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A Comparative Study of Various Intelligent Optimization Algorithms Based on Path Planning and Neural Controller for Mobile Robot

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ABSTRACT

In this paper, a cognitive system based on a nonlinear neural controller and intelligent algorithm that will guide an autonomous mobile robot during continuous path-tracking and navigate over solid obstacles with avoidance was proposed. The goal of the proposed structure is to plan and track the reference path equation for the autonomous mobile robot in the mining environment to avoid the obstacles and reach to the target position by using intelligent optimization algorithms. Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) Algorithms are used to finding the solutions of the mobile robot navigation problems in the mine by searching the optimal paths and finding the reference path equation of the optimal path. As well as, PSO algorithm is used to find and tune on-line the neural control gains values of the nonlinear neural controller to obtain the best torques actions of the wheels for the mining autonomous mobile robot. Simulation results by MATLAB showed that the proposed cognitive system is more accurate in terms of planning reference path to avoid obstacles and online finding and tuning parameters of the controller which generated smoothness control action without saturation state for tracking the reference path equation as well as minimize the mobile robot tracking pose error to zero value.

Keywords: path planning, mobile robot, neural controller, obstacles avoidance, cognitive system.

دراسة مقارنة لخوارزميات ذكية متنوعة أساسه تخطيط المسار ومسيطر عصبي لإنسان آلي متنقل

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الخلاصة

في هذا البحث، نظام إدراكي أساسه مسيطر عصبي غير خطي وخوارزمية ذكية والتي من شأنها توجيه الانسان آلي المتنقل الذاتي أثناء تتبع المسار المستمر والتنقل عبر العوائق الثابتة وبدون تصادم. الهدف من الهيكل المقترح هو تخطيط وتتبع معادلة المسار المرجعي للانسان آلي المتنقل الذاتي في بيئة المنجم من أجل تجنب العوائق والوصول إلى الهدف باستخدام الخوارزميات الذكية. خوارزميات سرب الجسيمات (PSO) وخوارزمية مستعمرات النحل الاصطناعي (ABC) قد استخدمت لإيجاد حلول لمشكلات توجيه للانسان آلي المتنقل الذاتي في المنجم عن طريق البحث عن المسارات المثالية وإيجاد المعادلة المرجعية للمسار الأمثل. بالإضافة إلى ذلك، تم استخدام خوارزمية PSO في ايجاد وتغنيم عناصر المسيطر العصبي الغير خطي بشكل حي ومتصل من أجل الحصول على أفضل رد فعل لعزم الدوران لعجلات ألانسان آلي الذاتي المتنقل التعديني.

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ظهرت نتائج المحاكاة باستخدام الماتلاب أن النظام الادراكي المقترح هو أكثر دقة من حيث تخطيط المسار المرجعي لتجنب العوائق وإيجاد تغنيم العناصر بشكل حي ومتصل للمسيطر والتي انشئت فعل سيطرة ناعم ودون حالة تشبع لتتبع معادلة المسار المرجعي وكذلك تقليل الخطأ التتابعي للانسان آلي المتنقل.

الكلمات الرئيسية: تخطيط المسار، أنسان آلي متنقل، مسيطر عصبي، تجنب العوائق، نظام أدراكي.

1. INTRODUCTION

In general, the term path-planning is a mission of navigating a mobile robot around a space in which a number of obstacles that have to be avoided. Optimal trajectories could be a trajectory that minimizes the number of turning, the number of braking or whatever a particular application needs **Mudasir, et al., 2015**. So the mobile robot control motion should track and execute the path planning because there are many applications in various life field such as: science; education; industry, mining; entertainment; security and military needed the wheeled mobile robot system therefore, the mobile robot is still active region of research **Muhammad , et al., 2015**.
In the recent years, different types of evolutionary techniques like: Genetic Algorithm, **Muhammad, et al., 2016**, Ant Colony Optimization, **Abdallan,** and **Hamzah, 2013**, Particle Swarm Optimization (PSO), **Shahab**, **et al., 2015** and Artificial Bee Colony (ABC), **Qianzhi**, and **Xiujuan, 2010**, which are widely used for path planning and solved the problems of static and dynamic obstacles in environment for various tasks. In addition to that, several types of control algorithms are designed based on the mobile robot mathematical model. It is proposed to solve the mobile robot motion control in order to track the reference path with high performance of the controller in terms of generating optimal control action that lead to minimizing tracking pose error during tracking reference path, such as nonlinear neural PID controller, **Dagher**, and **Al-Araji**, **2014**, fuzzy logic and PID controllers, **Salhi**, and, **Alimi, 2014,** neural networks controllers , **Jasmin**, **et al**., **2008** , adaptive fuzzy with back-stepping controllers, **Swadi**, **et al**., **2016**, adaptive sliding mode controllers, **Ghania**, **et al**., **2016**, and neural predictive controllers , **Al-Araji**, **et al**., **2011**.
The motivation for this research is focusing on generating an optimal path with obstacles avoidance, on tracking and stabilize the wheeled mobile robot on the reference path and get a preferable torque control action with no saturation state and no spike action in its.
The main research contribution is described as follow:

- Cognition path planning is generating an optimal path with high computational accuracy based on PSO and ABC algorithms to avoid the static obstacles with least distance.
- Neural network with PSO algorithm has derived the control law to generate the best torque action and also to follow the reference path question.
- Using a PSO algorithm to show the fast search ability in the global region to online find and tune the nonlinear neural controller best parameters.
- Tracking different optimal path equations to support the capability of the proposed cognitive system in terms of minimizing the wheeled mobile robot tracking pose error.
- To investigate the proposed controller robustness achievements by adding a dynamic disruption to the controller.
- To verify the adaptation achievements of the suggested controller by changing the initial pose state of a wheeled mobile robot.

The organization of this paper is as follows: Section two is a description of the dynamic wheeled mobile robot model. Section three is descript Intelligent Optimization Algorithms. Section four is deriving the proposed cognitive system. Section five is presented the simulation results of the cognitive system in the mining environment. In section six, the conclusions are drawn.

2. MOBILE ROBOT DYNAMIC MODEL

Fig. 1 shows the schematic diagram of the wheeled mobile robot cart that is made up of two DC motors which are driving the two wheels with one an Omni-Directional Castor Wheel in the front of the cart that will stabilize the mobile robot platform, **Mudasir, et al., 2015**.

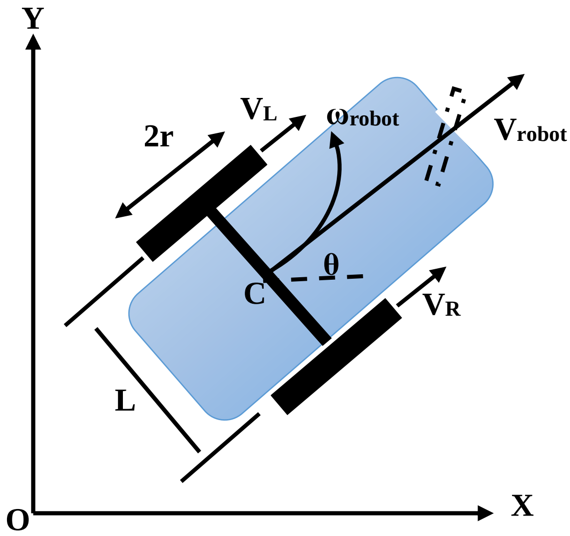


Figure 1. Mobile robot Platform model.

The mobile robot motion and orientation depend on two independent DC motors for the left and right wheels. r is the radius of the two same wheels and L is the distance between these two wheels and c is the mobile robot center of gravity.

Generally, $[O, X, Y]$ is defined as the global coordinate frame while the mobile robot pose vector in the surface is defined as Eq. (1):

$$q = (x, y, \theta)^T \tag{1}$$

(x,y) are the position coordinates at the point c while the orientation angle θ is measured with respect to the X-axis in the global frame therefore the configuration of the mobile robot can be expressed by these three popularized coordinates.
Inspection the wheeled mobile robot motion and orientation, two situations should be attained; the first is pure-rolling and the second is without-slipping so that the profiling velocity of the mobile robots will be equal to zero as Eq. (2) **Salhi**, and, **Alimi, 2014**.

$$-\dot{x}(t)\sin\theta(t) + \dot{y}(t)\cos\theta(t) = 0 \tag{2}$$

Then, the kinematic equations of the wheeled mobile robot cart in the global frame are symbolized as follows, **Jasmin**, **et al**., **2008**:

$$\dot{x}(t) = \frac{r(WRi(t) + WLe(t)}{2})\cos\theta(t) \tag{3}$$

$$\dot{y}(t) = \frac{r(WRi(t) - WLe(t))}{2}\sin\theta(t) \tag{4}$$

$$\dot{\theta}(t) = \frac{r(WRi(t) - WLe(t))}{L} \tag{5}$$

where *WRi(t)* and *WLe(t)* are the right angular velocity and left angular velocity respectively.
Based on Euler Lagrange formulation, **Ghania**, **et al**., **2016**, the mobile robot dynamic model can be described as follows:

$$\begin{bmatrix} Ma & 0 & 0 \\ 0 & Ma & 0 \\ 0 & 0 & In \end{bmatrix}\begin{bmatrix} \ddot{x} \\ \ddot{y} \\ \ddot{\theta} \end{bmatrix} = \frac{1}{r}\begin{bmatrix} \cos\theta & \cos\theta \\ \sin\theta & \sin\theta \\ \frac{L}{2} & \frac{-L}{2} \end{bmatrix}\begin{bmatrix} \tau_L \\ \tau_R \end{bmatrix} + \begin{bmatrix} -\sin\theta \\ \cos\theta \\ 0 \end{bmatrix}\lambda - \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}\tau d \qquad (6)$$

Where: τ_L is the left wheel torque; τ_R is the right wheel torque; *Ma* is the mobile robot's mass; *In* is the mobile robot's inertia; λ is the constraint forces; τ_d is bounded dynamic disturbances.

3. INTELLIGENT OPTIMIZATION ALGORITHMS

3.1 Particle swarm optimization algorithm (PSO)

Particle swarm optimization algorithm is an evolutionary computation method which was advanced by **James**, and **Russell, 1995**. Simulation the social behavior of bird's flocks and schools of fish are the major idea behind proposing PSO algorithm. The algorithm applies to solving problems in groups. When a fish flock and birds find an optimal path to the source of food, it directly trans-mate these facts to all swarm and therefore rest of the swarm moves slowly and gradually towards the food source, **Maurice**, and **James**, **2002**. Each solution in multi-dimensional space consists of a group of elements which represents a point. The solution is called "particle" and the group of particles (population) is called "swarm". In PSO, the position and velocity of the swarm are initialized randomly for every particle. Moreover, in the problem or function search space of, these particles are placed. The cost function of the problem is assessing with these particles, and the personal best of each particle is stored in P_{best} and the global best of all swarm are stored in G_{best} **James**, and **Russell, 1995** and **Maurice**, and **James, 2002**.

The PSO algorithm evolutionary equations are as follows, **Dagher**, and **Al-Araji**, **2013**:

$$Vh(x,y)_{i,D}^{n+1} = \beta Vh(x,y)_{i,D}^{n} + c_1 r_1 (pbest_{i,D}^{n} - P(x,y)_{i,D}^{n}) + c_2 r_2 (gbest_{D}^{n} - P(x,y)_{i,D}^{n}) \qquad (7)$$

$$P(x,y)_{i,D}^{n+1} = P(x,y)_{i,D}^{n} + Vh(x,y)_{i,D}^{n+1} \qquad (8)$$

where; n: number of iteration. $Vh(x,y)_{i,D}^{n}$: is the i^{th} particle velocity at *n* iteration, $P(x,y)_{i,D}^{n}$: is the i^{th} particle position at *n* repetition, c_1 and c_2 : are the acceleration coefficients and its equal to 1.25, r_1 and r_2 : are two independently random numbers between 0 and 1, $pbest_i$: is the best previous weight of i^{th} particle, $gbest_d$: is best particle among all the particle in the population and β: inertia weight equal to 0.65.

3.2 Artificial bee colony algorithm (ABC)

In 2005, Karaboga proposed the ABC algorithm to mimic the behavior of foraging bee colony, the rise of concerted intelligence of bee swarms count on the selection of foraging **Karaboga**, and **Akay**, **2009**. In the model of ABC algorithm, there are three main components: food sources, employed foragers and unemployed foragers. The food sources amount are defined by the "profitability" value. The position of food sources are extracted as the real problem solving, and the foraging bee's nectar process can be regarded as the search for the optimal solutions. The employed foragers are related to an exact food source which are currently "employed". The distance and direction information from the location to the hive can carry with them of the particular source. Unemployed foragers are looking for a good source to exploit continually. Unemployed foragers have two types: scouts bee and onlooker's bee. The scout's bee search arround the environment of the nest for new good sources, while the onlooker's bee waits in the nest and establishes a good source through the information shared by employed foragers **Abdul**

Wahid, **et al**., **2015**. This persistent utilization will make them become weary. Then, the exhausted employed bee will become a scout bee, and their food sources are deserted. In ABC algorithm, the food source location will serve likely as a solution to the issue, and the nectar quantity of the food source correlate with the quality (fitness) of the related solution and also the number of employed bees equals the number of food sources (solutions). The search carried out by the ABC algorithm can be summarized as follows **Abdul Wahid**, **et al**., **2015** and **Karaboga, et al., 2012**:

3.2.1 Initialization step

In this step, a population NS of food sources, i.e., $x_i = \{x_{i,1}, x_{i,2}, x_{i,3}, \ldots\ldots, x_{i,D}\}$, and its generation for each food source are as follows:

$$x_{i,j} = x_{min,j} + rand(0,1)(x_{max,j} - x_{min,j}) \quad (9)$$

Where; NS: number of food source, (is equal to the number of employed or onlooker bees), D: Dimension of each solution, j= 1,2,….,D , i = 1, 2…..,NS, $x_{max,j}$ = upper bound for dimension j, $x_{min,j}$ = lower bound for dimension j and rand(0,1) = random number between 0 and 1.

3.2.2 Employed bees step

Randomly, every employed bee transmits with another employed bee a new location to search for, i.e., $v_i = \{v_{i,1}, v_{i,2}, v_{i,3}, \ldots\ldots, v_{i,D}\}$, as shown in Eq. (10) **Abdul Wahid**, **et al**., **2015**.

$$v_{i,j} = v_{i,j} + \emptyset_{i,j}\{x_{i,j} - x_{k,j}\} \quad (10)$$

where the indices j ∈ $\{1,2,3, \ldots\ldots, D\}$ and k ∈ $\{1,2,3, \ldots\ldots, NS\}$, k $\neq i$ are randomly generated. A coefficient $\emptyset_{i,j}$ is a casual number amid (-1, 1). The employed bees estimate the new food source v_i and match it with their current food source x_i by the cost solutions. The equation to determine the cost is shown in Eq. (11) **Abdul Wahid**, **et al**., **2015**, where$f(x_i)$ appears as the objective value of the solution x_i.

$$fit(x_i) = \begin{cases} \frac{1}{1+f(x_i)}\ , & if\ f(x_i) \geq 0 \\ 1 + abs(f(x_i), & if\ f(x_i) < 0 \end{cases} \quad (11)$$

3.2.3 Onlooker bees step

In this step, onlooker bees get data from the employed bees and resolve on selecting some food sources for additional search. By using Eq. (12), the probability p_i is found by the food sources fitness. The onlooker bees go to the better food sources with higher probability, **Abdul Wahid**, **et al**., **2015**.

$$p_i = \frac{fit_i}{\sum_{n=1}^{NP} fit_n} \quad (12)$$

3.2.4 Scout bees step

Throughout the search, several food sources will be deserted. A *limit* is a character defined by the user to rule when a food source abandon. The employed bee of the abandoned food sources will become scout bee. A scout bee searches a new food source randomly to substitute the abandoned food source.

4. COGNITIVE SYSTEM DESIGN

In this section, the cognitive system approach based on intelligent optimization algorithm is used to plan optimal smoothness reference trajectory to avoid the static obstacle by a wheeled mobile robot assuming mining environment with the minimum distance to the target, then to track the reference path equation by using a nonlinear neural controller. The proposed cognitive system is described by the block diagram shown in **Fig. 2**. It includes two layers: a) Cognition Path Planning Layer and b) Nonlinear Neural Controller Layer.

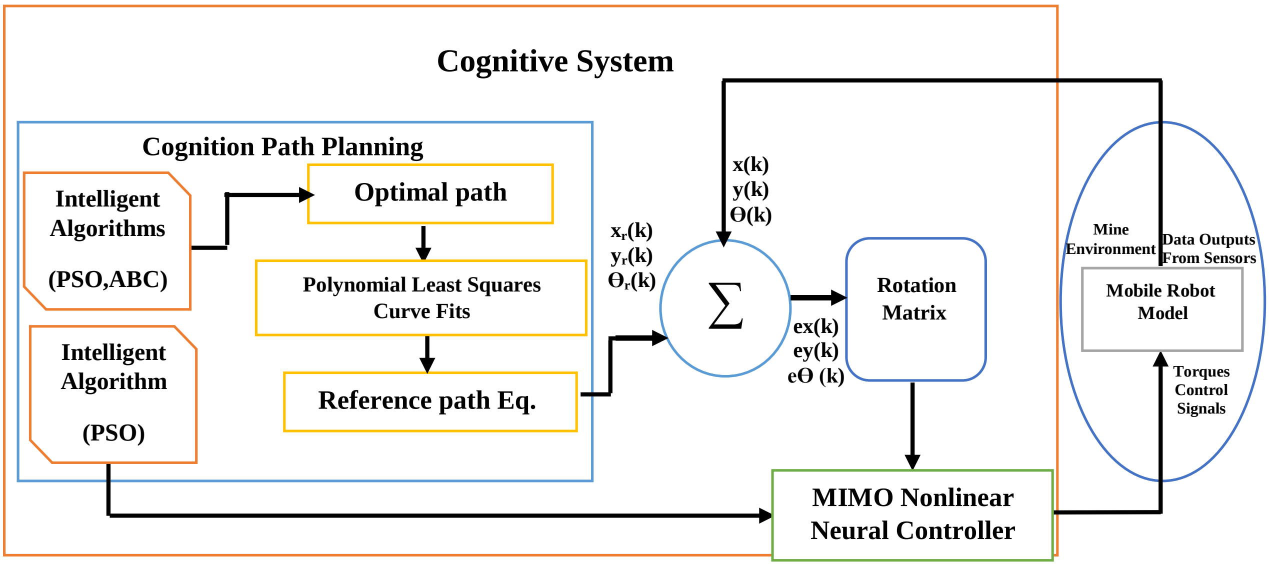


Figure 2. The mine mobile robot cognitive system structure.

4.1 Cognition path planning layer

The aim of the cognition path planning layer is to collect all the facts from the mining surroundings and then prepare the reference trajectory to reach the target in the mine and avoid any static obstacle by the wheeled mobile robot in the mining with no collision and free navigation. To achieve the operation of this layer, the model of the mining mobile robot cart and the dimensions of obstacles need to avoid any collision between the mining mobile robot cart and the obstacle. It uses the two Intelligent Optimization Algorithms (PSO and ABC) separately to plan the reference path with the smallest distance to keep away from the obstacles and reach the desired target based on the reference path equation. The goal of the two Intelligent Optimization Algorithms in the cognition path planning layer is to find the optimal trajectories and also to keep away from static obstacles through determining the points (x_i,y_i) (i=1, 2, 3…7 only seven points) of the equation, and obtain the optimal smoothness trajectories from the starting point to the target point. These point's (x_i,y_i) are determined by using the search space for each point of the mining mobile robot path and also elect the points specified by two-dimensional data. To evaluate the points, two evaluation functions are used into a fitness function, the first fitness function is collision avoidance and the second fitness function is the shortest distance. Collision avoidance is very important in path planning for a mobile robot to travel safely in the mining environment and can be explained in these two conditions:

The first situation is the point (x_i,y_i) should not be in the obstacle territory **Al- Araji, 2012** and **Dagher, 2017**.

$$CA_{Fit1} = \begin{cases} 1 & if \quad C_o = 0 \\ 0 & others \end{cases} \tag{13}$$

The second situation is the section (x_i,y_i) and (x_{i+1},y_{i+1}) should not intersect obstacle territory **Al- Araji, 2012** and **Dagher, 2017**.

$$CA_{Fit2} = \begin{cases} 0 & (x_i, y_i)(x_{i+1}, y_{i+1}) \cap obstacle \\ & 1 \quad others \end{cases} \tag{14}$$

The cost function of collision avoidance can be given by Eq. (15) **Al- Araji**, **2012** and **Dagher**, **2017**.

$$CA_{Fit} = \begin{cases} 1 & if \quad CA_{Fit1} \times CA_{Fit2} = 1 \\ 0 & others \end{cases} \tag{15}$$

The second cost function is a minimum distance, it makes the mobile robot moves in the mining environment with minimal time and minimize the travel distance, and it can be shown as follows **Dagher**, **2017** and **Al-Araji**, and **Dagher**, **2015**:

$$MD_{Fit} = \sum_{j=1}^{6} \sqrt{(x_{j+1} - x_j)^2 + (y_{j+1} - y_j)^2} \tag{16}$$

The eventual cost function is formulated in Eq. (17) as:

$$Fit = MD_{Fit} / CA_{Fit} \tag{17}$$

When the final cost function reaches the minimal value, the global smoothness optimal path is found.

The second step is to convert the points (x_i,y_i) (i=1, 2, 3…7 only seven points) of the optimal path to third order polynomial equation of the reference path equation as follows:

$$y(x) = b_3 x^3 + b_2 x^2 + b_1 x^1 + b_0 \tag{18}$$

where $b_{3,2,1,0}$ are the coefficients of the optimal reference path, and then by using Polynomial Least Squares Curve Fits to find the third order polynomial equation of the reference path equation.

The mean square error function (MSE), as shown in Eq. (19) is a benchmark function for estimating the reference points (x_i,y_i) (i=1, 2, 3…7 only seven points) after substituting x_i in the reference path equation then finding y_i.

$$MSE = \frac{1}{7} \sum_{i=1}^{7} (y_{ref(i)} - y_{(i)})^2 \tag{19}$$

To investigate the reference path equation, the optimal traveling time for the mobile robot, the mobile robot required linear velocity during tracking the optimal path should not override the V_{Imax} and can be determined using Eq. (20):

$$V_I = \frac{MD_{Fit}}{T} \rightarrow V_I < V_{Imax} \tag{20}$$

T must be determined, and it's the traveling time of the tracking between the start and goal points, using Eq. (21) based the sampling time T_s as follows:

$$T = N \times T_s \tag{21}$$

where N : is the number of samples.

4.2 Nonlinear neural network controller design

The proposed nonlinear neural network controller for the nonlinear MIMO system for the mobile robot can be shown in **Fig. 3**. The feedback control action is very important in the structure of the cognitive system because it is necessary to keep in steady state the tracking pose error of the mobile robot when the real position and direction of the mobile robot shift from the reference path in the mining environment.

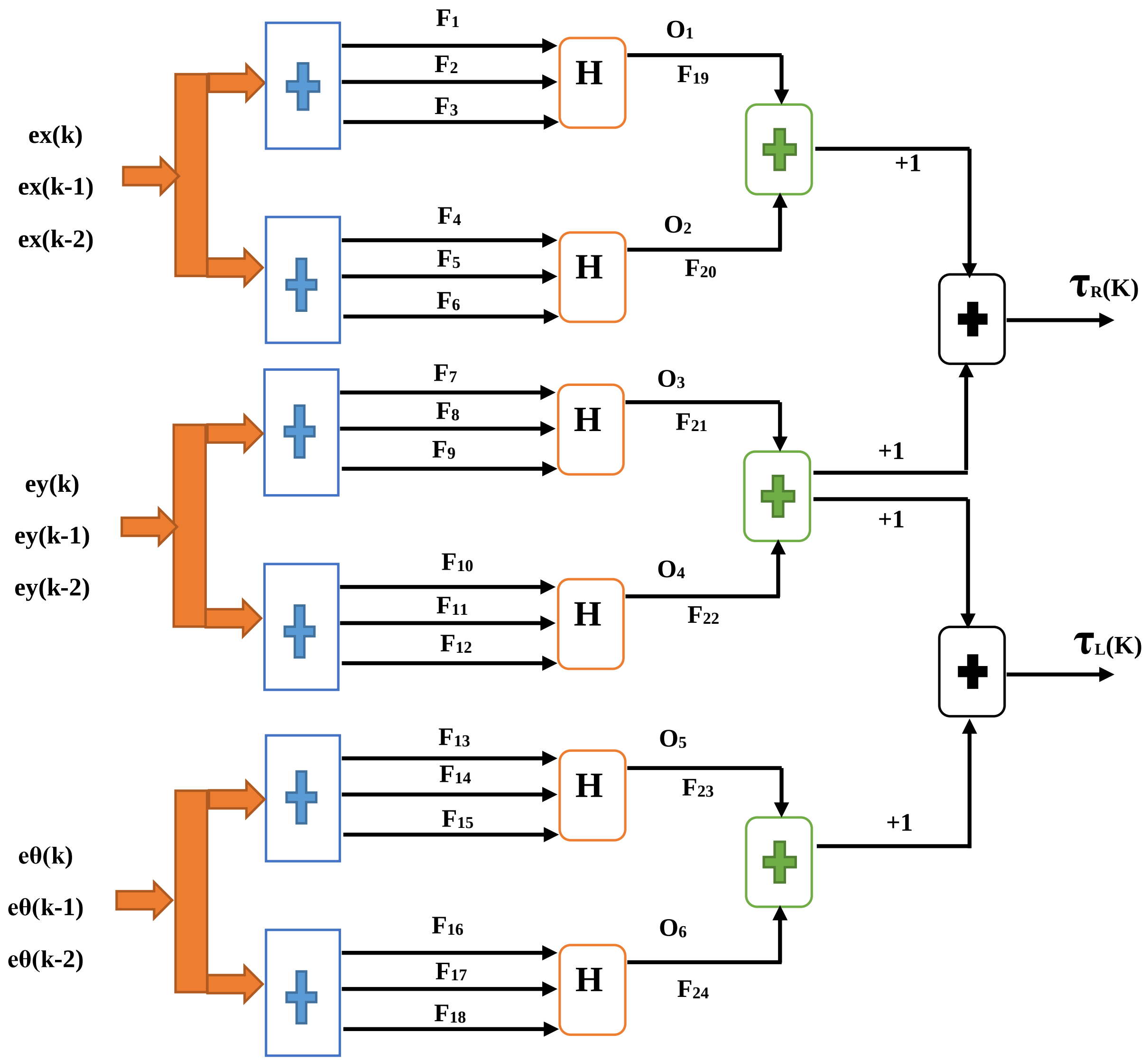


Figure 3. The proposed MIMO nonlinear neural controller structure.

The capabilities of the neural network control structure is strong flexibility, good dynamic behavior, and robustness performance. It used a non-linear sigmoid activation function in the hidden layer and linear activation function in the output layer **Al-Araji**, **2014**, and **Al-Araji**, and **Yousif**, **2017a**, and **Al-Araji**, and **Yousif, 2017b**, as shown in **Fig. 4**.
The proposed control law for the MIMO nonlinear neural network controller is as follows:

$$\tau_R(k) = O_1F_{19} + O_2F_{20} + O_3F_{21} + O_4F_{22} \tag{22}$$

$$\tau_L(k) = O_3F_{21} + O_4F_{22} + O_5F_{23} + O_6F_{24} \tag{23}$$

where o_1, o_2, o_3, o_4, o_5 and o_6 are the outputs of non-linear sigmoid activation functions of the neural networks and has non-linear relation as given in the following function **Al-Araji**, **2014**, and **Al-Araji**, and **Yousif**, **2017a**, and **Al-Araji**, and **Yousif, 2017b**:

$$O_\gamma = \frac{2}{1+e^{-net_\gamma}} - 1 \quad (24)$$

Where: $\gamma = 1,2,3,4,5,6$

$$net_1(k) = F_1[ex(k) - ex(k-1)] + F_2 ex(k) + F_3[ex(k) - ex(k-1) + ex(k-2)] \quad (25)$$

$$net_2(k) = F_4[ex(k) - ex(k-1)] + F_5 ex(k) + F_6[ex(k) - ex(k-1) + ex(k-2)] \quad (26)$$

$$net_3(k) = F_7[ey(k) - ey(k-1)] + F_8 ey(k) + F_9[ey(k) - ey(k-1) + ey(k-2)] \quad (27)$$

$$net_4(k) = F_{10}[ey(k) - ey(k-1)] + F_{11} ey(k) + F_{12}[ey(k) - ey(k-1) + ey(k-2)] \quad (28)$$

$$net_5(k) = F_{13}[e\theta(k) - e\theta(k-1)] + F_{14} e\theta(k) + F_{15}[e\theta(k) - e\theta(k-1) + e\theta(k-2)] \quad (29)$$

$$net_6(k) = F_{16}[e\theta(k) - e\theta(k-1)] + F_{17} e\theta(k) + F_{18}[e\theta(k) - e\theta(k-1) + e\theta(k-2)] \quad (30)$$

where the input vector is made up of $ex(k)$, $ey(k)$, $e\theta(k)$.

Twenty four $F_1 .... F_{24}$ weights control gain parameters are adjusted using PSO algorithm for the proposed MIMO nonlinear neural controller and initialized all particles randomly and updated the position and velocity of all particles using Eqs. (31 and 32) to find and tune on-line the control gains of proposed controller **Dagher**, and **Al-Araji**, **2013**:

$$\Delta\overline{F}_h^{d+1} = \beta\Delta\overline{F}_h^d + c_1 r_1 (pbest_h^d - \overline{F}_h^d) + c_2 r_2 (gbest^d - \overline{F}_h^d) \quad (31)$$

$$\overline{F}_h^{d+1} = \overline{F}_h^d + \Delta\overline{F}_h^{d+1} \quad (32)$$

Where; F_m^d :is particles weight *h* at *d* iteration; β: is the inertia weight operator; c_1 and c_2 are the positive values equal to 1.25; r_1 and r_2 are random values between 0 and 1.

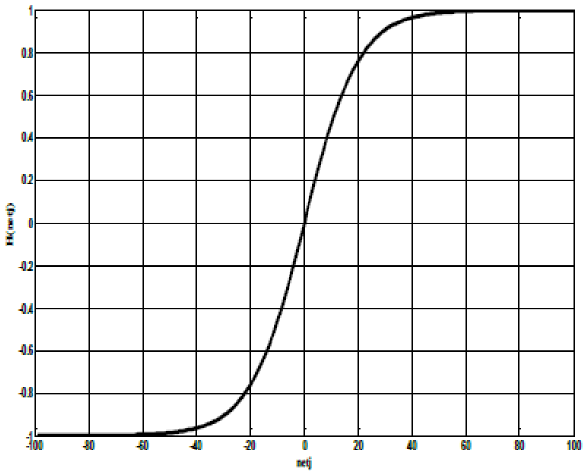


Figure 4. The sigmoid activation function.

The (MSE) mean square error function, as in Eq. (33) is a benchmark value to approximate the performance index of the pose tracking error.

$$MSE = \frac{1}{Nit}\sum_{i=1}^{Nit}[(x_{ref} - x)^2 + (y_{ref} - y)^2 + (\theta_{ref} - \theta)^2 \quad (33)$$

Nit: is the number of iteration.

5. SIMULATION RESULTS

MATLAB package was used to confirm the proposed cognition system of the path tracking for the mobile robot dynamic model. The Eddie mobile robot platform specifications are picked from

Internet website, **2017**: M=12kg, I=1. 536kg.m^2, r=0.075m and L=0.39m. The Matlab simulation is carried out off-line cognition path planning and on-line intelligent optimization algorithm with a proposed nonlinear neural controller as shown in **Fig. 2** to track a reference path equation and to avoid the static obstacles and 0.5 sec is the sampling time. In this work, the PSO and ABC algorithms are used to figure out the optimal paths. The PSO algorithm is used to tune the values of the nonlinear neural controller that leads to ideal and smoothness torque control action and also reduce the tracking pose error. **Tables 1** and **2** shows the PSO and ABC algorithms parameters used to achieve the cognition system.

Table 1. The PSO algorithm parameters.

PSO Parameters	**Path Planning**	**Nonlinear Neural Controller**
Number of Particles	20	10
Particle's weights	14	24
Β	0.65	0.65
c_1 and c_2	1.25	1.25
r_1 and r_2	Random (0,1)	Random (0,1)
Number of Iteration	10	10

Table 2. The ABC algorithm parameters.

ABC Parameters	**Path Planning**
Colony size	30
Limit	5
Food source	14
Rand	Random [-1,1]
Number of Iteration	25

5.1 Case study I

The mobile robot has initial pose $q(0)=[0,0.1,0]$. After applying the first layer from the structure of the proposed cognition system to generate the optimal path by using PSO and ABC algorithms as shown in **Figs**. **5** and **6** respectively, which has five paths to avoid the static obstacles as a first step, the distances of these five paths between start point to target point are (346, 343.12, 345.25, 340.09, and 333.52) and (335.79, 337.74, 338.72, 346.87, and 358.81) cm respectively depending on Eq. (16). Path5 is the optimal path form **Fig. 5**, and Path1 is the optimal path form **Fig. 6**, because they have the shortest distance (333.52) and (335.79) cm respectively. The second step in the same layer is obtaining the reference path equation for the two optimal paths by converting the point of the optimal path using Polynomial Least Squares Curve Fits third order polynomial equation of the reference path as follows:

$$y(x) = 2 \times 10^{-6}x^3 - 7.2 \times 10^{-4}x^2 + 0.52 \times x + 0.93 \tag{34}$$

$$y(x) = 1.75 \times 10^{-6} \times x^3 - 6.75 \times 10^{-4} \times x^2 + 0.54 \times x - 0.74 \tag{35}$$

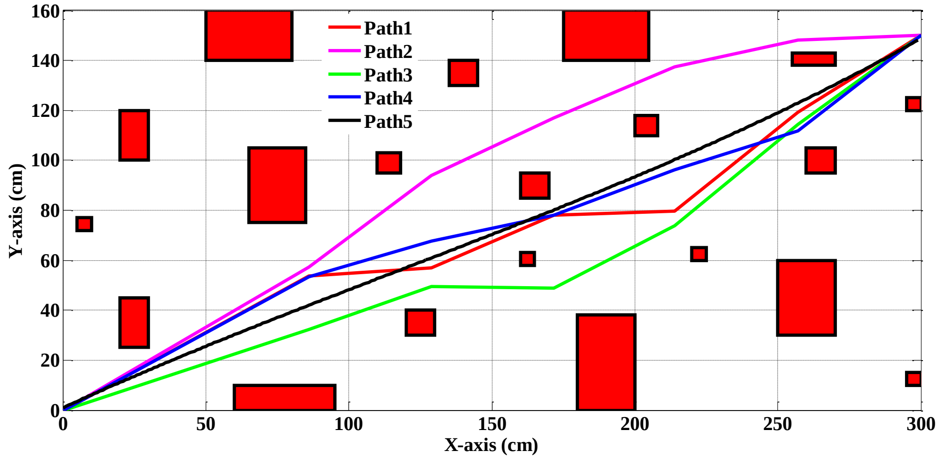


Figure 5. The optimal paths using PSO algorithm.

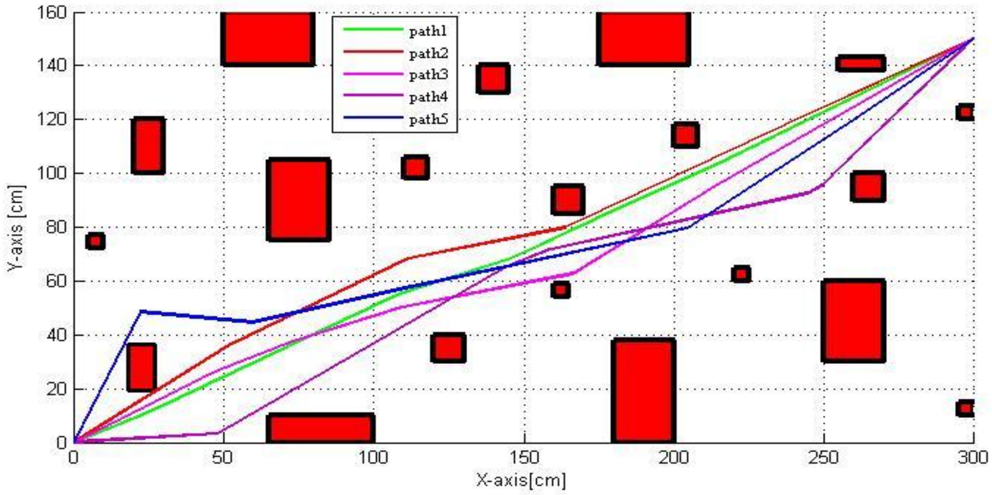


Figure 6. The optimal paths using the ABC algorithm.

PSO algorithm method is better than the ABC algorithm method because it avoids the static obstacle with smallest distance (333.52) cm to the goal and with minimum error (0.676%). The second layer in the cognitive system executed the mobile robot path tracking model based on the reference path Eq. (34) as shown in **Fig. 7**. It is clearly, the tracking excellent performance with free-navigation.**Fig. 8** shows the mobile robot orientation tracking performance with PSO algorithm. In this online control algorithm, the Mean Square Error (MSE) plainly refine the performance of the controller by viewing the pose error concourse for the mobile robot motion at 300 steps, as shown in **Fig. 9**. **Fig. 10** shows the response efficiency of the suggested nonlinear neural controller through resulting a smoothness torque control action without sharp spikes control action state to follow the reference path equation in less time. The linear and angular velocities responses for the platform wheeled mobile robot are smoothness without sharpened spikes, as shown in **Fig.** 11.

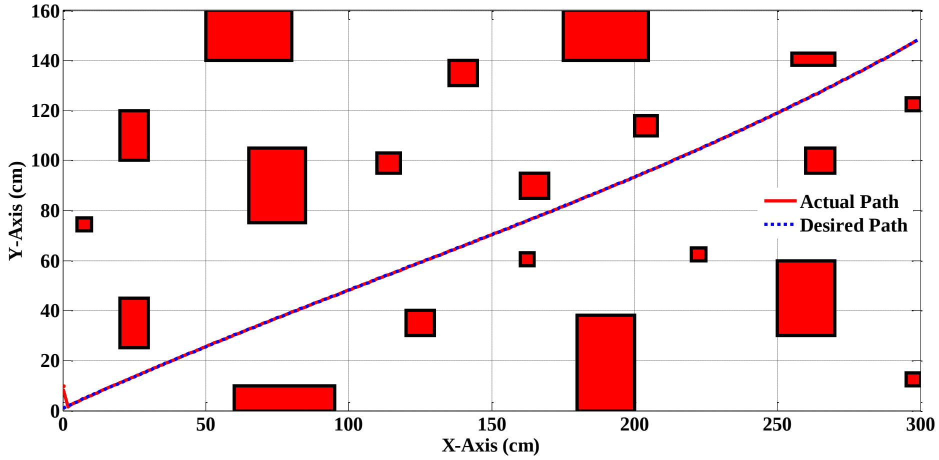


Figure 7. The reference path equation and actual path for a mobile robot.

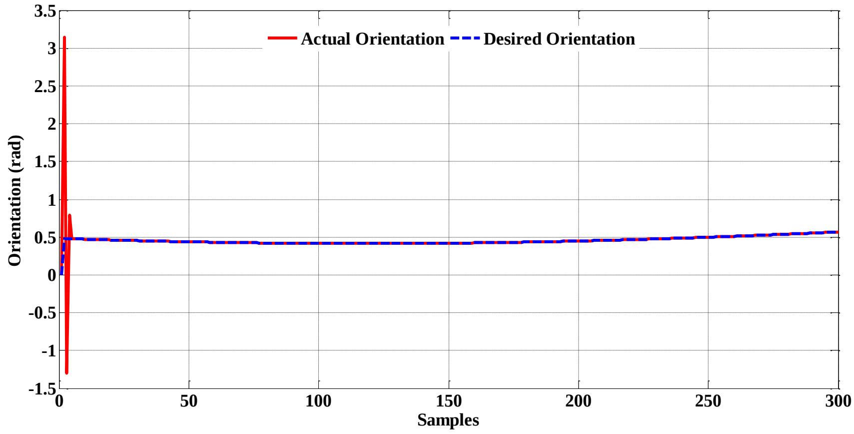


Figure 8. The desired and actual orientation for a mobile robot.

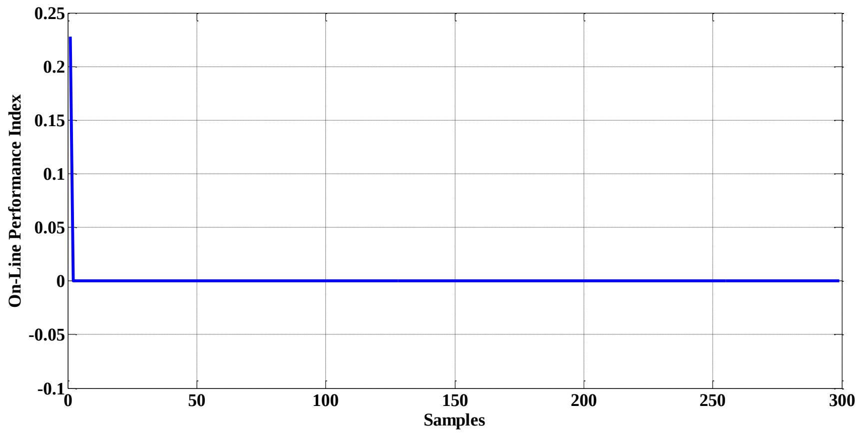


Figure 9. Online performance index.

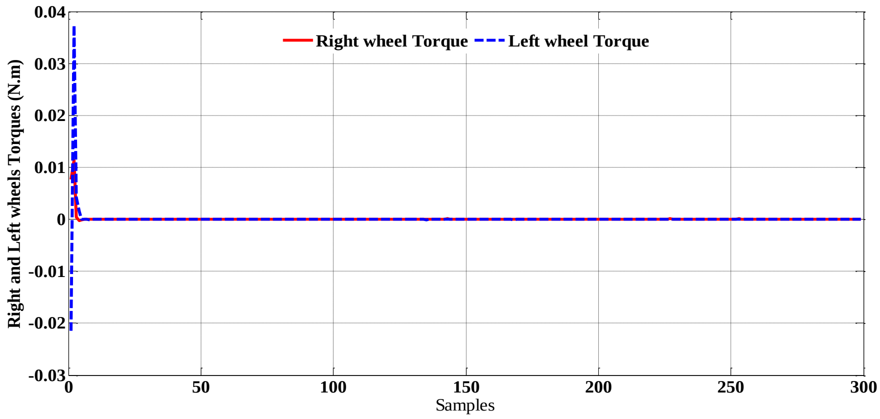


Figure 10. Torque control action.

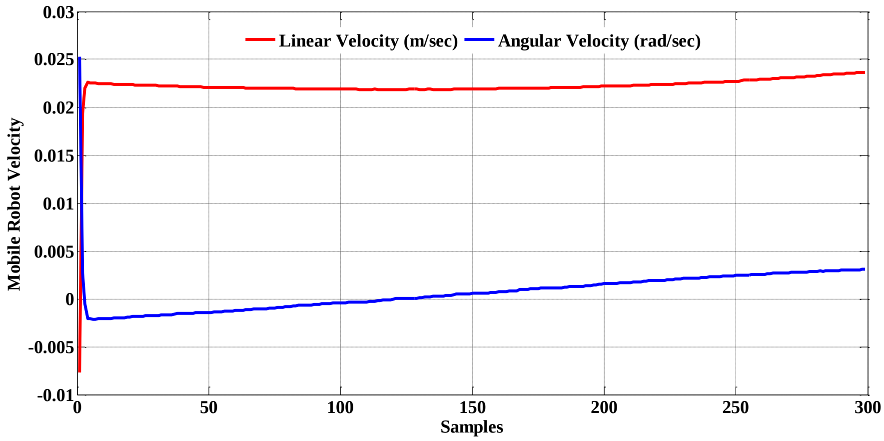
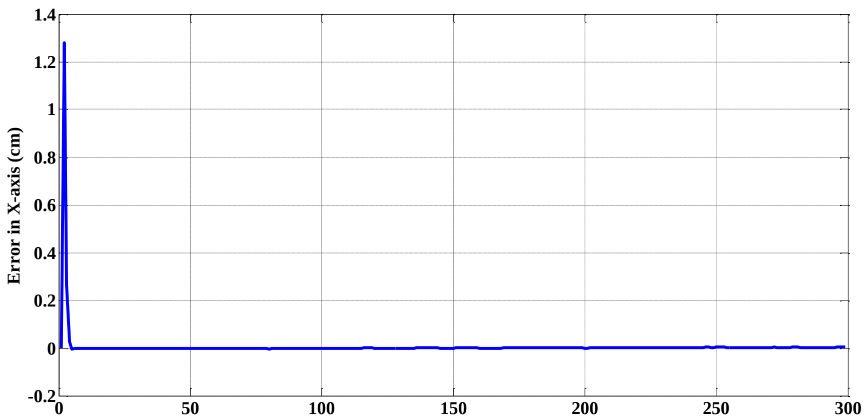


Figure 11. Mobile robot linear and angular velocities.

Figs. 12 a, b, c shows the hardiness and adaptability performance of the present cognitive system expression of preservation the wheeled mobile robot tracking pose error to minimum and settle down the mobile robot pose when it tries to shift from the right path because of the effect of bounded dynamic disturbances to the system as the term that had been taken from **Al-Araji**, **et al.**, **2013** $\overline{\tau d} = [0.01\sin(2t) \quad 0.01\sin(2t)]^T$.



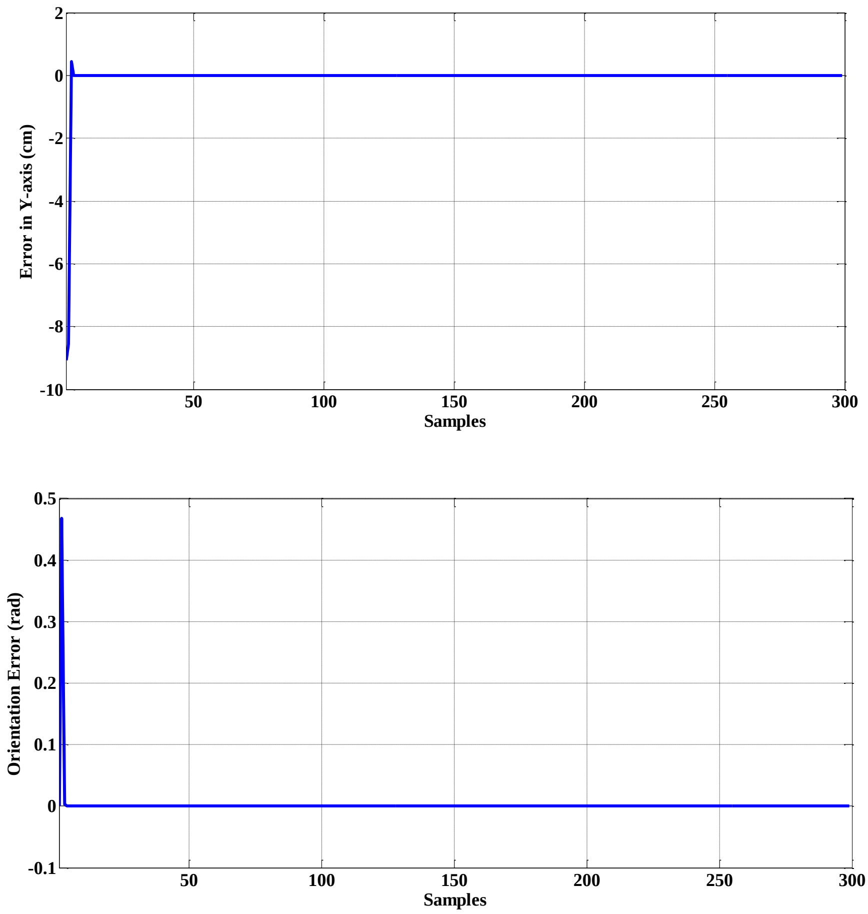


Figure 12. Pose error of the mobile robot: a) error in X-axis; b) error in Y-axis; c) orientation error.

5.2 Case study II

The mobile robot has initial pose as $q(0)=[0,1.45,0]$ and After applying the first layer from the structure of the proposed cognition system to generate the optimal path by using PSO and ABC algorithms as shown in **Figs. 13** and **14** respectively, which has five paths to avoid the static obstacles as a first step. The distances of these five paths between start point to target point are (348.47,354.61, 355.819, 344.54, and 335.84) and (336.66, 339.97, 372.11, 339.84, and 384.74) cm respectively depending on Eq. (16). Path5 is the optimal path form **Fig 13**, and Path1 is the optimal path form **Fig. 14**, because they have the shortest distance of Path5 is (335.84), and Path1 is (336.66) cm respectively. The second step in the same layer is obtaining the reference path equation for the two optimal paths by converting the point of the optimal path using Polynomial Least Squares Curve Fits third order polynomial equation of the reference path as follows:

$$y(x) = 2.07 \times 10^{-6} \times x^3 - 11 \times 10^{-4} \times x^2 - 0.34 \times x - 149.82 \tag{35}$$

$$y(x) = 9 \times 10^{-6} x^3 - 37 \times 10^{-4} x^2 - 0.185 \times x + 147.92 \tag{36}$$

PSO algorithm method is better than the ABC algorithm method because it avoids the static obstacle with minimal distance (335.84) cm to the target and with error (0.243%). The second layer in the cognitive system executed the mobile robot path tracking model based on the reference path Eq. (35) as shown in **Fig. 15**, which shows excellent tracking performance of the reference path equation with free-navigation for a mobile robot.

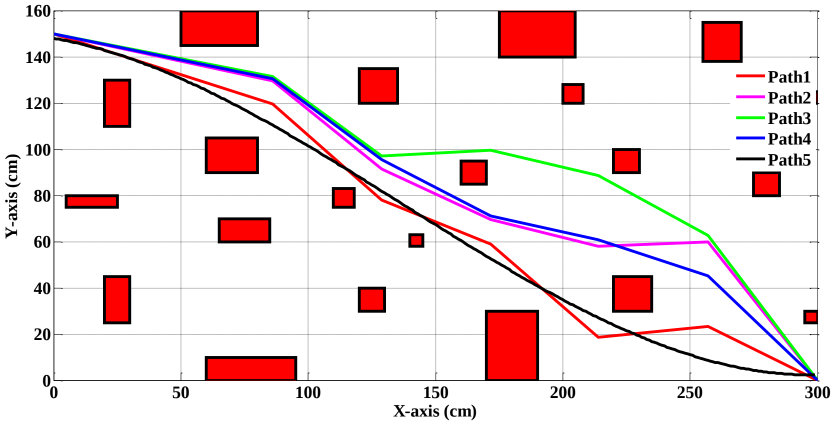


Figure 13. The optimal paths using PSO algorithm.

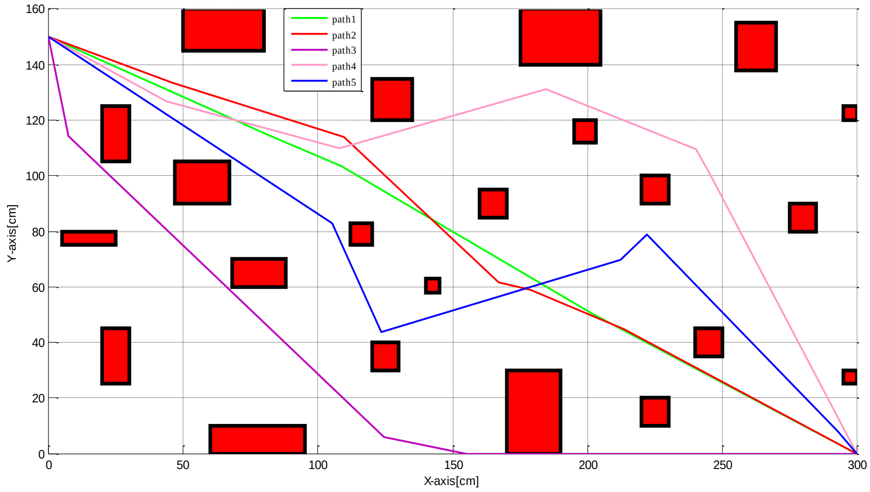


Figure 14. The optimal paths using the ABC algorithm.

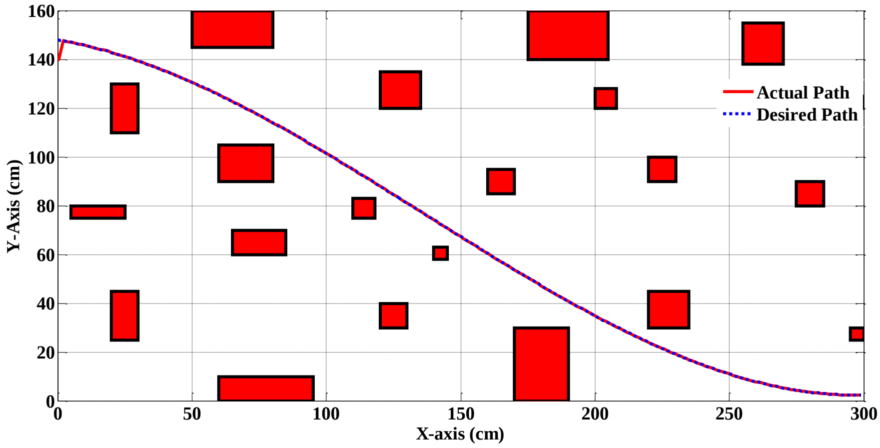


Figure 15. The reference path equation and actual path for a mobile robot.

Fig. 16 demonstrates the mobile robot orientation tracking performance with the PSO algorithm. **Fig. 17** shows the online control algorithm, the Mean Square Error (MSE) clearly enhances the controller performance by showing the pose error concourse for the mobile robot motion at 300 steps.

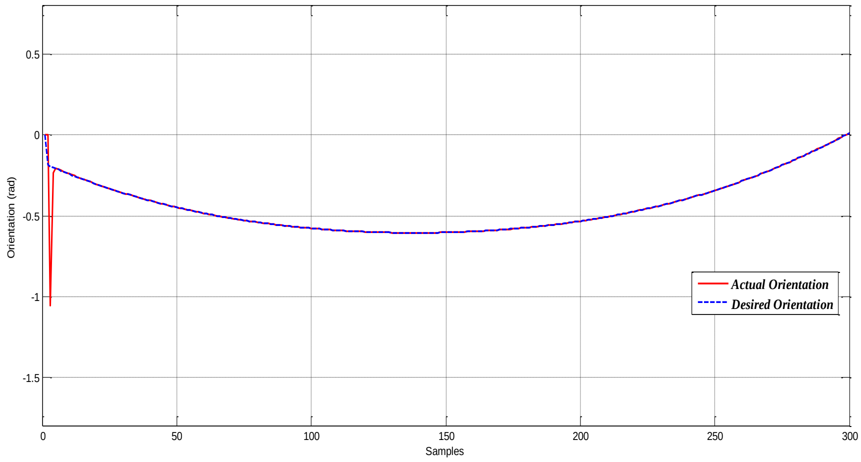


Figure 16. The desired and actual orientation for a mobile robot.

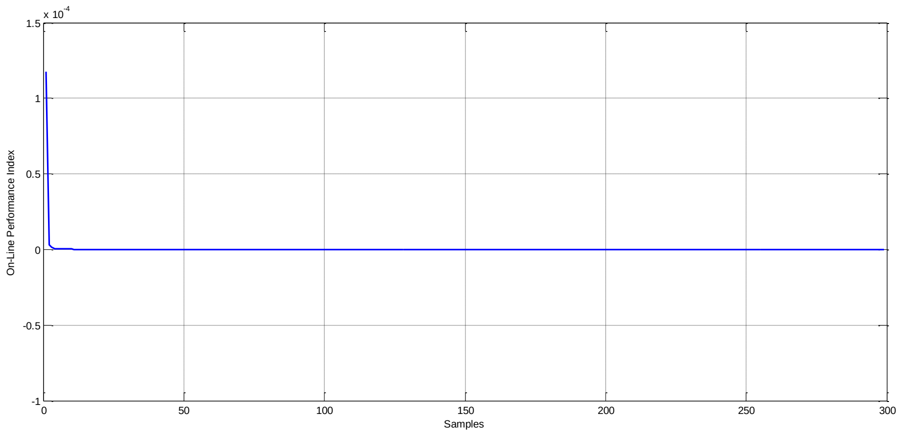


Figure 17. Online performance index.

Fig. 18 shows the smoothness torque control action for the right and left wheels while tracking the reference path equation. The mobile robot linear and angular velocities responses are smoothness without sharp spikes, as shown in **Fig. 19**. **Figs. 20 a, b, c** show the hardiness and adaptability performance of the present cognitive system in terms of preservation the less tracking pose error for the wheeled mobile robot. It settles down the pose of the mobile robot when it tries to shift from the right path because of the bounded dynamic disturbances effect on the system as the term is taken from **Al-Araji**, **et al.**, **2013** $\overline{\tau d} = [0.01\sin(2t) \quad 0.01\sin(2t)]^T$.

PSO algorithm method is better than the ABC algorithm method because it avoids the static obstacle with the smallest distance to the goal and with less error as explained in **Table 3**.

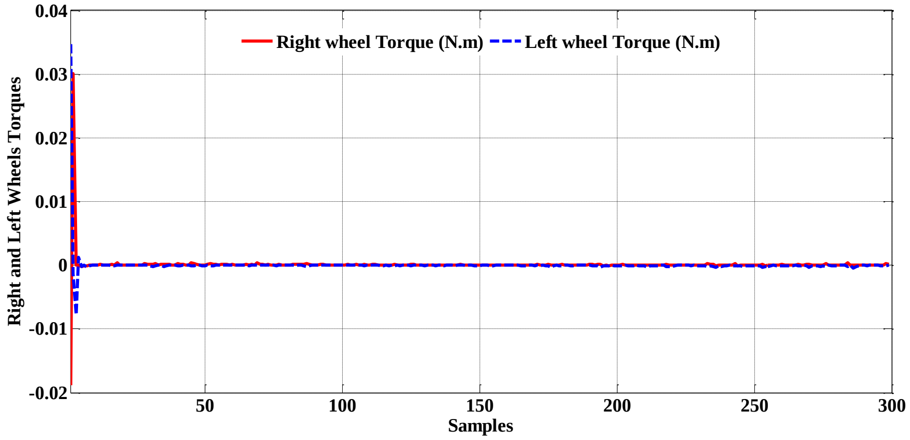


Figure 18. Torque control action**.**

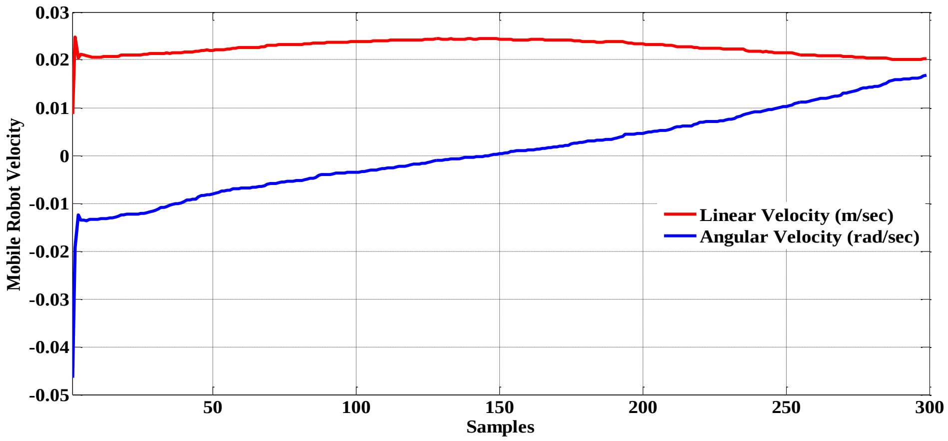
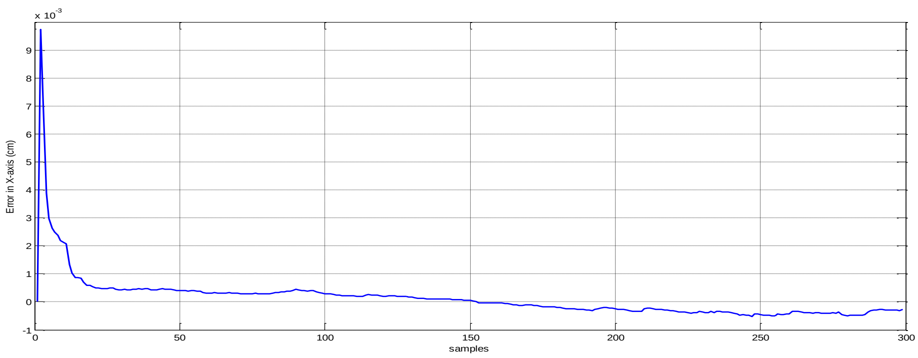


Figure 19. Mobile robot linear and angular velocities**.**



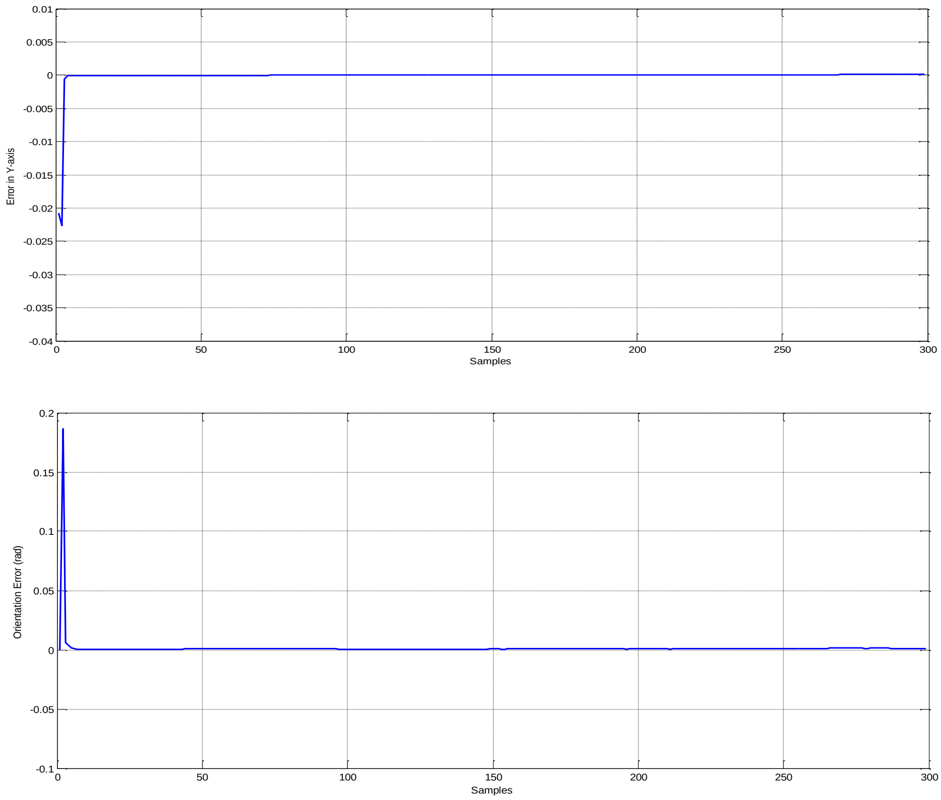


Figure 20. Pose error of the mobile robot: a) error in X-axis; b) error in Y-axis; c) orientation error.

Table 3. Error difference between PSO and ABC algorithms.

Methods / Case Studies	Beast path Distance with PSO Algorithm (cm)	Beast path Distance with ABC Algorithm (cm)	% Error
Case Study I	**333.52**	**335.79**	$\frac{335.79-333.52}{335.79}=0.676\%$
Case Study III	**335.84**	**336.66**	$\frac{336.84-335.84}{336.66}=0.243\%$

6. CONCLUSIONS

The simulation results of the proposed cognitive system based on cognition path planning and nonlinear neural controller with PSO and ABC algorithms are presented in this work for the mining wheeled mobile robot dynamic model which shows the following capabilities of:

1) Accurately generating optimal (minimum distance) reference path equation between start and goal position for the mobile robot in a working environment with static obstacles.
2) Online finding and tuning the parameters of the nonlinear neural controller using PSO algorithm.

3) Obtaining a smooth and best torque control action, without spikes as well as no saturation torque action state.
4) Tracking the reference path equation with minimum pose error and avoiding the static obstacles.
5) High adaptability performance when changing the mobile robot initial pose.
6) Strong robustness performance when adding the dynamic disturbances to the mobile robot.

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