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An Improved Neural Network Algorithm to Efficiently Track Various Trajectories of Robot Manipulator Arms

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ABSTRACT The tuning of the robot actuator represents many challenges to follow a predefined trajectory on account of the uncertainties of parameters and the model nonlinearity. Furthermore, the controller gains require proper optimization to achieve good performance. In this paper, the use of a modified neural network algorithm (MNNA) is proposed as a novel adaptive tuning algorithm to optimize the controller gains. Furthermore, a new mathematical modulation is introduced to promote the exploration manner of the NNA without initial parameters. Specifically, the modulation is formed by using a polynomial mutation. The proposed algorithm is applied to select the proportional integral derivative (PID) controller gains of a robot manipulator arms in lieu of conventional procedures of designer expertise. Another vital contribution is formulating a new performance index that guarantees to improve the settling time and the overshoot of every arm output simultaneously. The proposed algorithm is evaluated with different intelligent techniques in the literature, including the genetic algorithm (GA) and the cuckoo search algorithm (CSA) with PID controllers, where its superiority to follow various trajectories is demonstrated. To affirm the robustness and efficiency of the proposed algorithm, several trajectories and uncertainties of parameters are considered for assessing the response of a robotic manipulator.

INDEX TERMS Robot manipulator, nonlinear system, trajectory tracking, PID controller, neural networks.

I. INTRODUCTION

In the last years, the robot manipulator has been applied for different aspects such that aid the industry and human works. The robot can do the routine works and follow the object with more effectiveness and a short time than the human. The robot manipulator needs an efficient and accurate controller to do duties like the tracking of position [1]. The nonlinearity of the manipulator system and the variation of parameters represent the major challenges that opposite the designer to detect the controller of its arms [2], [3].

In the literature, different control techniques are applied to the manipulators, e.g. the proportional-integral-derivative (PID) control approach [4]–[6], fuzzy logic control [7]–[9], and adaptive control [10], [11]. Among these controllers, most of the industrial applications utilize the PID controller for the sake of its simple structure and implementation. However, this controller needs proper optimization to provide the perfect performance, particularly in complicated and nonlinear systems. Numerous techniques are applied to optimize the PID controller, such as conventional procedures that can involve Ziegler Nichols (ZN) technique [12], [13] and graphical procedures [14], [15]. The ZN technique is built on fixed rules for each system, and it fails to give a good performance [16], [17]. In respect of the graphical procedures, these procedures require the linear model of the system, long time-consuming, and it has complicated mathematical formulation, especially in the big systems [17]. Diverse robust

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adaptive sliding mode control methods have been introduced in [18]–[22] which are superior to the traditional sliding mode control schemes.

Meta-heuristic algorithms can cope with the optimization issue of the PID controller and provide the best results in various applications with short time consuming [23], [24]. There are various types of meta-heuristic techniques like the genetic algorithm (GA) [25], particle swarm optimization [26], ant colony optimization [27], and teaching-learning algorithm [28]. The catching in a local optimum position demonstrates the enormous problem which faces these techniques. Different strategies (e.g. mutation operator) are applied to overcome this problem and promote the exploration manner of the algorithms [29]. Indeed, the use of the mutation operator proves good results with various algorithms [29]–[32]. Many variants of mutation like random, non-uniform, and polynomial mutation can be applied to guarantee the exploration manner of the optimization algorithms [33]. Recently, the polynomial mutation proves better performance than the other procedures in many studied cases [34]. However, its usage for promoting the exploration manner of the neural network algorithm (NNA) for tracking various trajectories of robot manipulator arms is not yet investigated, which is covered in this work. Furthermore, trajectories and uncertainties of parameters are considered a challenge in the previous studies of robot manipulators to improve their response in terms of settling times and overshoots.

To cover the gap in the literature, this paper proposes a new mathematical modulation for the NNA by utilizing the polynomial mutation to promote the exploration manner of this algorithm. It has a global search characteristic built to relate to the criteria of artificial neural networks. Furthermore, it does not need initial parameters to start, unlike the other algorithms. The NNA proves good results in various optimization problems [35]–[37]. In that case, the inspired modified NNA algorithm is applied to detect the controller gains of the robot manipulator in lieu of conventional procedures of designer expertise. The introduced technique tunes the controller parameters for the sake of minimizing a new developed time-domain performance index to confirm the decreasing of the settling time and overshoot. The results of the introduced procedure are evaluated with the GA-PID controller and the cuckoo search algorithm (CSA)-PID controller. The progress of the proposed procedure is tested to follow non-regular trajectories. Besides, the parameters uncertainties experiment is formed to ensure the robustness of the inspired procedure.

The major contributions and novelty of this manuscript are listed below:

- A new polynomial mutation is applied to promote the exploration manner of the original NNA without initial parameters.
- The new algorithm is introduced to obtain the optimal gains of the robot manipulator controller instead of conventional procedures of designer expertise.
- A new performance index is created to guarantee the decreasing of the settling time and the overshoot at the same time.
- The suggested procedure is evaluated with the GA-PID controller [38] and the CSA-PID controller 39].
- The progress of the inspired procedure is confirmed against various trajectories and system parameter variations.

The remnant of the paper is listed as: Section 2 presents the procedure of NNA. In Section 3, the proposed modulation of the NNA is illustrated. The formulation of a robot manipulator with the controller is presented in Section 4. Section 5 shows the results and discussions of the proposed system. In the end, the conclusions are summarized in Section 6.

II. NEURAL NETWORK ALGORITHM

The neural network algorithm is a novel intelligent procedure created according to the biological manner of nervous systems [35]. The procedures of artificial neural network structure are the main process of the NNA. The NNA has the manner of global research to detect new solutions. Furthermore, it does not need initial parameters for the starting instead of the other algorithms. Specifically, it discovers the new solutions by adapting the weight variables between the predicted solution and the target. Systematically, it can reach an optimal solution during the search region. The NNA has a different procedure than the other algorithms to obtain the optimal solution. Its procedure works on the decreasing of the space between the optimal position and the different positions. This algorithm consists of four phases as follows:

A. INITIAL POPULATION STAGE

The NNA is started with a random initial population like other algorithms to generate initial solutions inside the defined search space. Each solution is named "pattern solution". At the start, a random pattern matrix of solutions "X" with size $N{\times}D$ is generated. Where N is the generation number and D is the number of variables. The pattern solutions can mathematically be symbolized as follows, $X = [X_1, X_2, .., X_i, ... X_N]'$ and $X_i = [x_{i1}, x_{i2}, ..., x_{iD}]$, where;

$$x_{ij} = L_j + rand\,(U_j - L_j), \quad i = 1, 2, \ldots\ldots, N, \quad j = 1, 2, \ldots\ldots, D \tag{1}$$

in which L and U are the minimum and maximum limits of the variables, respectively.

The NNA is similar to the artificial neural network where each solution X_i in the generation has a corresponding weight vector $W_i = [w_{i1}, w_{i2}, ..., w_{iN}]$. Note that the weight matrix for all population individuals has a size of $N{\times}N$. The NNA process is started with a random weight matrix between (0, 1). In each iteration, the weight matrix is updated regarding the network error. The summation of weights for every solution is constrained while it does not

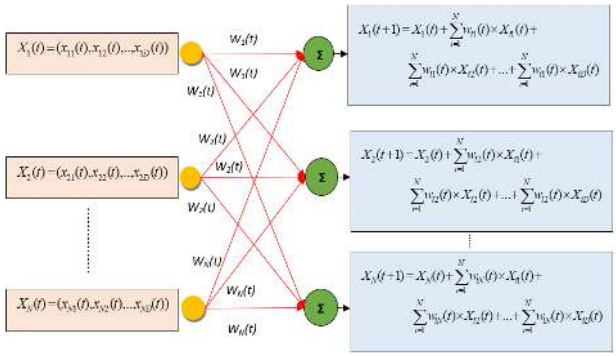

FIGURE 1. Mechanism of new population in NNA.

exceed 1 as follows,

$$\sum_{j=1}^{N} w_{ij} = 1, \quad i = 1, 2, \ldots\ldots, N \tag{2}$$

This constraint adjusts the bias of the solution movement and generation. It reserves the algorithm from the restriction in the local optimal solution. After the determination of random solutions and the corresponding weights, the fitness of every solution is calculated by the computation of the performance index. Then, the optimal solution with its weights is determined to produce the updated solution as follows,

$$X_j^{new}(t+1) = \sum_{i=1}^{N} w_{ij}(t) \times X_i(t), \quad j = 1, 2, \ldots\ldots, N \tag{3}$$

$$X_i(t+1) = X_i(t) + X_i^{new}(t+1), \quad i = 1, 2, \ldots\ldots, N \tag{4}$$

where $X_i(t)$ is the solution at iteration 't', $X_i^{new}(t+1)$ is the updated solution at the next iteration '$t+1$'. The new generation is presented in Fig. 1.

B. WEIGHT MATRIX UPDATING

In this stage, the weights between variables are updated as follows,

$$W_i(t+1) = W_i(t) + 2 \times rand \times (W^*(t) - W_i(t)), \quad i = 1, 2, \ldots\ldots, N \tag{5}$$

where $W^*(t)$ is the target vector of weights.

C. BIAS STAGE

The NNA uses a bias operator for good exploration. This operator is applied to change a percentage from generated solutions and the weight matrix. The bias operator is reduced adaptively with the increasing of iteration number. Any possible procedure can be applied for this purpose as follows,

$$\beta(t+1) = 1 - \left(\frac{t}{t_{\max}}\right), \quad t = 1, 2, \ldots\ldots, t_{\max} \tag{6}$$

or as follows,

$$\beta(t+1) = 0.99\,\beta(t), \quad t = 1, 2, \ldots\ldots, t_{\max} \tag{7}$$

where t_{max} is the final number of iterations. The decreasing of β with increasing the iteration promotes the exploitation manner of the algorithm to catch the best solution. In this stage, a random number is produced to detect the population number for biasing as follows,

$$N_P = Round(D \times \beta) \tag{8}$$

Then, the population and weights are modified as follows,

$$X_j = L + rand(U - L), \quad j = 1, 2, \ldots\ldots, N_P \tag{9}$$

Also, a random number is produced to detect the number of weights that must be modified as follows,

$$N_w = Round(N \times \beta) \tag{10}$$

$$W_j = m, j = 1, 2, \ldots\ldots, N_w \tag{11}$$

where m is a random variable within (0, 1).

D. TRANSFER FUNCTION STAGE

The transfer function operator is applied in the NNA to promote the exploitation manner of the algorithm. This operation transfers the new solutions from their original positions to new positions to decrease the gap between them and the target solution. The transfer operation is presented as follows,

$$X_i^*(t+1) = X_i(t+1) + 2 \times rand \times (X^*(t) - X_i(t+1)), \quad i = 1, 2, \ldots\ldots, N \tag{12}$$

where $X^*(t)$ is the best solution at iteration 't'.

III. THE PROPOSED MODULATION OF NNA

The trapping of most optimization algorithms in a local optimal represents a serious problem. This issue is occurred at the early stage of the optimization procedure due to the use of random patterns. The mutation operator proves an efficient function to overcome this problem with many single and multi-objective optimization techniques [30]–[32]. There are various procedures of mutation like random, uniform, non-uniform, and polynomial mutation [33]. It is demonstrated that the polynomial mutation provides good experimental results compared with the other procedures [34]. However, the polynomial mutation has a nonlinear probability to adopt the current solution to the best neighboring, and so it can guarantee the exploration manner of the optimization procedure. The exchange of the current agent to the neighboring value is formed as follows:

$$X_i(t) = X_i(t+1) + \alpha \times \delta_{\max}(X_i), i = 1, 2, \ldots\ldots, N_p \tag{13}$$

$$\alpha = \begin{cases} (2r)^{(1/(q+1))} - 1 & if\ r < 0.5 \\ 1 - [2(1-r)]^{(1/(q+1))} & otherwise \end{cases} \tag{14}$$

$$\delta_{\max\,ij}(t) = \max\,[X_{ij}(t) - L_j, U_j - X_{ij}(t)], \quad i = 1, 2, \ldots\ldots, N_p,\ j = 1, 2, \ldots\ldots, D \tag{15}$$

where q is a positive factor and named a shape variable, r is a random variable within (0, 1), $\delta_{\max\,ij}$ is the maximum

allowed change between the present solution and the mutated one. One of the contributions of this paper is to propose the mutation operation in lieu of the random exploration of the biasing stage in (9). The nonlinear probability in the proposed polynomial mutation can diverge the current solution to the best neighboring one; Therefore, it significantly improves the exploration manner of the optimization procedure, especially for the challengable robot manipulator. In respect of the prior stages of the NNA and the proposed modulation, the flowchart in Fig. 2 summarizes the procedures of the modified NNA (MNNA) to get the optimal solution, thanks to the proposed polynomial mutation.

IV. SYSTEM MODELING

This part demonstrates the formulation of the proposed robot manipulator. The robot dynamic is formulated by nonlinear differential equations. The equations have various parts like gravity, inertia, Coriolis, centrifugal torques, and load. The robot actuator in its arm needs a proper torque to move the end-effector in a predefined trajectory with limited speed. The next equation can govern the manipulator dynamics of various n-arms [38].

$$\tau = M(\theta)\ddot{\theta} + C(\theta, \dot{\theta}) + G(\theta) \tag{16}$$

where

τ	Torque vector of the arms with size $n\times 1$
$M(\theta)$	Positive matrix with dimensions $n\times n$
$C(\theta, \dot{\theta})$	Coriolis torque vector with size $n\times 1$
$G(\theta)$	Gravity torque vector with size $n\times 1$
θ	Angular position of arms
$\dot{\theta}$	Velocity of arms
$\ddot{\theta}$	Acceleration of arms
n	Number of arms

In this case, the suggested manipulator has two arms as clear in Fig. 3. The dynamics formulation of this robot are described as [40],

$$\begin{aligned}\tau_1 &= m_2 l_2^2 (\ddot{\theta}_1 + \ddot{\theta}_2) + m_2 l_1 l_2 c_2 (2\ddot{\theta}_1 + \ddot{\theta}_2) \\ &\quad + (m_1 + m_2) l_1^2 \ddot{\theta}_1 - m_2 l_1 l_2 s_2 \dot{\theta}_2^2 \\ &\quad - 2 m_2 l_1 l_2 s_2 \dot{\theta}_1 \dot{\theta}_2 + m_2 l_2 g c_{12} \\ &\quad + (m_1 + m_2) l_1 g c_1 \end{aligned} \tag{17}$$

$$\begin{aligned}\tau_2 &= m_2 l_2^2 (\ddot{\theta}_1 + \ddot{\theta}_2) + m_2 l_1 l_2 c_2 \ddot{\theta}_1 \\ &\quad + m_2 l_1 l_2 c_2 \dot{\theta}_1^2 + m_2 l_1 g c_{12} \end{aligned} \tag{18}$$

where $c_1 = \cos(\theta_1)$, $c_2 = \cos(\theta_2)$, $c_{12} = \cos(\theta_1 + \theta_2)$, $s_1 = \sin(\theta_1)$, and $s_2 = \sin(\theta_2)$. In this paper, the control signal of the PID represents the torque of every arm as follows,

$$\tau_i = K_{P,i} \times e_i + K_{I,i} \int e_i \,.\, dt + K_{D,i} \times \frac{d\, e_i}{d\, t}, i = 1, 2 \tag{19}$$

$$e_i = \theta_{d,i} - \theta_i \tag{20}$$

where e_i is the error, $\theta_{d,i}$ is the target trajectory, and θ_i is the output angular position.

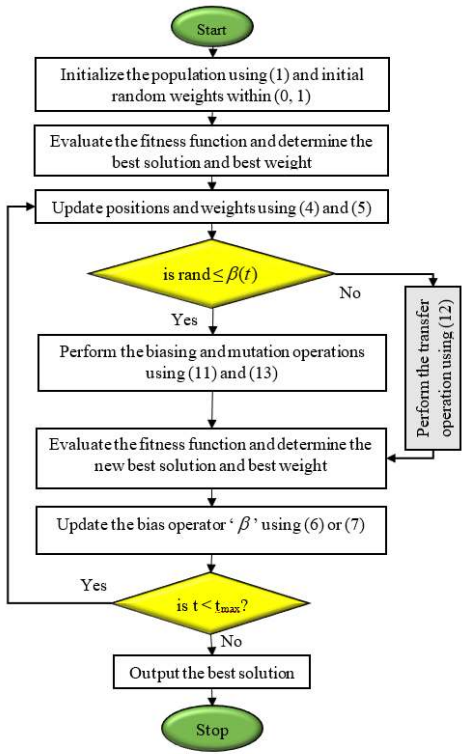

FIGURE 2. The flowchart of the MNNA.

V. RESULTS AND DISCUSSION

In this part, the MNNA is devoted to optimizing the PID controller gains to enhance the response of a robotic manipulator which is cleared in Fig. 3. The main target of the optimization procedure is the decreasing of settling time 't_s' and the maximum overshoot 'M_p' of every arm to achieve the target trajectory. This paper proposes a new performance index to confirm the decreasing of t_s and M_p of the output of every arm simultaneously. This performance index is named figure of demerit (FOD) and it is formulated as follows,

$$J = \sum_{i=1}^{2} (1 - e^{-\psi})(M_{P,i} + E_{SS,i}) + e^{-\psi}(t_{s,i} - t_{r,i}) \tag{21}$$

where

$M_{P,i}$	The wave overshoot.
$E_{SS,i}$	The steady-state error.
$t_{s,i}$	The wave settling time.
$t_{r,i}$	The wave rise time.
ψ	A weighting constant.
i	The index of each robot arm.

The previous performance index can achieve the decreasing of t_s and M_p of the output of every arm by selecting a proper value for the weighting factor 'ψ'. If the value of $\psi < 0.7$, it will minimize t_s. On the contrary, if the value of $\psi > 0.7$, it will minimize the M_p. This performance index is proved by simulation in [41]. In this case, the chosen weight '$\psi = 0.7$' to ensure the decreasing of both t_s and M_p

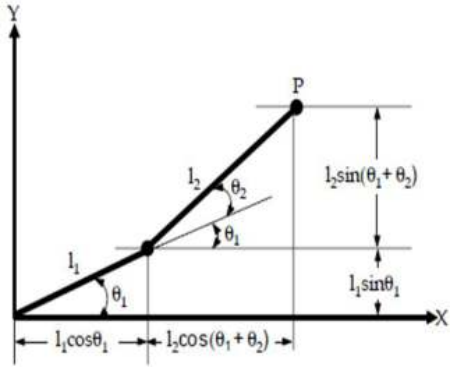

FIGURE 3. The schematic representation of a robotic manipulator with two-arms.

TABLE 1. The controller parameters due to each procedure with the corresponding performance index.

		GA-PID [38]	CSA-PID [39]	Proposed MNNA-PID
Controller Parameters	Arm_1	$K_{P,1}$=184.76, $K_{I,1}$=49.68, $K_{D,1}$=8.94	$K_{P,1}$=782.417, $K_{I,1}$=225.2123, $K_{D,1}$=35.1995	$K_{P,1}$=250, $K_{I,1}$=0.1792, $K_{D,1}$=11.820
	Arm_2	$K_{P,2}$=11.46, $K_{I,2}$=16.54, $K_{D,2}$=0.2	$K_{P,2}$=324.523, $K_{I,2}$=119.245, $K_{D,2}$=20.1025	$K_{P,2}$=244.524, $K_{I,2}$ =0, $K_{D,2}$=6.306
J		1.1758	0.3292	0.04196

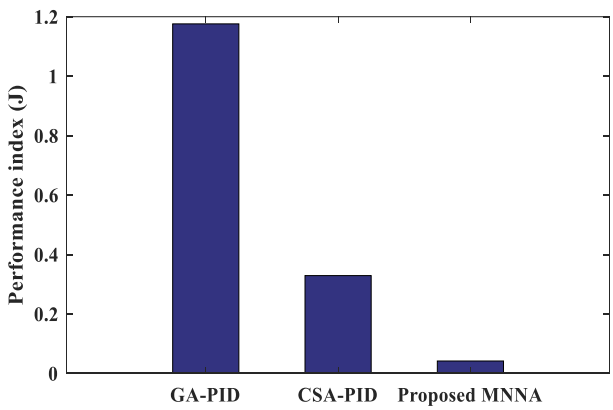

FIGURE 4. The performance index due to the different algorithms.

TABLE 2. The tuned factors of different techniques.

	Factors numbers	Tuning factors
GA-PID [38]	4	Population size, iterations, crossover, mutation
CSA-PID [39]	3	Nest size, elitism probability, iterations
Proposed MNNA-PID	2	Agent numbers, iterations

Algorithm 1 MNNA pseudo-code to detect the best gains

```
Start MNNA
Simulate the manipulator including the chosen controller
Determine the performance function in (21)
Select the best solution and best weights
While (t < iterationsmax)
    Carry out the steps of MNNA in Fig. 2
    Simulate the manipulator including the chosen
    controller
    Obtain the performance function in (21)
    Select the best fitness
zero: Select the new solution
End While
Stop
```

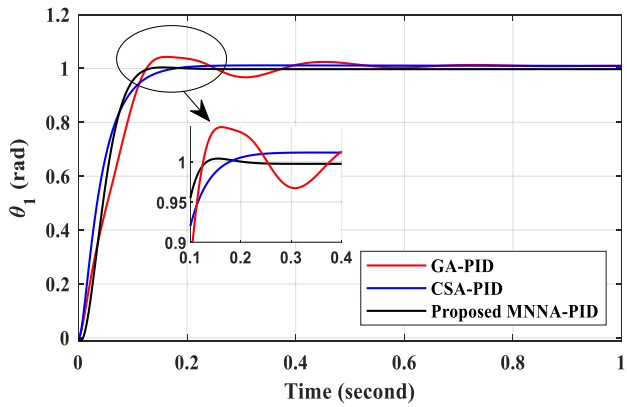

FIGURE 5. The output wave of the position arm_1 in the nominal case.

of every arm output together. The proposed MNNA search for the best PID controller gains by the decreasing of the performance index in (21). The optimization procedure is cried out at the system nominal parameters and a unit step target for the position of every arm. The nominal parameters of the main system are: $m_1 = m_2 = 0.1$ kg, $l_1 = 0.8$ m, $l_2 = 0.4$ m, and $g = 9.81$ m/s^2 [38]. The MNNA parameters are: The maximum agent's number is selected as 100 besides 50 iterations number. The selected limits of the controller gains are "[$K_{P1,min} = 0, K_{I1,min} = 0, K_{D1,min} = 0, K_{P2,min} = 0, K_{I2,min} = 0, K_{D2,min} = 0$]; "[$K_{P1,max} = 250, K_{I1,max} = 1, K_{D1,max} = 20, K_{D2,max} = 250, K_{I2,max} = 1, K_{D1,max} = 10$]". The results of the inspired MNNA is confirmed by comparing it with the GA-PID controller [38] and the CSA-PID controller [39]. The controller parameters computed by each procedure with the corresponding performance index value are recorded in Table 1. Furthermore, Fig. 4 shows the performance index due to the different algorithms in the vertical bar plot as an effective clarified way for comparison. The inspired MNNA has the least performance index, as clarified in Table 1 and Fig. 4. Moreover, the proposed MNNA has less tuning factors compared to other algorithms, as listed in Table 2. The procedures of the MNNA, to detect the best parameters, are concluded by the pseudo-code described by Algorithm 1.

Various test scenarios are formed in the next subsections to affirm the efficiency and robustness of the inspired MNNA. These scenarios are the nominal parameter check with unit step reference and variable trajectory experiment for the position of every arm. Furthermore, the robustness experiment of

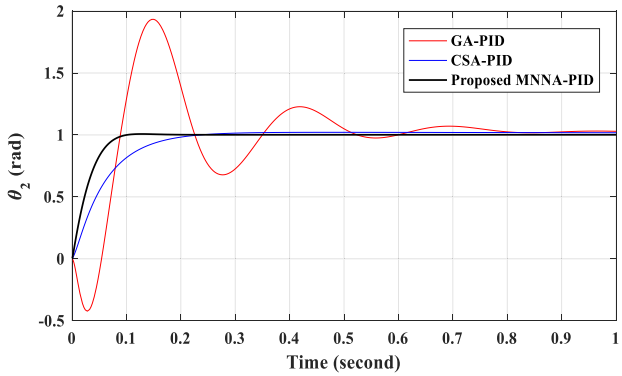

FIGURE 6. The output wave of the position arm_2 in the nominal case.

TABLE 3. The t_s and M_p of the system performance of nominal case due to the various procedures.

		GA-PID [38]	CSA-PID [39]	Proposed MNNA-PID
M_p	Arm_1	4.301%	1.1421%	0.3898%
	Arm_2	93.3058%	2.1193%	0.7554%
t_s	Arm_1	0.4899	0.1404	0.1114
	Arm_2	1	0.694	0.0846

the inspired MNNA versus the variations of system parameters is carried out.

A. SCENARIO 1: THE NOMINAL PARAMETER TEST WITH UNIT STEP REFERENCE

In this test, a unit step position reference is applied for every arm at system nominal parameters. Figs. 5 and 6 present the output wave of the robot manipulator arms to follow a unit step position reference. Table 3 records the values of t_s and M_p of the output wave due to the various procedures, which quantifies the improvement in the proposed objective function expressed by (21). Specifically, this table compares these two parameters for the proposed MNNA, GA-PID controller, and the CSA-PID controller. Furthermore, Fig. 7 shows the output response characteristics due to the different algorithms in the vertical bar plot as an effective clarified way for comparison. It is summarized from Figs. 5, 6, and 7, and Table 3 that the inspired MNNA-PID controller outperforms the GA-PID controller and the CSA-PID controller. Furthermore, the proposed MNNA has the lowest t_s and M_p values compared with the other procedures for the two arms.

B. SCENARIO 2: THE EFFICIENCY OF THE INSPIRED PROCEDURE AGAINST VARIOUS TRAJECTORIES

In this scenario, the inspired procedure is tested to follow various position trajectories. The test is done in two stages. The first one is created by applying a random step position trajectory on every arm as clarified in Fig. 8. The system output due to this stage is shown in Figs. 9 and 10. These figures illustrate that the inspired MNNA-PID controller can follow the random step trajectory with negligible steady state-error, minimum settling time, and negligible overshoots compared with other techniques.

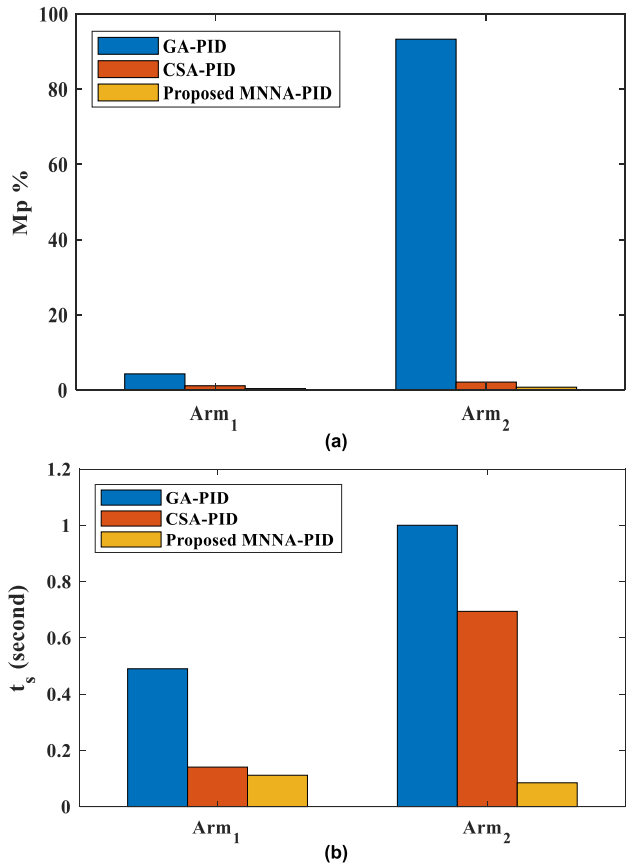

FIGURE 7. The output response characteristics due to the different algorithms (a) The maximum overshoot (M_P), (b) the settling time (t_s).

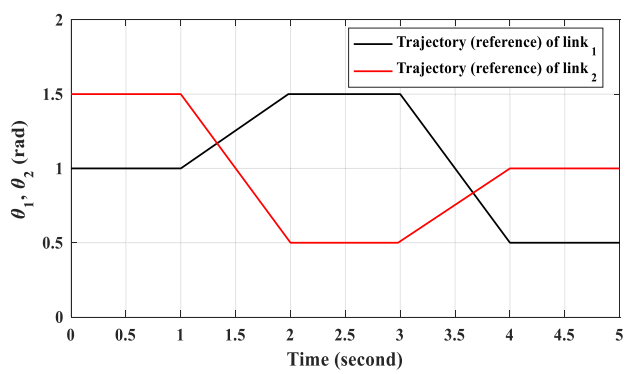

FIGURE 8. Random step position trajectory of each robot arm.

The second stage of this test is formed by applying a cubic position trajectory on every arm, as clarified in Fig. 11. This cubic trajectory is developed from the following equation [40],

$$\theta_{d,i} = c_{0,i} + c_{1,i} \times t + c_{2,i} \times t^2 + c_{3,i} \times t^3 \tag{22}$$

with end velocity and acceleration constraints that are determined in the following equations,

$$\dot{\theta}_{df,i} = c_{1,i} + 2\,c_{2,i} \times t_f + 3\,c_{3,i} \times t_f^2 \tag{23}$$

$$\ddot{\theta}_{df,i} = 2\,c_{2,i} + 6\,c_{3,i} \times t_f \tag{24}$$

TABLE 4. The initial and final parameters of the cubic trajectories.

	t_0	t_f (sec)	θ_{d0} (rad)	θ_{df} (rad)	$\dot{\theta}_{d0}$	c_0	c_1	c_2	c_3
Arm_1	0	4	0	0.5	0	0	0	0.09375	-0.015625
Arm_2	0	4	0	4	0	0	0	0.75	-0.125

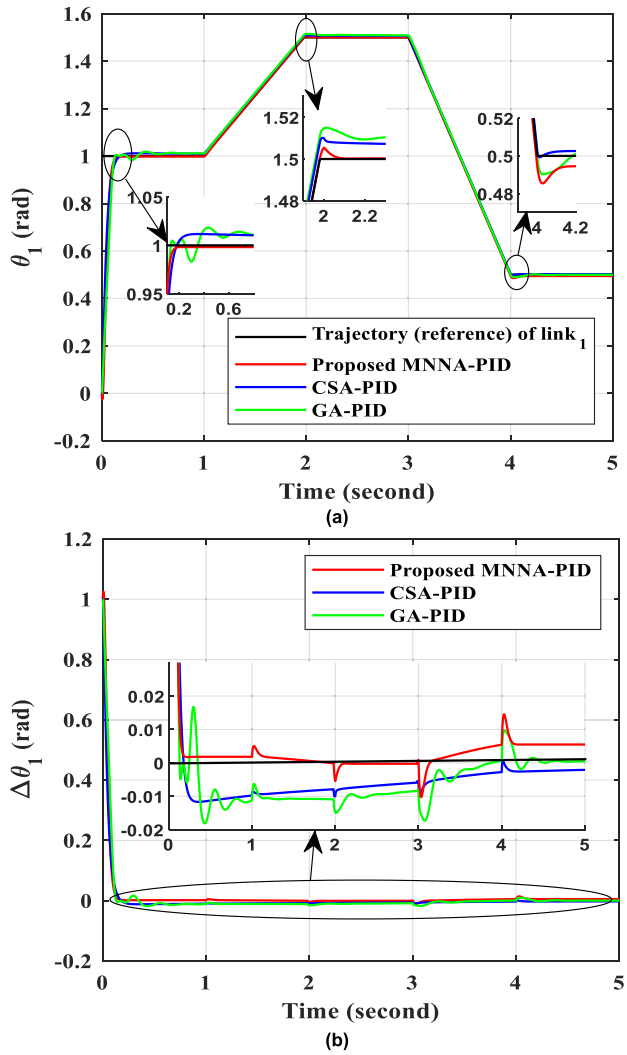

FIGURE 9. The output wave of arm_1 due to random step position trajectory; (a) The position of arm_1 (b) The position deviation of arm_1.

where $i = 1, 2$ is the indicator of every arm and t_f, $\dot{\theta}_{df}$, $\ddot{\theta}_{df}$ are the end time velocity, and acceleration, respectively. Where the initial and final parameters of the cubic trajectories are listed in Table 4. The constants '$c_{0,i}$, $c_{1,i}$, $c_{2,i}$, $c_{3,i}$' can be determined by solving (22) and (23) together with the starting and endpoints of the position and velocity. Therefore, the nonlinear trajectory can be sketched for each arm as clarified in Fig. 11.

The output wave of the model achieved by the inspired MNNA-PID controller in the situation of cubic position trajectory test is presented in Figs. 12 and 13. These figures clear that the proposed algorithm can follow the cubic position trajectory effectively.

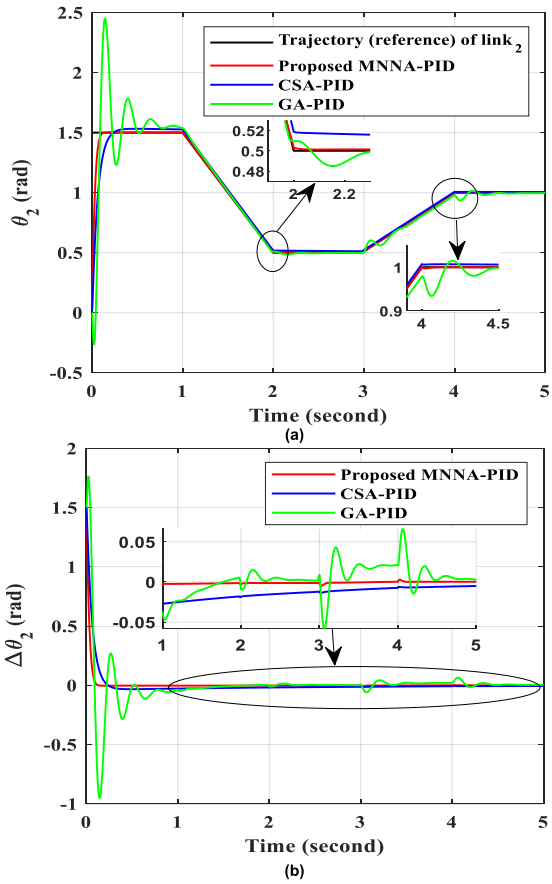

FIGURE 10. The output wave of arm_2 due to random step position trajectory; (a) The position of arm_2 , (b) The position deviation of arm_2.

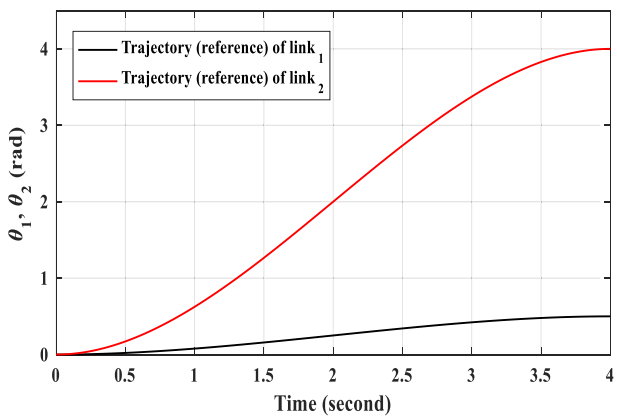

FIGURE 11. Cubic position trajectory of each robot arm.

C. SCENARIO 3: THE ROBUSTNESS EXPERIMENT OF THE INSPIRED PROCEDURE TOWARD PARAMETERS VARIATIONS

This scenario is performed by making uncertainty in masses and lengths of the robotic arms by ±20% from the

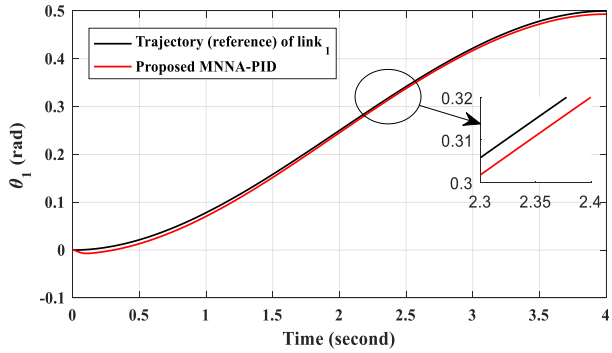

FIGURE 12. The output wave of arm_1 due to cubic position trajectory.

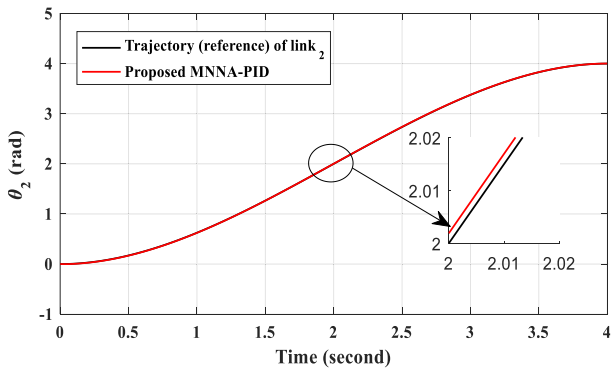

FIGURE 13. The output wave of arm_2 due to cubic position trajectory.

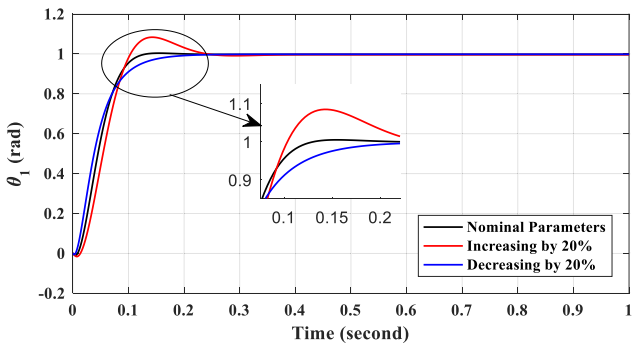

FIGURE 14. The output wave of arm_1 due to robustness test.

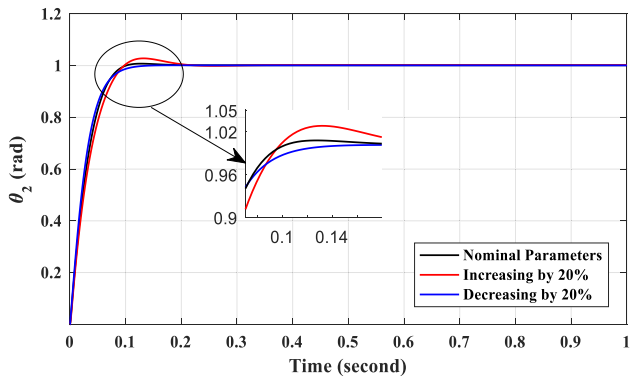

FIGURE 15. The output wave of arm_2 due to robustness test.

nominal values. Figs. 14 and 15 show the output wave of the model with respect to the inspired MNNA-PID controller. It is clarified from these figures that the introduced procedure diminishes the change in the system output in the case of parameter variations.

VI. CONCLUSION

In this paper, a proposed intelligence procedure, named MNNA, has been introduced for the optimization of a robot manipulator controller. Furthermore, a new performance index has been applied to confirm the decreasing of both the wave settling time and the overshoot of robot manipulator arms. Many experiments with different scenarios have been done to confirm the effectiveness of the introduced procedure. In addition, the performance of the inspired MNNA is evaluated with the GA-PID controller and the CSA-PID controller, in terms of the settling time and the overshoot. The inspired MNNA can follow the cubic position trajectory effectively while diminishing the change in the system output in case of parameter variations. The results prove that the inspired procedure superior to the other procedures and it is more efficient to follow various trajectories. Furthermore, the inspired procedure is robust versus uncertainties of the system parameters and diverse trajectories. Besides, most of the industrial applications utilize the PID controller for the sake of its simple structure, implementation, and the tuning process is carried out offline by MATLAB software. However, the proposed algorithm requires proper selection for the limits of the controller gains, number of agents, and the number of iterations. The future work will be directed to consider modern model predictive control schemes while investigating the application of the proposed MNNA-PID controller to industry 4.0.

REFERENCES

[1] B. Siciliano, L. Sciavicco, L. Villani, and G. Oriolo, *Robotics: Modelling, Planning and Control*. Cham, Switzerland: Springer, 2010, ch. 4, pp. 161–189.

[2] R. M. Murray, *A Mathematical Introduction to Robotic Manipulation*. Boca Raton, FL, USA: CRC Press, 1994.

[3] J. J. Craig, *Introduction to Robotics: Mechanics and Control*. New Delhi, India: Pearson Education, 2009.

[4] I. Cervantes and J. Alvarez-Ramirez, "On the PID tracking control of robot manipulators," *Syst. Control Lett.*, vol. 42, no. 1, pp. 37–46, Jan. 2001.

[5] J. Alvarez-Ramirez, R. Kelly, and I. Cervantes, "Semiglobal stability of saturated linear PID control for robot manipulators," *Automatica*, vol. 39, no. 6, pp. 989–995, Jun. 2003.

[6] Y. Su, P. C. Muller, and C. Zheng, "Global asymptotic saturated PID control for robot manipulators," *IEEE Trans. Control Syst. Technol.*, , vol. 18, no. 6, pp. 1280–1288, Nov. 2010.

[7] E. Kim, "Output feedback tracking control of robot manipulators with model uncertainty via adaptive fuzzy logic," *IEEE Trans. Fuzzy Syst.*, vol. 12, no. 3, pp. 368–378, Jun. 2004.

[8] R. Sharma, P. Gaur, and A. P. Mittal, "Design of two-layered fractional order fuzzy logic controllers applied to robotic manipulator with variable payload," *Appl. Soft Comput.*, vol. 47, pp. 565–576, Oct. 2016.

[9] K. Lochan and B. K. Roy, "Control of two-link 2-DOF robot manipulator using fuzzy logic techniques: A review," in *Proc. 4th Int. Conf. Soft Comput. Problem Solving*. New Delhi, India: Springer, 2015, pp. 499–511.

[10] J. Baek, M. Jin, and S. Han, "A new adaptive sliding-mode control scheme for application to robot manipulators," *IEEE Trans. Ind. Electron.*, vol. 63, no. 6, pp. 3628–3637, Jun. 2016.

[11] M. Rahmani, A. Ghanbari, and M. M. Ettefagh, "Robust adaptive control of a bio-inspired robot manipulator using bat algorithm," *Expert Syst. Appl.*, vol. 56, pp. 164–176, Sep. 2016.

[12] K. Ogata, *Modern Control Engineering*. Upper Saddle River, NJ, USA: Prentice-Hall, 2001.

[13] K. J. Åström and T. Hägglund, "Revisiting the Ziegler–Nichols step response method for PID control," *J. Process Control*, vol. 14, no. 6, pp. 635–650, Sep. 2004.

[14] Z. Shafiei and A. T. Shenton, "Tuning of PID-type controllers for stable and unstable systems with time delay," *Automatica*, vol. 30, no. 10, pp. 1609–1615, Oct. 1994.

[15] S. Srivastava and V. S. Pandit, "A PI/PID controller for time delay systems with desired closed loop time response and guaranteed gain and phase margins," *J. Process Control*, vol. 37, pp. 70–77, Jan. 2016.

[16] S. Tavakoli and M. Tavakoli, "Optimal tuning of PID controllers for first order plus time delay models using dimensional analysis," in *Proc. 4th Int. Conf. Control Autom. ICCA Final Program Book Abstr. (ICCA)*, 2003, pp. 942–946.

[17] H. Wu, W. Su, and Z. Liu, "PID controllers: Design and tuning methods," in *Proc. 9th IEEE Conf. Ind. Electron. Appl.*, Jun. 2014, pp. 808–813.

[18] K. Shao, J. Zheng, K. Huang, H. Wang, Z. Man, and M. Fu, "Finite-time control of a linear motor positioner using adaptive recursive terminal sliding mode," *IEEE Trans. Ind. Electron.*, vol. 67, no. 8, pp. 6659–6668, Aug. 2020.

[19] J. Zhang, H. Wang, J. Zheng, Z. Cao, Z. Man, M. Yu, and L. Chen, "Adaptive sliding mode-based lateral stability control of steer-by-wire vehicles with experimental validations," *IEEE Trans. Veh. Technol.*, vol. 69, no. 9, pp. 9589–9600, Sep. 2020.

[20] M. Ye and H. Wang, "A robust adaptive chattering-free sliding mode control strategy for automotive electronic throttle system via genetic algorithm," *IEEE Access*, vol. 8, pp. 68–80, 2020.

[21] M. Ye and H. Wang, "Robust adaptive integral terminal sliding mode control for steer-by-wire systems based on extreme learning machine," *Comput. Electr. Eng.*, vol. 86, Sep. 2020, Art. no. 106756.

[22] K. Shao, J. Zheng, H. Wang, F. Xu, X. Wang, and B. Liang, "Recursive sliding mode control with adaptive disturbance observer for a linear motor positioner," *Mech. Syst. Signal Process.*, vol. 146, Jan. 2021, Art. no. 107014.

[23] Z. Beheshti and S. M. H. Shamsuddin, "A review of population-based meta-heuristic algorithms," *Int. J. Adv. Soft Comput. Appl*, vol. 5, no. 1, pp. 1–35, 2013.

[24] S. Nesmachnow, "An overview of metaheuristics: Accurate and efficient methods for optimisation," *Int. J. Metaheuristics*, vol. 3, no. 4, pp. 320–347, 2014.

[25] O. Kramer, *Genetic Algorithm Essentials*, vol. 679. Cham, Switzerland: Springer, 2017.

[26] Y. Zhang, S. Wang, and G. Ji, "A comprehensive survey on particle swarm optimization algorithm and its applications," *Math. Problems Eng.*, vol. 2015, pp. 1–38, Feb. 2015.

[27] M. Dorigo and T. Stützle, "Ant colony optimization: Overview and recent advances," in *Handbook of Metaheuristics*. Cham, Switzerland: Springer, 2019, pp. 311–351.

[28] R. V. Rao, "Teaching-learning-based optimization algorithm," in *Teaching Learning Based Optimization Algorithm*. Cham, Switzerland: Springer, 2016, pp. 9–39.

[29] A. R. Jordehi, "Enhanced leader PSO (ELPSO): A new PSO variant for solving global optimisation problems," *Appl. Soft Comput.*, vol. 26, pp. 401–417, Jan. 2015.

[30] A. W. Mohamed and P. N. Suganthan, "Real-parameter unconstrained optimization based on enhanced fitness-adaptive differential evolution algorithm with novel mutation," *Soft Comput.*, vol. 22, no. 10, pp. 3215–3235, May 2018.

[31] A. W. Mohamed, "An improved differential evolution algorithm with triangular mutation for global numerical optimization," *Comput. Ind. Eng.*, vol. 85, pp. 359–375, Jul. 2015.

[32] R. Salgotra and U. Singh, "Application of mutation operators to flower pollination algorithm," *Expert Syst. Appl.*, vol. 79, pp. 112–129, Aug. 2017.

[33] P.-H. Tang and M.-H. Tseng, "Adaptive directed mutation for real-coded genetic algorithms," *Appl. Soft Comput.*, vol. 13, no. 1, pp. 600–614, Jan. 2013.

[34] G.-Q. Zeng, J. Chen, L.-M. Li, M.-R. Chen, L. Wu, Y.-X. Dai, and C.-W. Zheng, "An improved multi-objective population-based extremal optimization algorithm with polynomial mutation," *Inf. Sci.*, vol. 330, pp. 49–73, Feb. 2016.

[35] A. Sadollah, H. Sayyaadi, and A. Yadav, "A dynamic metaheuristic optimization model inspired by biological nervous systems: Neural network algorithm," *Appl. Soft Comput.*, vol. 71, pp. 747–782, Oct. 2018.

[36] M. S. AbouOmar, H.-J. Zhang, and Y.-X. Su, "Fractional order fuzzy PID control of automotive PEM fuel cell air feed system using neural network optimization algorithm," *Energies*, vol. 12, no. 8, p. 1435, Apr. 2019.

[37] Y. Zhang, Z. Jin, and Y. Chen, "Hybrid teaching–learning-based optimization and neural network algorithm for engineering design optimization problems," *Knowl.-Based Syst.*, vol. 187, Jan. 2020, Art. no. 104836.

[38] H. V. H. Ayala and L. dos Santos Coelho, "Tuning of PID controller based on a multiobjective genetic algorithm applied to a robotic manipulator," *Expert Syst. Appl.*, vol. 39, no. 10, pp. 8968–8974, Aug. 2012.

[39] H. Chhabra, V. Mohan, A. Rani, and V. Singh, "Multi-objective cuckoo search algorithm-based 2-DOF FOPD controller for robotic manipulator," in *Advanced Signal Processing for Communication*. Singapore: Springer, 2019, pp. 345–352.

[40] J. J. Craig, *Introduction to Robotics: Mechanics and Control, 3/E*. New Delhi, India: Pearson Education, 2009.

[41] Z.-L. Gaing, "A particle swarm optimization approach for optimum design of PID controller in AVR system," *IEEE Trans. Energy Convers.*, vol. 19, no. 2, pp. 384–391, Jun. 2004.

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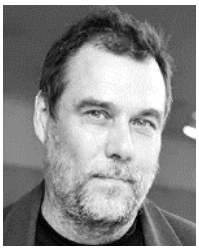

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