ISSN: 2414-1895 DOI: 10.6919/ICJE.202106_7(6).0069

Design of Neural Network Speed Controller for Marine Diesel Generator Set

Yi Ding, Weifeng Shi, Yuanrui Zhang and Haiming Guo

Logistics Engineering College, Shanghai Maritime University, Shanghai 201306, China.

Abstract

Aiming at the nonlinear characteristics of marine diesel generator power regulation process, fuzzy theory and artificial intelligence control methods are studied. A method of combining neural network and fuzzy control is proposed and applied to the power control of marine diesel generators. The compound control method can realize the joint control of feedforward and feedback, wherein the feedforward control neural network realizes feedback control by a conventional controller. A generator set control method combining neural network and fuzzy PID control is realized. By comparing and analyzing the simulation results of compound control and conventional control, it can be seen that when the ship load changes suddenly, this control method has smaller overshoot and shorter stabilization time than the traditional control method. Experiments show that the compound control can achieve better control effects, which is beneficial to improve the stability, rapid response and robustness of the ship's power system in operation.

Keywords

Diesel Generator Set Adjustment; Neural Networks; Compound Control.

1. Introduction

Diesel generator sets have been widely used as an important main power source or backup power source. The application and promotion of intelligent control systems in diesel generator sets can help improve the output power quality of diesel generator sets and the automation level of diesel generator sets. This article mainly studies the control part of diesel generator sets. Most of the existing engine speed control systems adopt traditional PID control schemes.

With the continuous increase in the number and scale of marine electrical equipment, the marine power system needs to be frequently suddenly added and unloaded during the operation of high-power loads. In this process, the characteristics of the controlled object are approximately unchanged. Automatic Voltage Regulator (AVR) control has been unable to meet the needs of the development of modern ship power systems, resulting in a pure PID control that has been difficult to meet the demand.

With the development of science and technology, modern diesel electronically controlled speed regulation systems are increasingly adopting high-end chips and intelligent control algorithms, greatly improving the speed regulation effect and other operating performance of diesel engines to the original extent. Therefore, this article aims to improve the power quality output by diesel generator sets, and designs a diesel generator set speed control system to ensure that the generator sets can output stable electrical energy.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202106_7(6).0069

2. CMAC Parallel Fuzzy PID Control Algorithm

2.1 Section Headings

The cerebellar neural network (CMAC-Cerebellar Model Articulation Controller) was originally proposed by Albus in 1975 based on neurophysiology. It is a simple and fast neural network based on local approximation, which can learn any multi-dimensional nonlinear fitting.

The traditional PID control strategy requires the controlled object to have an accurate mathematical model. If the controlled object is difficult to model, it can be combined with fuzzy control. Fuzzy control is to transform the technical staff's years of adjustment experience and summary into a fuzzy language, and write a series of control rules according to the standard. According to these control rules, the control target of the controlled object can be achieved. Through this combination, the two control methods interact, reduce the limitations of the two methods, and can better cope with the complex controlled objects and environment.

Due to the complexity of the control object, continuous online self-tuning of the control parameters is required. However, the traditional PID control method is powerless in this respect, and it needs to be combined with fuzzy control for functional realization. First, set the input variables according to the specific control requirements and the law of the PID control method. Generally, our input variables include input error and error rate of change. The two parameters represent the static and dynamic performance of the system respectively.The output variables of the fuzzy controller are PID real-time control parameters , , . By continuously updating the control parameters,, to realize online parameter self-tuning. Fuzzy PID can not only meet the basic control requirements required for production, but also improve the stability accuracy.

The feedforward-feedback parallel structure is adopted, in which the feedforward control is realized by the CMAC controller, and the feedback control is controlled by the fuzzy PID controller.

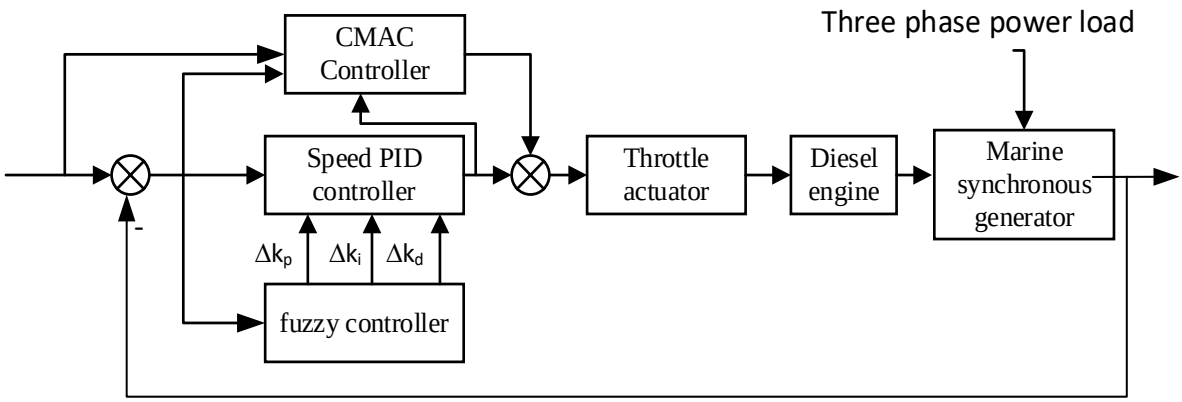


Figure 1. CMAC/Fuzzy PID compound control structure diagram

From the CMAC/Fuzzy PID composite control structure diagram shown in Fig.1, it can be seen that the speed PID controller and the fuzzy controller form an improved control. The fuzzy controller is used to improve the K_p, K_i and K_d of the PID controller, which is controlled by the PID The output of the device is used to train the CMAC neural network.When there is a deviation between the power output of the diesel engine and the power demand (given value), the fuzzy PID controller realizes the feedback control, and at the same time, the adjustment signal is transmitted to the CMAC controller to help its training; when the output power of the diesel engine and the power demand (to Fixed value) When the dynamic deviation is 0, the output of the fuzzy PID controller is zero, and the total output of the control system is the output of the CMAC controller. The CMAC controller will control the diesel engine according to the feedforward signal (power demand) to achieve feedforward Joint control with feedback. The structure of CMAC is shown in Fig.2.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202106_7(6).0069

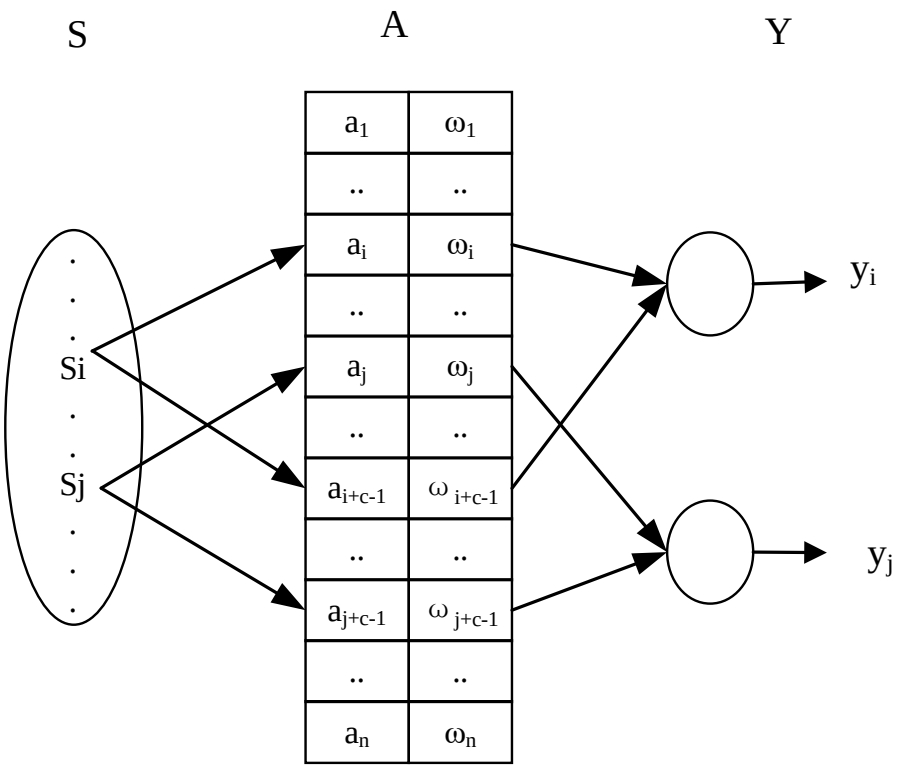


Figure 2. CMAC structure diagram

The control algorithm of CMAC parallel fuzzy PID control system is

$$u_n(k) = \sum_{i=1}^{c} \omega_i a_i \tag{1}$$

$$u(k) = u_n(k) + u_p(k) \tag{2}$$

In the formula, a_i is the binary selection value, which is 1 when activated, otherwise it is 0; $\omega=[\omega_1, \omega_2, \cdots, \omega_{n-1}, \omega_n]^{\mathrm{T}}$ is the weight vector of the mapping vector; c is the generalization parameter; $u_n(k)$, $u_p(k)$ are the output values of the CMAC controller and the PID controller, respectively.

In the compound control system, the CMAC network concept is mapped as: divide the input space S into $N_{+2}c$ quantization intervals in the interval $[S_{\min}, S_{\max}]$, namely

$$v_1 \quad \dots \quad v_c = S_{min} \tag{3}$$

$$v_j = v_{j-1} + \Delta v_j \quad (j = c+1, \dots, c+1) \tag{4}$$

$$v_{N+c+1} \quad \dots \quad v_{N+2c} = S_{max} \tag{5}$$

The actual mapping method of CMAC is: if $S_j \in [v_j, v_{j+c}] (j = c+1, \dots, c+N)$, then a_j take 1; otherwisetake 0.

It can be seen from Fig.1 that the CMAC network uses a learning algorithm with a tutor, and the fuzzy PID controller helps to train the CMAC neural network. At the completion of each control cycle, the control system compares the CMAC output value with the total control output value, and corrects the weight based on the comparison result to minimize the absolute value of the difference. After the continuous learning and weight correction of the CMAC network, the total control output of the system is finally the output value of the CMAC controller.

The adjustment index of CMAC is

$$E(k) = \frac{1}{2c}[u_n(k) - u(k)]^2 \tag{6}$$

ISSN: 2414-1895 DOI: 10.6919/ICJE.202106_7(6).0069

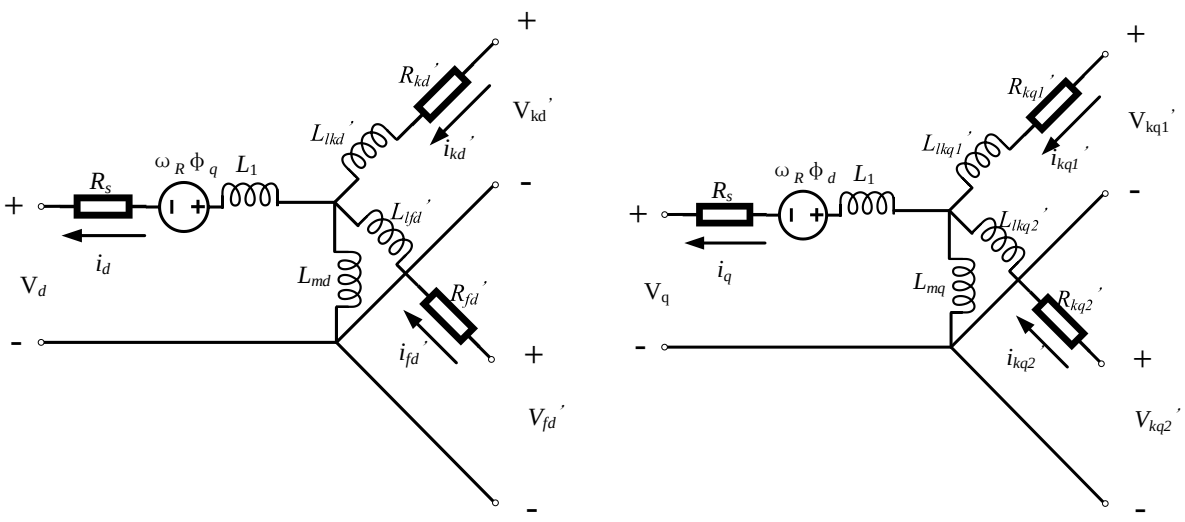
$$\Delta\omega_i(k) = -\eta\frac{\partial E(k)}{\partial\omega_i} = \eta\frac{u(k)-u_n(k)}{c}a_i = \eta\frac{u_p(k)}{c}a_i \tag{7}$$

$$\omega_i(k) = \omega_i(k-1) + \Delta\omega_i(k) + \alpha[\omega_i(k) - \omega_i(k-1)] \tag{8}$$

Where $\omega_i(k)$ is the modified weight of the activated unit, $\omega_i(k-1)$ is the weight before modification, $\Delta\omega_i(k)$ is the weight change; η is the network learning rate, $\eta \in (0,1)$; α is the inertia coefficient, $\alpha \in (0,1)$.

3. CMAC parallel fuzzy PID compound control modeling

The CMAC neural network parallel control system designed in this paper is used in a large-scale ship power simulation system for simulation tests. The simulation uses a 6.6kV, 60Hz ship medium voltage power system composed of four marine diesel generator sets, and the rated power of each generator is The power is 3MW, the small load of the system is some marine auxiliary pumps, and the large load is the ship propulsion (rated voltage is 6.6kV, rated power is 2.5MW). In the simulation system, the synchronous generator adopts a sixth-order model, as shown in Figure 3.



(a) d-axis reference model (b) q-axis reference model

Figure 3. Reference model of d-q axis of synchronous generator

In the figure, V_x represents voltage, R_x represents resistance, i_x represents current, φ_x represents magnetic flux, L_x represents inductance, V_{fd} represents excitation voltage, i_{fd} represents excitation current. The subscript d, q indicate the variables of the d-axis and the q-axis; the subscript s, R indicate the variables of the stator and rotor; the subscript l, m indicate the variables of the leakage and mutual inductance; the subscript f, k indicate the variables of the excitation winding and the damping winding. All electrical quantities are calculated from the stator side, and the variables marked with " ' " are converted to the rotor side electrical quantities on the stator side. For synchronous generators, there are the following differential equations:

$$V_d = -R_s i_d + \frac{d}{dt}\varphi_d - \omega_R\varphi_q, V_q = -R_s i_q + \frac{d}{dt}\varphi_q + \omega_R\varphi_d$$

$$V'_{fd} = R'_{fd}i'_{fd} + \frac{d}{dt}\varphi'_{fd}, V'_{kd} = R'_{kd}i'_{kd} + \frac{d}{dt}\varphi'_{kd}$$

$$V'_{kq1} = R'_{kq1}i'_{kq1} + \frac{d}{dt}\varphi'_{kq1}, V'_{kq2} = R'_{kq2}i'_{kq2} + \frac{d}{dt}\varphi'_{kq2},$$

ISSN: 2414-1895 DOI: 10.6919/ICJE.202106_7(6).0069

$$\varphi_d = L_d i_d + L_{md}\left(i'_{fd} + i'_{kd}\right), \varphi_q = L_q i_q + L_{mq} i'_{kq}, \varphi'_{fd} = L'_{lfd} i'_{fd} + L_{md}\left(i_d + i'_{kd}\right),$$

$$\varphi'_{kq1} = L'_{lkq1} i'_{kq1} + L_{mq} i_q, \varphi'_{kd} = L'_{lkd} i'_{kd} + L_{md}\left(i_d + i'_{fd}\right), \varphi'_{kq2} = L'_{lkq2} i'_{kq2} + L_{mq} i_q.$$

In the marine power system simulation system, the rated power of the marine generator is 3.125MW, the rated voltage is 6.6kV, and the frequency is 60Hz. The PID parameters of the control system are: the proportional coefficient is 40, the integral coefficient is 25, and the differential coefficient is 0.25. The realization of graphical interface realized by MATLAB programming composed of CMAC neural network parallel fuzzy PID controller and diesel prime mover is shown in Fi.4. The input "① — $wref(pu)$" is the specified unit value of the speed, "② — $w(pu)$" is the actual measured unit value of the speed, and the output "③ — $Pmec(pu)$" is the unit value of the output torque and power of the diesel engine. The CMAC neural network algorithm is implemented in MATLAB's m file format. The diesel engine outputs mechanical torque power, which is used to drive a synchronous generator to generate electrical power.

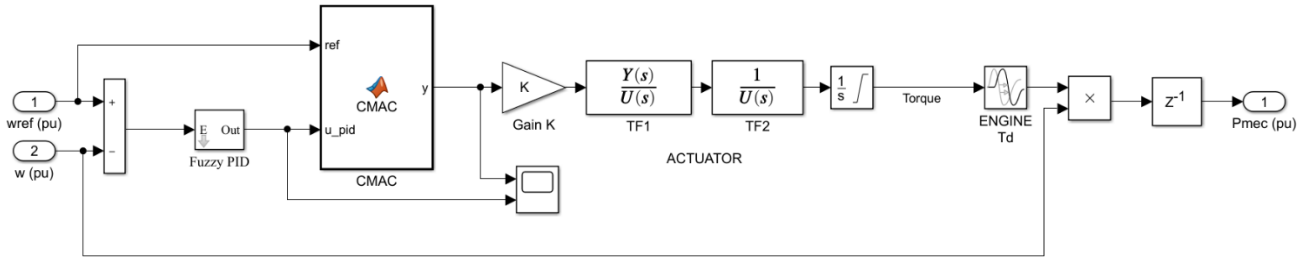


Figure 4. CMAC neural network parallel fuzzy PID control and diesel prime mover system structure

4. System simulation results

In the simulation, the generator of the marine power system is a 6.6kV synchronous generator, and the electrical parameters are: $P_n = 3.125\times10^6$ VA, $V_n = 6600$ V, $f_n = 60$ Hz; $R_s = 0.0036$; $p = 2$; $X_d = 1.56$, $X_d' = 0.296$, $X_d'' = 0.177$, $X_q = 1.06$, $X_q' = 0$, $X_q'' = 0.177$, $X_1 = 0.052$; $T_d' = 3.7$ s, $T_d'' = 0.05$ s, $T_{q0}'' = 0.05$s. Dimensionless is the standard unit value.

In order to form a comparison, this article first builds a simulation model of an ordinary PID controller to simulate the speed control of a diesel generator set with pure PID control.

The power system of marine diesel generator set speed PID control is tested with a sudden increase of 20% of the generator's rated power, and the input load is a sudden step signal characteristic load. The operation of the generator set system was measured. The torque power per unit value (pu) of the generator set and the speed per unit value (pu) of the generator set are shown in Figure 5. The abscissas in the figure are all time (s). It can be clearly seen from the figure that the simulated power system suddenly adds a load of 20% of the rated power of the diesel generator set in 5s. It can be seen from the simulation results that the overshoot of the PID control system is still very large, and the mechanical power output waveform has obvious spikes.

Next, the simulation test of the CMAC neural network parallel fuzzy PID controller designed in this paper is carried out. In order to reflect the rigor of the test and to better visualize the advantages of the results, the ship simulation system is the same as the PID control governor above. An input load is a characteristic load of sudden step signal, and the same size is 20% of the rated power of the generator set. When the CMAC neural network parallel fuzzy PID controller controls the generator set, the torque power per unit value (pu) of the generator set and the speed per unit value (pu) of the generator set are shown in Figure 6, and the abscissas in the figure are both Is the time (s).

ISSN: 2414-1895 DOI: 10.6919/ICJE.202106_7(6).0069

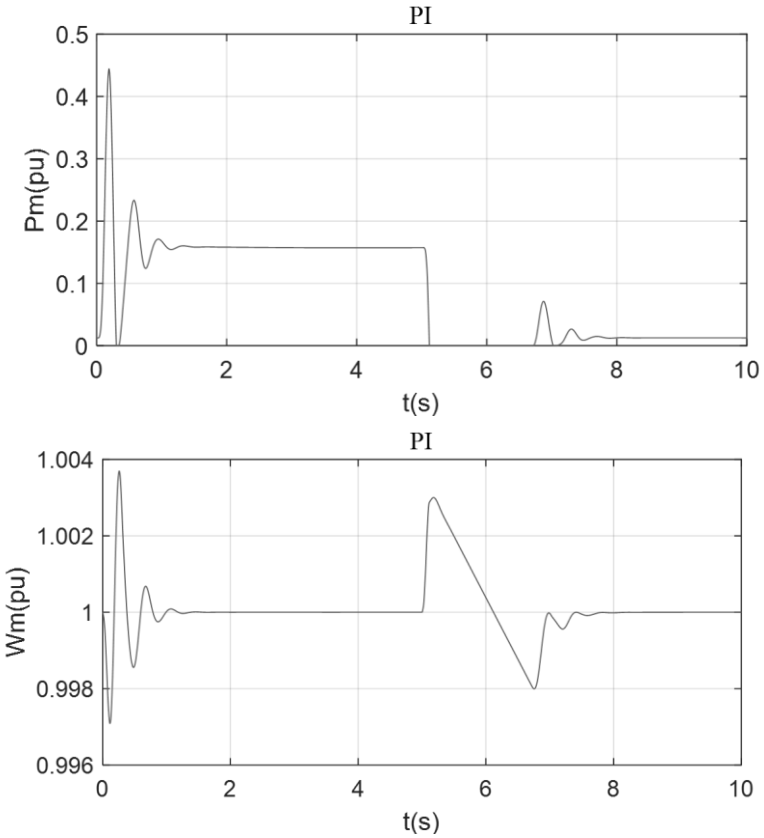


Figure 5. Speed response characteristic of PID control system suddenly reducing 20% load torque power

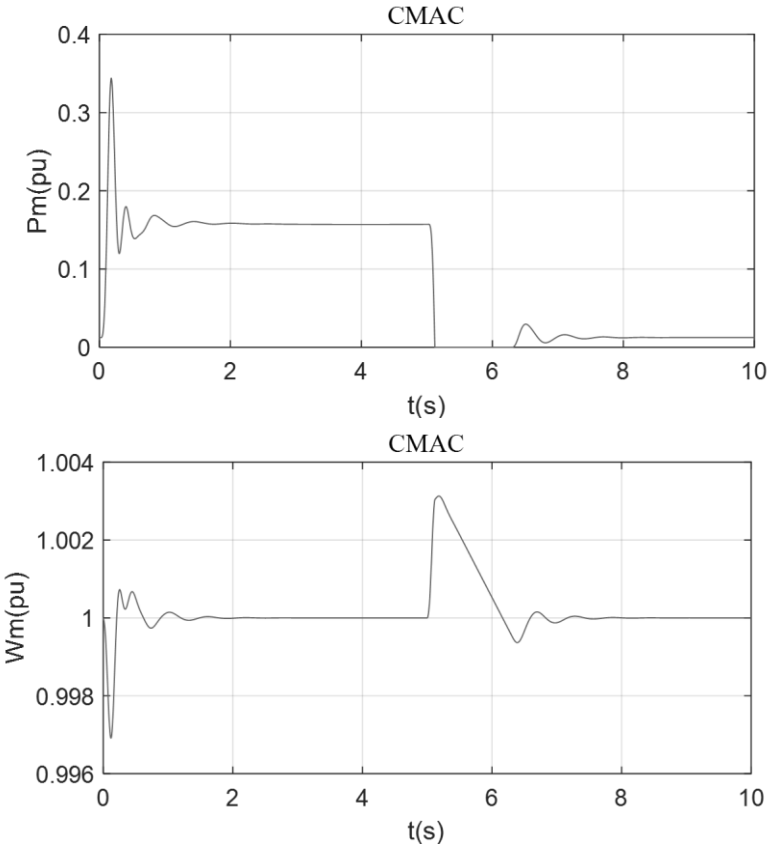


Figure 6. Speed response characteristics of CMAC neural network parallel fuzzy PID control system suddenly reducing 20% load torque power

ISSN: 2414-1895 DOI: 10.6919/ICJE.202106_7(6).0069

Comparing the simulation waveforms of PID controller and CMAC neural network parallel fuzzy PID controller controlling the speed of diesel generator set, it can be seen that the torque and speed overshoot under the control of CMAC neural network parallel fuzzy PID controller is smaller, and the time required for stability is longer. short. Greatly improve the stability, rapidity and robustness of diesel generator sets.

Acknowledgments

This works is supported by a fund project: The Shanghai Science and Technology Committee (STCSM) Project (Project Name: Research on Intelligent self-healing of ship regional distribution power system, Project No.:20040501200).

References

[1] Shin Kiyohara,Teruyasu Mizoguchi. Radial Distribution Function from X-ray Absorption near Edge Structure with an Artificial Neural Network[J]. Journal of the Physical Society of Japan,2020,89(10).

[2] J. Knudsen J. Bendtsen P. Andersen and K. Madsen "Self-tuning linear quadratic supervisory regulation of a diesel generator using large-signal state estimation" Proc. Aust. Control Conf. pp. 32-37 2016.

[3] J. Knudsen J. Bendtsen P. Andersen K. Madsen and C. Sterregaard "Control-oriented first principles-based model of a diesel generator" Proc. Eur. Control Conf. pp. 321-327 2016.2.

[4] L. Reznik, O. Ghanayem, and A. Bourmistrov, “PID plus fuzzy controller structures as a design base for industrial applications,” Eng. Appl. Artif. Intell, vol. 13, pp. 419–430, 2000.

[5] L. Angel and J. Viola, "Design and statistical robustness analysis of FOPID, IOPID and SIMC PID controllers applied to a motor-generator system," in IEEE Latin America Transactions, vol. 13, no. 12, pp. 3724-3734, Dec. 2015, doi: 10.1109/TLA.2015.7404900.

[6] J. Knudsen, J. D. Bendtsen, P. Andersen, K. K. Madsen and C. H. Sterregaard, "Supervisory Control Implementation on Diesel-Driven Generator Sets," in IEEE Transactions on Industrial Electronics, vol. 65, no. 12, pp. 9698-9705, Dec. 2018, doi: 10.1109/TIE.2018.2811389.

[7] D. J. McGowan, D. J. Morrow and B. Fox, "Integrated governor control for a diesel-generating set," in IEEE Transactions on Energy Conversion, vol. 21, no. 2, pp. 476-483, June 2006, doi: 10.1109/ TEC. 2006.874247.

[8] N. Moaddabi, S. H. Hosseinian, G. B. Gharehpetian. Practical Framework for Self-healing of Smart Grids in Stable/Unstable Power Swing Conditions[J]. Electric Power Components and Systems,2012,40(6).

[9] Zhang W, Shi W, Wang G, et al. AN IMPROVED MODEL-FREE ADAPTIVE CONTROL OF MARINE GENERATOR EXCITATION SYSTEM[J]. International Journal of Robotics & Automation, 2017, 32(6):616-624.