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Optimal robust control for self-balancing robot-based feedback linearization and Atom Search Optimization

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ABSTRACT

In this paper, a robust control method is suggested for attitude control of the two-wheeled self-balancing robot by combining feedback linearization with sliding mode control techniques. The proposed method takes into account important challenges such as external disturbance and system uncertainty. Feedback linearization cancels the nonlinearities in the dynamics of the robotic system, while the sliding mode control handles the uncertainties and the external disturbance. The parameters of the proposed controller are selected by tuning the controller with the Atom Search Optimization algorithm. MATLAB is used to simulate the proposed controller. Simulation results indicate a good performance of the presented controller with high robustness compared with the proportional-integral-derivative (PID) controller. Moreover, the proposed method reduces the rise time by approximately 40% and 50% with respect to PID. These results illustrate the feasibility of the presented control method to be used for real-time implementation in autonomous robotic balancing systems.

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1. INTRODUCTION

Self-balancing wheeled mobile robots (WMRs) are becoming a popular topic in the world of robotics and automation, because they are very maneuverable, highly mobile and have broad applications in transportation, warehouse automation, agriculture, and service robotics. These robots, however, are nonlinear underactuated systems with high coupling among the dynamic variables, which makes its control design difficult. Thus, different control methods have been devised to enhance stability, trajectory tracking and disturbance rejection. The simple and easy to implement classical linear control methods, like proportional-integral-derivative (PID) control, are still widely used. New methods proposed in the literature such as optimized PID controllers using genetic algorithms [1] and adaptive nonlinear PID control [2] were proposed. But the linear controllers are frequently not robust enough in the presence of uncertainties and disturbances. In order to overcome these problems, powerful and non-linear controls have been studied. Due to their robustness to uncertainties and external disturbances, sliding mode control (SMC) has been widely applied [3], [4]. Other strong methods were used, which involved neural networks and adaptive dynamic programming to enhance the tracking performance and stability [5]–[7]. Fuzzy control was also used to enhance the robot balancing and motion control in various operating conditions [8], [9]. Input–output feedback linearization has also been widely applied to correct the effect of nonlinear dynamics and reduce the complexity of the controller design for robotic systems [10], [11]. Simulation-based and data-driven approaches have also been applied to nonlinear robotic systems to improve trajectory tracking and dynamic performance of robotic manipulators [12]. Also, artificial neural networks (ANNs) [13]–[15] and radial basis function neural networks (RBFNNs) [16], [17] have been combined with nonlinear controllers for approximation of uncertainties and performance improvement of the system. Furthermore, H-infinity control techniques have proven to be effective for robustness against disturbances and modeling uncertainties [18]–[20]. Recently, researchers have been increasingly interested in the hybrid intelligent and robust control methods of self-balancing robots. Adaptive neural sliding mode control and hierarchical sliding mode control with nonlinear disturbance observers demonstrated the better performance of the disturbance rejection and robustness [21], [22]. Moreover, for uncertain environment, optimization-based and fuzzy intelligent control methods have been used to enhance the efficiency of controller tuning and tracking performance [23]. More recently, various review papers also pointed out the increasing demand for hybrid nonlinear control algorithms that could provide robust stability, fast convergence and good disturbance rejection in robotic balancing systems [24].

In spite of these advances, there are still some drawbacks with the current methods. The uncertainties may cause classical controllers to lose performance; sliding mode controllers may cause chattering phenomena; intelligent control techniques may increase computational complexity. Thus, it is a crucial research problem to develop an integrated robust nonlinear control architecture with accurate nonlinear compensation, disturbance rejection and systematic parameter tuning.

For a two wheeled self-balancing robot, a strong controller design is presented in this paper using the feedback linearization and sliding mode control techniques. In order to enhance transient response and robustness, the controller parameters are optimally tuned by the use of Atom Search Optimization (ASO) algorithm. The key achievements of this work are briefly summarized below:

– A robust control strategy based on feedback linearization is proposed to compensate for the nonlinear dynamics of the system.
– The ASO algorithm is used for optimal controller parameter tuning.
– The controller proposed in this work enhances the robustness of the system to disturbances and uncertainties.
– The proposed solution is tested with simulations and compared to other control solutions.

2. SELF-BALANCING ROBOT DYNAMICS

This section discusses the dynamic model of the wheeled self-balancing mobile robot. In this paper, the noise, road resistance, vibration, and friction between the wheels and the surface are considered as disturbances. The model is derived based on methods presented by [25] as shown Figure 1. The following differential equations describe the dynamic model of the robotic system based on Newton's second law.

$$m_b(\ddot{x} - l\sin\theta\,\dot{\theta} + l\cos\theta\,\ddot{\theta}) = F_H \tag{1}$$

$$m_b\left(-l\cos\theta\,\dot{\theta} + l\sin\theta\,\ddot{\theta}\right) = F_v - m_b g \tag{2}$$

$$J\ddot{\theta} = F_v l\sin\theta - F_H l\cos\theta \tag{3}$$

$$m_m\ddot{x} = u - F_H \tag{4}$$

Where, x denotes the displacement, θ represents the angle of the bar, m_b refers to the mass of the bar, m_m denotes the mass of the mobile platform, F_H represents the horizontal force, F_v represents the vertical force, u is the force applied by DC motor, l is the length of the bar, J denotes the inertia of the robot, and g represents the gravitational acceleration.

The moment of inertia can be expressed as (5).

$$J = \frac{1}{3}m_b l^2 \tag{5}$$

With simple substitutions, we obtain (6).

$$(m_b + m_m)\ddot{x} = u - m_b l(\cos\theta\,\ddot{\theta} - \sin\theta\,\dot{\theta}^2) \tag{6}$$

$$\frac{4}{3}m_b l^2\ddot{\theta} = m_b g l\sin\theta - l m_b\cos\theta\,\ddot{x} \tag{7}$$

This paper aims to design a control system that tracks the $\theta_d(t)$ in the presence of system uncertainty and external disturbances. Thus, to focus on attitude control, the dynamics of the robotic system are decoupled as (8) and (9).

$$\ddot{x} = \frac{\frac{m_m^2 l^2 g \sin 2\theta}{2} - (J + m_m l^2)(m_m l sin\theta)\dot{\theta}^2 - (J + m_m l^2)u}{a m_m l \cos\theta^2 - 4l/3} \tag{8}$$

$$\ddot{\theta} = \frac{-(m_m + m_b)(m_m l g sin\theta) + \frac{m_m^2 l^2 \dot{\theta}^2 \sin 2\theta}{2} + (m_m l cos\theta)u}{a m_m l \cos\theta^2 - 4l/3} \tag{9}$$

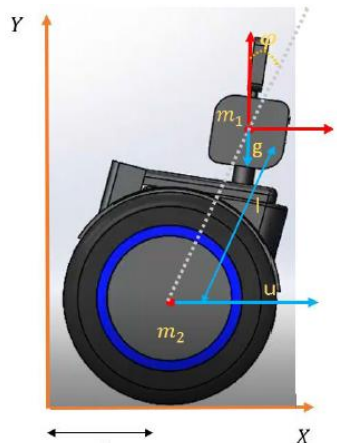

Figure 1. Two-wheeled self-balancing [25]

3. ATOM SEARCH OPTIMIZATION

Atom Search Optimization (ASO) is one of the promising metaheuristic optimization algorithms that has been widely used in engineering problems [26]. In this paper, ASO is used to design the controller because of its ability to provide a good balance between exploration and exploitation which leads to an enhanced search performance and faster convergence to the optimum.

ASO balances the interaction between particles according to their mass and distance, and does not suffer from premature convergence to local optima, as is the case with other metaheuristic algorithms in multimodal search space. The presented control system is highly nonlinear and has strong parameter interdependence, and ASO offers an effective and reliable way to obtain optimal controller gains.

Compared to other popular computational intelligence (CI) techniques such as particle swarm optimization (PSO) and genetic algorithm (GA), ASO provides more stable searching and better convergence in nonlinear optimization problems. Moreover, ASO has fewer parameters to be tuned and can also work robustly in multimodal optimization problems, which makes it highly applicable for controller gains tuning in the nonlinear systems of the robot. The ASO algorithm offers a more effective exploration–exploitation balance and a more stable convergence for nonlinear optimization problems than PSO and GA. However, performing a detailed sensitivity analysis is beyond the scope of this study but the simulation results confirm the effectiveness of the selected ASO parameters. ASO, originally proposed in [26] is inspired by molecular dynamics where there are two types of forces acting on the atoms: interaction and constraint forces. In the ASO algorithm, the atom's position is calculated as (10),

$$x_i(n+1) = x_i(n) + v_i(n+1) \tag{10}$$

where $x_i(n+1)$ and $x_i(n)$ are the positions of the i^{th} atom in the n^{th} and $(n+1)^{th}$ iterations respectively and $v_i(n+1)$ is the velocity of i^{th} atom in the $(n+1)^{th}$ iteration. This is determined as (11),

$$v_i(n+1) = rand * v_i(n) + a_i(n) \tag{11}$$

where $rand$ is a positive random number less than one, and $a_i(n)$ is acceleration of the i^{th} atom at the n^{th} iteration, and is calculated as (12) to (15),

$$a_i(n) = \frac{F_i}{m_i} \tag{12}$$

$$F_i = \sum_{j \in k\ best} rand_j F_{ij} \tag{13}$$

$$F_{ij} = \tau(t) * \frac{x_j - x_i}{\varepsilon + \|x_j - x_i\|} \tag{14}$$

$$m_i = \frac{M_i}{\sum_{j=1}^{N} M_j} \tag{15}$$

where F_i refers to the force acting on the atom i, $\tau(t)$ denotes the variable that balances between exploration and exploitation, and ε denotes a constant that prevents division by zero. where $kbest$ is a subset of the best atoms.

4. PROPOSED CONTROL SYSTEM

Sliding mode control-based Feedback linearization is used to control the angle of the robot body to track the desired angle with angular velocity approaching zero as time tends to infinity. Feedback linearization has been used to cancel the nonlinearities in the dynamics of the robotic system and transform it into a linear system however, good cancellation needs accurate dynamic model of the controlled system and this may not be achieved in practical implementations. To ensure robustness, SMC is used to compensate the system uncertainty and modelling errors. The combination of feedback linearization and SMC can benefit from trajectory tracking in feedback linearization and robustness in SMC. The dynamic model can be expressed as a general nonlinear second-order system as (16) to (18),

$$\ddot{\theta} = f(\theta, t) + g(\theta, t)u + d \tag{16}$$

$$f(\theta, t) = \frac{-(m_m + m_b)(m_m lg sin\theta) + \frac{m_m^2 l^2 \dot{\theta}^2 \sin 2\theta}{2}}{a m_m l \cos\theta^2 - 4l/3} \tag{17}$$

$$g(\theta, t) = m_m l cos\theta \tag{18}$$

where d is external disturbance. The desired angle is $\theta_d(t)$ and the error can be expressed as (19) and (20).

$$e = \theta_d(t) - \theta(t) \tag{19}$$

$$E = [e\ \dot{e}]^T \tag{20}$$

The sliding surface is chosen to guarantee stability of the error dynamics and rapid convergence to the desired equilibrium. The choice of the sliding variable defines the transient behavior of the closed-loop system, such as convergence rate and disturbance rejection. Appropriate design of the sliding surface ensures that the system trajectories converge to the sliding manifold and stay on it despite uncertainties and disturbances. The sliding variable is defined as:

$$s = cE \tag{21}$$

$$c = [c\ \ 1] \tag{22}$$

where c is a positive scalar. By feedback linearization, the proposed robust controller can be defined as (23) and (24).

$$u = \frac{u_x - f(\theta, t)}{g(\theta, t)} \tag{23}$$

$$u_x = \ddot{\theta}_d - c\dot{e} - \gamma sgn(s) \tag{24}$$

We define V as a Lyapunov function:

$$V = \frac{1}{2} s^2 \tag{25}$$

Then,

$$\dot{V} = s\dot{s} = s(\ddot{e} + c\dot{e}) = s(\ddot{\theta} - \ddot{\theta}_d + c\dot{e}) \tag{26}$$

$$= (f(\theta,t) + g(\theta,t)u + d - \ddot{\theta}_d + c\dot{e}) \tag{27}$$

By using the proposed control law in (23).

$$\dot{V} = s(u_x + d - \ddot{\theta}_d + c\dot{e}) \tag{28}$$

$$= s(-\gamma sgn(s) + d) \leq -\gamma|s| + d(t)s \leq 0 \tag{29}$$

The optimal value for the proposed controller parameters can be obtained by using the ASO algorithm by selecting a good objective function. In this paper, integral absolute error (IAE) is used to tune the controller:

$$IAE = \int_0^T |e(t)| \mathrm{dt} \tag{30}$$

where T refers to the duration of the simulation.

5. RESULTS AND DISCUSSION

In this section, the proposed robust control system for controlling the wheeled mobile self-balancing robot is evaluated by simulating the closed loop control system using MATLAB/Simulink 2024 with the following solver parameters: Solver type: Variable-step, Solver: ode45 and simulation time 10 s. The performance of the proposed controller is compared with the PID controller, whose parameters are tuned by PSO optimization algorithm and PD-SMC control method. The IAE performance index is used to compare between the performance of the controllers. The parameters of the optimized PID controller used in this simulation are: $k_p = 1, k_i = 2$ and $k_d = 2$. While the PD-SMC control law used in this simulation expressed as (31).

$$u_{PD-smc} = k_p e + k_d \dot{e} + k\ sign(s) \tag{31}$$

where $k_p = 10$, $k_d = 5$, $k = 15$, and $s = 1.5\ e + \dot{e}$. The setting parameters of ASO used in this simulation are listed in Table 1.

Table 1. ASO parameters

	Value
N	30
T	150
β	0.5

The parameters of the proposed controller after applying ASO algorithm are: $\gamma = 0.22$ and $c = 1.5$. The parameters of the dynamic system are listed in Table 2. Three cases are discussed in this simulation, the first case discusses the step tracking, the second case presents the sinusoidal tracking, while the third case discusses robustness of the proposed controller against system uncertainties.

Table 2. Dynamic model parameters [25]

	Parameter	Value
I	Inertia	0.0000761250 kg·m2
R	Armature resistance	0.35 Ω
L	Electrical inductance	0.018 H
B	Viscous friction	0.0038 N.m.s
k_a	Electromotive force	0.0082 N m/A
k_m	Motor torque	0.0098 N. m/A
M	Mobile robot mass	2.5 kg
m	Pendulum mass	0.65 kg
l	Pendulum length	0.3 m
J	Inertia mobile	0.197 kg·m2
g	Gravity	9.81 m/s2

Case 1: Tracking

To evaluate the performance of the proposed controller, step and sinusoidal reference inputs ($\theta_d(t) = 0.1sin\pi t$) with amplitude 0.1 rad are used as a reference. Figures 2 and 3 show the response of the controllers.

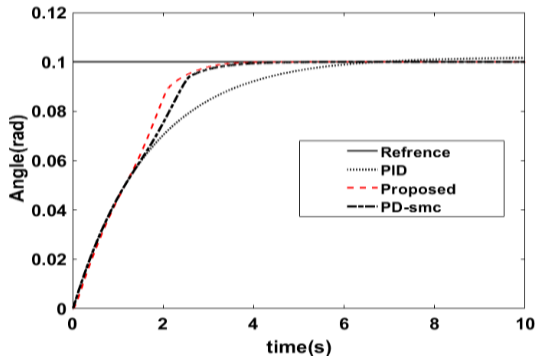

Figure 2. Step tracking performance comparison between PID, PD-SMC, and the proposed controller under a 0.1 rad reference input

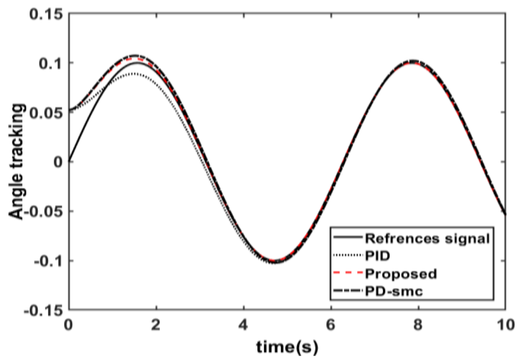

Figure 3. Sinusoidal tracking comparison of PID, PD-SMC, and the proposed controller

Figures 2 and 3 show that the response of the proposed controller has a shorter convergence time and smaller total error compared to other controllers. From a control theory point of view, enhanced transient performance is mainly due to the nonlinear cancellation effect of feedback linearization that converts the original system dynamics into an equivalent linear error system. Meanwhile, the sliding mode control contributes to a robust correction term that guarantees the fast convergence of the tracking error in the presence of disturbances and uncertainties of system parameters. Therefore, the overall control approach improves stability and robustness to disturbances while ensuring a fast convergence to the desired trajectory.

The transient performance indices, such as rise time, settling time and overshoot, are shown in Tables 2 and 3. It can be seen that the proposed controller has the smallest rise time and settling time without overshoot. This shows the capability of the feedback linearization to eliminate the nonlinearity of the robot system. Furthermore, the sliding surface speeds-up convergence without causing oscillations. The reduction in the IAE of the proposed controller indicates the reduction in steady-state error as well as the improvement in the transient performance as shown in Figures 4 and 5. The proposed approach has similar effects in different tracking cases because it transforms the system into an equivalent linear error system and then compensates the errors by using a robust control term. Thus, these performance criteria evidently show the effectiveness of the proposed control method.

Table 3. Transient specifications

Method	M_p	t_r(sec)	t_s(sec)
Proposed	0	2.01	3.124
PID	0	3.6943	6.4432
PD-SMC	0	2.2439	3.2555

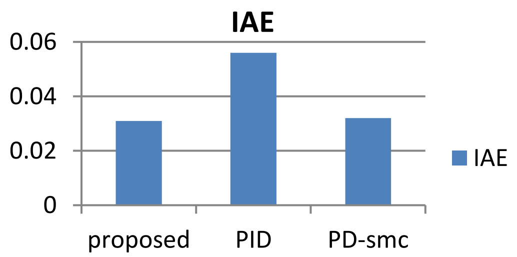

Figure 4. IAE variations for step tracking

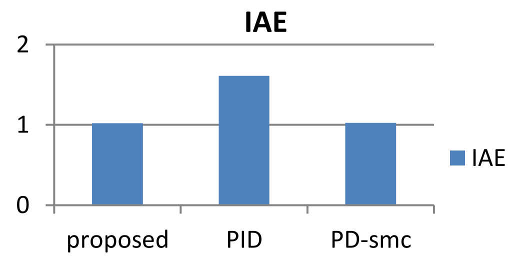

Figure 5. IAE variations for sin tracking

Case 2: Robustness test

In this case the robustness of the proposed controller is checked by applying a disturbance signal on the system. Figure 6 shows the disturbance used in this simulation. The simulation results are shown in Figure 7. The proposed control method maintains rapid convergence with small tracking deviation. The tracking error is still bounded and then converges to zero. With approximately 0.8 s, the controlled system recovers with zero steady-state error. This fast attenuation illustrates the robustness of the presented controller and this is related directly to the property of the robust term used in the presented controller. Furthermore, the ASO optimizes the parameters of the controller to balance between the speed of convergence and disturbance rejection. The best optimized parameters due to tuning by ASO enhances the robustness without oscillation. These results confirm that disturbance rejection is a structural property of the controller. The performance indices are shown in Figure 8 and these indices show robustness of the proposed controller against external disturbance.

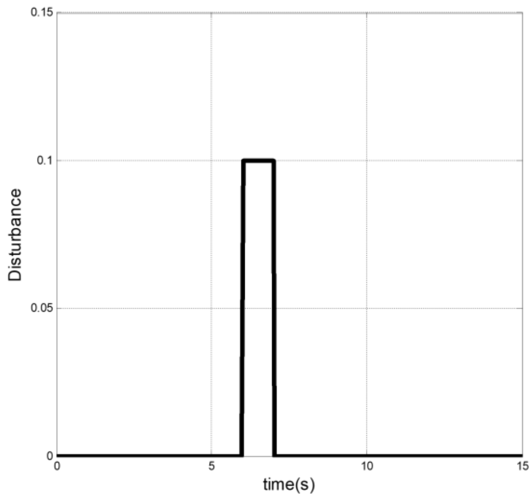

Figure 6. Disturbance in case 2

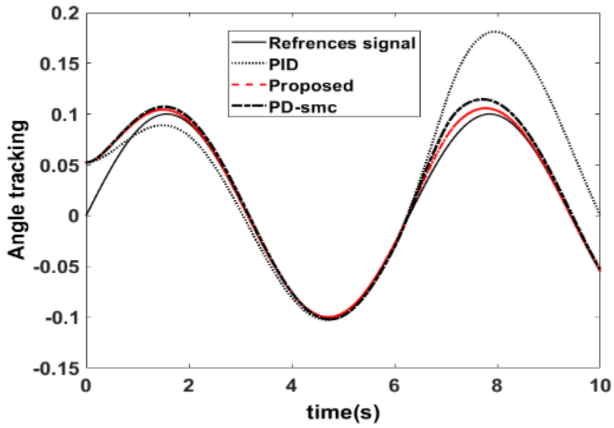

Figure 7. Robustness against disturbance

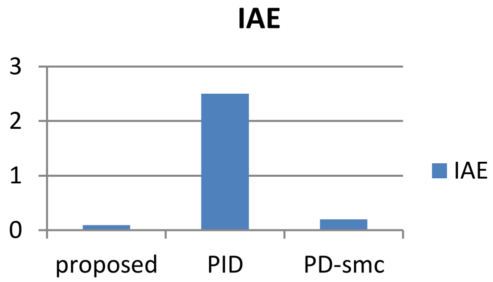

Figure 8. IAE variations of case 2

The proposed controller can be practically implemented on a real self-balancing robot with embedded controller, wheel encoders, and IMU sensor (which has an accelerometer and gyroscope). The feedback linearization portion is designed to eliminate the nonlinear characteristics of the robot and the sliding mode portion is designed to eliminate the effect of disturbances such as the effect of changes in the workspace, changes in load, and external pushes due to irregular floors. An autonomous mobile platform, inspection robots, and compact robotic carriers moving in confined manufacturing areas are examples of applications for which such a controller can be used in industrial environments.

The robot tilt angle and its angular velocity can be acquired from the IMU sensor in real time in the implementation, which could be acquired by fusing the data from the accelerometer and gyroscope of the IMU sensor. The wheel position and velocity can be supplied by wheel encoders to give motion feedback. Filtering (*e.g.* complementary filtering, Kalman filtering) may be necessary prior to the application of the control signal due to the effects of noise, bias and sampling delay in the sensor measurements. Thus, the proposed controller needs to be tested in future under realistic sensor noise and actuator saturation environments. The present study mainly focuses on transient response and disturbance rejection performance. Other assessments like energy consumption and computational complexity analyses as well as long-term stability analysis can give additional insight into the performance of the controller and will be taken into account in future work.

6. CONCLUSION

In this paper, robust control design using the combination of the sliding mode controller and the feedback linearization is presented to control the mobile self-balancing robots. The first step is to establish the mathematical model of the robot. Lyapunov's second theorem is used to demonstrate the stability of the proposed controller. The simulation was done for two scenarios; the first one is about tracking the desired trajectory and the second one is about the robustness with an external disturbance. The transient specifications, integral absolute error (IAE) and integral time absolute error (ITAE) are calculated to evaluate the performance of the proposed controller and the PID controller.

Since the optimization is offline, the computational cost has no significant effect on the real-time implementation. Once the optimal parameters are obtained, it will be implemented online. In particular, the proposed hybrid controller has the shortest settling time, smaller overshoot and better disturbance rejection performance. In presence of disturbances, the hybrid controller will keep the tracking error bounded and rapidly brings it to the desired dynamics. This highlights the robustness of the robust part of the hybrid controller. The above results justify the use of feedback linearization and SMC. A drawback is that high-frequency reference inputs require high switching gains, and thus high control effort. While the proposed controller demonstrates high robustness and good tracking performance in the simulation, it is limited to simulation studies. The controller performance must be tested experimentally with hardware limitations and sensor/actuator noise. In future work, it can be studied the performance of the controller on a real self-balancing robot to verify the real-time feasibility and computational efficiency with using machine learning algorithms for tuning the controller parameters.

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AUTHOR CONTRIBUTIONS STATEMENT

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Yahya Ghufran Khidhir	✓	✓				✓			✓	✓				
Adnan Jabbar Attiya	✓				✓		✓		✓	✓		✓		
Hisham H. Jasim	✓				✓					✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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