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BDI Agent and QPSO-based Parameter Optimization for a Marine Generator Excitation Controller

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ABSTRACT
An intelligent optimization algorithm for a marine generator excitation controller is proposed to improve dynamic performance of shipboard power systems. This algorithm combines a belief–desire–intention agent with a quantum-behaved particle swarm optimization (QPSO) algorithm to optimize a marine generator excitation controller. The shipboard zonal power system is simulated under disturbance due to load change or severe fault. The results show that the proposed optimization algorithm can improve marine generator stability compared with conventional excitation controllers under various operating conditions. Moreover, the proposed intelligent algorithm is highly robust because its performance is insensitive to the accuracy of system parameters.

KEYWORDS: Shipboard power systems, marine generator, excitation control, belief-desire-intention agent, quantum-behaved particle swarm optimization.

1 INTRODUCTION

ALL-electric ships are being developed rapidly for marine applications in the commercial and the military sectors (Apsley et al., 2009). Electric propulsion for ships not only enables marine generators to work under optimum conditions to reduce fuel consumption but also enhances the dynamic performance of the power system. With the development of power capacity for electric ships, the capacity of equipment, especially the propulsion motor, is increasing to the point where it is larger than that of the generator. This changes the working conditions of the shipboard power system, which could lead to severe faults in the equipment. Such faults could affect the stability of the entire shipboard power system (Rosado et al., 2009). Thus, an effective control method to improve stability and performance of marine generators under dynamic operating conditions is urgently required.

Excitation control, which is one of the most effective and economical techniques, has attracted considerable attention for improving the dynamic performance of power systems (Cheng, Malik, & Hope, 1988). Many types of power system control approaches have been reported in the literature, including feedback linearization control (Arif, Ray, & Chaudhuri, 2013), fuzzy logic control (Laghari et al., 2014; Jemai, Trabelsi, & Ouederni, 2014; Hosseini, Tousi, & Razmjooy, 2014), robust control (Zhang, Wang, & Xiao, 2011), nonlinear predictive control (Yao et al., 2014), artificial intelligence (Mehraeen, Jagannathan, & Crow, 2011; Ganesan, Vasant, & Elamvazuthi, 2014), and adaptive control (Fusco & Russo, 2008). To improve the dynamic stability of power systems, the particle swarm optimization (PSO) algorithm and the Takagi-Sugeno fuzzy algorithm have been studied for optimizing power system stabilizer (PSS) parameters (Soleymani, Yoosofi, & Kandi-D, 2015) and reducing the fuel consumption of a conventional medium-sized ship (Keumarsi, Simab, & Shahgholian, 2014).

Recently, an increasing number of researchers have been focusing on the multi-agent method, which is a typical distributed control method, especially for the belief-desire-intention (BDI) agent with logical reasoning characters and learning ability. Application of the abovementioned centralized control methods to shipboard power system control, which has an inherently distributed character, is difficult. For decentralized control, multi agent systems (MASs) have been applied to power engineering applications (McArthur et al., 2007), credit management (Jiang et al., 2016), and the BDI agent has been employed for

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integrated hybrid energy system management and control (Dou et al., 2016). MASs have outstanding characteristics, such as intelligence, flexibility, extensibility, and fault tolerance, rendering them suitable for application to excitation control for shipboard generators. The BDI agent, one of the typical deliberation agents, has been adopted in power restoration (Ren et al., 2014). Fuzzy cognitive mapping and PSO have been employed in a MAS deliberation study (Karavas et al., 2015). However, although the PSO algorithm converges fast, it is prone to become trapped in local optima (Cao, Zhu, & Yang, 2015). Many improved PSO method has been studied (Wang et al, 2016), inspired by trajectory analysis of the PSO and quantum mechanics, Sun, Liu, and Xu (2007) developed and proposed the quantum-behaved particle swarm optimization (QPSO) algorithm. The QPSO can not only find the optimal solution in a given search space but also has the advantages of fewer control parameters, simpler software programming, and relatively fast convergence. Experimental results obtained using prominent benchmark functions revealed that the QPSO performs better than the standard PSO and is therefore a promising algorithm. Fuzzy logic (Shen, O'Hare, & Collier, 2004; Casali, Godo, & Sierra, 2011) and even quantum cognition (Bisconti et al., 2015) have been used in BDI agent decision-making.

The present study was inspired by previous studies on QPSO, specifically its application to cognitive sciences (Bisconti et al., 2015), and BDI modelling of decision-making processes (Zhao X, & Son Y J., 2015). In this study, we merge the two aforementioned approaches into a single structure to improve the dynamic performance of an electric ship power system. To this end, we employ the proposed BDI agent and the QPSO combined algorithm to optimize the parameters of a marine generator excitation controller. A simulation is performed to determine the control performance of the proposed method for electrical propulsion in a shipboard power system and in a shipboard zonal power system under load change disturbance and severe fault conditions, respectively.

The remainder of this paper is organized as follows. In section 2, the basic excitation control system for electric ships is described. In section 3, the PSS parameter optimization strategy based on the BDI agent and QPSO is presented. To illustrate the effectiveness and efficiency of the proposed method, simulation examples of the electrical propulsion shipboard power system and the shipboard zonal power system under load change disturbance and severe fault are given in section 4. Finally, concluding remarks are provided in section 5.

2 EXCITATION CONTROL FOR ELECTRIC SHIPS

2.1 *Diesel engine generator set*

A marine generator consists of three main components, namely a diesel engine, a synchronous generator, and an excitation system. The diesel engine supplies mechanical power P_m to the synchronous generator and converts fossil fuel into electrical power P_e . A schematic diagram of the proposed marine generator system and its detailed description are shown in Figure 1.

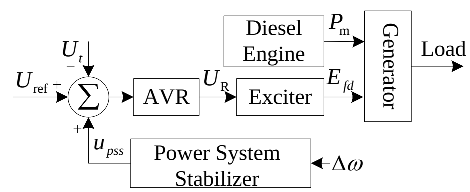


Figure 1. Schematic diagram of proposed marine generator system

As shown in Figure 1, the generator controls the diesel engine power P_m and the exciter E_{fd} . In this paper, changes in the diesel engine power have been ignored, which means that $P_m = \text{constant}$. The generator exciter control includes an automation voltage regulator (AVR) and the PSS; the PSS consists of a gain, a washout, and a lead-lag compensator. The input signal to the PSS is the deviation in rotor speed $\Delta\omega$, and the output of the PSS is the control signal to the exciter u_{pss} . The transfer function of the AVR is $G_{\mathrm{AVR}}(s) = K_A/(1+sT_A)$, where K_A and T_A are the gain and time constants, respectively.

2.2 *Excitation design for the marine generator set*

According to the schematic diagram of the proposed marine generator system shown in Figure 1, among the various characteristics of the electric shipboard power system, the reactance of the transmission line and the transformer is considered, whereas the resistance of the stator winding is ignored. Thus, the pragmatic model of the i th marine generator can be described by the following equation (Zhao et al., 2015):

$$\begin{cases}\dot{\delta}_i = (\omega_i - 1)\omega_s \\ \dot{\omega}_i = \dfrac{P_{mi} - P_{ei} - D_i(\omega_i - 1)}{2H_i} \\ \dot{E}'_{qi} = \dfrac{E_{fdi} - E'_{qi} - (x_{di} - x'_{di})I_{di}}{T'_{d0i}} \qquad (i = 1, 2, \cdots, n) \\ \dot{E}_{fdi} = \dfrac{K_{Ai}(U_{\text{ref}} - U_{ti} + u_{pssi} - E_{fdi})}{T_{Ai}}\end{cases} \tag{1}$$

where δ_i and ω_i are the rotor angle and rotor speed of the i th generator, respectively; ω_s is the generator synchronous speed; P_{mi} is the mechanical power output of the diesel engine; P_{ei} is the electric power of the i th generator, $P_{ei} = E'_{qi} I_{qi}$; E'_{qi} is q axis transient potential, in p.u. (per unit); D_i and H_i are the coefficient and inertia time constant, respectively; U_{ti} is the terminal voltage of the i th generator; and U_{Ri} and u_{pssi} are the AVR and PSS output singles, respectively.

The transfer function of the PSS of the i th generator is expressed as follows:

$$u_{pssi} = K_i \frac{sT_W}{1 + sT_W} \frac{1 + sT_{1i}}{1 + sT_2} \frac{1 + sT_{3i}}{1 + sT_4} \Delta\omega_i \tag{2}$$

where $\Delta\omega_i$ is the angular velocity deviation of i th generator, in rad/s; $T_W = 10$ is the washout time constant; $T_2 = 0.02$ and $T_4 = 0.54$ are the time constants (Shen et al., 2004); and T_{1i}, T_{3i}, and K_i are the parameters of the i th generator to be optimized.

The aim of PSS optimization is to reduce power oscillations and improve the dynamic performance of shipboard power system, which is associated with the generator active power, rotor speed, and frequency. To improve the generator power system stability, we select the rotor speed and the active power as the optimization goals. Then, the objective function can be expressed as follows:

$$\begin{aligned} J &= \min \int_{t_0}^{t} \left(k_1 \cdot |\Delta\omega| + k_2 \cdot |\Delta P_e|\right) \\ &= \min \int_{t_0}^{t} \left(k_1 \cdot |\omega(t) - \omega_{\text{ref}}| + k_2 \cdot |P_e(t) - P_{\text{ref}}|\right) dt \end{aligned} \tag{3}$$

where k_1 and k_2 are the weight factors; $\omega(t)$ and $P_e(t)$ are rotor speed and active power at moment t, respectively; and ω_{ref} and P_{ref} are reference rotor speed and reference active power, respectively.

3 BDI AGENT AND QPSO-BASED PARAMETER OPTIMIZATION FOR THE MARINE GENERATOR EXCITATION CONTROLLER

3.1 BDI agent

The BDI agent model refers to the deliberative agent developed by Bratman (1987). The BDI agent model is a software model for intelligent agents that enables them to select plans through deliberation. Each BDI contains four main components (Lorini & Piunti, 2010): beliefs, desires, intentions, and plans, as shown in Figure 2. The abstract model of a BDI agent can be defined as $\langle \Gamma, K, B, D, I, DG, ACT \rangle$ (Sardina & Padgham, 2011), which denote constructs obtained by perceptions, static causal knowledge, volatile beliefs, desires, intentions, desire-generating and planning rules, and a repertoire of basic actions, respectively.

Its process reasoning and logical formalism can be described as follows:

(1) If a given analysis task T can be solved, then create the process-solving objection based on the BDI agent.

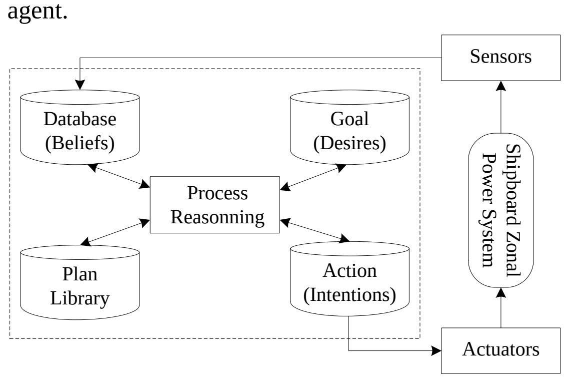


Figure 2. **Typical BDI agent architecture**

(2) $\Gamma(K, E) \to B$ denotes the creation of belief B by belief generator Γ according to knowledge K and shipboard power system working condition message E, which are obtained through transfers after feature extraction. The belief reflects an understanding of the shipboard power system operation condition.

(3) $DG(B, K, Object) \to D$ depicts the process aim during task T of solving the object function $Object$, which can realize desire D in accordance with knowledge K through the desire generator DG.

(4) $Analyse(B, D, K, Object) \to I$ shows the intention I selected through the best realizable desire D according to knowledge K.

(5) $ACT(I, K) \Rightarrow \alpha_1, \alpha_2, \cdots, \alpha_t$ expresses the executable actions $\alpha_1, \alpha_2, \cdots, \alpha_t$ created through the executable action generator based on the intention I

and knowledge K created by the intention generator and stored in the strategy library.

3.2 Quantum-behaved particle swarm optimization

The QPSO is a swarm intelligence algorithm developed by Sun et al. (2017). In the quantum model of QPSO, the state of a particle is depicted by a wave function $\psi_{(x,t)}$ rather than a position and velocity. The dynamic behaviour of the particle diverges from that of particle in traditional PSO systems because the exact values of x and v cannot be determined simultaneously. We can only obtain their probability density function $\left|\psi_{(x,t)}\right|^2$, the form of which depends on the potential field in which the particle lies. The particles move according to the following iterative equation (Sun, Zhu, & Yang, 2017):

$$\begin{cases} X_{(t+1)} = P_j - \beta \cdot \left|mbest - X_t\right| \cdot \ln(1/u) & \text{if } k_0 \ge 0.5 \\ X_{(t+1)} = P_j + \beta \cdot \left|mbest - X_t\right| \cdot \ln(1/u) & \text{if } k_0 < 0.5 \end{cases} \tag{4}$$

where

$$mbest = \frac{1}{N}\sum_{j=1}^{N} pbest_j \tag{5}$$

$$P_j = \varphi \cdot pbest_j + (1-\varphi) \cdot gbest \tag{6}$$

$$\varphi = c_1 r_1 / (c_1 r_1 + c_2 r_2) \tag{7}$$

$mbest$ is defined as the mean value of best positions of the particles, and k_0, u, and φ are random numbers distributed uniformly on [0,1]. Because the number of iterations and population size are common requirements in every evolutionary algorithm, β, also called the contraction-expansion coefficient, is the only parameter in the QPSO algorithm.

3.3 BDI agent and QPSO-based parameter optimization for the power system stabilizer

PSS parameter optimization is one of the effective methods for improving PSS performance and enhancing the dynamic stability of the shipboard power system. The main steps in application of the proposed BDI agent and QPSO-based parameter optimization to the marine generator controller are shown in Figure 3.

As shown in Figure 3, the optimization mechanism includes the following process:

(1) Definition of BDI agent environment. Let $A = \{a_1, a_2, \cdots, a_n\}$ stand for the BDI agent states; n stands for the marine generator number; and $\boldsymbol{X} = \{X_1, \cdots, X_n\}$ stands for the variables of the marine generator excitation controller parameters.

(2) Constraint variables of BDI agent state. Such as, define $x_{i1}, \cdots, x_{i4}$ as parameters for $T_{i1}, \cdots, T_{i4}$ and x_{i4} for K_i, as given by equation (2).

(3) Beliefs of optimization. From the definition of the BDI agent environment, the BDI agents acquire information about electrical parameters by using sensors to establish the belief formulated using $\boldsymbol{X}$, which reflects the running states of the shipboard power system.

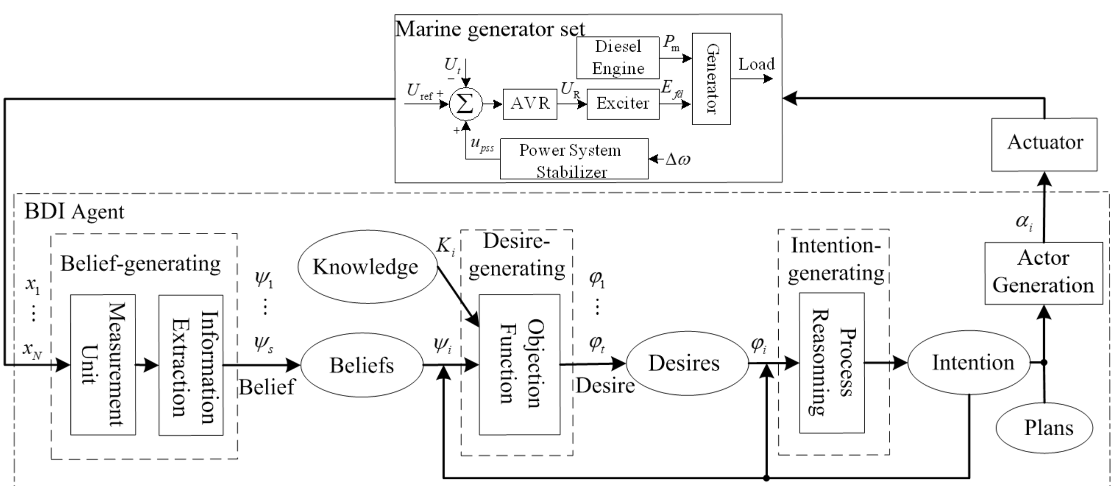


Figure 3. **Marine generator excitation controller parameter optimization mechanism**

(4) Optimization desires. The desires of the optimal marine generator controller are the same as those of the optimization object, that is, equation (3).

(5) Behavioral strategies of BDI agents. To achieve the optimal optimization strategy quickly and accurately, each BDI agent combined with QPSO optimization diffuses its best strategies across the entire environment. Then, the evolution mechanism of QPSO and its knowledge are used to generate the optimal strategy for the marine generator excitation controller. Based on such behaviors, three operators are designed for the agents.

The following main steps are involved in applying the proposed BDI agent and QPSO algorithm (QPBDI)-based parameter optimization to the marine generator controller:

(1) Beliefs that reflect the power system working condition are generated by information extraction unit. The input message for information extraction is the parameters that are received through the measurement and sensor units.

(2) According to the shipboard power system's beliefs and knowledge, the QPSO parameters are initialized as $Iter_{\max} = 100$, $x_{i1} \in [0.1, 0.5]$, $x_{i2} \in [0, 0.5]$, $x_{i3} \in [1, 5]$, $x_{i4} \in [0, 10]$, and $x_{i5} \in [5, 30]$.

(3) For simultaneous optimization of the shipboard PSS parameters by using the QPSO, the BDI agent generates beliefs used for parameter optimization on the basis of its knowledge and the objective function.

(4) The optimization of the shipboard PSS parameters is initiated by the reasoning process according to beliefs and the QPSO-optimized parameters.

4 SIMULATION RESULTS

In this section, the proposed BDI agent and QPSO algorithm are implemented to optimize the parameters of the PSS used in a shipboard zonal power system. To verify the effectiveness of the proposed PSS optimization design method, simulation results for the excitation controllers of the marine generator with PSS, without PSS (only including AVR), and with the proposed BDI agent and QPSO algorithm-optimized (QPBDI) PSS are compared. The controller performance is simulated for the shipboard power system under load changes disturbance or severe fault.

To further demonstrate the effectiveness of the proposed optimization algorithm for the optimization of an excitation controller in a marine generator excitation controller, another simulation of the shipboard zonal power system was conducted. Figure 4 shows the shipboard zonal distributed power system for an all-electric ship.

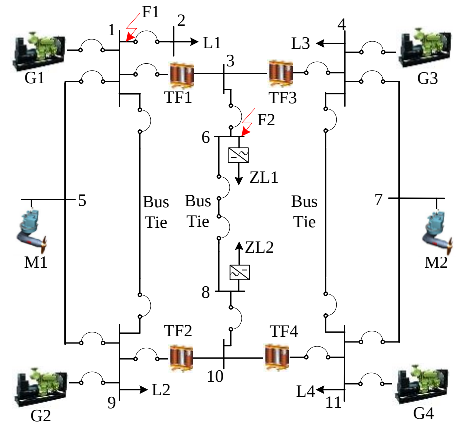


Figure 4. Architecture of the shipboard zonal power system

As shown in Figure 4, the shipboard zonal power system comprises four synchronous diesel engine generators (G1–G4) connected in parallel in a ring bus configuration to the 2400V medium voltage buses. Because the four generator buses form a square-shaped ring with four bus ties, the shipboard power system does not require an emergency generator. The loads in the shipboard zonal power system are classified into three levels: vital, semi-vital, and nonvital. The vital loads connect to power panels or switchboards directly via automatic or manual bus transfers. For vital loads, such as prolusion machine (M1, M2) and zonal loads (ZL1, ZL2), which get power from the boosting transformers (TF1–TF4), the lines have two paths (normal and alternate) to enhance the reliability of the power system, but only one of the paths is closed at any time to ensure the shipboard power system operates in a radial configuration. For semi-vital loads, such as L2, L3, and L4, the power is obtained from the main bus panels directly. L1, which stands for the nonvital loads, is supplied power only from the distribution bus panel. Finally, the load parameters and the generator parameters and bus types of the shipboard zonal power system are summarized in Tables 1 and 2, respectively. All the parameters for marine generator can be seen in the paper (Yeager, K. E., & Willis, J. R, 1993).

Table 1. Load Parameters

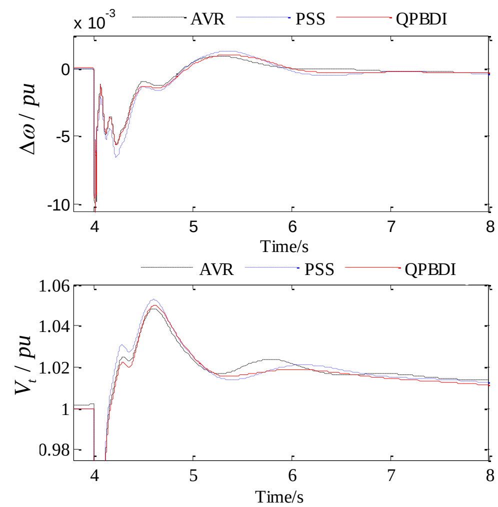
Component	Power/MW	Component	Power/MW
L1	0.5	L4	0.5
L2	0.3	ZL1	0.3
L3	0.5	ZL2	0.5

Table 2. Generator Parameters and the bus type

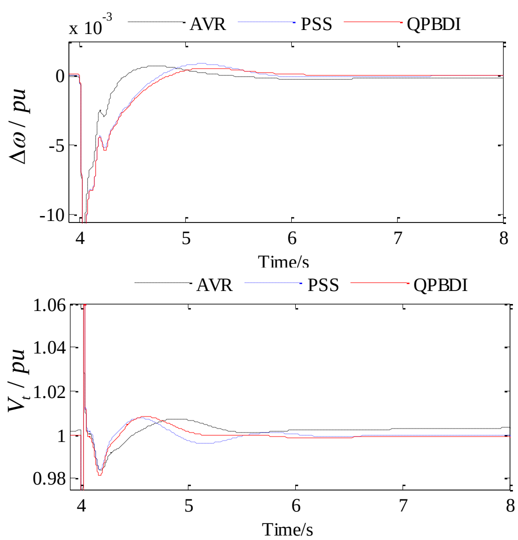
Generator	Active Power/MW	Reactive Power/MVar	Node Type
G1	5	-24.84	PQ
G2	5	-41.20	PQ
G3	2.5	1.7	PV
G4	2.5	0	swing

To verify the proposed method, numerous simulations are performed for three-phase short-circuits with load change disturbance near bus 1 (F1) and the zonal distribution ZL1 near bus 6 (F2). The simulation results are shown in Figures 5 and 6, respectively.

(1) The fault occurs near bus 1 (F1). Two types of faults occur at $t=4$ s near bus 1, as shown in Figure 8. One is an active load changes of 10% and the other is a short-circuit fault between buses 1 and 2 for a duration of 200 ms. The generator responses of rotor speed deviation and generator terminal voltage in the aforementioned cases are shown in Figures 5(a) and 5(b), respectively.



(a) Generator response to load changes

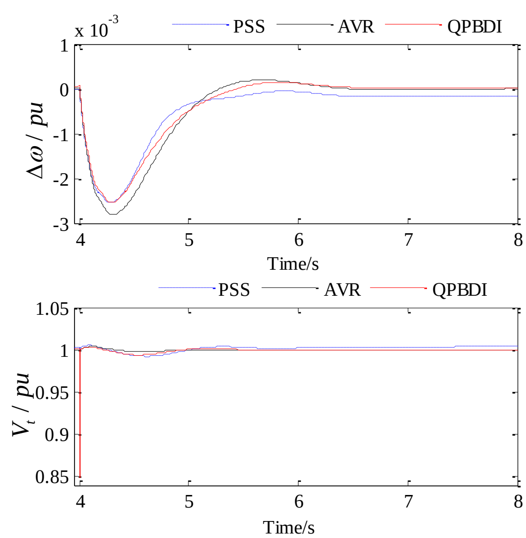


(b) Generator response to short-circuit

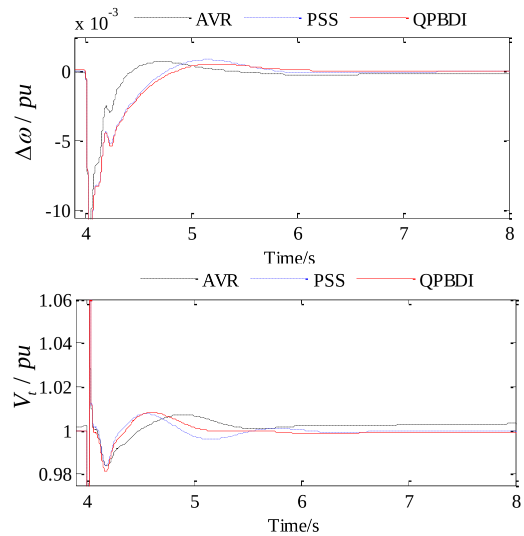
Figure 5. **G1 response to the fault near bus 1**

Figure 5 shows the simulation results of the different marine generator excitation controllers. The red lines indicate the QPBDI-optimized PSS, blue dashed lines denote the conventional PSS, and the dark dashed lines denote the generator with AVR only. Figure 5(a) indicates that as the shipboard zonal power system undergoes 10% active load changes, the marine generator voltage V_t drops to 0.838p.u., and the maximum amplitude of rotor speed deviation $\Delta\omega$ changes to 0.28%, 0.28%, and 0.35% with the PSS, QPBDI, and AVR controller, respectively. From the simulation result shown in Figure 5(b), as the short-circuit fault occurs, the generator terminal voltage V_t and rotor speed deviation $\Delta\omega$ decrease to 0.058p.u. and 1.3%, respectively. After the fault is cleared, the rotor speed oscillates severely twice, after which it attains a steady state. For these two fault conditions, the QPBDI-optimized PSS shows better control performance than the PSS and the AVR do. The QPBDI-optimized PSS gets better control performance than the PSS does, especially in terms of generator terminal voltage control.

(2) The fault occurs at the zonal distribution ZL1 near bus 6 (F2). Two types of the aforementioned fault occur at $t=4$ s near bus 6, as shown in Figure 4. One is an active load changes of 10% and the other is a short-circuit fault between buses 3 and 6 for 200 ms. The generator responses in terms of rotor speed deviation and generator terminal voltage for these two cases are shown in Figures 6(a) and 6(b), respectively.



(a) Generator response to load changes



(b) Generator response to short-circuit

Figure 6. G1 response to fault occurring in zonal distribution ZL1 near bus 6

Figure 6 indicates that the fault in distribution zone ZL1 near bus 6 (F2) has a weaker influence on the generator than that occurring near the main bus 1 (F1). With the 10% active load change at F2, the generator terminal voltage V_t falls to 0.848p.u., which implies better stability than the value of 0.838p.u. at F1. Moreover, the maximum amplitude of the rotor speed at F2 is 0.28%, which is lower than amplitude at F1 (0.35%). The red lines in Figure 6 reveal that the QPBDI-optimized PSS shows better control performance in terms of rotor speed control and generator terminal voltage control than does the PSS, which is denoted by blue dashed lines. However, the QPBDI-optimized PSS show worse control performance at the moment at which the fault is cleared.

5 CONCLUSION

To improve the dynamic performance of shipboard power systems, a BDI agent-based QPSO algorithm is proposed to optimize the marine generator excitation controller parameters. To verify the proposed method, simulations of the electrical propulsion shipboard power system and the shipboard zone were performed. The simulation results reveal that the proposed BDI agent and QPSO-based marine generator PSS optimization method could eliminate substantial disturbances in the shipboard power system under load change disturbance and severe short-circuit faults. The proposed method improved the stability of the marine generator terminal voltage and the rotor speed performance. Moreover, it demonstrably guaranteed the reliability of the shipboard power system.

6 ACKNOWLEDGMENT

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