Postprint of: Sokólski P., Rutkowski T.A., Ceran B., Horla D. (2021) Robustness Analysis of a Distributed MPC Control System of a Turbo-Generator Set of a Nuclear Plant – Disturbance Issues. In: Szewczyk R., Zieliński C., Kaliczyńska M. (eds) Automation 2021: Recent Achievements in Automation, Robotics and Measurement Techniques. AUTOMATION 2021. Advances in Intelligent Systems and Computing, vol 1390. Springer, Cham. https://doi.org/10.1007/978-3-030-74893-7_17

Robustness analysis of a distributed MPC control system of a turbo-generator set of a nuclear plant – disturbance issues

Paweł Sokólski[1], Tomasz A. Rutkowski[2], Bartosz Ceran[3], and Dariusz Horla[4]

[1] Poznań University of Technology, Faculty of Automatic Control, Robotics and Electrical Engineering, sokolski.p@gmail.com
[2] Gdańsk University of Technology, Faculty of Electrical and Control Engineering, tomasz.adam.rutkowski@pg.gda.pl
[3] Poznań University of Technology, Faculty of Environmental Engineering and Energy, bartosz.ceran@put.poznan.pl
[4] Poznań University of Technology, Faculty of Automatic Control, Robotics and Electrical Engineering, dariusz.horla@put.poznan.pl

Abstract. Typically, there are two main control loops with PI controllers operating at each turbo-generator set. In this paper, a distributed model predictive controller with local quadratic model predictive controllers for the turbine generator is proposed instead of a set of classical PI controllers. The local quadratic predictive controllers utilize step-response models for the controlled system components. The parameters of these models are determined based on the proposed black-box models of the turbine and synchronous generator, which parameters are identified on-line with the recursive least-squares algorithm. A robustness analysis of the control system with respect to different disturbances is presented in the paper. There are various configurations considered, such as change in disturbance levels from the side of electrical and thermal systems, or changes in prediction horizons.

Keywords: model predictive control, PI controller, power system, heat system, power plant, robustness

1 Introduction

The quality of electrical energy plays a unique and significant role in development of a modern society. The demand for the generation of electric power grows in accordance with the speed of economic development of societies. Accordingly, there is a growing need to increase the power plants' efficiency and improve the electrical energy quality. The conventional power plants, as well as nuclear ones, utilize turbine-generator sets with steam turbines cooperating with the synchronous generators to produce electrical energy. The major novelty of the results presented in the paper, is to show the means to improve the quality of the turbine generator control and, in consequence, the electrical energy quality delivered to the power system network.

Control systems currently used in the power industry are based on classic proportional/integral/derivative control system extended with additional modules and feedback loops, such as, e.g., system stabilizers. Despite the fact that they are often complex systems and take into account a number of phenomena occurring in a regulated system, they do not fully use the knowledge about the object. Currently, it is possible to use more complex algorithms, e.g., predictive control, which fully take advantage of the availability of the information about the structure of the object (mathematical models) and take the constraints imposed on the control and controlled values or state into account. Therefore, in the paper, it is proposed to use the QDMC predictive control, which allows to use the knowledge of the turbine-generator set model. Additionally, the article proposes using the algorithm to estimating parameters of the model in an online fashion, with the use of the recursive least squares method (RLS). This is to ensure that the discussed control system works with the current version of the plant model at all times.

Nuclear power plants generate a large amount of power and can significantly affect the stability of the entire electricity system (around 3/4 of electricity in France comes from nuclear energy). Due to the requirements for the quality of electricity and the safety of nuclear power plant operation, it seems important to analyze the behavior of the proposed solution in the event of various disturbances.

The steam turbine and the synchronous generator are complex objects with a non-linear character. Currently, the control methods for the turbine generator are typically based on the Proportional-Integral (PI) controllers [1–3]. With the current state of the control theory and access to the modern computing units, with high computing power, it is possible to use more complex and sophisticated control algorithms for control purposes [4–12]. In this paper, the distributed model predictive control (DMPC) methodology is discussed [13, 14] for the turbine generator control purposes. With the model predictive control (MPC) technology one can design a truly multi-variable optimizing control system that can handle the process constraints and accommodate the model-based knowledge combined with the hard measurements [15–17]. To achieve better closed-loop control performance, some level of communication should be established between local MPC controllers. The local controllers proposed in the paper are designed and implemented in the form of quadratic dynamic matrix control (QDMC) algorithm [5], [16]-[18], which exchanges **with each other** information about their control signal values. The QDMC consists of the on-line solution to a quadratic programming problem (QP) where a sum of squared deviations of controlled variable predictions from their set-points to maintaining predictions of constrained variables within bounds is minimized. In contrast to the DMC controller, where constraints are enforced via least squares method, the use of a QP provides rigorous handling of constraint violations by formulating them as inequalities linear with respect to the decision variables, and allowing tighter constraint violation control (comparison of DMC and QDMC for a turbine MPC controller can be found in [5]). The distributed model predictive controller for the nuclear power plant turbo-generator set based on the mentioned QDMC controllers and which is a basis for the research described in the paper is described in [19].

Potentially, there might exist configurations, in which a QP problem is infeasible as per constraints imposed on input and output signals simultaneously. There are several ways to relax the constraints that allow to restore feasibility, i.e. minimal-time approach, soft-constraint approach, or hard constraint relaxation with prioritization [20, 21]. In the discussed case, the MPC turbine predictive control system is subject to hard constraints imposed on the control valve opening level. This particular constraint cannot be relaxed in any way, and the only acceptable solution is a change of horizons, which increases the number of degrees of freedom in optimization [20].

QDMC controllers are based on the step-response model of the components of the considered system. Taking into account a potentially wide range of operating point changes in the system the step-response model parameters are calculated, based on a simplified linear or black-box models of the turbo-generator set components, which parameters are identified on-line with the recursive least squares algorithm (RLS) [22], [23]. The RLS method can include robustness modifications that will cope with estimation errors [23].

Two different types of turbine-generator set models are considered in the paper. In one group are simplified models used for the control system synthesis (as models mentioned above) and education or training [1, 3, 24–31]. In the second group, there are complex nonlinear models that recreate the object in a detailed way [12, 11, 32, 33]. A complex nonlinear model of the nuclear power plant's turbine-generator set is used as a reference model for the calculations performed for the research and all the discussed control systems are tested with such a plant simulation [4, 33].

The paper is organized as follows. In Section 2, the turbo-generator set DMPC control structure with local QDMC controllers is described. Section 3 describes the disturbances that may occur in the system. The results of simulation tests with varying disturbances are presented in Section 4. Finally, a brief summary of the obtained results is given in Section 5.

2 The turbo-generator set DMPC control structure with local QDMC controllers

Typical turbo-generator set control system consists of two control loops with the PI controllers. In this paper, instead of typical PI controllers the control structure with distributed model predictive controller (DMPC), in the form of two local QDMC controllers for turbine and synchronous generator control, is proposed. To achieve better closed-loop performance, the turbo-generator set control performance, some level of communication is established between the local QDMC controllers – assuming that the information about their control signal values is exchanged.

The diagram in Fig. 1 presents the proposed paper solution's main concept with the linear MPC - QDMC controller. A turbo-generator set is a typical nonlinear object. Hence the on-line identification algorithm, in the recursive least-squares (RLS) algorithm structure, is introduced for the linear model parameters used for the object output prediction purposes.

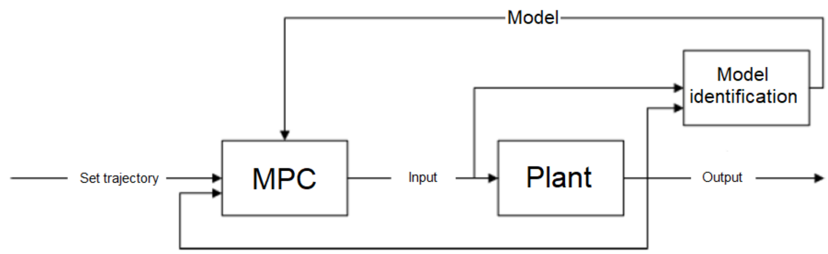


Fig. 1: Control structure with MPC - QDMC controller and with the RLS algorithm module for on-line model parameters identification for plant output prediction purposes.

In the paper, this solution will be compared with the well known from literature classical turbo-generator set control structure which consists of the typical PI controller and a simple power system stabilizer (Fig. 2).

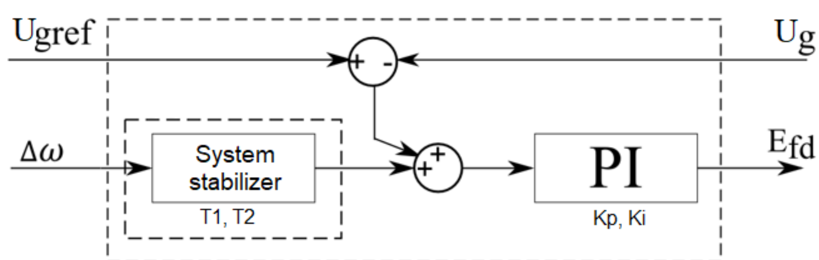


Fig. 2: The classical turbo-generator set control structure with the PI controller and power system stabilizer, where: U_{gref} - reference for the generator voltage, dw - deviation in the generator shaft rotational speed, U_g - generator voltage, E_{fd} - generator excitation voltage, T_1 and T_2 are lead-lag time constant of the system stabilizer, K_p and K_i are proportional and integral gains of PI controller.

The standard QDMC algorithm uses the linear process model in the form of a step response model for prediction purposes [15]-[18]. For the multiple-input, multiple-output (MIMO) systems, with s controller outputs (manipulated variables) and r measured variables, it may be presented as:

$$\underline{y}_{k+1|k} = \underline{y}_{k+1|k-1} + \boldsymbol{A}\Delta\underline{u}_k + \underline{y}^d_{k+1|k}, \tag{1}$$

where k is the current sampling instant, $\underline{y}_{k+1|k}$ is a value in instant $k+1$ based on information from instant k, $\underline{y}_{k+1|k}$ is a $(r{\cdot}p){\times}1$ vector representing the prediction of future output trajectory at $t = k$ on the prediction horizon p

$$\underline{y}_{k+1|k}=[(y_{1(k+1|k)},\dots,y_{r(k+1|k)}),\dots,(y_{1(k+p|k)},\dots,y_{r(k+p|k)})]^T, \tag{2}$$

the $\underline{y}_{k+1|k-1}$ is a $r{\cdot}p{\times}1$ vector representing the unforced output trajectory, which means the open-loop prediction while the controller output remains constant at the previous value

$$\underline{y}_{k+1|k-1} = [(y_{1(k+1|k-1)},\dots,y_{r(k+1|k-1)}),\dots,(y_{1(k+p|k-1)},\dots,y_{r(k+p|k-1)})]^T, \tag{3}$$

$\Delta\underline{u}_k$ is a $(s{\cdot}m){\times}1$ model manipulated variables adjustments vector defined on the control horizon m

$$\Delta\underline{u}_k = [(\Delta u_{1(k)},\dots,\Delta u_{s(k)}),\dots,(\Delta u_{1(k+m-1)},\dots,\Delta u_{s(k+m-1)})]^T, \tag{4}$$

$\underline{y}^d_{k+1|k}$ is a $(r{\cdot}p){\times}1$ vector representing the unmeasured disturbance estimates, assumed to be the difference between the actual measurements and the unforced output model trajectory components, and $\boldsymbol{A}$ is a $(r{\cdot}p){\times}(s{\cdot}m)$ dynamic matrix containing the MIMO system model step-response coefficients in the following form:

$$\boldsymbol{A} = \begin{bmatrix} \bar{a}_1 & 0 & 0 & \dots & 0 \\ \bar{a}_2 & \bar{a}_1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \bar{a}_p & \bar{a}_{p-1} & \bar{a}_{p-3} & \dots & \bar{a}_{p-m+1} \end{bmatrix} \tag{5}$$

where every matrix element $\bar{a}_i$ is a $r{\times}s$ matrix containing the $r{\cdot}s$ coefficients in the form of samples of the unit step response model, of each controller output to measured process variable pair, at each considered sampling period.

To compute the optimal changes in the manipulated variables vector $\Delta\underline{u}_k$, the multi-variable QDMC quadratic optimization problem (QP) is solved at each sampling instant k [15]-[18]

$$\begin{aligned} &\min_{\Delta\underline{u}_k} J = [\underline{y}^{\mathrm{ref}}_k - \underline{y}_{k+1|k}]^T \boldsymbol{\Gamma} [\underline{y}^{\mathrm{ref}}_k - \underline{y}_{k+1|k}] + [\Delta\underline{u}_k]^T \boldsymbol{\Lambda} [\Delta\underline{u}_k], \\ &\text{s.t.} \quad \underline{y}_{\min} \le \underline{y}_{k-1|k} \le \underline{y}_{\max}, \\ &\qquad \Delta\underline{u}_{\min} \le \Delta\underline{u}_k \le \Delta\underline{u}_{\max}, \\ &\qquad \underline{u}_{\min} \le \underline{u}_k \le \underline{u}_{\max}, \end{aligned} \tag{6}$$

where $\underline{u}_k$ is a $(s{\cdot}m){\times}1$ model manipulated variables vector on the horizon m

$$\underline{u}_k = [(u_{1(k)},\dots,u_{s(k)}),\dots,(u_{1(k+m-1)},\dots,u_{s(k+m-1)})]^T, \tag{7}$$

and the $\boldsymbol{\Gamma} > 0$ is a square-diagonal matrix of controlled variable weights, and $\boldsymbol{\Lambda} \geq 0$ is a square-diagonal matrix to penalize control updates. The first matrix is positive definite, the second - positive semi-definite, because there is no need to take explicit soft control limits into consideration.

In case of the described model, the following notation holds:

- outputs - $\underline{y} = [P_g,\, U_g,\, \omega_g]$,
- set values - $\underline{y}^{\mathrm{ref}} = [P_{g,\mathrm{ref}},\, U_{g,\mathrm{ref}},\, \omega_{g,\mathrm{ref}}]$,
- control signals - $\underline{u} = [\alpha,\, E_{fd}]$
- constraints - $\alpha \in [0, 100]$, $E_{fd} \in [-0.1, 0.1]$.

Finally, the optimal vector of changes in manipulated variables is obtained based on the solution of above-mentioned QP (6) with constraints. Only the first elements from the optimal solution are applied as the control signal to the plant. In the next time instant, the optimization task is solved again, according to the receding horizon rule.

The sampling period has been selected on the basis of the GTHW-600 generator's model description [24], where a dominating time constant of the generator has been identified as $\hat{T} = 0.0017\,\mathrm{s}$ (all turbine's time constraints are larger than those of the generator). The resulting sampling period - $T = 0.00001\,\mathrm{s}$ - abides a rule of thumb to fit at least approximately 10 sampling periods per dominating time constant and avoiding simulation errors occurring for larger time constants. This does not give rise to any problems with the excessive output-averaging properties of the predictive controller, as the considered prediction horizons in the span $40 \div 50$ refer to time ranges $0.0004 \div 0.0005\,\mathrm{s}$.

The functional structures of turbine QDMC and synchronous generator QDMC are presented in Figs. 3-4, respectively. Both QDMC controllers require the unit step response models. It is proposed that their parameters are determined based on the appropriate black-box models (Eq. 18-20), which parameters are subsequently identified on-line according to the wide range of turbo-generator set operating point changes. In the paper, the RLS identification algorithms for that purposes is proposed [22]. The unknown black-box models parameters are estimated on-line based using the RLS, with respect to the set of the input and output measurements data.

The proposed black-box model for the turbine QDMC controller purposes, in the form of a discrete-time model, is presented with following structure:

$$P_g(k)=\sum_{j=1}^{n} a(j)P_g(k-1-j) + \sum_{j=1}^{n} b(j)\alpha(k-j) + \sum_{j=1}^{n} c(j)E_{fd}(k-j), \quad (8)$$

$$U_g(k)=\sum_{j=1}^{n} d(j)U_g(k-1-j) + \sum_{j=1}^{n} e(j)\alpha(k-j) + \sum_{j=1}^{n} f(j)E_{fd}(k-j), \quad (9)$$

$$\omega_g(k)=\sum_{j=1}^{n} g(j)\omega_g(k-1-j) + \sum_{j=1}^{n} h(j)\alpha(k-j) + \sum_{j=1}^{n} i(j)E_{fd}(k-j), \quad (10)$$

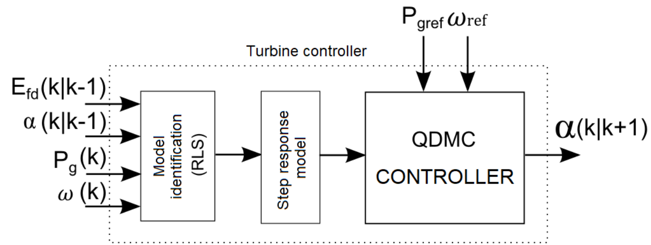


Fig. 3: Turbine QDMC controller's structure

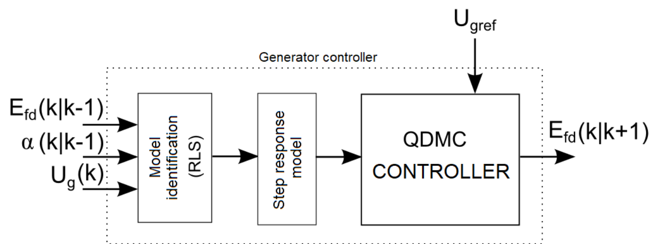


Fig. 4: Generator QDMC controller's structure

where a, b, c, d, e, f, g, h and i are turbine black-box model parameters that are calculated on-line using a recursive least squares estimation method.

The synchronous generator MPC controller uses the same model structure, but the generators' MPC has a different set of parameters estimated in parallel (turbine's and generator's models are independent).

The number of successive samples n considered in black-box models equations (Eq. 8-10), was chosen arbitrary ($n = 7$) taking into consideration the order of turbine-generator model in the most complex model path ($\alpha \rightarrow U_g$). The number 7 was selected as a compromise between a simple model (e.g., $n = 2$) and an overparametrization. **The order of the model has been calculated on the basis of the sum of the orders of the consecutive components taken into consideration, namely: order of a steam turbine (equal 2) [34] and the order of the synchronous generator (equal 5)[32], which sums up to 7.**

3 Parameters' tuning

Before performing experiments with disturbances parameters of compared control systems were tuned in an optimization process.

The PI controller parameters were tuned using the turbine-generator set simulation and assessed using the ISE (Integral of Squared Error) criterion in such a form:

$$f_{\mathrm{ISE}} = \int_{t_0}^{t_f} \left(a(P_{g,\mathrm{ref}} - P_g)^2 + b(U_{g,\mathrm{ref}} - U_g)^2 + c(\omega_{g,\mathrm{ref}} - \omega_g)^2 \right) dt \quad (11)$$

where:
P_g, $P_{g,\mathrm{ref}}$ – active power and active power set point.
U_g, $U_{g,\mathrm{ref}}$ – voltage and voltage set point.
ω_g, $\omega_{g,\mathrm{ref}}$ – speed and speed set point.
a, b, c – weights (for P_g, U_g, ω_g, respectively),
t_0, t_f denote the ranges for which the ISE is calculated.

A continuous-time representation of the performance index has been selected to capture all possible rapid changes in values of the signals in the system, which would potentially remain unindentified if a discrete-time domain were selected.

Individual parameters of the controllers were changed and used in the simulation of a the control system with a turbine-generator set model and the quality of the control was assessed. A gradient optimisation method was used with a Simulink simulation output for the objective function calculation purposes (equations describing the turbo-generator set cooperating with the infinite-bus system used by the optimizer in implicit form as a simulation model) - Fig. 5. To find the best parameters of the PI controllers (K_p, K_i, T_i - both for the turbine and the generator controllers, and T_1 and T_2 parameters for a simple power system stabilizer) 100 iterations of gradient algorithm were performed starting from the random initial point.

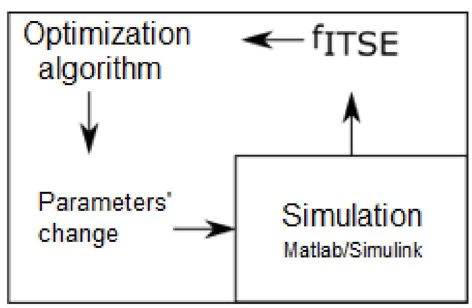


Fig. 5: Tuning of controllers' parameters

Parameters for the turbine MPC controller were selected using a similar method. Two different sets of weights were taken to distinguish between system responses subject to a pair different controller actions: following set trajectory of power P_g and stabilization of voltage U_g and angular speed ω_g. These two actions stand in contrast, i.e. when the system reacts faster to the power set point, it introduces more disturbances to U_g and ω_g. On the other hand, if the system is configured to cope with the disturbances better, it reacts slower after a set point change. To expose this difference one, of the ISE criteria was selected in such a way as to react more to the P_g error (all weights a, b and c are equal to 1) and the second one was chosen to emphasis the U_g component of criterion (weight $b = 100{,}000$). Additionally, due to the stability issues only the scope of the prediction horizon $40 \leq p_T \leq 50$ was analysed (in some test cases the system with the prediction horizon less than 40, and bigger than 50 became unstable). Using a Simulink simulation plots of the ISE quality indicator ware created for the prediction horizon (p_T) for two different sets of weights in the (Fig. 6, Fig. 7).

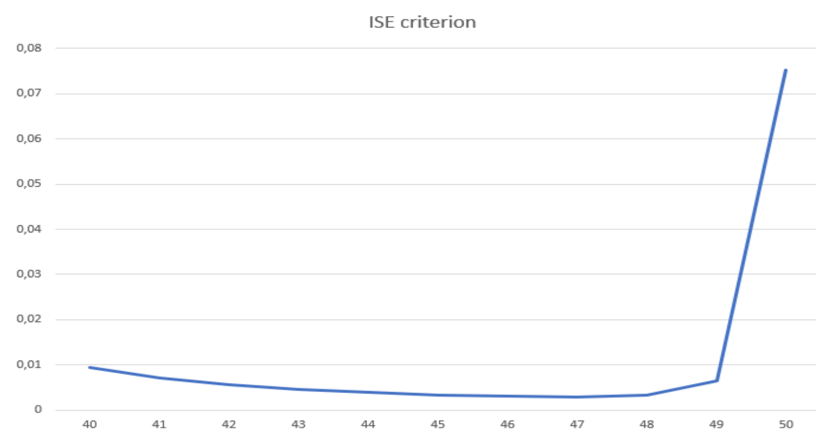


Fig. 6: ISE criterion in function of the prediction horizon p_T - weights $a = 1$, $b = 1$, $c = 1$

Table 1 shows the results of the ISE criterion calculation for different prediction horizons and different ISE criterion's weights. As in the case of the PI controller, the MPC parameters taken as the minimizers were selected. In this case, 10 iterations were performed as per integer value of the prediction horizon p_T. During each of the calculations, power, voltage and speed components were calculated. That allowed to obtain value of a complete ISE criterion with different weights without the need of repeating the simulation. Based on this two different ISE criteria with different sets of weights were used for quality assessment. The parameter values obtained in the optimization process are presented in Table 2.

4 Disturbances

The synchronous generator works nominally with a useful power of 470 MW (1 in relative units), a voltage at the generator terminals of 21 kV (1 r.u.) and an angular speed of 314 $\frac{\mathrm{rad}}{\mathrm{s}}$ (1 r.u.). However, this system works in an environment (Fig. 8), which strongly influences it. This leads to a significant change in the

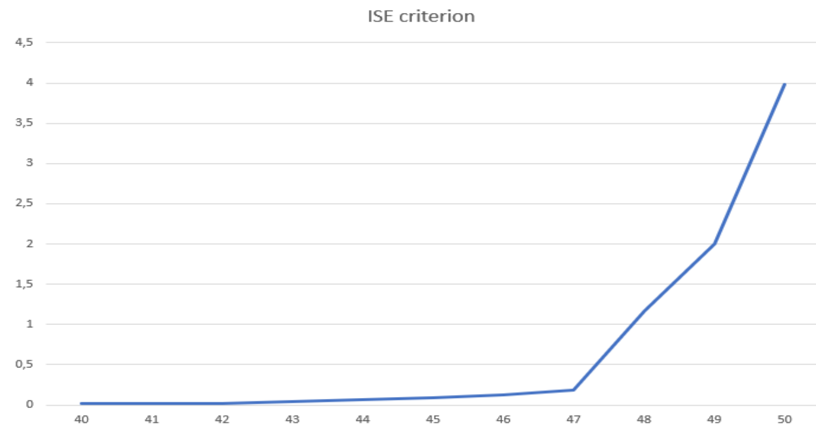


Fig. 7: ISE criterion in function of the prediction horizon p_T - weights $a = 1$, $b = 100{,}00$, $c = 1$

Table 1: ISE criterion value for the step of active power set point in function of prediction horizon p_T

p_T	ISE_1 - $a = 1$, $b = 1$, $c = 1$	ISE_2 - $a = 1$, $b = 100{,}000$, $c = 1$
40	0.0095	**0.0146**
41	0.0071	0.0170
42	0.0057	0.0240
43	0.0046	0.0388
44	0.0039	0.0640
45	0.0034	0.0920
46	0.0030	0.1302
47	**0.0029**	0.1879
48	0.0032	1.1652
49	0.0064	1.9984
50	0.0752	3.9861

Table 2: Controllers' parameters

	K_p	K_i	K_d	T_1	T_2		
PI+PSS	12.82	29.03	0	0.65	1.74		
	p_T	p_G	s_T	s_G	T	$diag(\Gamma_T)$	Λ
DMPC_1	**40**	17	1	1	0.01	1;1;1	0
DMPC_2	**47**	17	1	1	0.01	1;1;1	0

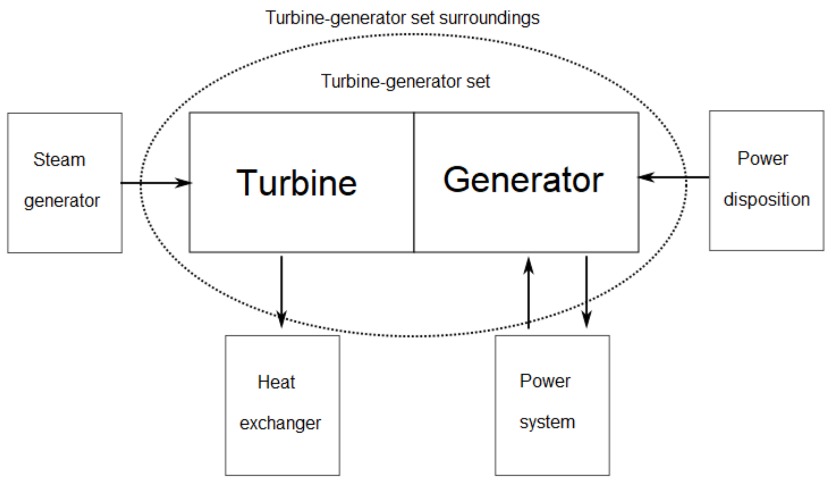


Fig. 8: Turbine-generator set surroundings

operation condition of the system. Non-linear nature of the object and changes in the environment alter the properties of the model of the plant. On the other hand, to to ensure the speed of calculations needed for a real-life implementation, it was decided to use a linear control system with a linear model of the turbine-generator set. Taking this two facts into consideration - frequent changes in the non-linear model and linear control solutions - it was decided to use the on-line model identification, which allows the system to follow up the changes in the plant and to use the control horizon $s = 1$. This is to ensure that decisions about the control signal are made only at the current instant. As due to the change of the operation point of the plant or some disturbances the model may change every instant, also the control signal is calculated every instant using the constantly updated model to follow this changes.

Apart from the impact of the set value of the power through the power disposition, there may also be disturbances from the primary circuit of the power plant, namely, the heat consumption or the power system. After analyzing the operation of the turbo-set predictive control system [5, 19], an attempt was made to analyze the impact of external influences on the system operation and to compare the quality of the proposed solutions with classical solutions in the presence of disturbances. As in previous research, only influence from the power disposition was analysed (a change in set points) further research - described in this paper - focused on the rest of the turbine-generator set i.e. the power system, the heating system and a steam generator (primary circuit of the power plant). This concludes the analysis of the system behaviour influenced by its environment.

The main experiment which the parameters of the control system were determined for was the simulation in the change of power set point value by ±10%, in the 15th second of simulation (from the level 85%). The power of the turbine is regulated by the turbine control system and the control valve, and the voltage by the generator control system and the excitation system. A similar experiment is described in more details in [19] - in this case it was used to tune up predictive controllers' parameters for further experiments.

The influence of the change in heat consumption load is the first analysed external influence on the operation of the turbine (with co-generation of heat). The aim of the experiment was to introduce abrupt changes into steam consumption for the needs of co-generation while following the set active power trajectory. This corresponds to a jump in temperature in the heating system, which, through the heat exchanger, leads to a jump in steam intake from the turbine passage.

In the second experiment, in order to visualize the influence of disturbances from the side of the primary circuit of the nuclear power plant on the operation of the turbine set, a simulation was carried out, in which, with a constant electric load 85% of the active power of the generator), the parameters of the steam generator (steam pressure at the input of the control valve) were changed every 30 seconds of the simulation (-5%, -5%, $+10\%$).

The final experiment was carried out to analyze the impact of disturbances originating from the power system on the operation of the turbine set. The simulation was performed in which the voltage value was changed (-10%, $+5\%$, $+5\%$) every 30 second of the simulation.

The next section describes these experiments in details with a summary and conclusions.

5 Simulation test results

The proposed control system and the reference process model were simulated with Matlab/Simulink environment. The results obtained with three different controller sets for turbine-generator were compared, including:

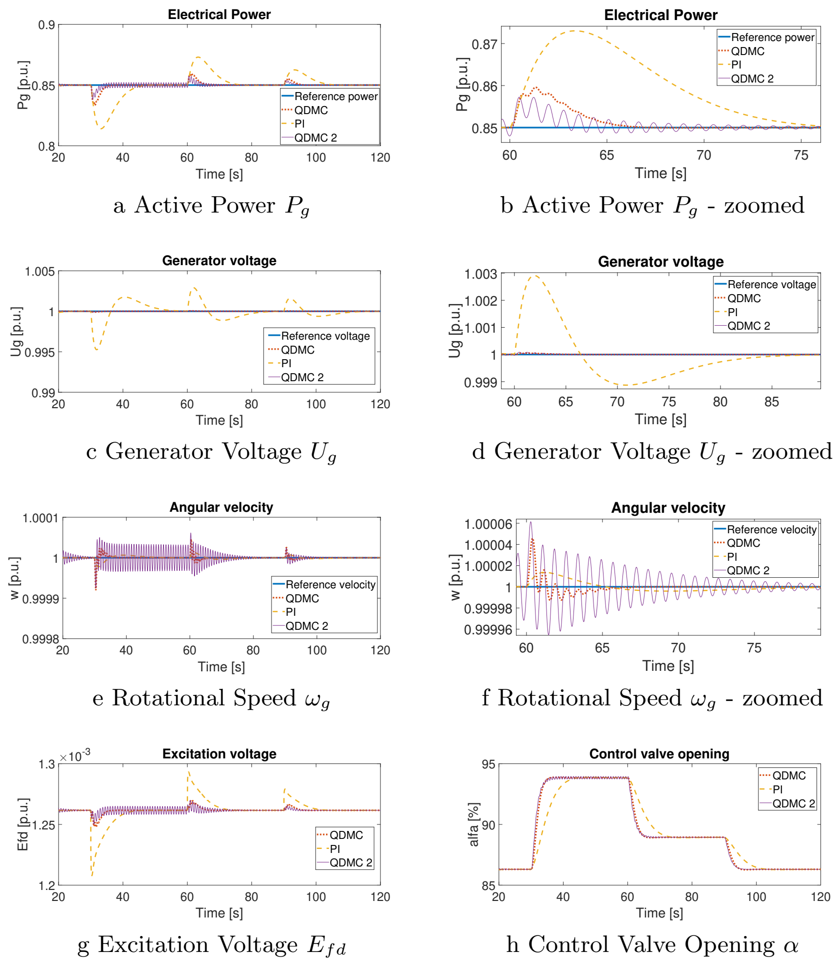
- a typical PI controller with a simple power system stabilizer [4, 6],
- two distributed MPC controllers with different parameters marked as DMPC_1 and DMPC_2, respectively.

It was assumed that the turbine-generator set operated in the power system via the simple infinite-bus [4, 6].

The synchronous generator PI controller and power system stabilizer were characterized by the following set of the parameters [6]: K_P, K_I, T_1, T_2 relating to the proportional, integral, derivative gains and integral/derivative time constants, respectively. Their numeric values may be found in Table I. The QDMC controllers are characterized by following parameters: the control step T, the prediction horizon p, the control horizon s, and the weights on the diagonal of the weights matrix $\boldsymbol{\Gamma}_T$ in the objective function solved by the turbine QDMC controller. Theirs numeric values may be either found in Table I.

The constraints considered in the simulation test with the QDMC controllers include the lower and upper bounds on the manipulated variable:s turbine control valve opening degree $\alpha \in [0, 100]$, and synchronous generator excitation voltage $E_{fd} \in [-0.1, 0.1]$.

To make some of the details more visible, along with the results of the whole experiment, also zoomed plot fragments for the short period after the 60th second will be shown (each experiment includes a different disturbance at this time).



a Active Power P_g b Active Power P_g - zoomed

c Generator Voltage U_g d Generator Voltage U_g - zoomed

e Rotational Speed ω_g f Rotational Speed ω_g - zoomed

g Excitation Voltage E_{fd} h Control Valve Opening α

Fig. 9: System response to a step change (+90%, −60%, −30%) of the heat demand in 30, 60 and 90th second of the simulation (with 60th second zoomed)

The results show that due to different controller parameters (prediction horizon) different robustness properties can be achieved. The QDMC controller with $p_T = 40$ follows the set power value, slower, though due to this property, it is capable of rejecting disturbances better, originating both from the side of the heat

Table 3: ISE criterion value for the heat demand step experiment (ISE_1 - $a = 1$, $b = 1$, $c = 1$ and ISE_2 - $a = 1$, $b = 100{,}000$, $c = 1$)

	PI	$DMPC_1$	$DMPC_2$
ISE P_g	1.03E − 02	6.90E − 04	2.60E − 04
ISE U_g	1.27E − 04	1.94E − 08	3.37E − 08
ISE ω_g	1.90E − 09	3.52E − 09	2.40E − 08
ISE_1	1.04E − 02	6.81E − 04	**2.63**E **− 04**
ISE_2	1.27E + 01	**2.62**E **− 03**	3.63E − 03

Table 4: ISE criterion value for the power system voltage step experiment (ISE_1 - $a = 1$, $b = 1$, $c = 1$ and ISE_2 - $a = 1$, $b = 100{,}000$, $c = 1$)

	PI	$DMPC_1$	$DMPC_2$
ISE P_g	1.88E − 03	7.18E − 02	3.30E − 01
ISE U_g	2.63E − 03	2.82E − 04	3.48E − 04
ISE ω_g	5.99E − 08	2.36E − 05	1.08E − 04
ISE_1	**4.51**E **− 03**	7.21E − 02	3.30E − 01
ISE_2	2.63E + 02	**2.83**E **+ 01**	3.51E + 01

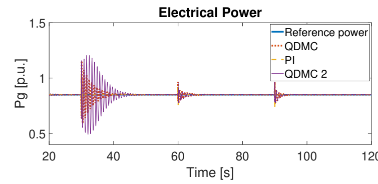
Table 5: ISE criterion value for the steam pressure step experiment (ISE_1 - $a = 1$, $b = 1$, $c = 1$ and ISE_2 - $a = 1$, $b = 100{,}000$, $c = 1$)

	PI	$DMPC_1$	$DMPC_2$
ISE P_g	9.17E − 01	6.41E − 01	6.57E − 01
ISE U_g	2.92E − 02	3.89E − 07	3.57E − 06
ISE ω_g	5.04E − 08	2.12E − 06	6.30E − 06
ISE_1	9.20E − 01	**6.41**E **− 01**	6.57E − 01
ISE_2	2.93E + 02	**6.80**E **− 01**	1.01E 00

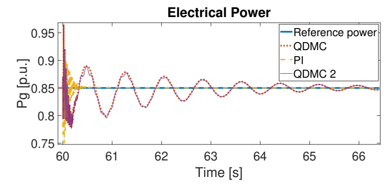
system, as well as from the power system. In both cases, the $QDMC_2$ controller - due to the stronger power stabilizing action - introduces much larger voltage and rotational speed oscillations.

6 Summary

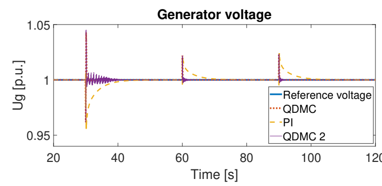
As part of the research, the impact of disturbances from the heating system and the power system on the operation of the control system of the nuclear power plant turbine-generator set was analyzed. This research is the follow up of the previous analysis of the model predictive control of the turbine-generator set of the nuclear power plant [5, 19] extending previous conclusions by the analysis



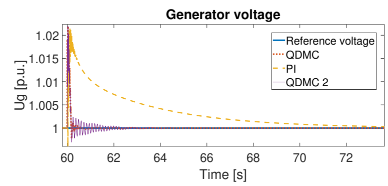
a Active Power P_g



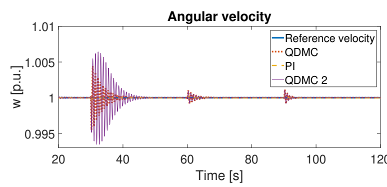
b Active Power P_g - zoomed



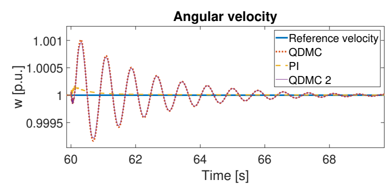
c [Generator Voltage U_g



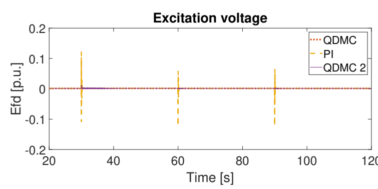
d Generator Voltage U_g - zoomed



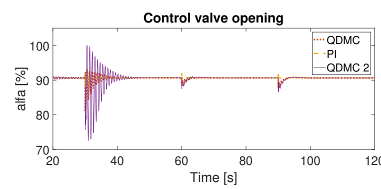
e Rotational Speed ω_g



f Rotational Speed ω_g - zoomed



g Excitation Voltage E_{fd}

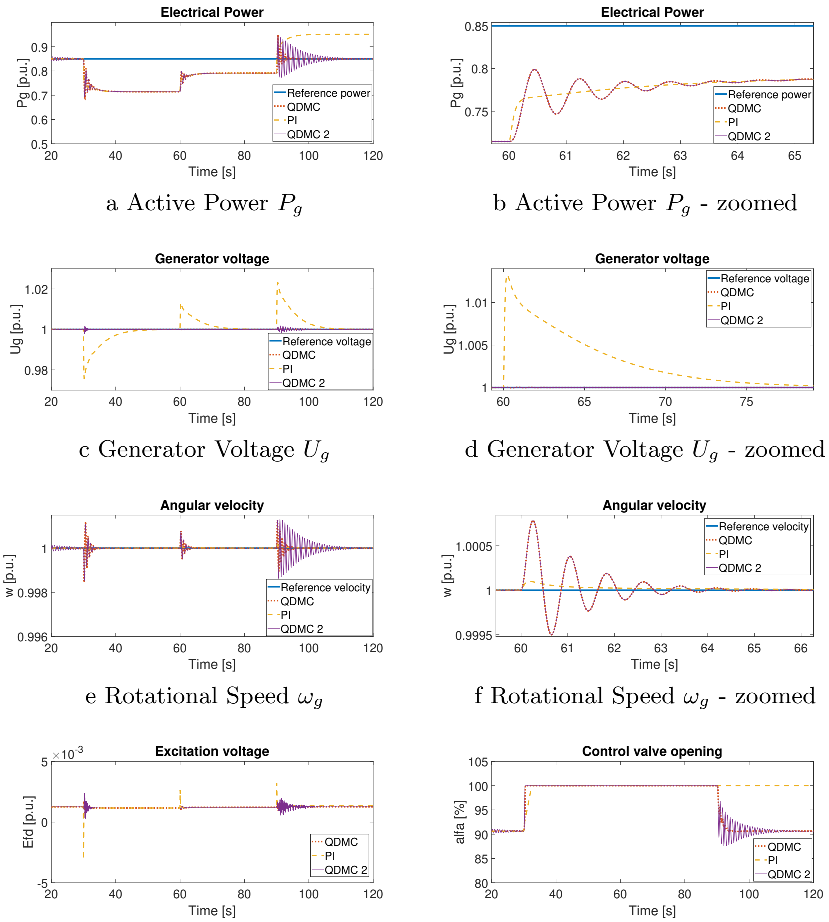


h Control Valve Opening α

Fig. 10: System response to a step change (-10%, $+5\%$, $+5\%$) of the power system voltage in 30, 60 and 90th second of the simulation(with 60th second zoomed)

of the system behaviour in the presence of external disturbances. Due to the requirements for the quality of electrical power and the operational safety of a nuclear power plant, it is necessary to analyze the system's robustness. The previous research performed by the authors on the distributed DMPC control of the turbine set required to be supplemented with tests and analysis of the proposed solution in the presence of various disturbances.

With respect to the reference-like PI performance for the heat load change experiment (Fig. 9), the maximum overshoot identified during transients in the case of QDMC1 control is reduced from 2.4% to 0.9%, and in the case of QDMC2 controller – to 0.55% as per electrical power measurements, but it comes with



a Active Power P_g

b Active Power P_g - zoomed

c Generator Voltage U_g

d Generator Voltage U_g - zoomed

e Rotational Speed ω_g

f Rotational Speed ω_g - zoomed

g Excitation Voltage E_{fd}

h Control Valve Opening α

Fig. 11: System response to a step change (-10%, $+5\%$, $+5\%$) of the steam pressure before the turbine's control valve in 30, 60 and 90th second of the simulation(with 60th second zoomed)

the cost of appearing power oscillations. It is related to high angular velocity oscillations with long settling time. For both QDMC1 and QDMC2, in the case of generator voltage, the overshot is almost two orders of magnitude smaller. In this case - as the overshoots are simmilar for QDMC1 and QDMC2 and better in both electric power and voltage stabilisation than the PI solution and because the slightly faster controller QDMC2 introduces unwanted oscillations it can be indicated that the QDMC1 shows the best performance in this experiment.

In the second experiment (Fig. 10) – step changes in the power system voltage - the overshoots identified during transients in the case of QDMC1, QDMC2 and PI control are similar, but PI and QDMC controllers show completely different behaviour. The system with the PI controller restores the set power faster than the QDMCs, but with the cost of slow setting of the generator voltage. On the other hand the QDMCs are much faster in stabilizing the voltage while introducing longer oscillations to the active power. In this case, QDMC2 – unlike in the previous experiment - shows worse performance as both QDMC1 and PI controllers.

The third experiment (Fig. 11) included the disturbance of the steam pressure at the control valve of the turbine. Because of the hard limitations of the valve neither of the controllers was able to keep the requested electrical power level. In the case of the generator voltage however both QDMCs allowed to achieve smaller disturbances (2.3% PI's overshoot to 0.1% for QDMCs) or to avoid them completely (in 60th second). In this experiment lack of the anti-windup in the PI controller also influences the results. Both QDMC controllers include the knowledge about plant model and it's limits. Due to the lack of the anti-windup the PI controller is not able to set the power at 85% after the nominal pressure is restored. Also in this experiment the QDMC2 introduced the bigest oscilations to the system.

The presented results together with the general analysis of the MPC control system of the turbine and the generator of a nuclear power plant [5, 19] confirm the possibility of using predictive control in the control of this type of facility. Adequate choice of controllers' parameters can change the systems behaviour from a faster one (quickly acting to the changes of the set active power steps or disturbances) to the more robust one (minimising all the oscillations of important process values after a disturbance). Even though the purpose of the power plant is to produce electrical energy and it is determined by the power provided to the power system, the quality of the energy is also very important. It is very important to provide voltage and frequency stabilization, and in this context $DMPC_1$ shows better performance as the $DMPC_2$ and PI controllers.

The value of a proper choice of prediction horizons is visible also in the newest research, see for example the paper [35]. This might be a potentially attractive direction to couple MPC optimization with parallel tuning of prediction horizons, using, e.g. [36].

Subsequent works will focus on analysing the behaviour of the generator controller (with constant turbine MPC parameters) and a precise multi-parameter tuning of the whole distributed control system in presence of external disturbances.

References

1. T. Lipo, "Analysis of synchronous machines," *CRC Press*, 2012.
2. P. Kundur, "Dynamic models for steam and hydro turbines in power system studies," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-92, no. 6, pp. 1904–1915, 1973.
3. ——, "Analysis of synchronous machines," *Power system stability and control*, 1994.

4. P. Sokolski, T. Rutkowski, and K. Duzinkiewicz, "The excitation controller with gain scheduling mechanism for synchronous generator control," *2015 20TH International Conference on Methods and Models in Automation and Robotics (MMAR)*, pp. 23–28, 2015.
5. ——, "The QDMC model predictive controller for the nuclear power plant steam turbine control," *Trends in Advanced Intelligent Control, Optimization and Automation. KKA 2017. Advances in Intelligent Systems and Computing*, vol. 577, pp. 241–250, 2017.
6. P. Sokólski, A. Kobylarz, K. Kulkowski, K. Duzinkiewicz, T. Rutkowski, and M. Grochowski, "Advanced control structures of turbo generator system of nuclear power plant," *Acta Energetica*, vol. 3, pp. 83–96, 2015.
7. M. Grochowski and T. Rutkowski, "Supervised model predictive control of wastewater treatment plant," *21ST International Conference on Methods and Models in Automation and Robotics (MMAR)*, pp. 613–618, 2016.
8. A. Ciminski and K. Duzinkiewicz, "Optimized robust model predictive control - application to drinking water distribution systems hydraulics," *IFAC Proceedings Volumes*, vol. 43, no. 8, pp. 395–400, 2010.
9. M. Drewa, M. Brdys, and A. Cimiñski, "Model predictive control of integrated quantity and quality in drinking water distribution systems," *IFAC Proceedings Volumes*, vol. 40, no. 5, pp. 95–100, 2007.
10. B. Puchalski, K. Duzinkiewicz, and T. Rutkowski, "Multi-region fuzzy logic controller with local PID controllers for u-tube steam generator in nuclear power plant," *Archives of Control Sciences*, vol. 25, no. 4, p. 429444, 2015.
11. M. Czapliński, P. Sokólski, K. Duzinkiewicz, R. Piotrowski, and T. Rutkowski, "Comparison of state feedback and PID control of pressurizer water level in nuclear power plant," *Archives of Control Sciences*, vol. 23, no. 4, pp. 381–398, 2013.
12. B. Puchalski, T. Rutkowski, J. Tarnawski, and K. Duzinkiewicz, "Comparison of tuning procedures based on evolutionary algorithm for multi-region fuzzy-logic PID controller for non-linear plant," *20th International Conference on Methods and Models in Automation and Robotics*, pp. 897–903, 2015.
13. E. Camponogara, D. Jia, B. Krogh, and S. Talukdar, "Distributed model predictive control," *IEEE Control Systems*, vol. 22, no. 1, pp. 44–52, 2002.
14. P. Cristofides, R. Scattolini, D. de la Pena, and L. Jinfeng, "Distributed model predictive control: A tutorial review and future research directions," *Computers and Chemical Engineering*, vol. 51, pp. 21–41, 2013.
15. E. Camacho and C. Alba, "Model predictive control," *Springer Science & Business Media*, 2013.
16. J. Rossiter, "Model-based predictive control: A practical approach," 2013.
17. P. Tatjewski, "Advanced control of industrial processes," 2007.
18. E. Carlos and A. Morshedi, "Quadratic programming solution of dynamic matrix control (QDMC)," *Chemical Engineering Communications*, vol. 46, no. 1-3, pp. 73–87, 1986.
19. P. Sokólski, T. Rutkowski, and K. Duzinkiewicz, "The distributed model predictive controller for the nuclear power plant turbo-generator set," *Trends in Advanced Intelligent Control, Optimization and Automation. KKA 2017. Advances in Intelligent Systems and Computing*, vol. 577, pp. 682 – 687, 2017.
20. R. Afonso and R. Galvão, "Infeasibility handling in constrained MPC," *Frontiers of Model Predictive Control*, pp. 47 – 64, 2012.
21. J. M. Maciejowski, "Predictive control: With constraints," 2002.
22. R. Hakvoort, "System identification for robust process control : nominal models and error bounds," *Technische Universitet Delft*, 1994.

23. P. Sokolski, "Implementation of robust estimation methods for regulatory purposes predictive MPC type," *Innovative solutions in the automation area*, vol. 22, no. 1, pp. 44–52, 2011.
24. A. Imieliński, "Mathematical model of synchronous generator for full-scope simulator," *Gdañsk University of Technology, Faculty of Electrical and Control Engineering*, 1987 - unpublished.
25. S. Perycz and W. Próchnicki, "The mathematical model of a nuclear power plant VVER block steam turbine allowing to study transient processes with $w = var$," *Gdañsk University of Technology, Faculty of Electrical and Control Engineering*, 1989 - unpublished.
26. B. Puchalski, T. Rutkowski, and K. Duzinkiewicz, "Multinodal PWR reactor model -methodology proposition for power distribution coefficients calculation," *21st International Conference on Methods and Models in Automation and Robotics*, pp. 385–390, 2016.
27. K. Kulkowski, A. Kobylarz, M. Grochowski, and K. Duzinkiewicz, "Dynamic model of nuclear power plant steam turbine," *Archive of Control Science*, vol. 25, no. 1, pp. 65–86, 2015.
28. K. Kulkowski, M. Grochowski, K. Duzinkiewicz, and A. Kobylarz, "Nuclear power plant steam turbine - modeling for model based control purposes," *Applied Mathematical Modelling*, vol. 48, pp. 491–515, 2017.
29. D. Juszczuk, J. Tarnawski, T. Karla, and K. Duzinkiewicz, "Real-time basic principles nuclear reactor simulator based on client-server network architecture with webbrowser as user interface," *Advances in Intelligent Systems and Computing*, vol. 577, pp. 344–353, 2017.
30. J. Tarnawski and T. Karla, "Real-time simulation in non real-time environment," *21st International Conference on Methods and Models in Automation and Robotics (MMAR)*, pp. 577–582, 2016.
31. T. Karla, J. Tarnawski, and K. Duzinkiewicz, "Cross-platform real-time nuclear reactor basic principle simulator, journal = 20th International Conference on Methods and Models in Automation and Robotics (MMAR), year = 2015, pages = 1074-1079,."
32. C. Loo, L. Vanfretti, E. Liceaga-Castro, and E. E. Acha, "Synchronous generators modeling and control using the framework of individual channel analysis and design: Part 1," *International Journal of Emerging Electric Power Systems*, vol. 8, no. 5, 2007.
33. P. Sokolski, T. Rutkowski, and K. Duzinkiewicz, "Simplified, multiregional fuzzy model of a nuclear power plant steam turbine," *21ST International Conference on Methods and Models in Automation and Robotics (MMAR)*, pp. 379–384, 2016.
34. P. S. D. P. Committee, "Dynamic models for turbine–governors in power system studies," *IEEE Power & Energy Society*, 2013.
35. M. R. Nebeluk, "Tuning of multivariable model predictive control for industrial tasks," *Model Predictive Control: Algorithms and Applications*, 3 January 2021.
36. W. Giernacki, D. Horla, T. Báča, and M. Saska, "Real-time model-free minimum-seeking autotuning method for unmanned aerial vehicle controllers based on Fibonacci-search algorithm," *Sensors*, vol. 19, p. 312, 2019.