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FUZZY-WIND DRIVEN OPTIMIZATION BASED MOBILE ROBOT PLAN PATH FOR STATIC AND DYNAMIC CONDITION

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ABSTRACT

For autonomous mobile robot navigation and collision avoidance in an unknowable static and dynamic environment, this paper introduces a singleton type-1 fuzzy logic system (T1-SFLS) controller and Fuzzy-WDO hybrid. To optimise and fine-tune the input/output membership function parameters of the fuzzy controller, one uses the WDO (Wind Driven Optimization) algorithm. Based on the atmospheric motion of minuscule, microscopic air parcels moving over an N-dimensional search region, the WDO algorithm operates. With the help of the mobile robot Khepera-III, numerous computer simulations and real-world tests have been conducted to compare the performance of the suggested technique. The Fuzzy-WDO algorithm is shown to have good agreement for mobile robot navigation when compared to the T1-SFLS controller.

1.INTRODUCTION

One of the most difficult jobs is "path planning and control" of an autonomous mobile robot in a dynamic environment that is unknown. Fuzzy logic readily manages the ambiguity in the system since it is a mimic of human behaviour. Fuzzy logic is one of the techniques used in mobile robots that is frequently discussed. For mobile robot navigation, soft computing techniques like fuzzy logic [1], neural networks [2], neuro-fuzzy [4], and nature-inspired algorithms are frequently used. These include the Genetic Algorithm [8], Particle Swarm Optimization [12,13], Ant Colony Algorithm [10,11], Simu- lated Annealing Algorithm [14,15], and Bacterial Foraging Optimization [5]. Each technique (algorithm) does, however, have advantages and disadvantages.

Over the past 20 years, there has been a lot of research done on the motion control problem of an autonomous wheeled mobile robot. For the best path tracking of wheeled mobile robots, Abadi and Khooban [1] presented Mamdani-type fuzzy logic controller integrated with random inertia weight Particle Swarm Optimization (RNW-PSO) (WMRs). Algabri et al[2] .'s combination of fuzzy logic and Other soft computing methods, such as Genetic Algorithm (GA), Neural Networks (NN), and Particle Swarm Optimization (PSO), can be used to optimise the fuzzy controller's membership function parameters and boost the mobile robot's navigational performance. Hui and Pratihar [3] have designed and developed a comparative study between two soft computing approaches, namely genetic-fuzzy and genetic-neural, and the traditional potential field method for an adaptive navigation planning of a car-like mobile robot moving in the presence of some dynamic obstacles. The sensor-based Adaptive Neuro Fuzzy Inference System (ANFIS) controller has been presented by Pothal and Parhi [4] for the navigation of single and multiple mobile robots in the highly congested environment.

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In order to proceed from any start location to the destination position in an unknown environment between moving obstacles, Montiel et al. [5] and Hossain et al. [6] investigated the application of the Bacterial Foraging Optimization (BFO) method in mobile robot navigation. The low-cost embedded neuro-fuzzy controller was created by Baturone et al. [7] for safe and collision-free navigation of an autonomous car-like robot among potential obstacles toward a goal configuration. To choose the optimum membership functions from a fuzzy system and manage a mobile robot in a partially understood environment, Ming et al. [8] developed a genetic algorithm. Castillo et al. [11] have developed a hybridization of an ACO algorithm with the PSO algorithm to optimise the membership function of a fuzzy controller in order to create an optimal intelligent controller for an autonomous wheeled mobile robot. Chung and co.

PSO and fuzzy control algorithms have been developed by [12] to guide the robot through an uncharted terrain. The sensor-based PSO-fuzzy model has been put forth by Allawi and Abdalla [13] for the navigation of multiple mobile robots. Where the PSO is utilised to establish the best input/output membership functions and fuzzy type-2 controllers' best rules. The simulated annealing metaheuristic approach has been suggested by Yanar and Akyurek [14] for tweaking Mamdani type fuzzy models.

The difficulty of creating and fine-tuning the appropriate membership function grade is one of the main issues with fuzzy logic [22]. As a result, the authors have sought to use the WDO algorithm to try and overcome this problem. In this article, a hybrid fuzzy-WDO method for mobile robot navigation and collision avoidance in an unidentified static and dynamic environment has been described. To adapt and optimise the antecedent and consequent parameters of the generalised bell-shaped membership function, the WDO is combined with the fuzzy controller. A population-based iterative global optimization approach for problems involving several dimensions and models, the WDO [16e18] method has the ability to impose restrictions on the search domain. A number of tiny, simultaneous air parcels or prospective solutions are kept in the search domain by this technique. The membership function parameters (objective function), which are tuned based on the fitness function of that solution, are used to evaluate each air parcel for each iteration of the algorithm. The main goal of this study is to use the WDO algorithm to optimise the fuzzy controller's membership function parameters.

2.T1-SFLS controller for the mobile robot navigation

In this section, the T1-SFLS rule-based controller has been designed and implemented for mobile robot navigation and

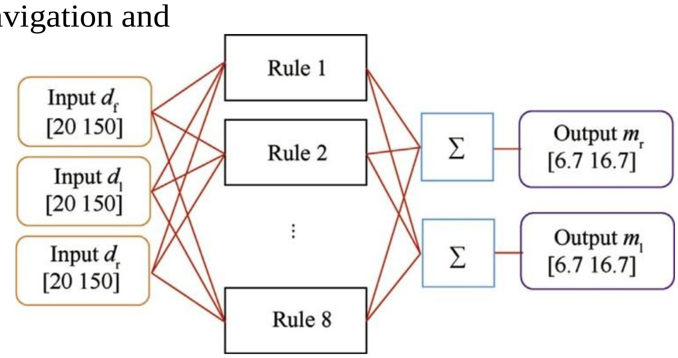

Fig. 1. The structure of a T1-SFLS controller for mobile robot navigation.

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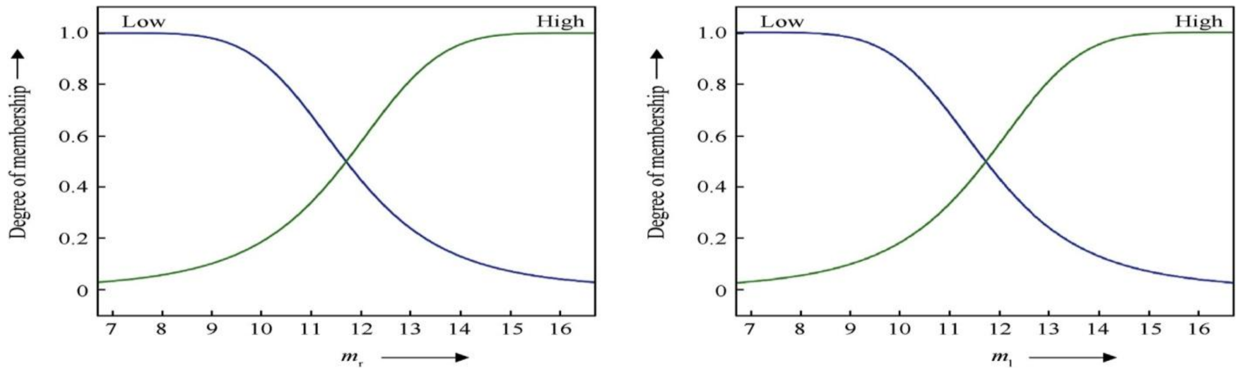

Fig. 3. Fuzzy membership functions for the outputs (m_r , and m_l).

Table 1

Fuzzy rules set.

If (d_f is Far) and (d_l is Far) and (d_r is Far) then (m_r is High) and (m_l is Low)

If (d_f is Near) and (d_l is Near) and (d_r is Near) then (m_r is Low) and (m_l is High) If (d_f is Far) and (d_l is Near) and (d_r is Far) then (m_r is Low) and (m_l is High) If (d_f is Far) and (d_l is Far) and (d_r is Near) then (m_r is High) and (m_l is Low) If (d_f is Near) and (d_l is Far) and (d_r is Far) then (m_r is Low) and (m_l is High) If (d_f is Near) and (d_l is Near) and (d_r is Far) then (m_r is Low) and (m_l is High) If (d_f is Near) and (d_l is Far) and (d_r is Near) then (m_r is High) and (m_l is Low)

Table 2

Adjusting parameters of the inputs before optimization.

Inputs	Membership function	*a*	*b*	*c*
d_f	Near	65	2.5	20
	Far	65	2.5	150
d_l	Near	65	2.5	20
	Far	65	2.5	150
d_r	Near	65	2.5	20
	Far	65	2.5	150

If (d_f is Far) and (d_l is Near) and (d_r is Near) then (m_r is Low) and (m_l is High)

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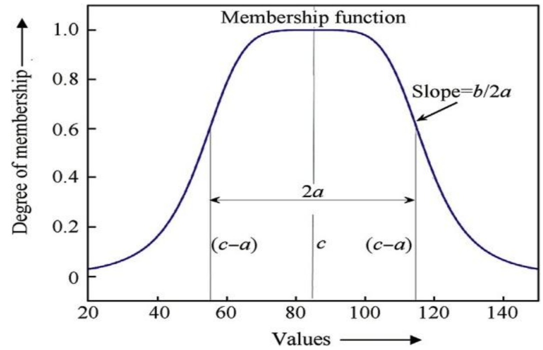

Fig. 4. The general structure of the generalized bell-shaped membership function.

collision avoidance in an unknown static and dynamic environ- ment. The proposed controller controls the right motor velocity and left motor velocity of the mobile robot using sensory data inter- pretation. The T1-SFLS controller has three inputs: Forward

Table 3

Adjusting parameters of the outputs before optimization.

Outputs	Membership function	*a*	*b*	*c*
m_r	Low	5	2.5	6.7
	High	5	2.5	16.7
m_l	Low	5	2.5	6.7
	High	5	2.5	16.7

illustrated in Figs. 2 and 3, respectively. The fuzzy rule set of the T1- SFLS controller is described in Table 1. The two generalized bell- shaped (Gbell) membership functions are used for inputs and outputs. The range of inputs is divided into two linguistic variables: Near and Far. These inputs are located at 20 cme150 cm. Similarly, the two Gbell membership functions (MFs) Low and High respec- tively have been used for the outputs, and it is located at 6.7 cm/s to
16.7 cm/s. The designed T1-SFLS controller is directly implemented in the mobile robot for simulations and experiments. The T1-SFLS controller is composed through Mamdani-type fuzzy model in the following form
Obstacle Distance (d_f), Left Forward Obstacle Distance (d_l) and $Rule_n$:
If dis d; d is d; and d_r *is d*
Right Forward Obstacle Distance (d_r); and two outputs: Right
f fð*i*Þ l
lð*j*Þrð*k*Þ
Motor Velocity (m_r) and Left Motor Velocity (m_l), which are logi- cally connected by eight rules (see Fig. 1). The T1-SFLS controller receives inputs (obstacle distances) from the front, left, and the right group of sensors of the robot, and output from T1-SFLS controller is right motor velocity and left motor velocity of the mobile robot. These sensors read the obstacle from 20 cm to 150 cm approximately. The input and output variables of the controller are Then m_r is $m_{rðijkÞ}$ and m_l is $m_{lðijkÞ}$

where n ¼ 1, 2, …,8 (eight rules), the i ¼ 1, 2, j ¼ 1, 2 and k ¼ 1, 2 because d_f , d_l and d_r have two Gbell membership functions each. The df ðiÞ, dlðjÞ, and drðkÞ are the fuzzy sets of the inputs df , dl , and d_r respectively. Similarly, the $m_{r ð ijk Þ}$, and $m_{l ð ijk Þ}$ are the fuzzy sets of the outputs m_r, and ml respectively. The fuzzy set (inputs and outputs) uses the following Gbell membership function.

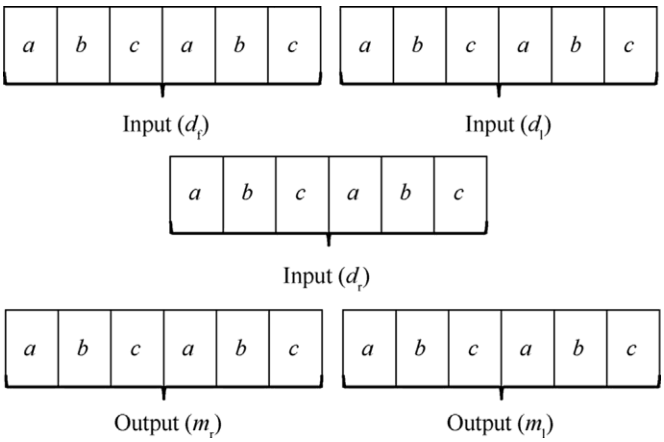

Fig. 5. Air parcels representation of the WDO algorithm.

Let d_f , d_l, and d_r are presented by x_1, x_2, and x_3 respectively. Similarly, m_r, and ml are denoted by y_1, and y_2 respectively.

The defuzzification of the outputs (y_1 and y_2) are accomplished by the weighted average method

Fig. 6. Fuzzy membership functions for the inputs (d_f , d_l , and d_r) after optimization.

1. Fuzzy-WDO algorithm for the mobile robot navigation

WDO [16] algorithm is inspired by the earth's atmosphere,

P$_8$
y

$_1$ðmn1ðx_1Þmn$2ð$x_2$Þ$mn3ðx_3ÞÞ$$y_1$

(7)where the wind blows are trying to equalize the horizontal

P$_8$ 1 ¼ n¼

n¼1ðmn1ðx_1Þmn$2ð$x_2$Þ$mn3ðx_3ÞÞimbalance in the air pressure. WDO is a new type nature-inspired global optimization based on atmospheric motion developed by Bayraktar et al. [16] in 2013. This method is working on the

y_2 ¼8 1ðmn1ðx_1Þmn$2ð$x_2$Þ$mn3ðx_3ÞÞ$$y_2$(8)population-based iterative heuristic global optimization algorithm for multi-dimensional and multi-modal problems with the poten-

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n¼1ðmn1ðx1Þ$mn2ðx2Þ$mn3ðx3ÞÞ

The adjusting parameters *a*, *b*, and *c* of the inputs and outputs are listed in Table 2 and Table 3, respectively, which will be opti- mized through the WDO algorithm in Section 3 below.tial to implement constraints on the search domain. WDO is similar to other nature-inspired optimization algorithms, in which population-based heuristic iterative process can be found for solving multi-dimensional optimization problems [18]. At its

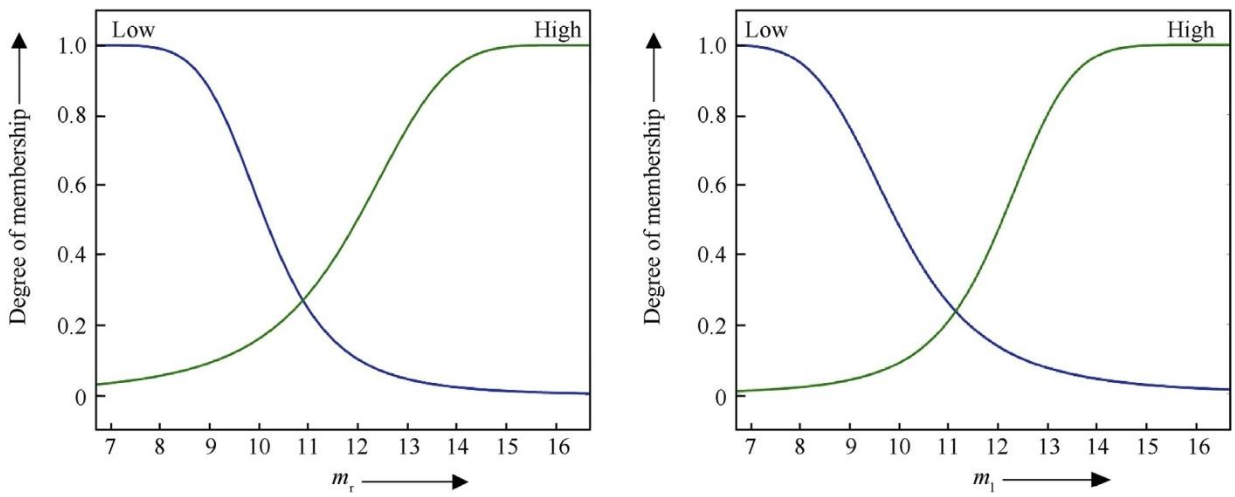

Fig. 7. Fuzzy membership functions for the outputs (m_r , and m_l) after optimization.

Table 4

Adjusting parameters of the inputs after optimization.

Inputs	Membership function	*a*	*b*	*c*
d_f	Near	55.11	2.14	25
	Far	59.6	1.88	149.4
d_l	Near	58.3	2.44	22.4
	Far	62.41	1.76	148.3
d_r	Near	57.42	2.33	23.1
	Far	60.29	1.55	148.9

Table 5

Adjusting parameters of the outputs after optimization.

Outputs	Membership	*a*	*b*	*c*

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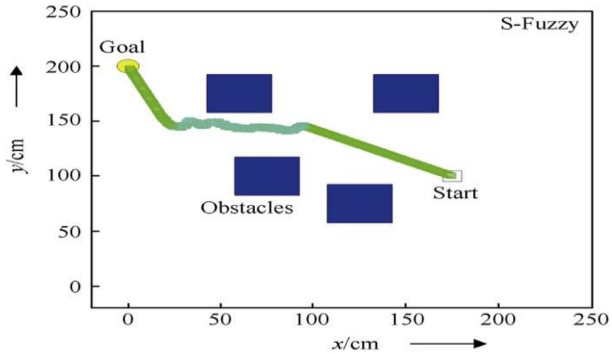
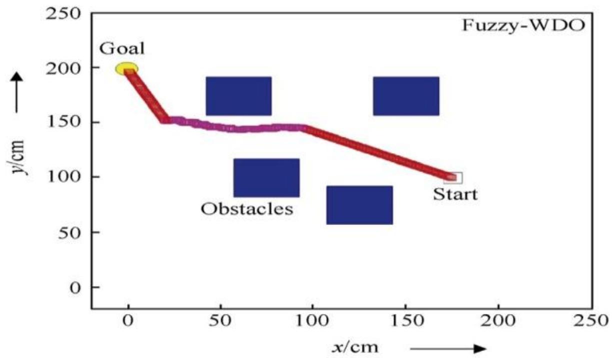
	function			
m_r	Low	3.61	2.601	6.515
	High	4.22	2.14	16.2
m_l	Low	3.97	2.21	5.96
	High	4.32	2.96	16.4



(a) T1-SFLS



(b) Fuzzy-WDO controller

center, a population of infinitesimally small air parcels navigates over an N-dimensional search space, employing Newton's second law of motion that is used to express the motion of air parcels inside the earth's atmosphere. As compared to other particle based opti- mization algorithm (e.g., PSO), the WDO algorithm has additional terms in the velocity update equation such as Gravitation and Co- riolis forces, which provides robustness and extra degrees of freedom to the algorithm.

The WDO algorithm is working based on the atmospheric mo- tion of infinitesimal small air parcels navigating over an N- dimensional search domain. The starting step of this algorithm is supported by the Newton's second law of motion, which provides accurate results when applied to the analysis of atmospheric mo- tion. It states that the total force applied on an air parcel causes it to accelerate with an acceleration a in the same direction as the applied total force.

$$r\$a \text{ ¼ } \sum F_i \qquad (9)$$

where r is the density of air for an infinitesimally small air parcel, and F_i represents all the individual forces acting on the air parcel. To relate the air pressure to the air parcel's density and temperature, the ideal gas law can be utilized and is given by

Fig. 8. Mobile robot navigation between the obstacles using (a) T1-SFLS and (b) Fuzzy- WDO controller.

F_G ¼ r$d*V*$*g* (13)

F_C ¼ —2U*u* (14)

where, V*P* is the pressure gradient, d*V* represents the infinite air volume, U represents the rotation of the earth, *g* is the gravitational acceleration, a is the friction coefficient and *u* is the velocity vector
of the wind.
The sum of all forces (gravitational force, pressure gradient force, friction force, and Coriolis force) described above can be entered on the right-hand side of Newton's second law of motion given in equation (9), which leads to

D*u*

r

$Dt ¼ ðr$d*V*$*g*Þþ ð—V*P*$d*V*Þþ ð—ra*u*Þþ ð—2U*u*Þ (15)

where the acceleration term in equation (9) is rewritten as *a* D*u*=D*t*, and a time step D*t* 1 is assumed for simplicity. For an infinitesimally small, dimensionless air parcel, the volume is set as d*V* ¼ 1, which simplifies equation (15) to

r$D*u* ¼ ðr$*g*Þþ ð—V*P*Þþ ð—ra*u*Þþ ð—2U*u*Þ (16)

Putting the ideal gas law equation (10) in equation (16), the density r can be written in terms of the pressure, with temperature and the universal gas law constant

u_{new} ¼ ð1 — aÞ$$u_{cur}$ — *g*$$x_{cur}$ þ RT 1 — 1 x_{opt} — x_{cur} cÞ

Fig. 9. Mobile robot navigation between the walls using (a) T1-SFLS and (b) Fuzzy- WDO controller.

P ¼ r*RT* (10)

cur

where *P* is the pressure, *R* is the universal gas constant, and *T* is the temperature.
Four major forces can be included in equation (9) that either where u_{new} is the velocity in the next iteration, u_{cur} is the velocity in current iteration, x_{cur} is the current location of the air parcel, x_{opt} is the optimum location of the air parcel, *i* represents the ranking between all air parcels, $u^{other\ dim}$ is the velocity influence from another randomly chosen dimension of the same air parcel, and all other coefficients are combined into a single term *c* (i.e.,*c* 2,U,*RT*). equation (17) represents the final form of the ve-
locity update utilized in WDO [16,19]. The following function up- dates the position of the air parcel

x_{new} ¼ x_{cur} þ ð$u_{new}$$D*t*Þ (18)

where x_{new} is the new position of the air parcel in the next iteration. If the new velocity

¼

u_{new} exceeds the initialize maximum velocity ($u_{\max}$ 0.3) in any dimension, then the velocity in that dimension is limited according to the following condition
cause the wind to move in a certain direction at a certain velocity or that deflect it from its existing path. The most observable force causing the air to move is the pressure gradient force F_{PG} defined in

new$u$max if $u$new > $u$max

u

-

¼

—$u$max if $u$new < — $u$max

(19)

equation (11). Another force is the friction force F_F defined in equation (12), which simply acts to oppose the motion started by the pressure gradient force. In our three-dimensional physical at- mosphere, the gravitational force F_G in equation (13) is a vertical force directed toward the earth's surface. The Coriolis force F_C in equation (14) is caused by due to the rotation of the earth and deflects the path of the wind from one dimension to another.

F_{PG} ¼ —VP\$dV (11)

F_{F} ¼ —r\$a\$$u$ (12)

where the direction of motion is preserved but the magnitude is limited to be no more than $u_{\max}$ at any dimension and u^* rep- resents the adjusted velocity after it is limited to the maximum speed.

The pseudo-code of the WDO algorithm can be summarized as follows:
Step 1. Start.

Step 2. Initialize the population size (i.e., group of air parcels), number of dimensions of the optimization problem, maximum number of iterations, coefficients (such as RT , g, a, c, $u_{\max}$), pressure function (fitness function of the ptimization prob- lem), lower and upper boundaries of the optimization problem.

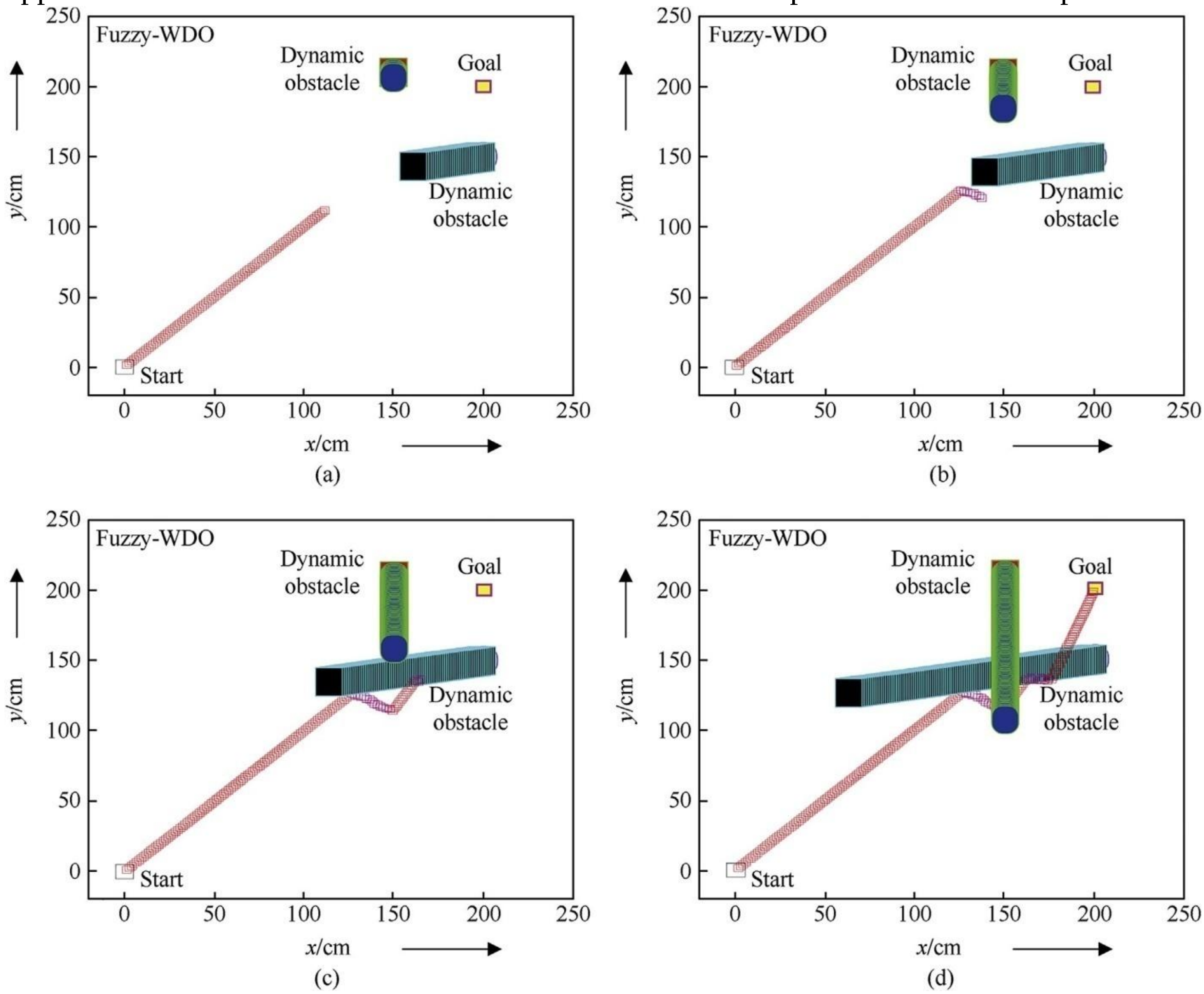


Fig. 10. Mobile robot navigation in the dynamic environment using Fuzzy-WDO controller.

Table 6

The simulation results of T1-SFLS and Fuzzy-WDO controllers.

Figure no.	Controller	Navigation path length /cm	Navigation time /s
Fig. 8	T1-SFLS	78.6	7.2
	Fuzzy-WDO	74.4	6.9
Fig. 9	T1-SFLS	103.7	9.1
	Fuzzy-WDO	98.2	8.7

Step 3. Assign random position and velocity of the air parcels. *Step 4*. Evaluate the pressure (fitness) values of each air parcel at its current position.
Step 5. Once the pressure values have been evaluated, the pop- ulation is ranked based on their pressure (ascending order), and the velocity updated according to equation (17) along with the restrictions are given in equation (19).
Step 6. Update the position of the air parcel for the next iteration according to equation (18) and also check the boundaries of the air parcel.
Step 7. Stop if a maximum number of iterations are achieved, else go to step 4.
When the maximum number of iterations is completed, the best pressure (fitness) value is achieved.
This section describes the WDO algorithm used for the

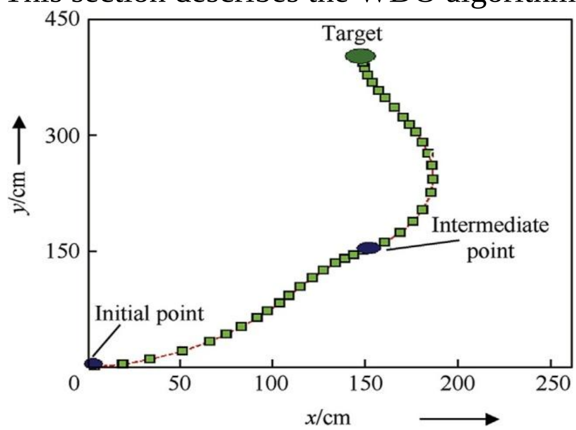


Fig. 11. Mobile robot navigation in an environment without obstacle using fuzzy controller [23].

membership function parameter optimization of the T1-SFLS controller for the optimum navigation and collision avoidance in an unknown static and dynamic environment. One major problem with the fuzzy logic is the difficulty of constructing and tuning the

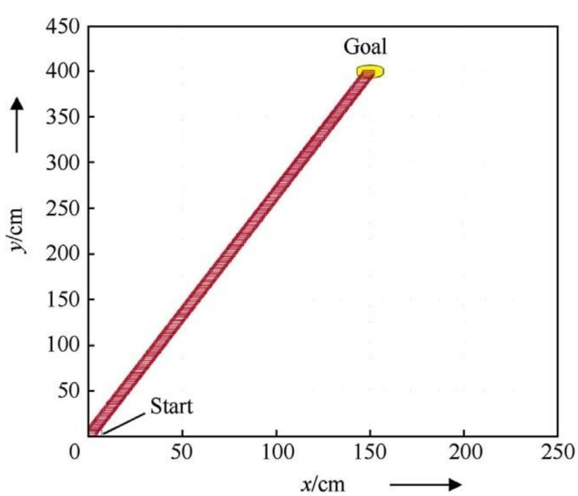


Fig. 12. Mobile robot navigation in an environment without obstacle using Fuzzy-WDO controller.

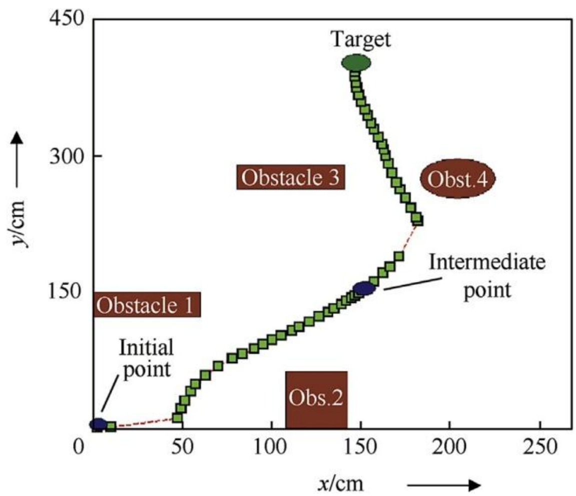


Fig. 13. Mobile robot navigation in an environment with four obstacles using fuzzy controller [23].

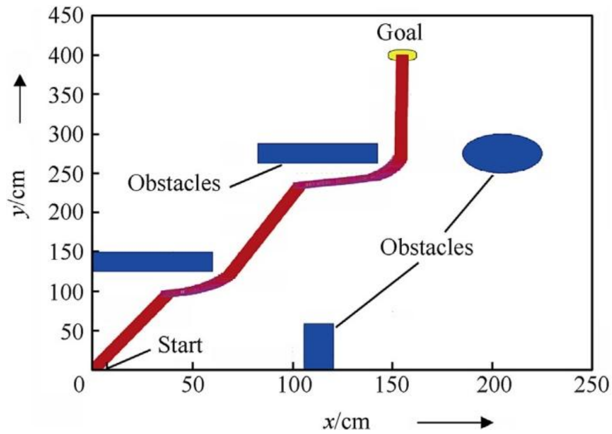


Fig. 14. Mobile robot navigation in an environment with four obstacles using Fuzzy-WDO controller.

Table 7

The simulation result comparison between the fuzzy controller [23] and proposed Fuzzy-WDO controller.

Figure no.	Method	Navigation path length /cm
Fig. 11	Fuzzy controller [23]	181
Fig. 12	Fuzzy-WDO controller	165
Fig. 13	Fuzzy controller [23]	183

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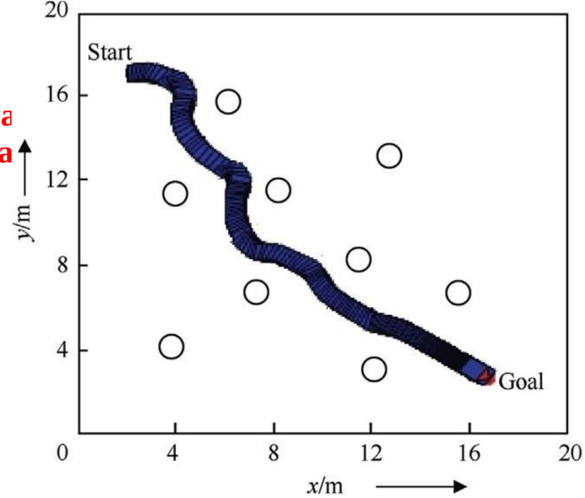

Fig. 14	Fuzzy-WDO controller	173

Fig. 15. Mobile robot navigation between many obstacles using fuzzy model [24].

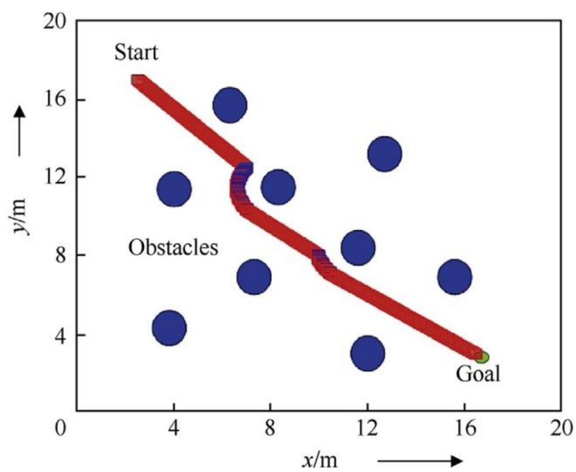

Fig. 16. Mobile robot navigation between many obstacles using Fuzzy-WDO controller.

Table 8

Comparison of simulation results between fuzzy model [24] over proposed Fuzzy- WDO controller.

Figure no.	Method	Navigation path length /cm
Fig. 15	Fuzzy model [24]	91
Fig. 16	Fuzzy-WDO controller	84

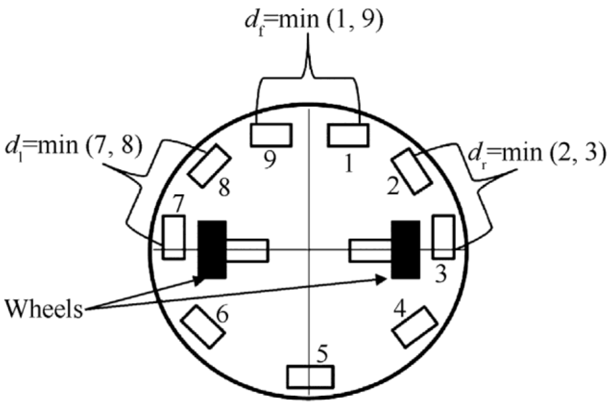

Fig. 17. Infrared proximity sensor distribution of Khepera-III mobile robot.

correct membership function grade [22]. Because of this problem, the WDO algorithm is used to tune the adjusting parameters of the inputs and outputs. From Section 2, two Gbell membership func- tion are considered for the inputs (d_f , d_l, and d_r) and outputs (m_r , and m_l). Each Gbell membership function has three adjusting parameters (*a*, *b*, and *c*). Therefore, each input has six adjusting pa- rameters. Similarly, each output has six adjusting parameters. So the total number of adjusting parameters is to be thirty {5 (3 inputs þ 2 outputs) × 2 (membership function) × 3 (adjusting parameters *a*, *b*, and *c*) ¼ 30}.

The ranges of adjusting parameters are defined as [a_{min}, a_{max}] [b_{min}, b_{max}] and [c_{min}, c_{max}] respectively, for lower and the upper boundary of the WDO algorithm. The a_{min} and a_{max} are 30 and 65 for the membership function of the inputs. The b_{min} and b_{max} are 1 and 3.5 for the membership function of the inputs. The parameters c_{min} and c_{max} are 20 and 150 for the membership function of inputs respectively. Similarly, the a_{min} and a_{max} are 2 and 5 for the membership function of outputs. The b_{min} and b_{max} are 1 and 3.5 for the membership function of the outputs. The parameters c_{min} and c_{max} are located at 6.7 and 16.7 for the membership function of outputs respectively. Fig. 5 shows the air parcels representation of

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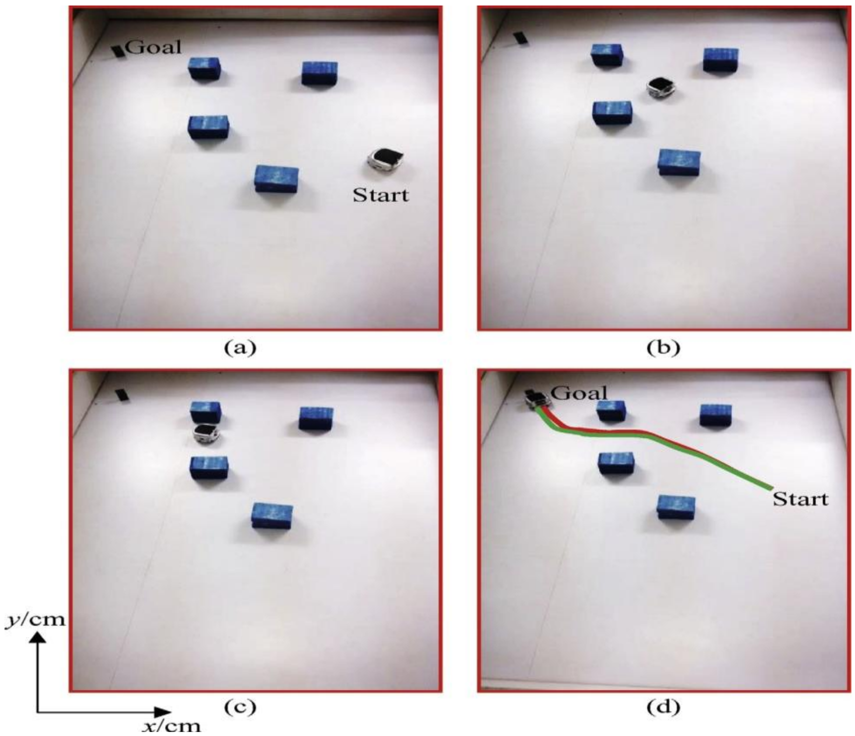

Fig. 18. Real-time navigation of Khepera-III mobile robot between the obstacles using T1-SFLS and Fuzzy-WDO controller.

the WDO algorithm. The optimized membership functions of the inputs (d_f , d_l, and d_r) and the outputs (m_r, and m_l) are shown in Figs. 6 and 7, respectively. The results of the adjusting parameters (a, b, and c) of the inputs and outputs after optimization are listed in Table 4 and Table 5, respectively.

The most important step in applying the WDO algorithm is to select the fitness function, which is used to evaluate the optimum pressure of the air parcels. In during the optimization process, the combined root mean square errors (CRMSE) are used to evaluate the fitness of the fuzzy controller controller covers shorter distance to reach the goal as compared to previous model [23] because WDO algorithm adjusts the membership function of the fuzzy controller, which provides better result compared to the standalone fuzzy model. Besides, the pro- posed Fuzzy-WDO controller also helps the mobile robot to reach the goal without taking any intermediate point. And due to this, it takes less time to reach the goal as compared to previous model [23]. Table 7 illustrates the path traced (in cm) by the robot to reach the goal using proposed controller and previous model [23].

Figs. 15 and 16 show the mobile robot navigation result comparison between the fuzzy model [24] and proposed Fuzzy-WDO controller, respectively. From the simulation results, it can be seen that the proposed controller provides the better trajectory

CRMSE ¼ $RMSE_{mr}$ þ $RMSE_{ml}$ (22)

where m^{actual} and m^{actual} are the actual value of right and left motor model. Table 8 shows the path covered (in cm) by the robot to reach

the goal using proposed controller and previous model [24]. The centimetre measurements

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are taken on the proportional basis.

SIMULATION RESULTS

This section describes the successful simulation results using T1-SFLS and Fuzzy-WDO controllers in the various unknown static and dynamic environments. The simulations are conducted using the MATLAB software on the HP 3.40 GHz processor. Figs. 8 and 9 show the navigation result of the mobile robot between the ob- stacles and walls respectively, using the T1-SFLS and Fuzzy-WDO controller in the unknown environments. Similarly, Fig. 10 dem- onstrates the navigation of a mobile robot in an unknown envi- ronment with the presence of two dynamic obstacles using Fuzzy- WDO controller. It is assumed that the position of the start point and goal point are known. But the positions of all the obstacles in the environment are unknown for the robot. In the simulation re- sults, the green and red color trajectory indicates the path gener- ated by the T1-SFLS and Fuzzy-WDO controllers respectively. Simulation results show the Fuzzy-WDO controller gives smooth and optimal path compared to the T1-SFLS controller. Table 6 shows the navigation path length and time taken by the robot us- ing the T1-SFLS and Fuzzy-WDO controller in the various unknown environments.

COMPARISON WITH PREVIOUS WORKS

This section describes the computer simulation result compar- ison between the previous model [23] and proposed Fuzzy-WDO controller in the same path planning problems. In the article [23], the authors have used two simple fuzzy controllers such as tracking fuzzy logic control (TFLC) and obstacle avoidance fuzzy logic con- trol (OAFLC) without adjusting its membership function for mobile robot navigation. Figs. 11 and 12 show the mobile robot navigation in the same environment without obstacle using fuzzy controller
[23] and proposed Fuzzy-WDO controller, respectively. Similarly, Figs. 13 and 14 present the path covered by the robot in the same environment with the four obstacles using fuzzy controllers [23] and proposed Fuzzy-WDO controller, respectively. From the simu- lation figures, it can be seen that the proposed Fuzzy-WDO *Khepera-III mobile robot description*

The experiments are conducted using the Khepera-III mobile robot in unknown environments. The Khepera-III mobile robot has two wheels controlled by two DC servo motors and one caster wheel. The diameter and height of the robot are 13 cm and 7 cm respectively. The Khepera-III mobile robot is equipped with nine infrared proximity sensors and five ultrasonic sensors, as shown in Fig. 17. The Infrared proximity sensor reads obstacles up to 30 cm, and the ultrasonic sensor reads obstacles from 20 cm to 4 m approximately. In this study, we have set the minimum and maximum velocity of Khepera-III mobile robot between the 6.7e16.7 cm/s.

Experiments

In the experiments, the controllers are implemented in the Khepera-III mobile robot using HP laptop. The width and height of the experimental platform are 250 cm and 250 cm, respectively. Fig. 18 and Fig. 19 shows the real-time navigation of the Khepera-III

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mobile robot in unknown environments with the obstacles and walls, respectively. In Fig. 18, the start position of the robot is (175,
100) cm, and the position of the goal is (0, 200) cm. The starting angle between the robot and the goal is 29.74○. Similarly, in Fig. 19, the start position of the robot is (50, 50) cm, and the goal position is (250, 200) cm. The starting angle between the robot and the goal is 36.87○. In the experiments, it is assumed that the position of the start point and goal point are known, but the positions of all the obstacles in the environment are unknown for the robot. The T1- SFLS and Fuzzy-WDO controller generate the motor velocity con- trol command for obstacle avoidance using on-board sensor in- formation. The successful experimental results in the various unknown environments are shown below to verify the effective- ness of the T1-SFLS and Fuzzy-WDO controllers. Table 9 shows the experimental path length and time taken by the Khepera-III mobile robot to reach target using the T1-SFLS and Fuzzy-WDO controllers in the various unknown environments. Tables 10 and 11 present the traveling path length and navigation time comparison between the simulation and experimental results. In the comparison study be- tween the simulation and experiments, it is observed that some errors have been found, these happen due to slippage and friction during real time experiment.

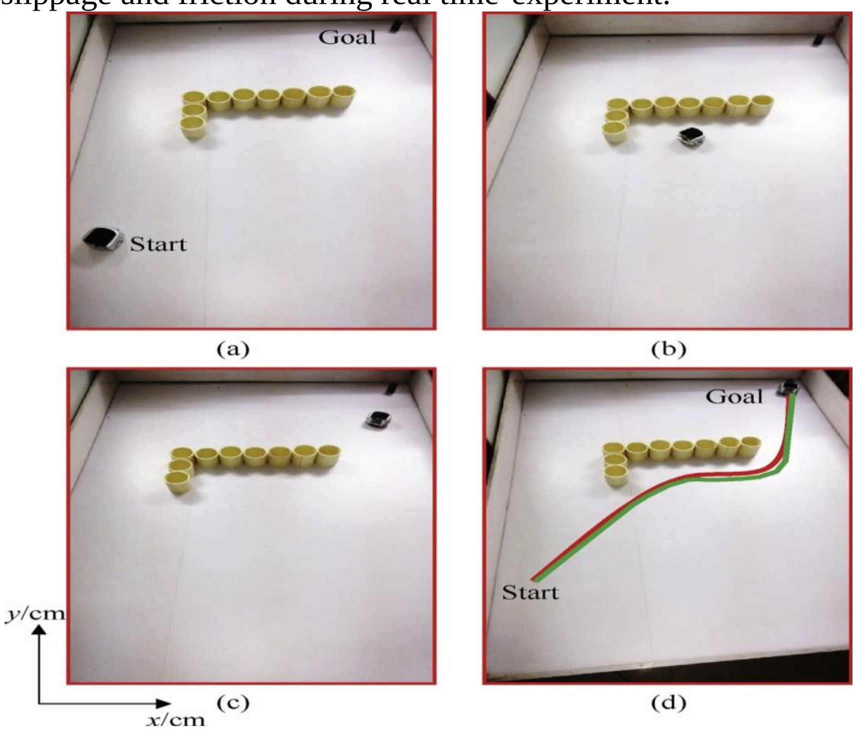

Fig. 19. Real-time navigation of Khepera-III mobile robot between the walls using T1-SFLS and Fuzzy-WDO controller.

7. CONCLUSION

In this work, the mobile robot navigation has been addressed using the T1-SFLS controller and the hybrid Fuzzy-WDO algorithm. The antecedent and consequent parameters of the fuzzy controller are optimised using a new population-based optimization approach called Wind Driven Optimization (WDO). Through simulations and in-the-moment trials in various contexts, the proposed methods are successfully validated. Results from simulations and experiments show that the Fuzzy-WDO controller performs better than the T1-SFLS controller.

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