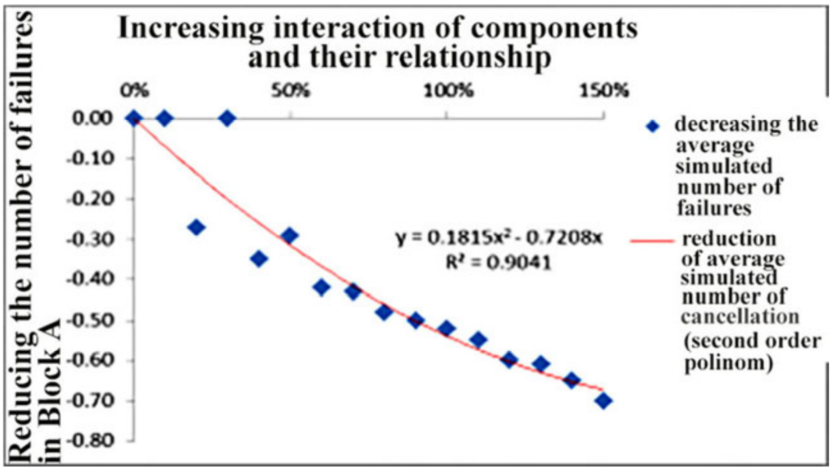

Fig. 8 Decrease in the average simulated number of failures in block A in relation to the increase in the interaction of components K8 and K5

Because of the influence of component K8, it is important to show the decrease in the average number of failures in the entire system, as well as its influence both on component K5 and component K12 for a comparison and possible allocation of resources for preventive maintenance activities to where the greatest effects on the reliability of the system can be achieved. The comparison is shown in Fig. 9.

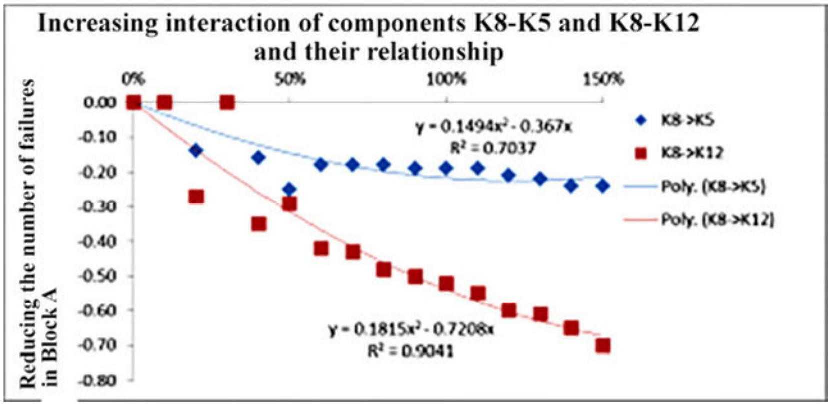

Fig. 9 Relationship between the reduction in the average simulated number of failures in block A and the increase in the interaction between component K8 and components K5 and K12

What is important is that the simulation yielded similar values of the influence precisely in terms of the increase in the interaction of both components with K8 with a value of 50%, which was taken as an indicator of future operation. However, it turned out that the differences in the decrease in the number of failures is very large. This is clearly indicated by the regression function, and precisely this function could be an excellent indicator for what should be planned for the case of failure of component K8 and also for how to allocate resources for undertaking the best preventive maintenance activities. The model enables us to carry out such series of simulations for each of the cases of component interaction.

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