FUZZY CONTROL ROBOT ENERGY SAVING METHOD BASED ON PARTICLE SWARM OPTIMISATION ALGORITHM

Zuqiang Long,* Yunmeng Wang,* and Zelong Luo*

Abstract

To obtain a long running time for battery-powered mobile robots, implementing energy-efficient control over their motion process is important. In this study, a fuzzy logic control (FLC) optimisation method is proposed to diminish the energy expenditure of a differential drive wheeled mobile robot (WMR) during its movement by using the particle swarm optimisation (PSO) algorithm. Unlike conventional energy-saving methods, such as reducing the robot acceleration, this study designs a fuzzy logic controller based on a planned optimal path to control the left- and right-wheel angular velocities of the differential drive WMR to enable it to navigate from its initial position to the target location. The membership function of the fuzzy logic controller is optimised based on the PSO algorithm, and an optimal fuzzy logic controller can be obtained to decrease the energy loss of the battery. Compared with other methods, the proposed method can save over 85% in energy consumption.

Key Words

Differential drive wheeled mobile robot, fuzzy logic control, particle swarm optimisation, optimal control

1. Introduction

Differential drive wheeled mobile robots (DDWMR) has been used in many applications. To perform the specified tasks in various applications, all require the robot to be able to move from the initial point to the target point in known or unknown situations. Therefore, the proper operation of functions related to path planning, autonomous navigation, obstacle avoidance, trajectory tracking, and localisation of mobile robots are fundamental issues that must be addressed. These problems have been intensively studied by some scholars and many important results have been achieved. For example, Chen *et al.* proposed the path planning method for mobile robots in unknown environments [1]–[3], Nguyen *et al.* designed an efficient navigation system for autonomous mobile robots [4]–[6], Wang *et al.* studied the obstacle avoidance method of mobile robots in dynamic environments [7], [8]. Hassan *et al.* designed neural network-based trajectory tracking situation for mobile robots [9], while De *et al.* proposed the mobile robot localisation method [10]–[13]. The aforementioned results are important for solving the smooth operation of mobile robots, but they do not guarantee the minimum energy consumption of mobile robots during the motion.

In recent years, the use of optimisation algorithms to solve problems related to fuzzy logic control (FLC) was widely examined by researchers, especially in the field of mobile robots, such as robotic systems based on fuzzy visual serving [14], the combination of a optimisation algorithm and FLC to solve path-planning or position tracking problems [15], [16], and FLC optimisation using optimisation algorithms to dynamically adjust the parameters of type-2 fuzzy systems [17], [18].

The main methods to reduce energy consumption are reducing energy consumption by planning optimal paths [19], choosing to use less energy-intensive robot components [20], avoiding sudden acceleration or deceleration of wheeled mobile robot (WMR) [21], and extending the runtime by increasing the battery size [22]. Among the aforementioned methods, reducing energy consumption by planning optimal paths is the most effective. In this study, the optimal path can be understood as the shortest path. The sharp-turn for WMR must accelerate and decelerate according to the path requirements, which results in additional energy consumption. Therefore, this paper proposes a better solution to combine optimisation of FLC and minimum energy consumption.

The core problem of motion control for DDWMR is designing a controller to control the speed of the left and right drive wheels effectively, wherein the target position is reached smoothly. Classical control methods often rely on mathematical modelling of the controlled object. In the absence of an accurate model, classical control methods make it difficult to design a suitable controller. Robots, as a common nonlinear system, need to handle complex

* College of Physics and Electronic Engineering, Hengyang Normal University, Hengyang, China; e-mail: dragon51@126.com, 1012445253@qq.com, luozelong@outlook.com
Corresponding author: Yunmeng Wang

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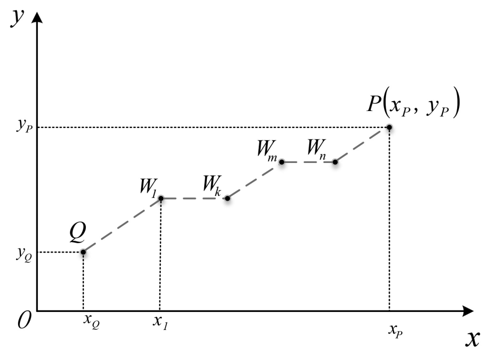

Figure 1. The DDWMR tracks the optimal path.

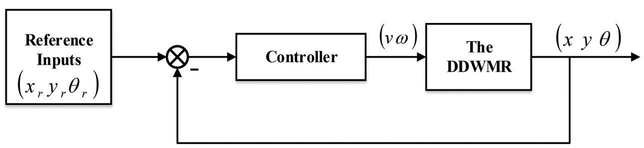

Figure 2. Block diagram of DDWMR control system.

tasks in uncertain or unknown environments, and obtaining an accurate mathematical model is difficult. The largest advantage of FLC method is that the system can achieve better dynamic performance and steady-state performance even without the mathematical model of the controlled object. Therefore, this paper adopts a FLC method for the control of DDWMR. This paper proposes to optimise the parameters of the FLC using particle swarm optimisation (PSO) to decrease the energy consumed by the DDWMR in the moving process.

The remaining four parts of this study as follows. In Section II, the structure of DDWMR is introduced; Section III describes the optimisation method of FLC; Section IV describes the simulation experiment process and the operation results; the last section is the conclusion.

2. Description of the Problem

Assuming that the optimal path was planned based on the A* algorithm (the A* algorithm is a commonly used path-finding and graph traversal algorithm that can search for optimal paths through a cost function containing heuristic information), the DDWMR energy-efficient motion control aims to enable the robot to reach the target through all the path points in an efficient manner.

In Fig. 1, DDWMR traces the optimal path from the initial point (x_Q, y_Q) to the destination point (x_P, y_P) from point Q through points W_1, W_k, W_m, W_n.

DDWMR navigation from the initial position to the target position can be achieved by a variety of control algorithms. Figure 2 shows a generic motion control system for a DDWMR with a control system scheme that may be applied to most DDWMR performing navigation tasks.

The function of the FLC is to enable the DDWMR to move from its initial position to the target location. We optimise the FLC membership functions (MFs) online using PSO. In the optimisation procedure, we call the PSO algorithm through the "*pymoo*" library.

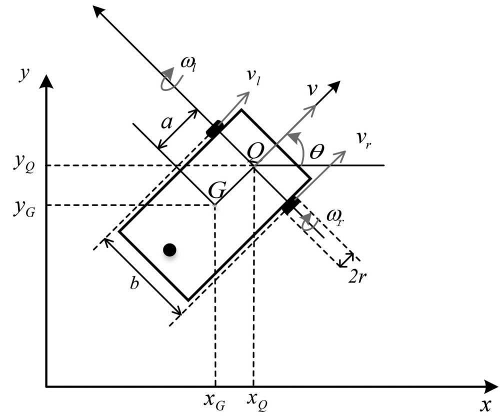

Figure 3. Model of differential drive wheeled mobile robot.

The kinematic and energy models of DDWMR need to be used in the design of FLC. Figure 3 shows the geometric parameters of the DDWMR [23].

The parameters of the DDWMR geometric model are shown in Fig. 3, including: Q, which represents the centre of the axis between the left and the right wheels; G, which is the centre of gravity of the DDWMR; a represents the distance between the centre of gravity G and the centre Q of the two wheels; b represents the distance between the two wheels; r, is the radius of both the left and right wheels; ν, is the robot linear velocity; θ, is the orientation of the robot; ω_r and ω_l denote the angular velocities of the left and right wheels, respectively; v_l and v_r denote the linear velocities of the left and right wheels, respectively.

The kinematics of DDWMR is based on the pure rolling assumption, with no slip between the wheel and the surface. From Fig. 3, the kinematic model of DDWMR is:

$$\begin{cases} \dot{x} = \nu \cos\theta \\ \dot{y} = \nu \sin\theta \\ \dot{\theta} = \omega \end{cases} \tag{1}$$

In this study, the energy consumed by the motor is converted into the kinetic energy required by the DDWMR. The energy loss of DDWMR includes part of the loss caused by friction and that inside the motor [24].

An appropriate energy model is essential for the design of energy-efficient controllers. Only the portion of kinetic energy lost by the robot is considered and other losses are neglected in this study. The kinetic energy of DDWMR at any moment is:

$$E_{\text{kinetic}} = \frac{1}{2} m \left[v\left(t\right)\right]^2 + \frac{1}{2} I \left[\omega\left(t\right)\right]^2 \tag{2}$$

where m indicates the mass, I means the moment of inertia of the DDWMR; v is the linear velocity of the DDWMR at time t, ω is the angular velocity of the robot at time t.

To simulate the operation of the DDWMR using software, we calculate the kinetic energy of the robot at time t_i using a discrete time representation. Equations (3)

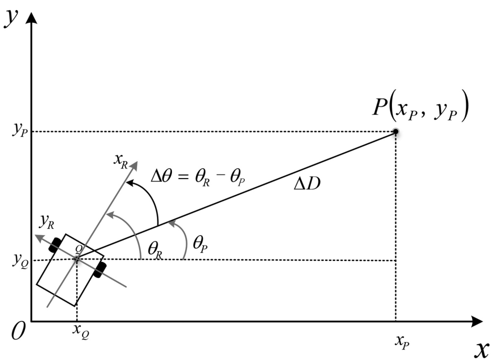

Figure 4. The DDWMR and the path point.

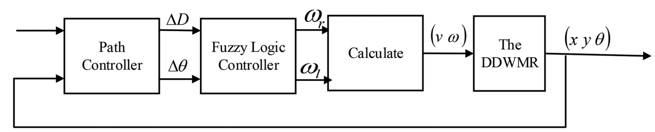

Figure 5. Fuzzy logic controller block diagram of DDWMR.

and (4) are presented, as follows:

$$E_{\text{kinetic}(i)} = \frac{1}{2}m\left[v\left(t_i\right)\right]^2 + \frac{1}{2}I\left[\omega\left(t_i\right)\right]^2 \tag{3}$$

$$\Delta E_{\text{kinetic}(i)} = E_{\text{kinetic}(i)} - E_{\text{kinetic}(i-1)} \tag{4}$$

The motion state of the DDWMR can be divided into three types: acceleration, deceleration, and uniform velocity. When the kinetic energy is not recycled back into the battery, energy will be lost during acceleration or deceleration. The calculation of the energy loss of the DDWMR must discern the state of the robot. During the simulation, we use (3) and (4) to calculate the DDWMR energy loss.

3. Design of the Fuzzy Logic Controller and Optimisation of Particle Swarm Optimisation

To achieve the overall optimisation of FLC, the design of the FLC ensure that the DDWMR to move from the initial point to the target point; PSO is then used to decide the parameters of the membership function to ensure the minimum energy consumption generated by the robot during the motion.

3.1 Function of Fuzzy Logic Controller

Figure 4 describes the DDWRM moving from its initial position Q to the target location P.

From Fig. 4 we obtain:

$$\Delta D = \sqrt{\left(x_P - x_Q\right)^2 + \left(y_P - y_Q\right)^2} \tag{5}$$

$$\Delta\theta = \theta_R - \theta_P \tag{6}$$

$$\tan\theta_P = \frac{y_P - y_Q}{x_P - x_Q} \tag{7}$$

ΔD And $\Delta\theta$ are the difference between the distance and angle between the robot's initial points to the target point.

The function of FLC is to direct the DDWMR to move from its initial position Q to the destination location P. The FLC block diagram for the DDWMR is shown in Fig. 5 The FLC is a double-input and double-output (DIDO) system, with ΔD and $\Delta\theta$ as the inputs, and ω_l and ω_r as the outputs. We use (8) and (9) to convert the FLC outputs into the DDWMR inputs, as follows:

$$v = \frac{1}{2}\left(v_r + v_l\right) \tag{8}$$

$$\dot{\theta} = \omega = \frac{1}{b}\left(v_r - v_l\right) \tag{9}$$

Table 1
Right Wheel Angular Velocity Rule Table

ΔD	$\Delta\theta$				
	NB	***NS***	***Z***	***PS***	***PB***
VN	*RR*	*SR*	*RR*	*TR*	*LR*
N	*RR*	*SR*	*SR*	*TR*	*LR*
Z	*RR*	*SR*	*LR*	*TR*	*LR*
R	*RR*	*SR*	*TR*	*TR*	*LR*
VR	*RR*	*SR*	*LR*	*TR*	*LR*

3.1.1 Dividing the Universes of Discourse

For the division of the universe of discourse according to the actual situation of the DDWMR, we define the input universes of discourse of ΔD as [0 10], the input universes of discourse of $\Delta\theta$ as $[-180° \ 180°]$, and the output universes of discourse of ω_l and ω_r as [0 30].

3.1.2 Construction of the Membership Functions

The triangular MFs are selected for this experiment. The MFs of ΔD are VN, N, Z, R, VR, indicating very near, near, moderate, remote, and very remote, respectively. The MFs of $\Delta\theta$ are NB, NS, Z, PS, PB, indicating negative large, negative small, zero, positive small, and positive large. The MFs of ω_r are RR, SR, MR, TR, LR, indicating rarely to the right, slightly to the right, moderately, to the right, and large to the right, respectively. The MFs of ω_l are RL, SL, ML, TL, LL, indicating rarely to the left, slightly to the left, moderately, to the left, and large to the left. The input and output MFs are shown in Fig. 6.

To ensure that the DDWMR can move from its initial position to the target location, we construct the FLC rule base using a heuristic approach [25] and defined it in Tables 1 and 2.

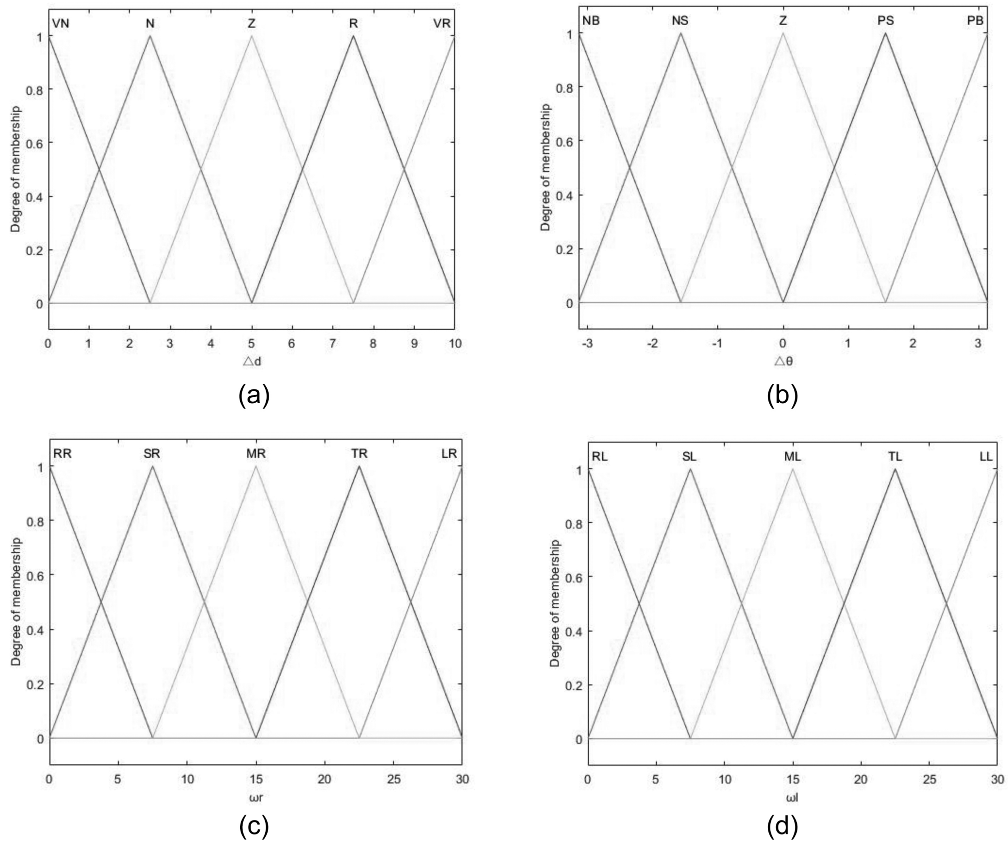

Figure 6. (a) The MFs of ΔD, (b) the MFs of $\Delta\theta$, (c) the MFs of ω_r, and (d) the MFs of ω_l.

Table 2
Left Wheel Angular Velocity Rule Table

ΔD	$\Delta\theta$				
	NB	***NS***	***Z***	***PS***	***PB***
VN	*LL*	*TL*	*RL*	*SL*	*RL*
N	*LL*	*TL*	*SL*	*SL*	*RL*
Z	*LL*	*TL*	*ML*	*SL*	*RL*
R	*LL*	*TL*	*VL*	*SL*	*RL*
VR	*LL*	*TL*	*VL*	*SL*	*RL*

3.2 Fuzzy Logic Controller Optimisation Based on the Particle Swarm Optimisation

The division of the MFs and the establishment of the rule base are crucial to the control effect of FLC. To optimise the membership function, this section describes the process of finding the optimal membership function parameters using the optimisation algorithm.

Domestic and foreign researchers have proposed numerous heuristic algorithms, including those that simulate the evolutionary behaviour of organisms in nature, group intelligence algorithms, physical rules prevalent in the universe, and those based on human behaviour or perceptual phenomena. Researchers continue to apply these heuristic algorithms to control engineering, defence modernisation, economic scheduling and other fields. Among them, the population intelligence algorithm is a class of commonly used heuristic algorithms, which can also be subdivided into particle swarm algorithm, ant colony optimisation algorithm, firefly algorithm, and so on. We choose the PSO algorithm, which is easy to implement and has fewer adjustment parameters, to optimise the membership function parameters of FLC.

3.2.1 Parameterisation of the Membership Functions

The MFs commonly used in fuzzy logic system include Gaussian, trapezoidal, and triangular. Triangular functions are widely used in WMRs [26], mainly because their form is simple and straightforward, and they are easy to understand and apply. Triangular functions also have satisfactory controllability, require only three parameters, have a simple implementation method and require only some simple numerical and logic operations to achieve. Their computation complexity is relatively simple, and their computation speed is fast, making them suitable for real-time systems. Therefore, in this study, we choose the commonly used triangular MFs.

We used the parameter representation method shown in Fig. 7 to define the five triangular MFs. Among, the MFs set of NV is determined by $(\min, D2)$; which can be described using 11 parameters each $(D1-D8,\ \ W1-W3)$. Since the FLC is a TITO, there are a total of 44 parameters. ΔD (D1, D2, W1, D3, D4, W2, D5, D6, W3, D7, D8); $\Delta\theta$ (D9, D10, W4, D11, D12, W5,

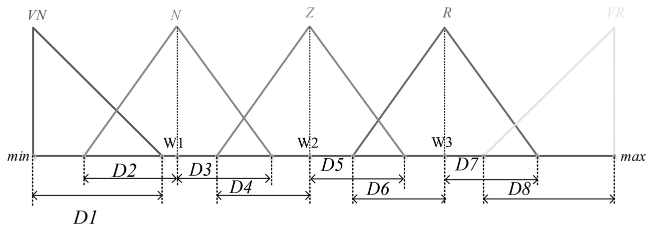

Figure 7. The representation method for triangle membership functions.

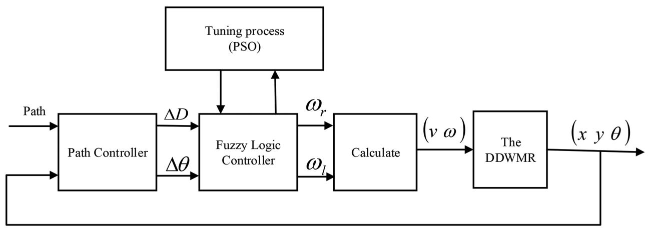

Figure 8. The process of PSO for fuzzy logic controller.

D13, D14, W6, D15, D16); ω_l(D17, D18, W7, D19, D20, W8, D21, D22, W9, D23, D24); ω_r (D25, D26, W10, D27, D28, W11, D29, D30, W12, D31, D32). These parameters are used as particles in the PSO algorithm to represent the MFs.

3.2.2 Particle Swarm Optimization Execution

The fitness function (FF) in the PSO algorithm can determine which particles in the population can enter the next generation. In this study, (2) is chosen as the FF of the PSO to ensure the minimum energy loss of DDWMR.

The design of the optimal FLC should be able to ensure that the DDWMR can move from the initial position to the target position. Next, we used the "*pymoo*" library to perform the PSO optimisation process in *Jupyter notebook* using *Python* language to determine the optimal parameters of the membership function. The optimisation process for the membership function in FLC is shown in Fig. 8.

The FLC is created according to the partial, which represents all parameters of the MFs, and consequently, its behaviour is tested by a simulation process. We use the simulation results as the FF of the PSO to perform online optimisation. The programme flow chart of the PSO is shown in Fig. 9.

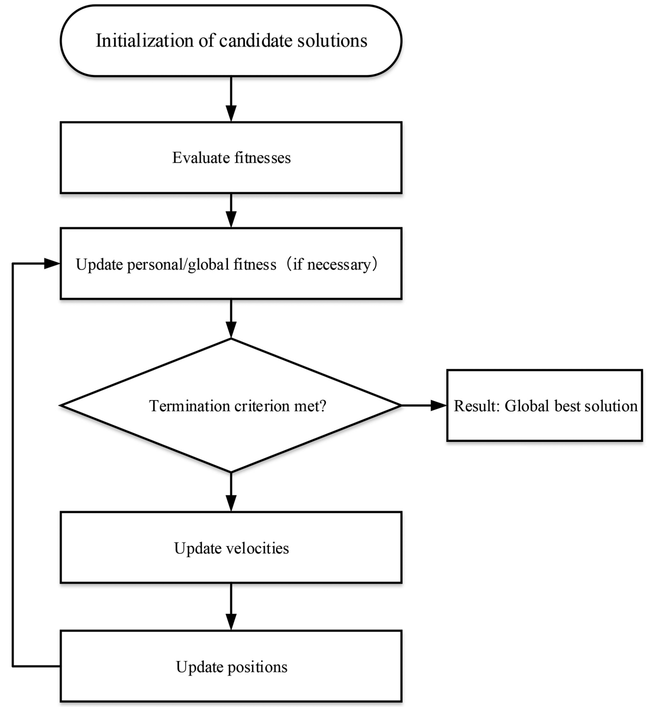

Figure 9. Flow chart of particle swarm optimisation programme.

Table 3
Parameters Values of the DDWMR

Parameters	Value
r	0.0925 m
b	0.37 m
m	9 kg
I	0.16245 kgm^2
J	0.01 kgm^2/s^2
x_G	0 m
y_G	0 m
θ_G	45°

4. Experimental and Simulation Result

4.1 Simulation Experiments

The simulation uses parameters for the DDWMR obtain from [23], and the specific values are shown in Table 3.

This experiment tracks trajectories comprising path points, such as (0, 0), (10, 0), (10, 10), (20, 10), (20, 20). To demonstrate the effectiveness of the proposed method in this paper, PSO_FLC is compared with expert experience-based FLC [27], Circular-based controller [28], and Robins Mathew-based controller [29], [30]. The optimal controller designed in this study is applicable in the specific operating environment of Z path.

We implement the simulation on the *Jupyter Notebook* platform using *Python*. We initialise the parameters and establish the kinematic and energy models of the DDWMR. We design the FLC to ensure that the DDWMR can move from its initial position to the target location. We use the PSO algorithm to optimise the parameters of the MFs and facilitate the optimisation process by calling the algorithm through the "*pymoo*" library. Then, we compare the obtained optimal controller with the other controllers under a given path. The results of the experiments in the 200th generation of the Z path are shown in Figs. 10–12

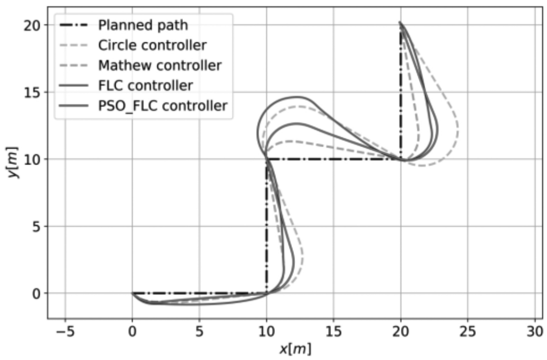

Figure 10. Trajectory tracking of DDWMR.

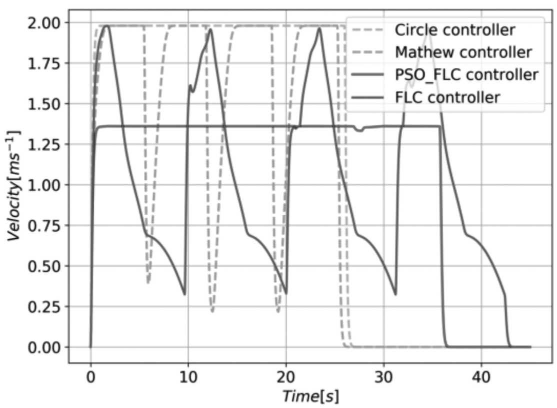

Figure 11. The velocity over time when the DDWMR tracks path.

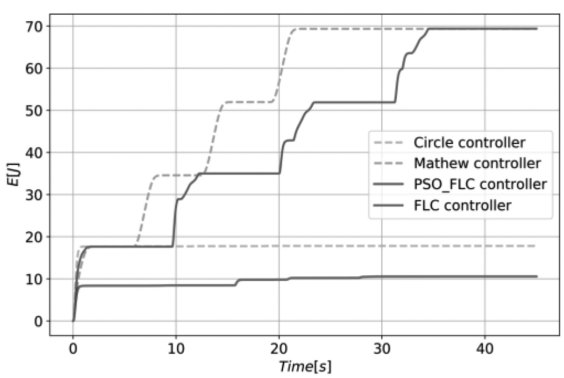

Figure 12. Energy consumption of DDWMR.

and Table 4. Figure 13 shows the condition before and after the MFs optimisation.

The speed of the mobile robot will play a crucial role in its performance. When the speed of the DDWMR is too fast, energy will be partially lost, and when the speed of the DDWMR is too slow, the control performance will be affect [23]. Therefore, the magnitude of the linear velocity is set at [0 m/s−2 m/s] and the angular velocity is set at [−0.75 rad/s−0.75 rad/s].

Table 4
Energy Consumption and Tracking Distance of Robots With Different Controllers

Controller name	Energy [J]	Distance [m]
Circle	17.802493	51.486728
Robins–Mathew	69.339948	42.992399
Designed FLC	69.383742	49.018313
Optimised FLC	10.566899	46.027612

4.2 Discussion

After experimental tests, when using PSO to optimise FLC, the population size was set to 50 and the number of iterations was set to 200, a parameter that is can well combine the optimisation algorithm with FLC. When the population size is set less than 50, it leads to an increase in energy consumption, while when the population size exceeds 50, the optimisation leads to a slower optimisation process.

Figure 10 shows that when controlling DDWMR through PSO_FLC, the tracking error is the smallest except for Mathew-base's controller. Figure 11 shows that the velocity of DDWMR controlled by expert experience-based FLC, Circular-based controller, and Robins Mathew-based controller have oscillated over time. However, when the PSO_FLC is used, the velocity of DDWMR is almost constant during the movement, even when the DDWMR moves through the corner. Therefore, the issues about the robot vibration have been solved quite well by the PSO_FLC and the stability of the mobile robot is ensured. To compare the difference in energy consumption between PSO_FLC and other controllers, the data in Fig. 12 and Table 4 show that the energy consumption of DDWMR when tracking a given path with PSO_FLC is 10.566899, which is much smaller than the energy consumption of DDWMR when using other controllers. This shows that the PSO_FLC in this paper consumes less energy than other control methods while ensuring that other control performance is not affected.

In this study, the primary problem to be solved is the reduction of the DDWMR energy loss in the process of motion. In this study, PSO_FLC demonstrates less energy consumption than other control methods whilst ensuring that the control performance is not affected.

5. Conclusion and Future Work

We use PSO to optimise the FLC MFs to solve the problem of high energy consumption during the operation of the DDWMR. In optimisation problems involving FLC, many researchers focused only on optimising the output MFs. In this study, we use the PSO algorithm to optimise all the MFs simultaneously. The results indicate that the energy consumption of the DDWMR is 10.566899 when we use PSO_FLC to track a given path. Compared with other

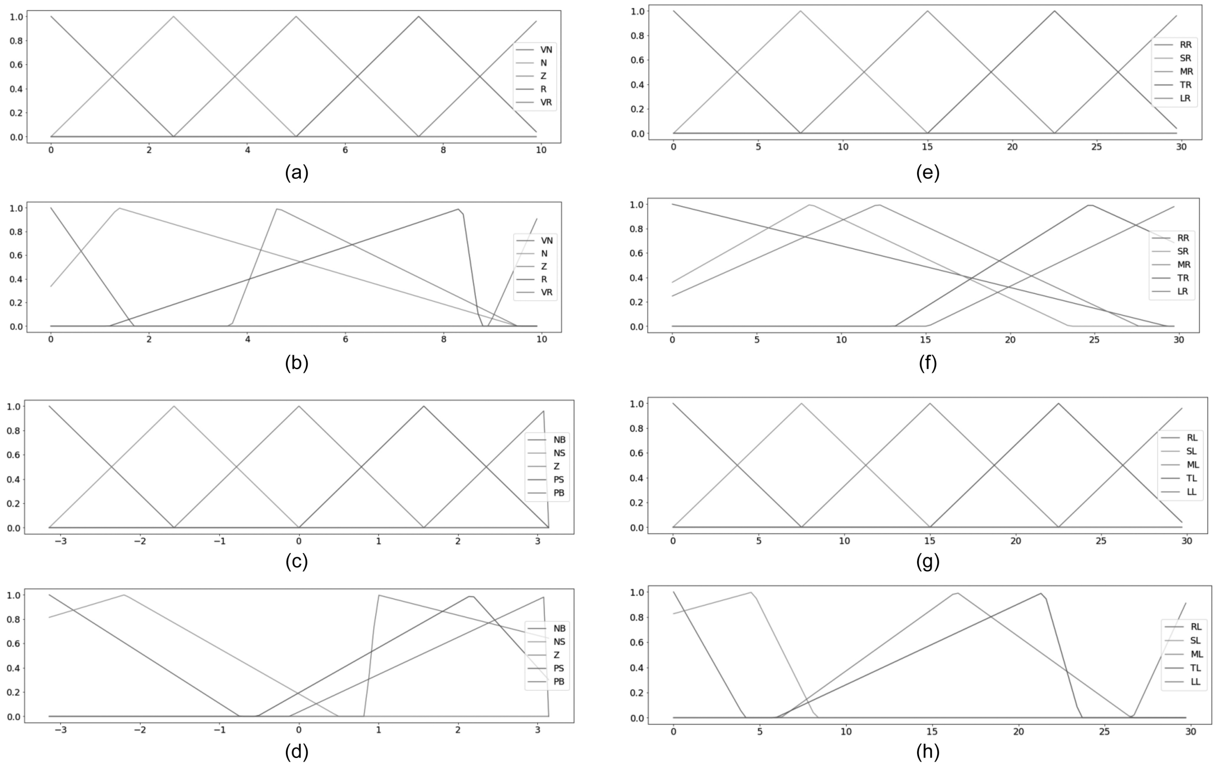

Figure 13. (a) The ΔD MFs before optimisation, (b) the ΔD MFs after optimisation, (c) the $\Delta\theta$ MFs before optimisation, (d) the $\Delta\theta$ MFs after optimisation, (e) the ω_r MFs before optimisation, (f) the ω_r MFs after optimisation, (g) the ω_l MFs before optimisation, and (h) the ω_l MFs after optimisation.

controllers, PSO_FLC can save more than 85% in energy consumption.

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Biographies

Zuqiang Long received the Ph.D. degree and the master's degree from Central South University, China, in 2011 and 2004, respectively. He was a Visiting Professor with the Department of Electrical and Computer Engineering, Wayne State University, USA, in 2014–2015. At present, he is a Professor with the College of Physics and Electronic Engineering, Hengyang Normal University, China, His research interests include nonlinear control systems, fuzzy control, and control system application.

Yunmeng Wang received the B.S. degree in automation from the School of Art and Information Engineering, Dalian University of Technology in 2021. She is a postgraduate student with the Department of Physics and Electronics Information Science, Hengyang Normal University, since 2021. Her current research interests include fuzzy control and optimisation algorithm.

Zelong Luo received the B.S. degree in automation from South China University of Technology, China, in 2019. He is a postgraduate student with the Department of Physics and Electronics Information Science, Hengyang Normal University, since 2021. His current research interest includes structure analysis of type-2 fuzzy logic controllers.