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Speed Control of Marine Diesel Engine Based on Lyapunov Neural Network Combined with Adaptive Backpropagation Algorithm

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Abstract

The speed control system of a vessel's diesel engine plays a crucial role in the operation and utilization of the machinery, directly impacting maritime economic efficiency. All types of vessels operating at sea require a system to control and monitor the speed of diesel engines, ensuring that the rotation speed of the engines remains stable in the face of changes in load and the impact of the marine environment. This study proposes a marine diesel engine speed control system based on a Lyapunov-Stabilized Neural Network (LSNN) with a novel adaptive backpropagation algorithm. Accordingly, unlike the traditional gradient-based backpropagation algorithm, the weights of the Neural Network (NN) are adjusted according to an adaptive law. In addition, the evaluation of the stability of the NNs using Lyapunov theory is also discussed. The stability of the speed system with the proposed controller is evaluated by the Bode stability criterion. Simulating and comparing the proposed solution with the traditional weight update of the NN in various scenarios to demonstrate its effectiveness.

Keywords: marine diesel engine, speed control system, neural network, backpropagation, lyapunov stability.

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1. Introduction

The ship power system (Ship Power System – SPS) provides electricity for purposes such as propulsion, navigation, cargo handling, and heating. This electrical system includes a combination of generators that convert diesel fuel into electricity [1], which is then supplied to the electrical equipment used on the ship. The ship's electrical system is relatively complex, performing numerous functions and requiring high flexibility, as illustrated in Figure 1. Therefore, the vessel's onboard electrical system must meet international standards and ensure the safety of the electrical system. To convert fuel and promote environmental sustainability, diesel engines are widely utilized in ship transportation, and regulating diesel engine speed becomes a crucial issue as the performance and lifespan of the ship depend significantly on the ability to control engine speed [2].

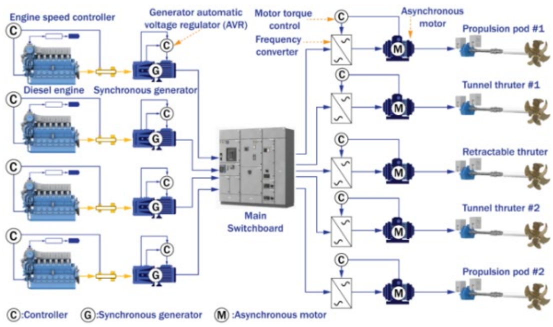

Figure 1. The vessel's electrical power system [3]

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However, diesel engines have highly nonlinear and time-varying dynamic characteristics, making them difficult to control. Therefore, to achieve optimal performance, the speed controller needs to have good load noise immunity and fuel efficiency [4]. Engine speed control operates through these main components: the camshaft, the fuel injectors, and the governor. These three main components, working together, ensure the engine runs at the desired speed. In this, the diesel engine governor serves as the control object to achieve optimal control performance, as the vessel's cruising speed largely depends on the rotational speed of the diesel engine's crankshaft, which is necessary to maintain a stable moving speed [5]. The governors used in marine main engines are mainly of the proportional type due to the convenience of this part in sharing the load between different machines when operating in parallel [6-7].

Currently, most marine engine speed control systems use PID controllers. However, as mentioned above, diesel engines are easily affected by the marine environment, such as waves, wind, and sudden load changes. At the same time, it is impossible to accurately develop a mathematical model under these conditions, resulting in undesirable control performance such as unstable speed fluctuations and slow speed response. In recent years, with the rapid advancement of science and technology, various optimization methods for PID controllers have been developed to enhance the speed control performance of marine engines. Fuzzy logic–based strategies for ship engine speed control have been investigated in [8] and further extended in [9]. To improve conventional PID controllers under disturbance conditions, the authors in [10] employed the Salp Swarm Algorithm (SSA) to adaptively tune PID parameters in real time, explicitly addressing interference rejection, which was not considered in the earlier studies. A design of a ship speed stabilization system using a dual-loop RBF neural network to tune PID controller parameters is proposed in [11], based on the self-learning ability of the NN to adjust and overcome the difficulties and limitations of the traditional PID controller. A novel control model based on Multiple Model Predictive Functional Control (MMPFC) is proposed in [12] to solve the complex and time-consuming parameter tuning problem of the marine diesel engine speed controller. By combining the traditional PID controller with a hybrid nonlinear engine model, a new approach was developed to evaluate the performance of the controller, thereby assessing its adaptability and robustness against system load disturbances, which has not been discussed in studies [10-11]. Some other control algorithms can also be applied in controlling the speed of marine engines such as genetic algorithms [13-14], or using active disturbance rejection controller (ARDC) [15-16] thanks to the ability to resist disturbances of unstable and unpredictable loads and the strategy of controlling the speed of marine engines with the Backstepping Controller and Fuzzy Controller [17]. Compared with other research works, the design method and performance of the controller give simulation assumptions that are more suitable for actual marine conditions.

In addition, with the rapid development of artificial intelligence and neural network (NN) algorithms, self-tuning control strategies for marine engine speed regulation have been widely investigated. For example, the deep reinforcement learning based self-tuning control algorithm proposed in [18] significantly reduces speed fluctuation amplitude and shortens stabilization time. Furthermore, the learning-based ship speed tracking control system presented in [19] demonstrates strong adaptive capability in adjusting PID controller parameters in response to external disturbances and variations in system output. Similarly, Huang et al. [20] implement adaptive speed control based on timely learning for marine engines by establishing a two-layer adaptive control scheme. A backpropagation neural network is used to optimize the control parameters. The results achieve better control performance compared to traditional PID controllers.

We observed that many algorithms have been implemented and achieved certain effectiveness in stabilizing the moving speed of vessels while operating in the marine environment. However, most studies have not addressed the convergence problem of prediction tracking errors, nor have they addressed the reliability and stability of NNs when used in controller design. To address the above limitations, this study proposes a novel approach for controlling the speed of vessel diesel engines based on a Lyapunov-stable neural network with an adaptive backpropagation algorithm. The main contents of the study include: i) Establishing mathematical model of marine diesel engine speed control system, ii) Designing a speed control system using a NN with an adaptive weight update rule, while also considering the reliability and stability of the NN according to Lyapunov standards, iii) Simulating the system with hypothetical scenarios to access the effectiveness of the proposed solution. The stability of the diesel engine speed control system with the new controller has been verified using the Bode stability criterion.

2. Marine diesel engine

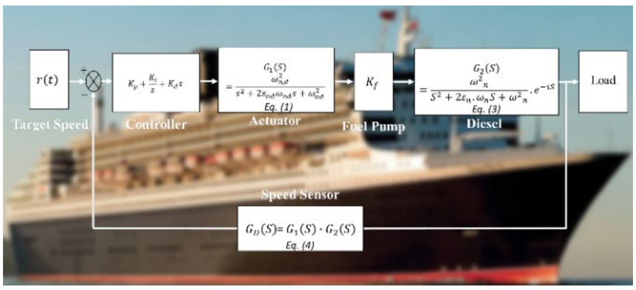

Figure 2. The marine engine speed control system

In practice, it is very challenging to accurately establish a mathematical model for a complex object like a ship's diesel engine, as it involves numerous functions, including the fuel injection and combustion processes inside the engine cylinder, as well as the operating conditions and performance of the ship. However, it is possible to rely on the principle of the vessel engine speed control system as shown in Figure 2, thereby establishing a mathematical model based on the operating principle and system structure, including main components such as: controller, actuator, integration of fuel pump system with engine, and rotational speed sensor, whose configuration and feedback structure follow the approaches reported in [8-9].

Drive system: The drivetrain of a DC servo motor marine diesel engine is typically modeled as a first or second-order inertial link. In this study, the transmission system is a typical quadratic link, with the following transfer function as.

$$G_1(S) = \frac{\omega^2{}_{nd}}{S^2 + 2\varepsilon_{nd}\omega_{nd}S + \omega^2{}_{nd}} \tag{1}$$

where ω_{nd} expresses the natural oscillation frequency of the drive with ε_{nd} being the damping coefficient of the drive ($0.4 \le \varepsilon_{nd} \le 0.8$).

Integration of diesel engine: To simplify the calculation and simulation system, the diesel engine model is typically represented by a first-order inertia stage combined with a time delay stage, which accounts for the change in the rack position to the corresponding torque by the diesel engine.

$$G(S) = e^{-\tau S}\frac{1}{T_a S + 1} \tag{2}$$

whereas T_a denotes the time constant of the marine diesel engine, and τ indicates the time delay constant of the fuel throttle opening process.

In this study, a diesel engine with a turbocharger is considered, and the transfer function is described as follows:

$$G_2(S) = \frac{\omega^2{}_n}{S^2 + 2\varepsilon_n\omega_n S + \omega^2{}_n}e^{-\tau S} \tag{3}$$

in which, ω_n denotes the undamped natural frequency and ε_n indicates the damping coefficient of the diesel engine.

Speed sensor module: The speed sensor measures the rotational speed of the motor shaft, converting the mechanical signal (speed) into an electrical signal, which is sent to the controller. In speed sensor control, it is assumed to be much faster in dynamics compared to other stages. Therefore, the speed sensor can be approximated as a static element with a gain of 1. From there, the transfer function of a marine diesel engine with a turbocharger, without considering the effects of turbulence, can be described as.

$$G_D(S) = \frac{\omega^2{}_{nd}}{S^2 + 2\varepsilon_{nd}\omega_{nd}S + \omega^2{}_{nd}} \tag{4}$$

$$\frac{\omega^2{}_n}{S^2 + 2\varepsilon_n\omega_n S + \omega^2{}_n}e^{-\tau S}$$

This study employs a 12E390V marine diesel engine, whose specifications are listed in Table 1 [13].

Table 1. Parameters of the marine diesel engine

Parameters	Symbol	Value
Drivetrain natural frequency	ω_{nd}	35.4
Drivetrain damping ratio	ε_{nd}	0.707
Undamped natural frequency	ω_n	1.324
Engine damping ratio	ε_n	1.75
Fuel throttle opening time constant	τ	0.24 s
Engine diameter	D	390 mm
Rated speed	ω	450 rpm

Assumption 1: The speed control system is a stable system with bounded input and bounded output (BIBO): $|\omega_d(k)| < \infty, \forall |u(k)| < \infty$. In the case that the system is BIBO unstable, it can be stabilized by implementing appropriate feedback mechanisms.

Remark 1: To ensure BIBO stability for the speed control system, the output speed of the diesel engine must be limited within the allowable range. The limitation is essential to provide stability in the event of device failure or activation of protection mechanisms. This limit is expressed as follows:

$$|\omega_d(t)| \le \omega_{d,max}, \left|\frac{d\omega_d(\mathrm{t})}{dt}\right| \le R_{\omega,max} \;\forall t \tag{5}$$

where $\omega_{d,max}$, $R_{\omega,max}$ denote the maximum allowable engine speed and the maximum allowable rate of change of the diesel engine speed, respectively.

In addition, the effects of environmental disturbances under real marine operating conditions, such as waves, wind, and propeller load variations, are assumed to be bounded and slowly varying. This assumption helps ensure that the adopted model accurately represents the behavior of the diesel engine during practical operation.

3. Controller design

To overcome and further improve the limitations in the diesel engine speed control system mentioned above, we employ an NN method based on Lyapunov stability theory with a new backpropagation algorithm. This mechanism enables the linear controller to achieve specific tracking in the real-time domain while simultaneously tuning the controller parameters, thereby improving the performance and stabilizing the speed, as shown in Figure 3.

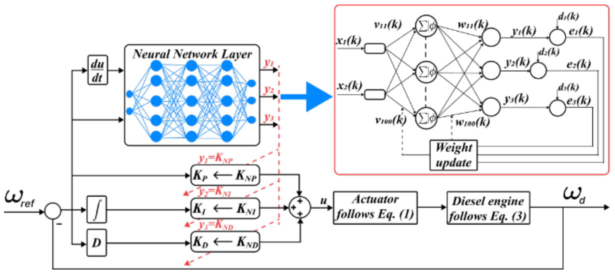

Figure 3. Diesel engine speed control structure applying the NNs

The structure of the proposed LSNN controller is fundamentally similar to that of a conventional PID controller. However, instead of employing fixed proportional, integral, and derivative gains, the proportional (K_{NP}), integral (K_{NI}), and derivative (K_{ND}) control actions are generated by multilayer feedforward neural network modules designed under Lyapunov stability constraints. The neural network receives two input signals are the speed error and the derivative of the error, and produces three output signals $y_1 = K_{NP}$, $y_2 = K_{NI}$, $y_3 = K_{ND}$, which adaptively tune the PID gains in real time based on the instantaneous error and its rate of change.

The control signal of the system is represented as.

$$u(s) = K_{NP}(s)e(s) + K_{NI}(s)\int_0^S e(s)ds + K_{ND}(s)\frac{de}{ds} \tag{6}$$

3.1. Neural network system

The NN model consists of 3 layers: 2 input layer neurons $x_j(j = \overline{1,2})$ (the speed error $x_1 = e$, and the speed error differential $x_2 = de/dt$, and the output layer consists of 3 neurons $y_i = i(\overline{1,3})$, and a hidden layer consisting of 20 neurons $q = q(\overline{1,20})$. The input neurons transmit signals to the hidden layer neurons through the weights $v_{qj}(k)$. Applying the activation function $\varphi(f)$ and passing it to the output neurons via $y_i(k)$, weights $w_{iq}(k)$, the output signal of the q hidden layer neuron is computed as.

$$S_q(k)= \varphi \sum_{j=1}^{2} v_{qj}(k)\, x_j(k) \tag{7}$$

where $\varphi(f) = sigmoid(\alpha) = 1/(1 + e^{-\alpha})$ and α is a positive constant. The i neuron signal of the output layer is computed by

$$\begin{aligned} y_i(\mathrm{k}) &= \sum_{q=1}^{20} w_{iq}(k) S_q(k) \\ &= \sum_{q=1}^{20} w_{iq}(k)\, \varphi \sum_{j=1}^{2} v_{qj}(k)\, x_j(k) \end{aligned} \tag{8}$$

Determining the tracking error $e_i(k)$ between the actual output $y_i(k)$ and the target output $d_i(k)$ specified as [21]

$$e_i(k) = y_i(k) - d_i(k) \tag{9}$$

Different from the conventional method, which is based on the traditional gradient method, the weights of the NN are updated according to the adaptation rule as follows:

$$w_{iq}(k) = \frac{\beta^{\frac{1}{2}} e_i(k-1) + d_i(k)}{20 S_q(k-1)} \tag{10}$$

$$v_{qj}(k) = \frac{1}{2x_j(k)}\varphi^{-1}\left(\frac{\beta^{\frac{k}{2}}.\, e_i(k-1) + d_i(k)}{20.\, w_{iq}(k)}\right) \tag{11}$$

where β is the learning coefficient of the neural network satisfying $0 < \beta < 1$, and $\varphi(\beta)^{-1}$ is the inverse of the sigmoid activation function.

Assumption 2: The input signal of the NN is constrained as follows:

$$0 < x_{min} \le |x_j(k)| \le x_{max}, \forall\ \mathrm{j}, k \tag{12}$$

Assumption 3: the error, the error derivative, and the network noise are constrained by

$$|e_i(k)| \le e_{max}, |de_i(k)| \le\ de_{max}, |d_i(k)| \le d_{max}, \forall k \tag{13}$$

with $d_i(k)$ denotes the noise of the NN.

Remark 2: The input excitation signal $x_j(k)$ affects the convergence of the tracking error $e_i(k)$, which represents the relationship between the weights $w_{iq}(k)$ and $x_j(k)$.

3.2. Reliability assessment

The NN's reliability can be indicated by its ability to withstand changes in system parameters, disturbance, or measurement errors without learning incorrectly. The resilience prevents oscillations and instabilities that could negatively impact the performance of a controller employing the NN. The NN's reliability is evaluated based on three criteria:

Convergence of weighted bounds: These weights ($w_{iq}(k)$ and $v_{qj}(k)$) must be bounded in time (expressed in (14)), ensuring that the network does not suffer from weight explosion or internal instability. If the weight increases without limit, the network output will fluctuate significantly, leading to diesel engine speed instability.

$$|w_{iq}(k)\,| \le\ w_{max}, |v_{qj}(k)| \le\ v_{max}, \forall k \tag{14}$$

From (7) and (8), the output of the hidden layer with the sigmoid activation $S_q(k-1)$ is always positive and confined within the range [0,1]. Combining (12) and (13), $e_i(k-1)$ and $d_i(k)$ are bounded as.

$$\left|w_{iq}(k)\right| \leq \frac{\beta^{\frac{1}{2}} e(k-1)_{max} + d_{max}}{20 S_q(k-1)} = \frac{M_{max}}{S_{min}} \quad (15)$$

in which $M_{max} = \beta^{1/2} e(k-1)_{max} + d_{max}$, and $0 < S_{min} = 20 S_q(k-1) < 1$. The weight $w_{iq}(k)$ is always bounded $0 < w_{min} \leq |w_{iq}(k)| \leq w_{max}$. We get

$$\left|v_{qj}(k)\right| \leq \left|\frac{1}{2x_{min}}\right| \left|\varphi^{-1} \frac{M_{max}}{20 w_{min}}\right| \quad (16)$$

The weight $v_{qj}(k)$ is also bounded, indicating that the weights $w_{iq}(k)$ and $v_{qj}(k)$ are both bounded and converge to a stable value when $e_i(k) \to 0$. Thus, it guarantees that the neural network does not oscillate on its own and that each neuron operates stably in the linear region.

Neural networks remain stable in the presence of noise when the system experiences a load torque disturbance or a change in fuel pressure; the speed deviation $e_i(k)$ changes accordingly. If the neural network reacts too quickly, the network's output will fluctuate strongly, causing speed oscillations or mechanical vibrations. In (10), the component $d_i(k)$ can be viewed as the effect of disturbance or fuel pressure in the diesel engine system. With a coefficient of 1/20 in the network, it can be estimated that as the noise increases, the weight variation $w_{iq}(k)$ will gradually decrease, allowing the network to react smoothly without being too quick, avoiding instability. Similarly, the coefficient $1/2x_j(k)$ in $v_{qj}(k)$ in (11) enables the NN to achieve a reasonable delay, ensuring stable learning despite the influence of noise. Thus, it can be concluded that the network is stable against the effects of random noise.

The error decreases over time, which indicates that the system is asymptotically stable and predictable. For the motor speed control system, the speed error gradually decreases after each cycle, bringing the motor speed back to a stable nominal speed, without overspeed or phase lag. According to (9), we get

$$e_i(k) = y_i(k) - d_i(k) \quad (17)$$

and

$$e_i(k) = \sum_{q=1}^{20} w_{iq}(k) S_q(\mathrm{k}) - d_i(k) \quad (18)$$

Substituting (7) into (18), the error $e_i(k)$ is rewritten as

$$e_i(k) = \sum_{q=1}^{20} w_{iq}(k)\, \varphi \sum_{j=1}^{2} v_{qj}(k)\, x_j(k) - d_i(k) \quad (19)$$

where $v_{qj}(k)$ is given by (11). Therefore, equation (19) can be expressed as.

$$e_i(k) = \sum_{q=1}^{20} w_{iq}(k)\, \varphi \sum_{j=1}^{2} \left(\frac{1}{2x_j(k)} \varphi^{-1} \left(\frac{\beta^{\frac{1}{2}} e_i(k-1) + d_i(k)}{20 w_{iq}(k)} \right) \right) x_j(k) - d_i(k) \quad (20)$$

and

$$e_i(k) = \sum_{q=1}^{20} w_{iq}(k)\, \varphi \varphi^{-1} \left(\frac{\beta^{\frac{1}{2}} \cdot e_i(k-1) + d_i(k)}{20.\, w_{iq}(k)} \right) - d_i(k) \quad (21)$$

From (21), it can be simplified into (22) as

$$\begin{aligned} e_i(k) &= \left(\beta^{\frac{1}{2}} \cdot e_i(k-1) + d_i(k) \right) - d_i(k) \\ &= \beta^{\frac{1}{2}} \cdot e_i(k-1) \end{aligned} \quad (22)$$

We have $e_i(k) = \beta^{1/2} e_i(k-1)$. In the case of a learning rate of $0 < \beta < 1$, the error of the NN gradually decreases and asymptotically approaches zero as time increases. With the three criteria discussed above, it is evident that the proposed NN ensures reliability in controller design.

3.3. Stability assessment

The NN utilizes stability theory by selecting a candidate Lyapunov function, which is constructed based on the network's dynamic error. The Lyapunov function is chosen as follows:

$$V(k) = {e_1}^2(k) + {e_2}^2(k) + {e_3}^2(k) \quad (23)$$

where $V(k) = 0$ if $e_i(k) = 0$ and $V(k) > 0$ if $e_i(k) \neq 0$. According to Lyapunov stability, a NN is stable if $\Delta V(k) = V(k) - V(k-1) < 0$. We get

$$\Delta V(k) = V(k) - V(k-1) \quad (24)$$

and

$$\begin{aligned} \Delta V(k) &= [{e_1}^2(k) + {e_2}^2(k) + {e_3}^2(k)] \\ &\quad - [{e_1}^2(k-1) \\ &\quad + {e_2}^2(k-1) + {e_3}^2(k-1)] \\ &= [{e_1}^2(k) - {e_1}^2(k-1)] \\ &\quad + [{e_2}^2(k) - {e_2}^2(k-1)] \\ &\quad + [{e_3}^2(k) - {e_3}^2(k-1)] \end{aligned} \quad (25)$$

The equation (25) can be written a

$$\Delta V(k) = \sum_{i=1}^{3} \Delta V_i(k) \tag{26}$$

with

$$\begin{aligned}\Delta V_i(k) &= e_i{}^2(k) - \ e_i{}^2(k-1) \\ &= [y_i(k) - d_i(k)]^2 - e_i{}^2(k-1)\end{aligned} \tag{27}$$

Substitute (8) into (27), we have

$$\begin{aligned}\Delta V_i(k) = &\left[\sum_{q=1}^{20} w_{iq}(k)\, \varphi \sum_{j=1}^{2} v_{qj}(k)\, x_j(\mathrm{k}) \right. \\ &\left. - d_i(\mathrm{k})\right]^2 - e_i{}^2(k-1)\end{aligned} \tag{28}$$

The weight $v_{qj}(k)$ is given in (11); therefore, (28) can be transformed as follows

$$\begin{aligned}&\Delta V_i(k) = \\ &\left[\sum_{q=1}^{20} w_{iq}(k)\, \varphi \sum_{j=1}^{2} \left(\frac{1}{2.x_j(k)} \varphi^{-1} \left(\frac{\beta^{\frac{1}{2}}.e_i(k-1) + d_i(k)}{20.w_{iq}(k)}\right)\right) x_j(k) \right. \\ &\left. - d_i(k)\right]^2 - e_i{}^2(k-1)\end{aligned} \tag{29}$$

and

$$\begin{aligned}\Delta V_i(k) &= \left[\left(\beta^{\frac{1}{2}}.e_i(k-1) + d_i(k)\right) - d_i(k)\right]^2 \\ &\quad - e_i{}^2(k-1) \\ &= \beta \cdot e_i{}^2(k-1) - e_i{}^2(k-1)\end{aligned} \tag{30}$$

So, we get $\Delta V_i(k)$ as

$$\Delta V_i(k) = -(1 - \beta) \cdot e_i{}^2(k-1) \tag{31}$$

Since $0 < \beta < 1$, $\Delta V_i(k) < 0$. From that, according to (26), $\Delta V(k) < 0$. Therefore, the NN is stable according to the Lyapunov criterion. The weights of the first NN's output layer are updated according to (10), then their values are kept fixed. The weights will be updated according to (11). The weight update process, as described in (11), plays a crucial role in ensuring the stability of the system according to the Lyapunov criterion when $\Delta V(k) < 0$.

3.4. LSNN training process

The proposed LSNN controller operates with parameters constrained as Assumptions 1, 2, and 3. Therefore, the study focuses on states within the equilibrium region during training, ensuring Lyapunov stability. The process of training the LSNN to optimize the parameters of a diesel engine speed controller is carried out according to Algorithm 1.

Algorithm 1: Optimization of the LSNN by NN

Input: $x_1=e(k)$, $x_2=(d/dt)e(k)$; $|x_1|\le e_{max}$, $|x_2|\le e_{max}$

Output: $[K_{NP}(k), K_{NI}(k), K_{ND}(k)]$; $K_{NP,min} \le K_{NP} \le K_{NP,max}$, $K_{NI,min} \le K_{NI} \le K_{NI,max}$, $K_{ND,min} \le K_{ND} \le K_{ND,max}$

1 **Initialize:** Choosing weights $w_{iq}(0)$, $v_{qj}(0)$
Setting a learning rate ← $0<\beta<1$
Setting the activations ← $\varphi(f)$
Lyapunov tolerance ← $\varepsilon = 1e-5$

2 Computing the NN's output $y_i(k)$ ← (8)

3 Determining the control error $e_i(k)$ ← (17)

4 Updating weights ← (10), and (11)

5 Defining the Lyapunov function: $V(k)$ ← (23)

6 **If** $|\Delta V(k)|<\varepsilon$ **then** stopping the training process

7 **else** go back step 2

8 **end if**

9 Computing the control signal $u(k)$ ← (6)

10 **end**

The learning rate β has a significant impact on the stability and convergence of the NN's output. Small values of β (close to 0) will slow down the convergence of the error process, while larger values (close to 1) may lead to oscillatory convergence behavior.

4. Results and evaluation

4.1. Training results

In this study, the neural network is trained using a hybrid learning strategy that combines offline initialization and online adaptation. First, the network parameters are trained offline using the Bayesian Regularization algorithm with a learning coefficient of $\beta = 0.1$. After deployment, the neural network continues to update its parameters in real time through the Lyapunov-based adaptive learning laws derived in (10) and (11). The network's performance is evaluated using the mean squared error (MSE), with the best convergence result reaching 2.8248×10^{-13} as shown in Figure 4.

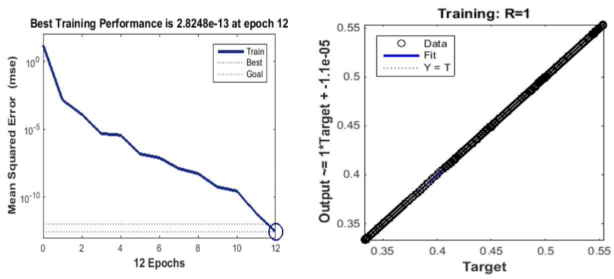

Figure 4. Results of neural network training

The offline training stage provides a well-initialized set of neural network weights, while the Lyapunov-based adaptive laws (10) and (11) enable online weight adjustment during real-time operation. This mechanism compensates for model uncertainties, measurement noise, parameter variations, and external disturbances, ensuring closed-loop stability and high control performance. The MSE, reflecting both the offline initialization and online adaptation over 12 learning cycles, remains very small and satisfies the Lyapunov stability condition under varying operating conditions.

4.2. Simulation results

To evaluate the effectiveness of the proposed solution, simulations are performed and compared with the control strategy using a NN with a weight update rule according to the traditional gradient method in diesel engine speed control [22]. Simulations were performed in a MATLAB/Simulink environment with a fixed time step of 1 ms, using the ode4 solver to ensure numerical stability. Three simulation scenarios were clearly established, with input signals, disturbance timing, and initial conditions fully specified: acceleration to the rated speed of 450 rpm, speed reduction to 405 rpm under load conditions, and operation under random disturbances simulating the effects of ocean waves. The controlled object in this study is the 12E390V marine diesel engine, modeled based on the engine's actual kinematic parameters and operating characteristics. The engine's rotational speed is measured using an incremental rotary encoder, which provides feedback to the speed control loop.

Case 1: The diesel engine starts and reaches the set speed of 450 rpm. The speed response and speed error, as shown in Figures 5 and 6, demonstrate the effectiveness of the LSNN controller.

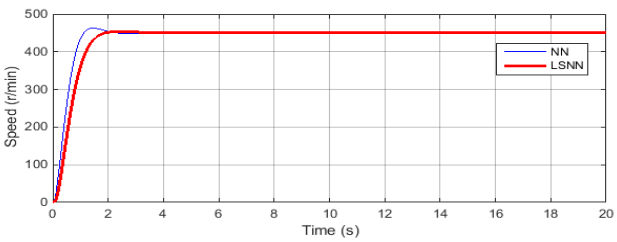

Figure 5. Response speed of the simulation case 1

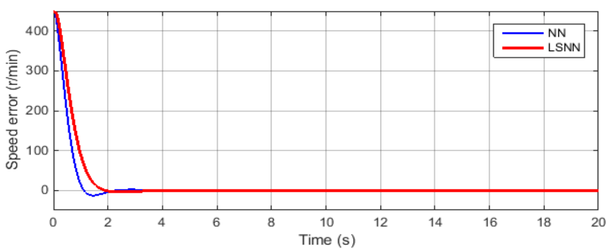

Figure 6. Speed deviation of the simulation case 1

Case 2: The motor reaches the rated speed of 450 rpm in 5 s and decelerates to 405 rpm after 15 s in a simulation time of 20 s. The speed response is illustrated in Figure 7, and the speed error is depicted in Figure 8, demonstrating that the LSNN controller provides significantly superior performance compared with the NN controller.

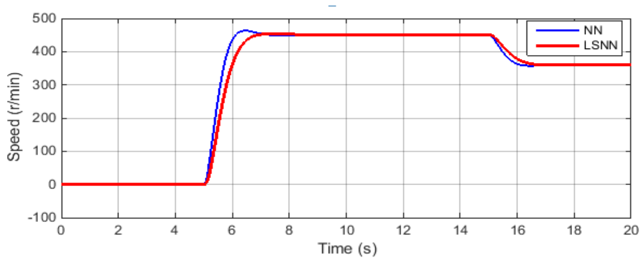

Figure 7. Response speed of the simulation case 2

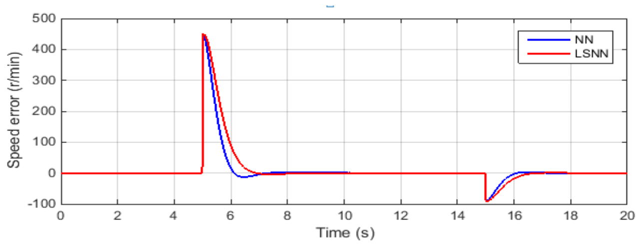

Figure 8. Speed deviation of the simulation case 2

Case 3: The system is affected by noise after 15 s to 20 s. Then, the speed response and speed error of the diesel engine are shown in Figures 9 and 10, indicating that with the LSNN controller, the speed is less affected by noise than with the NN controller.

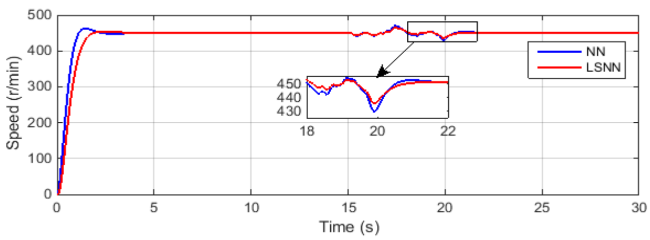

Figure 9. Response speed under the impact noise in simulation case 3

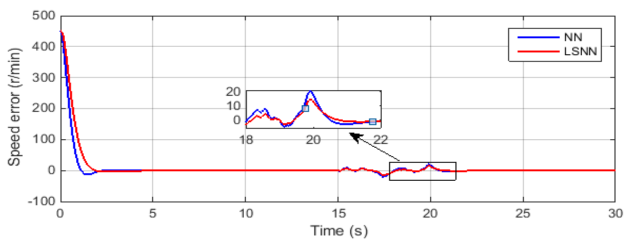

Figure 10. Speed deviation under the impact noise in simulation case 3

Based on the evaluation of the simulation results for the three possible operating scenarios of the marine diesel engine, the effectiveness of the LSNN with the new weight update law in speed stabilization is confirmed. The LSNN achieves a settling time of 2.05 s and an overshoot of 0.75%, whereas the corresponding indices of the NN controller are 3.5 s and 2.92%, respectively. These results demonstrate that the proposed approach satisfies the conditions stated in Remarks 1 and 2.

4.3. Evaluation of the system stability

The stability of the marine diesel engine speed control system with an LSNN controller is evaluated based on the Bode stability criterion. The open transfer function of the system when using an LSNN based on the new weight update law to adjust the speed control parameters of the ship engine, with the time delay considered to be ignored, is as follows:

$$G_H(S) = \frac{\omega^2{}_{nd}}{S^2 + 2\varepsilon_{nd}\omega_{nd}S + \omega^2{}_{nd}} \cdot \frac{\omega^2{}_{n}}{S^2 + 2\varepsilon_{n}\omega_{n}S + \omega^2{}_{n}} \cdot \left(K_{NP} + \frac{K_{NI}}{s} + sK_{ND}\right) \quad (32)$$

Combining the LSNN controller parameters ($K_{NP} = 4.25, K_{NI} = 1.52,\ K_{ND} = 0.3344$) with diesel engine parameters as above, the open system transfer function can be rewritten as

$$G_H(S) = \frac{418s^2 + 5313s + 1900}{0.57s^5 + 31.14s^4 + 345.5s^3 + 3350s^2 + 1250s} \quad (33)$$

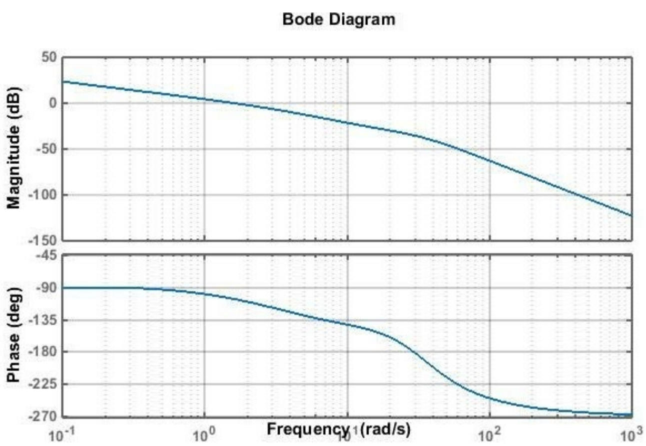

Figure 11. Bode diagram of marine diesel engine speed control system

Figure 11 shows the Bode diagram of the system, showing the following values $\omega_c = 1.9(\text{rad/s})$; $\omega_{-\pi} = 46.5(\text{rad/s}) \rightarrow GM = 32.8dB, PM = 75^0$. Thus, the values $GM > 0$ and $PM > 0$ should make the diesel engine speed control system with the LSNN controller stable according to the Bode standard.

In terms of practical implementation, LSNN has a compact structure and low computational requirements, allowing it to be deployed on embedded microcontrollers such as DSP or ARM platforms without exceeding real-time processing constraints. However, several practical challenges must be considered, including hull-induced vibrations that may affect speed measurement accuracy and variations in fuel quality that can alter combustion characteristics. Therefore, appropriate signal filtering mechanisms and adaptive parameter correction algorithms should be incorporated to ensure stable long-term operation. Despite these potential limitations, the simulation and analysis results indicate that LSNN represents a promising solution for marine engine speed control under complex operating conditions.

5. Conclusion

This study presents a method for designing a marine diesel engine speed control system using the LSNN with a new adaptive weight update method to tune the control parameters. In which the reliability and stability of the NN are mentioned before using it to design the controller for the system, and at the same time, through simulation with different scenarios to compare with the traditional NN controller, and the stability of the speed control system is verified by the Bode stability criterion to show the effectiveness of the proposed solution. In the future, it will be necessary to consider issues such as fuel injection flow and pressure timing, as well as the combustion process in the diesel engine speed control system, to ensure maximum engine performance and optimize the controller.

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