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Intelligent controller design of an autonomous system using a social spider optimizer for path navigation and obstacle avoidance

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ABSTRACT

This research paper proposes a hybrid fuzzy logic controller for achieving autonomous path navigation and obstacle avoidance through the use of the Social Spider Optimizer algorithm. The proposed controller employs kinematic modelling to determine the mobile robot's path navigation and utilizes a fuzzy logic system for effective control. The Social Spider Optimizer algorithm optimizes the parameters of the fuzzy controller, while the FLC is responsible for obstacle avoidance. The effectiveness of the proposed controller has been analyzed, and a comparative study has been carried out with optimization techniques like particle swarm optimization (PSO) and cuckoo search optimization (CSO) controllers. The study aims to propose a hybrid fuzzy logic controller, that provides efficient navigation and obstacle avoidance for mobile robots. In a simulation, the starting point is considered as (0,0) and the destination point is set as $X_k = 1.1$ and $Y_k = 1.2$. The performance of the proposed method is compared with FLC and methods like PSO and CSO. With the SSO-based FLC, the proposed mobile robot identifies the obstacle distance and travels towards the destination with smooth navigation. The results show the efficacy of the proposed controller in comparison to other controllers for mobile robots in terms of path navigation and obstacle avoidance.

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Mobile robot; social spider optimization; particle swarm optimization; cuckoo search optimization; fuzzy logic controller; path navigation

1. Introduction

In the modern era, robots are utilized for actual existing software and are performing human duties. Robotics in the field of commercial manufacturing has flourished to great heights. Two billion industries can be accommodated by a robot manipulator [1–4]. Despite having several advantages, individuals may suffer from poor mobility. In robotics, movement is the first task to be completed. In mobile robots, there are a few difficult scenarios to navigate, such as how to move the robot and what effective locomotion strategy may be employed to make use of the locomotion mechanism [5].

Through the Robotic Process Automation (RPA) application, employees of a company can configure robotic or computer software. This preparation is carried out to capture and seize the standard programmes for information manipulation, spoken communication with other digital systems, eliciting replies and transaction processing [6–8].

There are numerous types of robots, and they are utilized to deliver exceptional items in a luxurious setting. Robotics uses its electrical components to control its energy and machinery. The adaptability of robots has improved, enabling them to complete various applications and tasks with more accuracy than manual labour. With the speed of robotics, the profit margin and productivity are increased. Automatic machinery lessens the need for human electricity. These man-made machines can be used in any dangerous task that increases the risk of injury, increasing the safety of the working environment [9–11].

The use of mobile robots is expanding every day, and they are already being employed for a variety of purposes including exploration, rescue, and other forms of entertainment. Since the legged robots have a large number of degrees of freedom, they don't require much planning or management. While legged mobile robots (LMR) require contact with the ground to move, wheeled mobile robots (WMR) have higher effective power, which results in a simpler mechanical structure. They also have simpler dynamics when compared to LMR. Three-wheeled robots that could make dynamics even easier could be used to attain the static balance. Since the stability of the supporting polygon is increased at a higher cost, the vehicles use four-wheeled robots. When two-wheeled robots are compared to other wheeled robots, they have additional advantages

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[12]. These robots are easier to manipulate the robots than legged robots however hard to govern than solid-wheeled robots [13–16]. The robot kinematic is the look at robot movement regardless of pressure and torque which caused it. It also computes the orientation and role of robotic manipulators' end effectors that are related to the manipulator base as a characteristic of joint variable [17].

Since wheeled robots are taller, they are more suited for interior spaces. Robotics' biggest issue is keeping track of it from the beginning to the end without it crashing [18]. A wheeled cell robotic's basic functions are direction planning and direction locating. A Cartesian coordinate system is used in path planning to generate the robot's acceleration and deceleration profile [19]. The path is found using a few manipulated rules. A linear controller is used to track a synchronous robotic's direction [20]. Additionally, the suggested controller incorporates a mobile robot's steering, pricing, route planning, global navigation, and local navigation.

Artificial intelligence (AI) refers to the process of continuously carrying out any task without the involvement of a human to improve the comfort, efficiency, and security of the apparatus. Depending on the machine's motivation, the automatic tool's regulating range can vary. Li et al. [21] develop a visual serving system that adopts a desired position. The authors [22] proposed a novel technique for multi-robot cooperation in stick-carrying tasks. It integrates modified Q-learning with an improved version of particle swarm optimization and intelligent water drop algorithm. The resulting hybrid algorithm computes collision-free paths while optimizing path distance, energy usage, and smoothness.

Furthermore, it concurrently accepts input with undetermined intensity. Based on quantifiable alarms in the polar coordinate system, device errors were selected. Then, kinematic modelling was developed with an undetermined intensity. At the same time, it does a thorough stability analysis to demonstrate depth identity and posits regulating errors that converge to zero. Both the experimental and simulation results served as examples of how the suggested strategy could work. The primary drawback of a well-established method was that it was impossible to accomplish visible serving assignments with the development of intensity identification without the needed images.

The development, operation and layout of the robots address robotics also which is utilized within the computer gadget to record processing, sensory remarks and so forth. Those technologies are advanced for the motive of replacing people with robots that execute human actions. Yoo et al. [23] developed a disbursed connectivity which preserves corresponding routing problems for a selection of unsure nonholonomic robotics which occurs within a constrained communiqué range. Initial connectivity sample and synchronized tracking had been preserved by means of introducing a new dispensed error floor and this became the primary intention of this paper. Lyapunov feel had mentioned the connectivity and fidelity of the closed-loop synchronized gadget. The proposed synchronized tracking scheme has to be carried out for the diverse WMRs which is the hardiest drawback of this method.

For more than one-cell robots, authors [24] added a brand new war decision method for cluttered and dynamic environments even as making ensure their movement-aliveness. In this paper, the overall travel time of the robots had been reduced by way of a mathematical feature. A sophisticated method of gathering may be delivered to exceed the computational value in the implementation. The suggested approach becomes relevant to actual-time an application that was established with the simulation consequences.

The inherently unstable characteristic of a two-wheel self-balancing robot has attracted the attention of many researchers. To achieve stability, several AI techniques, including neural network control and fuzzy logic control can be utilized in designing an appropriate controller and the Sugeno Fuzzy logic technique was developed in [25] to control the two WMRs. As part of the analysis, various parameters were computed to ensure the stability of the two-wheeled mobile robot during navigation. These included inputs like the tilt angle, current acceleration, and current velocity, as well as outputs like the final acceleration and final velocity. The authors [26] proposed a hybrid algorithm combining improved Q-Learning (IQ) and democratic robotic particle swarm optimization (DRPSO). The algorithm achieves collision-free paths and synchronizes robot pairs in terms of steps, turns, direction, and distance.

Adaptive sliding mode trajectory tracking control was developed in [27] for WMRs with regard to the inertia uncertainties as well as exterior conflicts. This work explains the distributed tracking issue in multiple-wheeled mobile robots. Multiple agents/robots are controlled by an important technique named Formation control in the control area while maintaining a desired formation geometry. The consequence of the suggested technique was confirmed by the simulation results.

An adaptive tracking control scheme was presented by the authors [28] for an asymmetrically actuated WMR. This paper also addresses the challenging previous issues. This work initially creates a WMR with an uncertain mass centre because of the impact of uncertain load. Next, a new value was introduced to transform the constrained problem into one without constraint. At last, a user-friendly scheme was created by norm bounding skill. Also, it was authenticated theoretically by the Lyapunov method. But this paper does not explain the impact of tracking control performance.

For autonomous Mobile Robot Navigation, the authors [29] developed an interval type-2 fuzzy parameter adaptation using the Bee Colony Optimization (BCO) algorithm. The trajectory of the autonomous mobile robot is controlled by this BCO algorithm. This work has utilized the perturbation model.

With regard to self-governing driving, the authors [30] exhibited the requirement for and potential for methodically coordinated vision and semantics answers for visual sense-making. A general neurosymbolic strategy for online visual sense-making is efficiently formalized and completely executed utilizing answer set programming (ASP). The analysis demonstrates the capabilities, offers practical examples, and demonstrates how to integrate innovative and intelligent deliberative engineering for human-robot collaboration. According to test results, [31] demonstrates how requiring unavoidable, human-level semantics within the robot's deliberative framework leads to clear-cut information the executives – both representative and mathematical – becoming crucial to more extravagant and regular human-robot relationships.

The robot operates in a less than stage-aware manner, and any planning impasse brought on by missing administrators is resolved online by asking a human educator for the next action to take in light of the observed state advances. The methodology used in [32] quickly identifies the missing administrators by weighing the importance of various cause impact options in equal measure using a likelihood gauge, which compensates for the high vulnerability that is innate when gaining access to financial information. The authors [33] introduced an intelligent approach to path planning and collision avoidance for twin robots carrying sticks by integrating modified cuckoo search, sine cosine algorithm, and particle swarm optimization (PSO).

Khan et al. [34] conducted a comparative analysis of controller designs for speed control of DC motors in two-wheeled mobile robots, focusing on the performance evaluation of different controllers. The study compared the effectiveness of various controllers, shedding light on their respective advantages and limitations. In a related work, Khatoon et al. [35] proposed a PID controller design specifically tailored for DC motors used in wheeled mobile robots. Their study highlighted the utilization of PID controllers and their efficacy in achieving desired speed control, contributing valuable insights into practical implementation aspects.

Further extending their investigation, Khan et al. [36] revisited the comparison of various controller designs for speed control of DC motors in two-wheeled mobile robots. This work likely provided additional perspectives on controller performance and possibly refined methodologies for evaluation and comparison. Expanding the scope of their research, Khan et al. [37] delved into a comparative study of ANFIS, Fuzzy, and PID controllers for speed control of wheeled mobile robots. Their findings contributed to understanding the comparative advantages of these control techniques in achieving stable and efficient speed control.

In recent developments, Khan, Khatoon, and Gaur [38] proposed a novel approach to wheeled mobile robot stabilization using a social spider algorithm-based PID controller. This study likely offered innovative insights into controller design methodologies, exploring nature-inspired algorithms for enhanced performance. In a related work by Khan et al. [39], the authors introduced a nature-inspired social spider algorithm-based PID controller for speed control of wheeled mobile robots. Their research likely contributed to advancing the state-of-the-art in controller design, offering promising solutions for practical implementation. In the broader context of mobile robot navigation, Parhi and Mohanty [40] presented an IWO-based adaptive neuro-fuzzy controller for navigation in cluttered environments. This work likely provided valuable insights into navigation strategies applicable to wheeled mobile robots operating in challenging terrains.

Kim and Kim [41] addressed trajectory planning for omni-directional mobile robots, focusing on minimum-energy cornering trajectories with self-rotation. Their study likely contributed to advancing trajectory planning techniques for wheeled mobile robots, enhancing efficiency and manoeuverability. The authors [42] introduced a hybrid path planning algorithm based on the membrane pseudo-bacterial potential field for autonomous mobile robots. Continuing on path planning, [43] proposed a membrane evolutionary artificial potential field for mobile robot path planning. Their research, published in Applied Soft Computing, presented a method to generate efficient and smooth trajectories, enhancing the navigational capabilities of mobile robots. Furthermore, [44] developed a mobile robot path planning algorithm using a QAPF (Quorum Artificial Potential Field) learning algorithm for both known and unknown environments.

Rossomando [45] explored sliding mode control combined with adaptive neural networks for trajectory tracking of non-holonomic mobile robots, aiming to achieve precise and robust control performance. This research likely advanced the understanding of control methodologies applicable to wheeled mobile robots.

Moreover, the integration of optimization techniques with fuzzy logic controllers has garnered attention. Juang and Lo [46] proposed a fuzzy systems design aided by clustering-aided Ant Colony Optimization, while Bouallegue et al. [47] introduced PID-type fuzzy logic controller tuning based on particle swarm optimization, and Bingül and Karahan [48] presented a fuzzy logic controller tuned with PSO for robot trajectory control. These studies likely contributed to

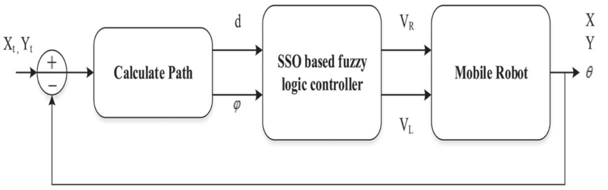


Figure 1. The workflow of the proposed method

enhancing the performance and adaptability of fuzzy logic controllers in various applications.

Furthermore, Liu et al. [49] addressed speed optimization control for wheeled robot navigation with obstacle avoidance based on viability theory, offering insights into robust navigation strategies. Additionally, Anuranj and Anitha [50] conducted a comparative analysis of optimal node selection algorithms for data transmission in VANET, showcasing the importance of optimization techniques in improving communication reliability in mobile networks.

The main contribution of our proposed work is as follows;

- The SSO-, PSO- and CSO-based Fuzzy models have been designed.
- The optimum values have been obtained for the fuzzy controller using the Social Spider Optimization (SSO) technique.
- The proposed SSO algorithm has been compared with the existing PSO and CSO algorithms optimized FLC for obstacle avoidance and path navigation.

2. Proposed methodology

In this paper, FLC values are enhanced with the help of the SSO procedure. Initially, kinematic modelling is applied to design a wheeled robot.

The desired velocity of the mobile robot has been obtained using the FLC which utilizes the path planning controller. Figure 1 illustrates the workflow model of the suggested method.

2.1. Demonstration of mobile robot

A kinematic and dynamic model of mobile robots is explained in this section. Mathematical formulations of mobile robot design are explained in the given below subsections.

2.1.1. Kinematic model

The behaviour of the robot has been designed using the kinematics model [51]. This model additionally validates the motion of a mobile robot, as shown in Figure 2.

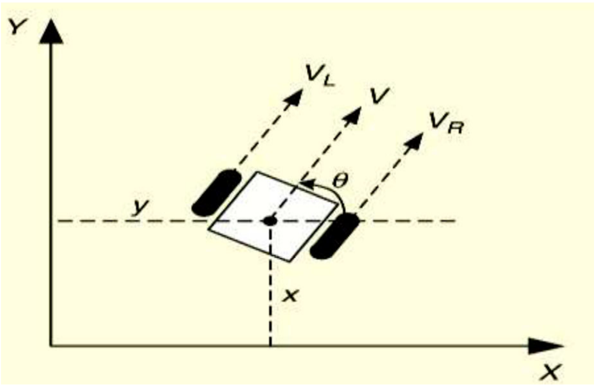


Figure 2. Kinematic model of robot.

Mobile robots are represented in the coordinate which is represented as (O, X, Y). V and W present the robot velocity and angular velocity, respectively. Additionally, the radius of the driving wheel or r, stands for the orientation of the mobile robot, the middle space between the two moving wheels, or 2b, stands for the velocity of the left and right driving wheels, or $\mathrm{V_L}$ and $\mathrm{V_R}$, respectively, and the x and y axes represent the robot's position.

A mobile robot's motion differential drive is defined by the expressions presented below.

$$V_L = w_L r \tag{1}$$

$$V_R = w_R r \tag{2}$$

w_L (Left) and w_R (Right) refer to the angular line speeds of both wheels.

Moreover, the following equations computed the non-holonomic limitation of the robot.

$$x \sin\theta - y \cos\theta = 0 \tag{3}$$

The following expressions can directly be deduced from the previous expression.

$$\begin{aligned} v &= \frac{w_R + w_L}{2} r \\ w &= \frac{w_R - w_L}{2b} r \end{aligned} \tag{4}$$

The following expressions mention the dynamic functions of the robot.

$$x = v \cos\theta \tag{5}$$

$$y = v \sin\theta \tag{6}$$

$$\theta = w \tag{7}$$

The following expression is based on the combination of the above-mentioned equations.

$$\begin{bmatrix} x \\ y \\ \theta \end{bmatrix} = \begin{bmatrix} \frac{r}{2}\cos\theta & \frac{r}{2}\cos\theta \\ \frac{r}{2}\sin\theta & \frac{r}{2}\sin\theta \\ \frac{-r}{2b} & \frac{r}{2b} \end{bmatrix} \begin{bmatrix} w_L \\ w_R \end{bmatrix} \tag{8}$$

where x and y are just associated with v and θ which is related to w. So, the following expression explains the mobile robot's kinematic conventional model.

$$\begin{bmatrix} x \\ y \\ \theta \end{bmatrix} = \begin{bmatrix} \cos\theta 0 \\ \sin\theta 0 \\ 0 \quad 1 \end{bmatrix} \begin{bmatrix} v \\ w \end{bmatrix} \tag{9}$$

In the X- and Y-axis directions, the robot's velocity is denoted as x and y, θ and v mentions the robot's rotational velocity and linearity. The standard kinematics model of the mobile robot is thus illustrated by the matrix that is presented below.

$$\begin{bmatrix} v \\ \theta \end{bmatrix} = \begin{bmatrix} \frac{r}{2} & \frac{r}{2} \\ \frac{r}{2b} & -\frac{r}{2b} \end{bmatrix} \begin{bmatrix} w_L \\ w_R \end{bmatrix} \tag{10}$$

2.1.2. Dynamic model

This subsection explains the dynamic model of mobile robots based on a non-holonomic model [52]. The location of the central point of the robot is defined by the complete coordination system X, O, Y.

$$I_v\phi = D_R I - D_L I \tag{11}$$

$$Mv = D_R + D_L \tag{12}$$

$$I_w\phi_1 = ku_i - rD_i \;\; (i = r, I) \tag{13}$$

where the azimuth of the robot is denoted by ϕ, I_v mentions the robot's moment of inertia, D_R and D_L denote the forces for the right and left moving wheel, I defines the space edged by the left and right steering wheels mass is mentioned by M, linear speed is declared as v, moment of inertia of wheel is stated as I_w, viscous friction factor is specified as c, driving gain factor is indicated as k, radius of the wheel is designated as r and the driving input is labelled as u_i. The geometrical relationships between the three variables such as ϕ, v, θ are presented in the following expressions.

$$r\theta_R = v - I\phi \tag{14}$$

$$r\theta_L = v - I\phi \tag{15}$$

The dynamic portion of the robot in mathematical order is described by state space. Here, $x = [\phi, v, \theta]$ illustrates the state variables of the robot also, it defines flexible input variables like $s = [s_R, s_L]$ and flexible output variables $y = [v, \theta]$.

$$x = Ax + Bu \tag{16}$$

$$y = Cx \tag{17}$$

where

$$A = \begin{bmatrix} a_1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & a_2 \end{bmatrix} \tag{18}$$

$$B = \begin{bmatrix} b_1 & b_1 \\ 0 & 0 \\ b_2 & -b_2 \end{bmatrix} \tag{19}$$

$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{20}$$

$$a_1 = \frac{-2c}{Mr^2 + 2I_w} \tag{21}$$

$$a_2 = \frac{-2cI^2}{I_v r^2 + 2I_w I^2} \tag{22}$$

$$b_1 = \frac{kr}{Mr^2 + 2I_w} \tag{23}$$

$$b_2 = \frac{-krI}{I_v r^2 + 2I_w I^2} \tag{24}$$

The following expressions explain the connection between the input torques and the output of the controller.

$$s_R = s_v + u_\phi \tag{25}$$

$$s_L = s_v - u_\phi \tag{26}$$

where u_ϕ and s_v mention the angle and linear speed of the mobile robot.

3. Fuzzy logic controllers (FLC)

Navigation of movable robots is controlled by FLC which is already studied in many research papers. The main blocks of FLC are fuzzification, inference, and defuzzification. As a result, Fuzzification changes every single real value input into outputs of membership functions in the initial stage. The subsequent part of fuzzy interference performs the fuzzy reasoning process which is a mixture of rule-base fuzzification. Membership functions depend on some techniques of fuzzy interference systems [53]. Here, the Mamdani algorithm is used in a fuzzy logic controller. Figure 3 shows the basic structure of FLC.

The fuzzy rule is created by considering membership functions, and input and output variables in the form of "if (antecedents) then (conclusion)" rules.

For the proposed FLC, distance (d) and angular position (ϕ) are considered as two different inputs. The output of the controller is considered as the speed of the wheels. The following expression is written for two different types of inputs which are given to the FLC system.

$$d = \sqrt{(X_T - X)^2 + (Y_T - Y)^2} \tag{27}$$

$$\phi = \theta_T - \theta \tag{28}$$

where X_T, Y_T mentions the target position, X, Y mentions the current position and $\theta_T = \tan^{-1}\frac{(Y_T - Y)}{(X_T - X)}$.

3.1. Membership function structure

The trapezoidal and triangular membership functions use the fuzzification block. Five triangular membership functions such as high (H), very high (VH), medium

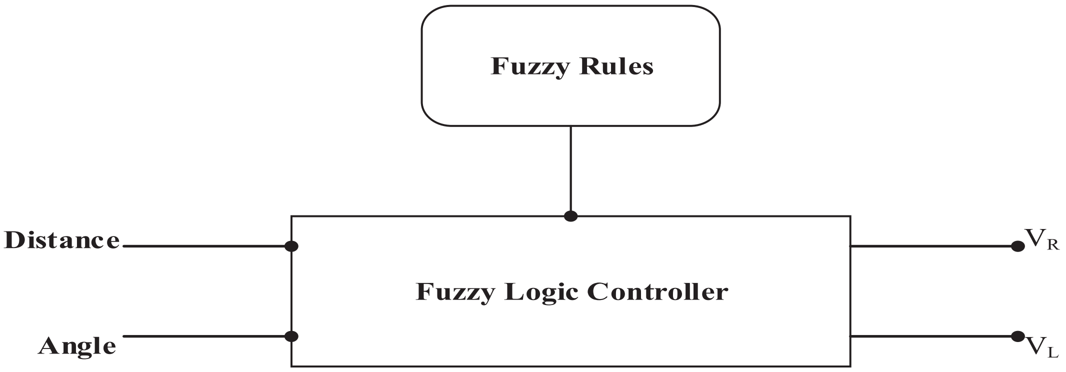


Figure 3. Conventional tracking Fuzzy control system.

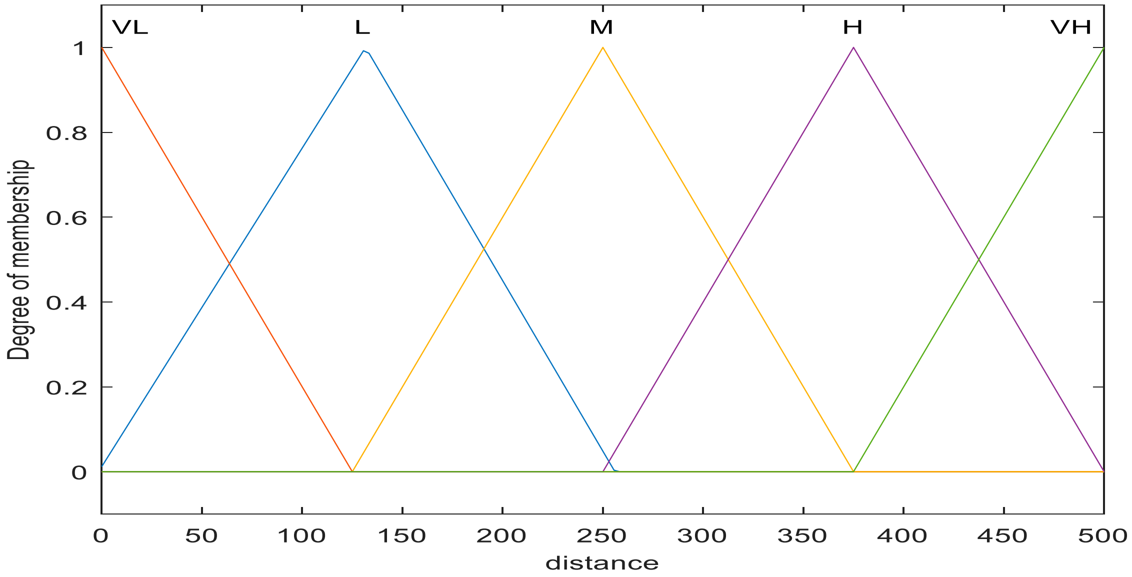


Figure 4. Input membership function for distance.

(M), low (L), and very low (VL) are defined in the variable d which is separated in discourse space [0 500 mm] and it is displayed in Figure 4. Low positive (LP), medium positive (MP), high positive (HP), high negative (HN), medium negative (MN), low negative (LN) and Zero (Z) are seven membership functions that are partitioned in a universe of discourse angles [$-180°$ $180°$]. The input membership function for the angle is represented in Figure 5.

3.2. Structure of fuzzy rule bases

The mobile robots utilize fuzzy control for inputs and outputs so, the design of FLC is considered a critical problem for mobile robot's real velocities. The fuzzy rules are defined after the creation of membership functions. 35 IF–THEN rules are used to establish the expert system. Table 1 represents rule bases of fuzzy.

3.3. Obstacle avoidance based on SSO-based FLC

For obstacle avoidance of two-wheel mobile robots, this paper also developed an SSO-based Fuzzy logic model. It is developed based on only distance from obstacles, angle and distance from the target. Figure 6 shows the block diagram of obstacle avoidance of a two-wheel mobile robot model.

In our mobile robot, the sensors are already fixed to find out the distance of the obstacle from their starting point. Based on the position of an obstacle, the current position of the robot, and the position of the target, the distance from the target (d), angle ϕ and distance from sensors d_0 are calculated and these are fed to the fuzzy logic controller as input. For the absolute location of the two-wheel mobile robot in the x and y directions as well as the robot heading angle, this controller decides the left and right wheel voltages of the motors. The motor speed of a two-wheel mobile robot is controlled by this SSO-based FLC model. The inputs like distance from the target, angle and distance from sensors are fed to the controller and two outputs like the velocity of the left and right wheel are obtained. The distance of the robot from the target is considered as either zero or less than zero (the robot crossed the target) with a zero membership function. Based on the location of the target and obstacle, the membership functions are adjusted adaptively. Figure 7 displays the input membership functions.

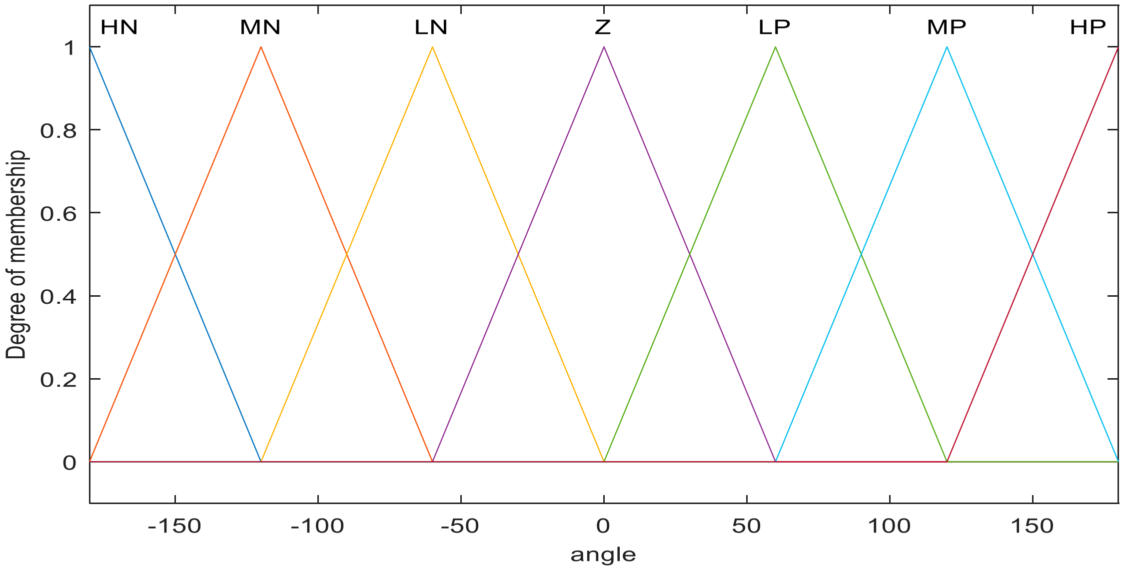


Figure 5. Input membership function for angle.

Table 1. Fuzzy rules for the controller.

		Angle (ϕ)													
		HN		MN		LN		Z		LP		MP		HP	
		V_R	V_L	V_R	V_L	V_R	V_L	V_R	V_L	V_R	V_L	V_R	V_L	V_R	V_L
Distance	VL	H	Z	M	Z	F	Z	M	F	Z	F	Z	F	Z	M
	L	VH	Z	H	Z	M	Z	M	F	Z	M	Z	H	Z	VH
	M	VH	Z	VH	Z	H	Z	M	M	Z	H	Z	VH	Z	VH
	H	VH	Z	VH	Z	VH	Z	H	H	Z	VH	Z	VH	Z	VH
	VH	VH	Z	VH	Z	VH	Z	VH	VH	Z	VH	Z	VH	Z	VH

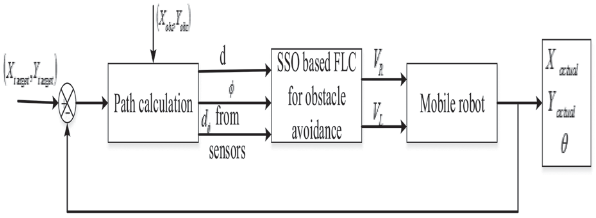


Figure 6. Block diagram of obstacle avoidance based on FLC.

The distance (d) and angular position ϕ of the mobile robot are calculated from Equations (27) and (28). So, the distance of the obstacle from the sensor is calculated by the following expression.

$$d_0 = \sqrt{(X_0 - X)^2 + (Y_0 - Y)^2} \tag{29}$$

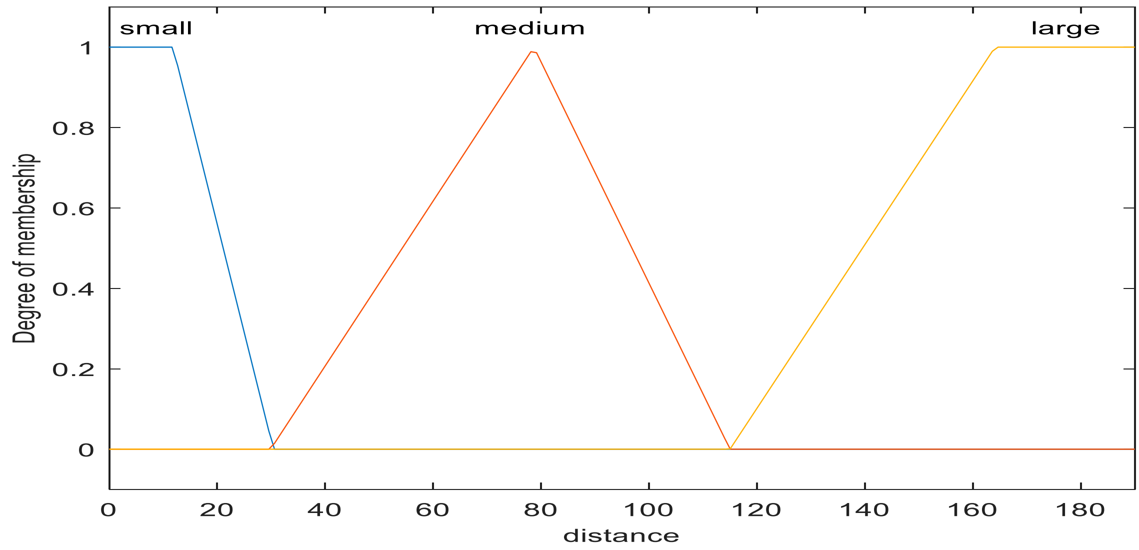
where d_0 mentions the distance of the obstacle from the sensor, X_0, Y_0 mentions the obstacle's target position and X and Y mention the current position. Table 2 illustrates the Fuzzy rules to avoid obstacles in the navigation. Here, L denotes Large, M mentions Medium, S mentions Small, Z denotes Zero, P mentions Positive, N mentions Negative, and VS denotes Very Small.

Table 2. Fuzzy rules for obstacle avoidance.

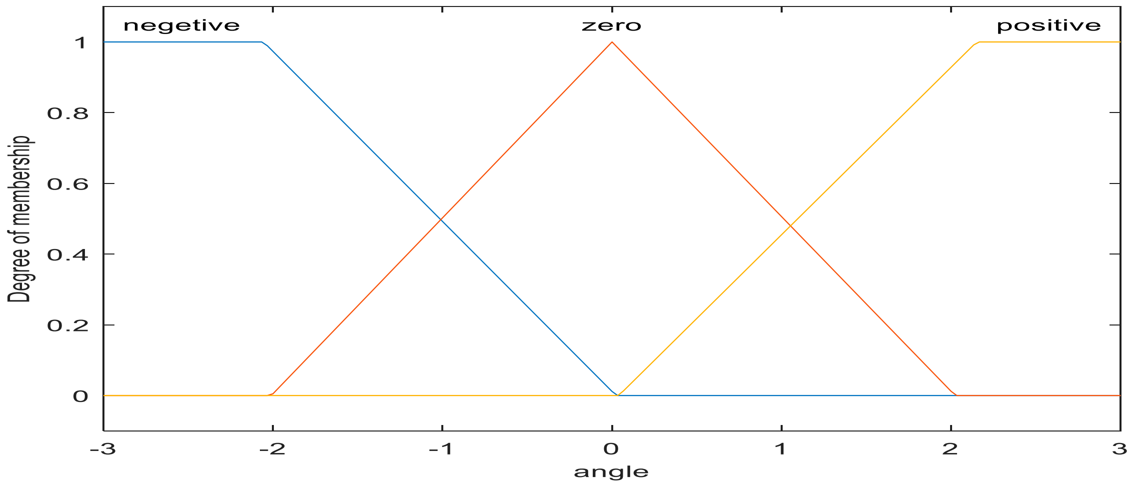
Input			Output	
Distance from target	Angle	Distance from sensor to obstacle	V_L	V_R
L	Z	F	L	L
L	P	F	M	S
L	P	M	S	M
L	P	M	S	S
L	P	M	S	M
L	N	F	S	M
L	N	M	M	S
L	N	M	S	S
L	N	M	M	S
M	Z	F	M	M
M	Z	F	S	L
M	Z	M	S	M
M	P	F	S	L
M	N	F	L	S
M	Z	Near	L	VS
M	P	Near	VS	L
M	N	Near	L	VS
S	N	F	L	M
S	P	F	S	M
S	P	M	VS	M
S	P	N	VS	L
S	P	F	VS	M
S	P	F	S	DL

4. FLC optimization based on the optimization algorithm

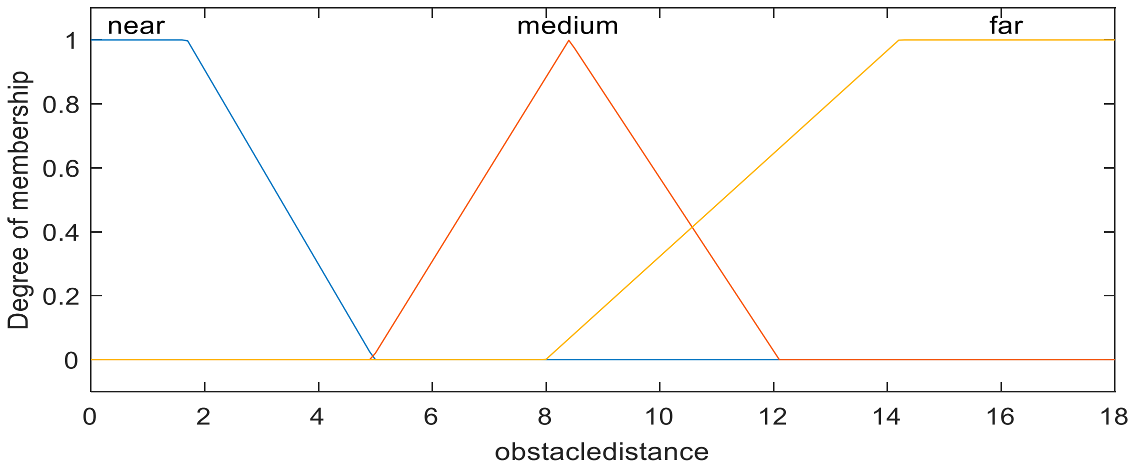
This section explains the optimization algorithm which is used in our work. The SSO algorithm is mainly



(a) Distance from target



(b) Angle of robot from target



(c) Distance of obstacle form sensor

Figure 7. Input membership functions for obstacle avoidance. (a) Distance from the target; (b) Angle of the robot from the target; (c) Distance of obstacle from the sensor.

utilized to optimize the controller values for better performance. The performance of SSO-based FLC is compared with two existing algorithms PSO and CSO. So, this section briefly explains the PSO as well as the CSO algorithm.

4.1. *PSO algorithm*

The PSO method is a kind of searching through technique reliant on the swarm, in which each individual is referred to a particle described as potential management of the optimized issue in D-dimensional hunt space, and it can hold the perfect position of the swarm and its own. Particles change their states ceaselessly in the multi-dimensional space, until they arrive at an equality or perfect state, or pass beyond as possible. Unique relationship among different components of the issue space is exhibited by methods for the objective limits.

4.2. *CSO algorithm*

The CSO algorithm is meta-heuristic that draws inspiration from the reproductive behaviour of cuckoo birds. In this algorithm, the potential solutions are treated as key elements. Cuckoo birds have a habit of laying their eggs in the nests of other cuckoo birds, relying on the other birds to raise their offspring. However, cuckoos may occasionally encounter eggs that are unsuitable for them in their nests. We can conclude that both the existing methods like PSO and CSO algorithms are not perfect for our FLC-based mobile robot navigation. Because both the algorithms easily fall into the local optimum in high-dimensional space as well as they have a low convergence rate in the iterative process. But, our proposed SSO algorithm has some advantages like fewer initial solutions, strong optimization searching ability and fast convergence speed. So, we can achieve better path navigation as well as obstacle avoidance with the help of a SSO optimized fuzzy logic controller.

4.3. *SSO algorithm*

The supportive behaviour of spiders inside a common group is imitated in the SSO algorithm [29] which is considered a swarm computation method. The form of the SSO algorithm is utilized to calculate the global solution of a non-linear optimization problem.

$$\begin{aligned} &\min\, F(y)\, y = (y^1, \ldots\ldots, y^d) \in L^d \\ &\textit{subject to}\, y \in Y \end{aligned} \tag{30}$$

where $F : L^d \to L$ is a function of nonlinear which is constrained by lower as well as upper limits whereas a bounded feasible space mentioned by; $Y = \{y \in L^d | l_j \leq y^j \leq u_j, j = 1, \ldots., n\}$. The population **P** of N candidate solution solves the problem formulated in Equation (34). Search space Y mentions the general web and the spider position mentions each and every candidate solution. Males (**M**) and females (**F**) are two different kinds of spider population Pin SSO. The number of female F is denoted as R_f and it is selected from the whole population S within a range of 65-90%. Likewise, the remaining population is considered as R_m which is male individuals ($R_m = R - R_f$). The group of female individuals are represented by ($F = \{f_1, f_2, \ldots.. f_{R_f}\}$), while male members are denoted by ($M = \{m_1, m_2, \ldots.., m_{R_m}\}$), where $P = F \cup M(P = \{p_1, p_2, \ldots.., p_R\}$), such that $P = \{p_1 = f_1, \ldots\ldots p_{R_f} = f_{N_f}, p_{R_{f+1}} = m_1, \ldots.., p_N = m_{R_m}\}$. Based on the solution quality, every single spider i maintains a weight w_i. Therefore, the following expression is utilized to calculate the weight w_i.

$$w_i = \frac{\textit{fitness}_i - \textit{worst}}{\textit{best} - \textit{worst}} \tag{31}$$

where the location of i$^{\text{th}}$ spider $i \in 1, \ldots. R$ is calculated to produce the fitness value by which it is represented $\textit{fitness}_i$. Best and worst mentions the best and worst fitness value of the entire population P. The main process of SSO is to exchange the information in the optimization procedure which simulates the vibrations generated in the communal web.

Minimum speed and azimuth miscalculation of optimal value is produced by applying a dispassionate function named an Integral of Squared Error (ISE) in this algorithm.

$$ISE = \int e^2(t)dt \tag{32}$$

where $e(t) = ev^2(t) + e\theta^2(t)$.

The fitness function is calculated based on the following expression.

$$\textit{fitness function} = \min(ISE) \tag{33}$$

The flow chart for the proposed optimization algorithm-based FLC design is displayed in Figure 8.

The above-mentioned flow chart describes the whole process of our proposed optimization-based robot design using FLC.

5. Simulation results and discussions

The simulation results of the proposed optimization-based FLC system of the wheeled robot are explained in this section. This method is implemented with the help of the MATLAB platform. Beginning location of the mobile robot is (X_0, Y_0) and ending location is mentioned by (X_T, Y_T). Moreover, different configurations and desired positions are carried out in this section. The parameter values for mobile robots is taken as $\mathrm{M} = 24$, $\mathrm{kgr} = 0.057$, $\mathrm{c} = 0.15833\,\mathrm{kg/s}$, $\mathrm{I_w} = 0.0198\,\mathrm{kg.m^2}, \mathrm{I_v} = 0.4732\,\mathrm{kg.m^2}, \mathrm{l} = 0.36\,\mathrm{m}$, and

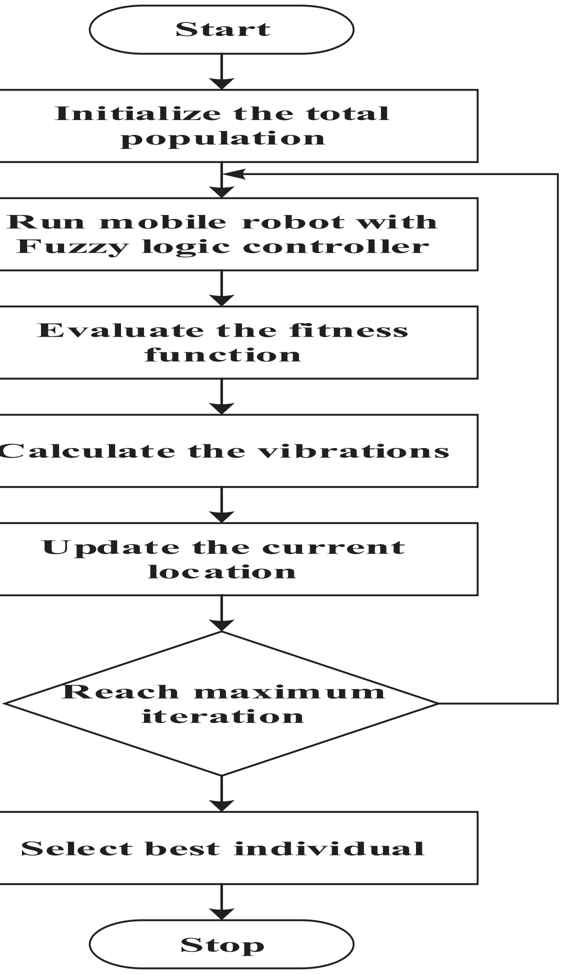


Figure 8. Flow chart for SSO.

k = 1.7. The performance of the proposed methodology is compared with existing methods like PSO and CSO algorithms.

The fitness function evaluation of both the proposed and existing methods is displayed in Figure 8. In our work, we have utilized PSO and CSO algorithms for comparison purposes. In this comparison, the proposed SSO algorithm achieves optimal value in the 10th iteration. When compared to existing algorithms, they achieve optimal values in the 15^{th} and 18^{th} iteration times. With this value, we can say that the proposed method achieves the optimum value with a minimum number of epochs.

The starting and ending points of the mobile robot in the XY axis are represented in Figure 10. Here, the initial point is considered as X = 0 and Y = 0 as well as the target point is set as $X_k = 0.8576$ and $Y_k = 0.7961$. This figure explains the navigation result of the proposed method with existing methods like PSO and CSO algorithms as well as the normal FLC logic. When compared to the existing algorithms with path navigation, our proposed SSO-based FLC achieves better navigation. It is clearly shown that the proposed method achieves the destination point with smooth navigation. But, existing methods are not able to reach the destination in a smooth navigation. This is because those algorithms do not perform the correct fine-tuning in FLC.

Table 3. Comparison of methodologies for time to reach the destination.

Sr. No.	Method	Time to reach the target (Sec)
1	FLC	110
2	CSO-FLC	100
3	PSO-FLC	95
4	SSO-FLC	80

The mobile robot's path tracking in the XY axis is presented in Figure 10. Here also, the initial point is taken as X = 0 and Y = 0 as well as the target point is set as $X_k = 0.8525$ and $Y_k = -0.7946$. In this simulation, the target point is initially predefined. This figure explains the navigation result of the proposed method with existing methods like PSO and CSO algorithms as well as the normal FLC logic. When compared to the existing algorithms with path navigation, our proposed SSO-based FLC achieves better navigation. It is clearly shown that the proposed method achieves the destination point with smooth navigation. But, existing methods can't able to reach the destination in a smooth navigation. This is because those algorithms donot perform the correct fine-tuning in FLC.

Figure 12 displays the navigation location with some obstacles. In this simulation, the starting point is considered as (0,0) and the destination point is set as $X_k = 1.4$ and $Y_k = -1.2$. Moreover, some obstacles are also intentionally created by the user in a fixed location. Here, the obstacles are mentioned in red colour. The performance of the proposed method is compared with normal FLC as well as the existing methods like PSO and CSO. With the SSO-based FLC, our proposed mobile robot identifies the obstacle distance and travels towards the destination with smooth navigation. Whereas in the existing algorithm-based FLC, the mobile robots are not able to identify the obstacle location accurately because of their low-level fine-tuning of the parameters.

Figure 13 displays the navigation location with some obstacles. In this simulation, the starting point is considered as (0,0) and the destination point is set as $X_k = 1.1$ and $Y_k = 1.2$. Moreover, some obstacles are also intentionally created by the user in a fixed location. The performance of the proposed method is compared with normal FLC as well as the existing methods like PSO and CSO. With the SSO-based FLC, our proposed mobile robot identifies the obstacle distance and travels towards the destination with smooth navigation. But, in the existing based FLC, the mobile robot can't be able to identify the obstacle location accurately because of their low-level fine tuning of the parameters.

Figure 14 shows the angle orientation with respect to the simulation time. This angle orientation is also

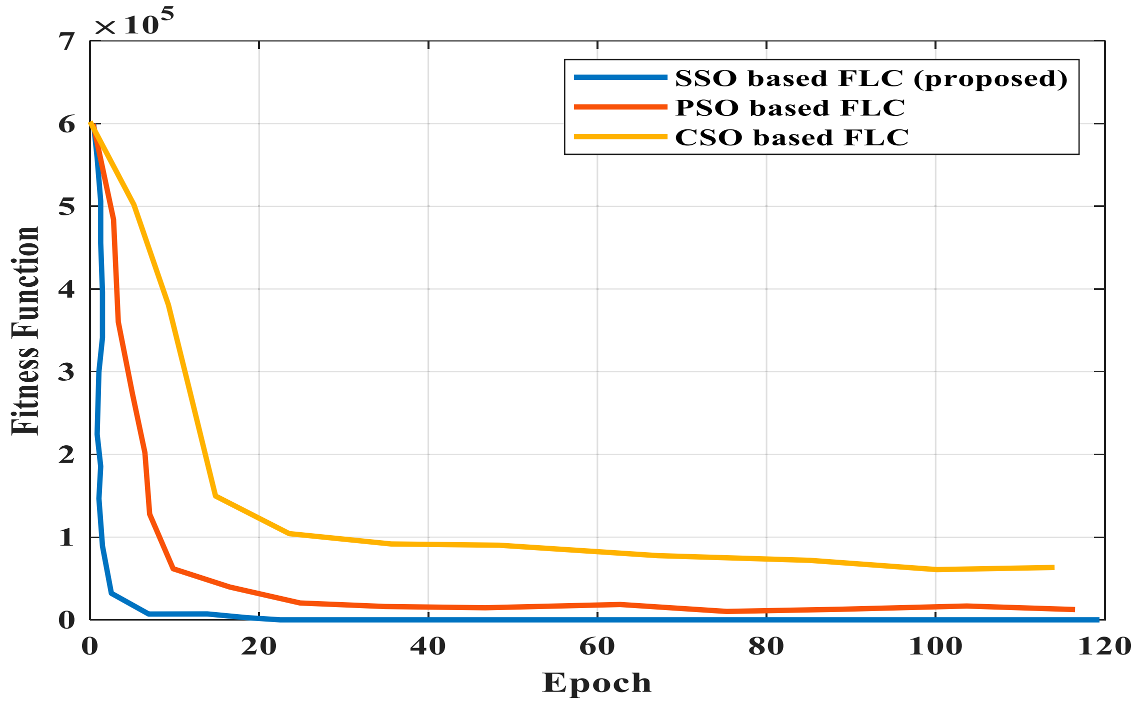


Figure 9. Fitness Function calculation.

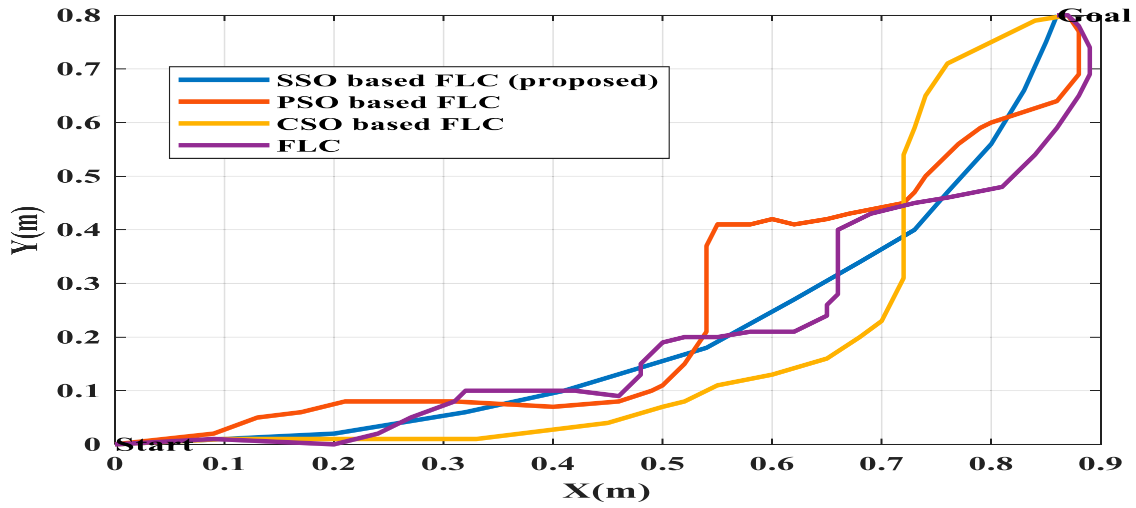


Figure 10. Position of Navigation with respect to $X_k = 0.8576$ and $Y_k = 0.7961$.

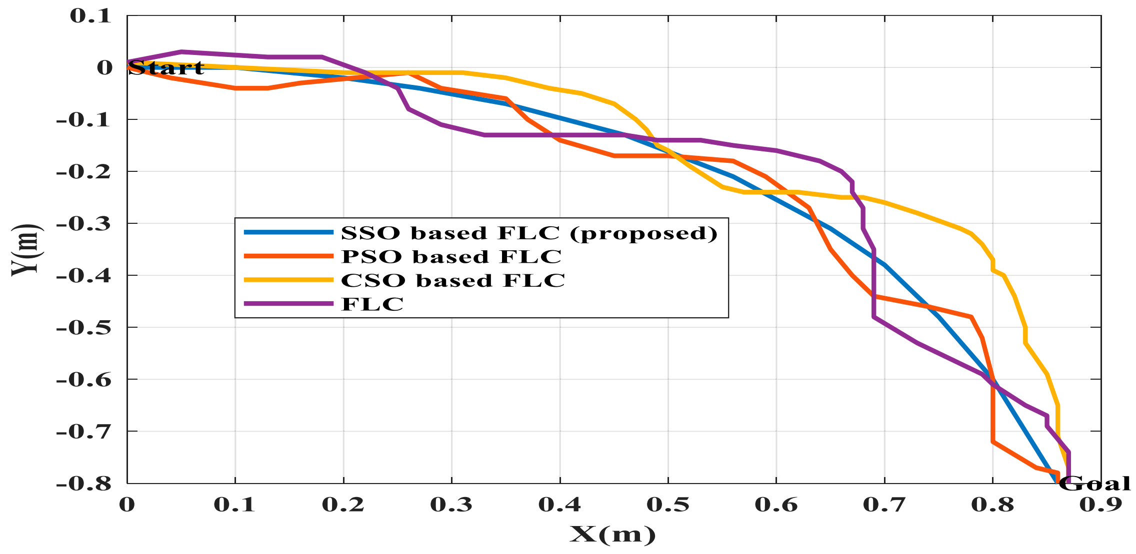


Figure 11. Navigation location with respect to $X_k = 0.8525$ and $Y_k = -0.7956$.

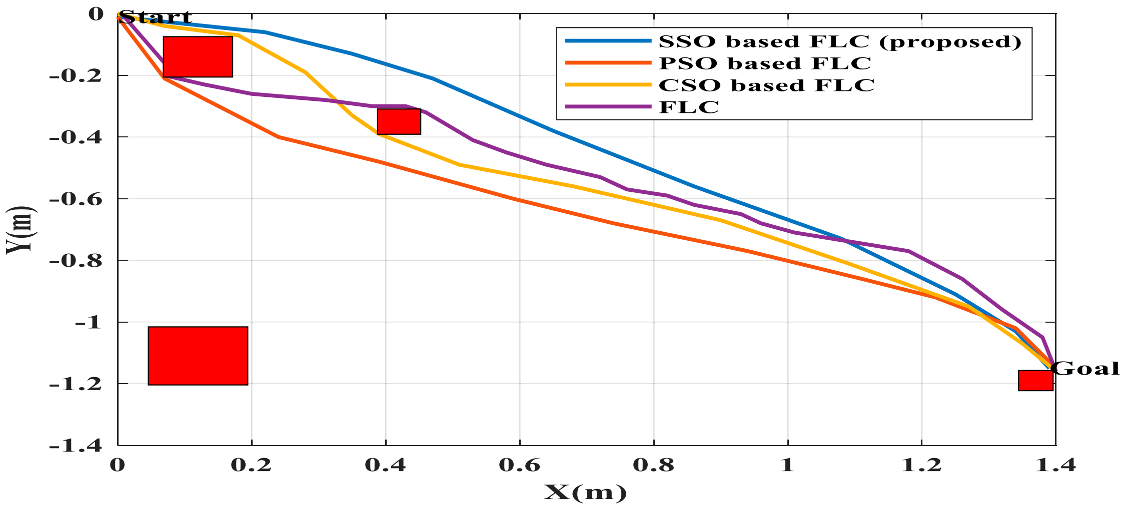


Figure 12. Navigation location with respect to $X_k = 1.4$ and $Y_k = -1.2$ with obstacles.

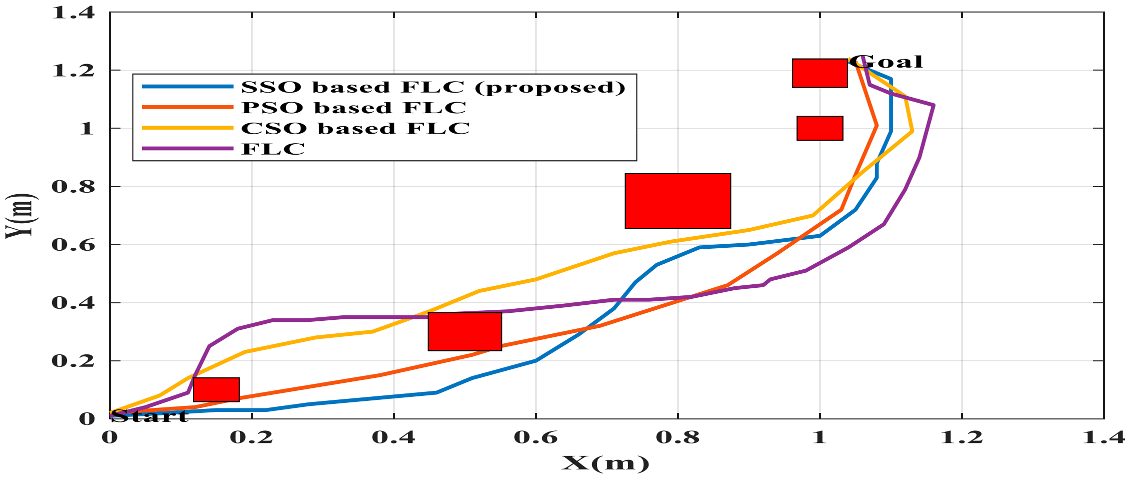


Figure 13. Navigation with respect to $X_k = 1.1$ and $Y_k = 1.2$ with some obstacles.

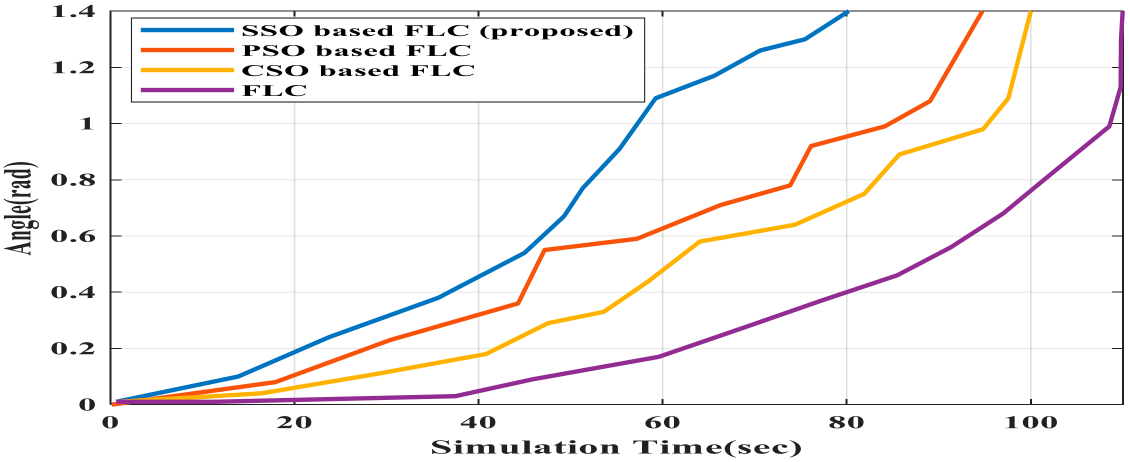


Figure 14. Angle values during navigation.

compared with existing PSO and CSO algorithms as well as the FLC logic. Initially, the mobile robot starts navigation at a distance of 1.22 mm. It also achieves an angle value of 1.4 radians. An increase in angle could not create the desired resultant force for its movement. The comparison of the considered methodologies in this proposed work is as follows in Table 3.

6. Conclusion

First of all, the kinematic structure is utilized for the layout of the movable robot and its mobility is managed by the use of FLC. Additionally, the developed controller makes the robot capable of tracking distinctive paths precisely to function in unsafe and hard situations. The recommended SSO algorithm is specifically utilized to optimize the controller values for higher performance. Also, obstacle avoidance of the proposed cell robotic is carried out on the basis of the SSO primarily based FLC. Moreover, the presented controller efficaciously resolves target tracking troubles for various paths which are ensured by the simulation results. From the studies assessment shown in plots of Figures 9–14, it's far proven that the advised technique performs better with the aid of tracking capability for different paths as well as avoids the obstacles with its correct input value. The mobile robot starts navigation at a distance of 1.22 mm and achieves an angle value of 1.4 radians whereas existing PSO-optimized Fuzzy, CSO-optimized fuzzy and Conventional Fuzzy achieve angle values 95, 100 and 110, respectively and increases in angle couldn't create desired movement. The performance of proposed methodology has been compared with current techniques like PSO and CSO algorithms. From the assessment, it's far regarded that the cell robot based on SSO-based FLC reaches its destination fastest.

The advantage of this paper is to give the option for researchers in future to find the better method of optimization for controlling the speed, angle, navigation and obstacle avoidance for wheeled mobile robots. The designers of the differential drive service robot can utilize this work for controlling the system in case of obstacle avoidance and tracking control in real -time environment. The limitation of the proposed method is its complexity when added with FLC which requires expertise in FLC and SSO Algorithms.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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