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A Novel Enhanced Metaheuristic Algorithm for Automobile Cruise Control System

Davut İzci[1], Serdar Ekinci[2], Murat Kayri[3], Erdal Eker[4]

[1]Department of Electronics & Automation, Batman University, Batman, Turkey
[2]Department of Computer Engineering, Batman University, Batman, Turkey
[3]Department of Computer and Instructional Technology Education, Van Yüzüncü Yıl University, Van, Turkey
[4]Accounting and Tax Department, Muş Alparslan University, Muş, Turkey

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ABSTRACT

The development of a novel enhanced metaheuristic algorithm is considered in this paper. Such a structure was achieved through enhancement of the arithmetic optimization algorithm by employing the opposition-based learning mechanism together with the Nelder–Mead simplex search method. The developed algorithm (ObAOANM) adopts the opposition-based learning scheme to enhance the algorithm in terms explorative behavior, and the Nelder–Mead method in terms of exploitative behavior. The developed ObAOANM was firstly tested against well-known unimodal and multimodal benchmark functions through comparisons with the original arithmetic optimization algorithm, as it was previously shown to be superior to other efficient algorithms. The benchmark functions and related statistical results demonstrated greater capability of the ObAOANM algorithm. Then, the ObAOANM algorithm was utilized to achieve an optimum design of a proportional-integral-derivative controller adopted in an automobile cruise control system. The performance of the ObAOANM algorithm was compared with the arithmetic optimization algorithm algorithm through statistical, transient response, frequency response, and disturbance rejection analyses, which have shown better capability of the enhanced ObAOANM algorithm. Furthermore, the capability of the ObAOANM-based proportional-integral-derivative-controlled automobile cruise control system was compared with other available approaches in the literature by performing time domain analysis, which also confirmed the superior capability of the proposed approach for such a task.

***Index Terms*—**Automobile cruise control, metaheuristic algorithms, proportional-integral-derivative controller.

I. INTRODUCTION

An automobile cruise control system [1] is one of the real-world optimization problems that is gaining a greater importance nowadays due to its inclusion in most of the recently manufactured vehicles. This system helps reducing the driver's fatigue significantly in long journeys, which consequently decreases the risk of accidents attributed to tired drivers. Moreover, it also contributes greatly toward lowering the fuel consumption [2]. Due to these reasons, it is quite important to come up with novel approaches that have better efficiencies to achieve an optimally controlled automobile cruise control system [3]. The latter case requires the achievement of the desired variables with the best method possible, which makes the optimization methods significant, as they are the tools for dealing with such problems [4].

Deterministic techniques are early methods to deal with optimization problems, which have so far been adopted to achieve decision variables [5]. The latter techniques attempt to reach the point at which the derivative is zero, which makes them deficient as they require complicated mathematical computations and stack local optimum easily, and pose implementation-related difficulties [6,7]. Utilization of non-deterministic approaches is an efficient way of tackling the latter listed issues, and the metaheuristic optimization algorithms are good candidates for such a purpose. The latter type of algorithms have already been widely utilized in the last decades for optimization problems to overcome the difficulties observed in deterministic approaches [8]. Therefore, in the literature, the implementation of such algorithms can be observed for a wide variety of fields.

Corresponding Author:
Davut İzci

E-mail: davut.izci@batman.edu.tr

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It is worth noting that the appearance of newly developed algorithms is a major trend in the field of metaheuristics. The famous “no free lunch theorem” [9] is the main motivation for such a trend. According to this theorem, all stochastic-based algorithms will end up with a similar performance on average if all available optimization problems are considered. Such a case occurs because some of the algorithms are quite good for specific issues, whereas not significantly effective for the rest. The arithmetic optimization algorithm (AOA) was proposed as a novel population-based approach [10] as part of this motivation. Several test functions and engineering design problems have so far been used to demonstrate the promise of AOA. However, the showcase of the promise of AOA algorithm does not ensure that it is convenient for solving all available optimization problems with desired efficiency. As discussed above, such a case occurs due to its stochastic nature, which may not accommodate the desired balance between diversification and intensification stages.

Nevertheless, the performance improvement of the AOA algorithm is feasible by enhancing it with other existing algorithms with complementary features. Such an approach is a widely adopted alternative to achieve efficient novel algorithms for a wider scope [11], instead of developing novel metaheuristics from scratch. Considering the latter discussion, the ability of the AOA algorithm can further be expanded in terms of diversification by adopting a modified version of the opposition-based learning (OBL) scheme [12]. Similarly, the intensification capability of the AOA can further be enhanced via utilization of the Nelder–Mead (NM) simplex search algorithm [13]. Bearing this perspective and the importance of the automobile cruise control system in mind, this work aims to construct a novel enhanced metaheuristic algorithm, named the opposition-based arithmetic optimization with the Nelder–Mead algorithm (ObAOANM), which holds a good balance between enhanced phases of exploration and exploitation due to the complementary features of the OBL scheme and the NM method. Thus, it can be used as an efficient tool for optimization problems. Considering the latter point of view, together with the importance of the automobile cruise control system, this work proposes the constructed novel ObAOANM algorithm as an effective optimization tool to design a better performing proportional-integral-derivative (PID) controller that is adopted in an automobile cruise control system.

Initially, the performance of the developed ObAOANM algorithm was comparatively assessed statistically through minimization of well-known unimodal and multimodal benchmark functions. In terms of comparison, only the AOA algorithm was used, as the latter has already been demonstrated to be superior to 11 popular and capable algorithms [10]. The results achieved by the developed ObAOANM algorithm have shown it to be greater than the original AOA algorithm in terms of statistical performance. Further performance of the ObAOANM was evaluated by utilizing a PID-controlled automobile cruise control system. Then, the constructed ObAOANM was compared with the original form of AOA in terms of statistical performance. In addition, time domain, frequency domain, and disturbance rejection performances were also assessed comparatively. Similar to the initial assessment, the related analyses were performed comparatively by using the original form of the AOA algorithm together with the other approaches (PID [14], fuzzy logic [14], state space [14], genetic algorithm-based PID (GA-PID) [15], and antlion optimizer based on bode ideal model for PID (ALO-BODE-PID) [16]) available in the literature for automobile cruise control systems. The results from the respective evaluations have also demonstrated the greater capability of the ObAOANM algorithm for efficient design of a PID-controlled automobile cruise control system. The following statements provide the contributions of this work with a better perspective:

- A novel enhanced metaheuristic algorithm has been constructed by improving the AOA algorithm with the aid of the NM simplex search method and a modified OBL scheme.
- The proposed ObAOANM algorithm was constructed in such a way that the modified OBL scheme has enhanced the exploration ability, whereas the NM method enhanced the exploitation significantly.
- The constructed enhanced algorithm was confirmed to have a better balance in terms of diversification and intensification phases by using well-known unimodal and multimodal benchmark functions.
- The constructed ObAOANM was proposed as an efficient approach to design a PID controller for better regulation of an automobile cruise control system.
- The proposed approach was compared with other available and effective approaches, and it was shown to be a highly competitive option for better regulation of an automobile cruise control system.

II. AOA

This algorithm is inspired from a fundamental component of number theory known as arithmetic [10]. The simple mathematical operators of addition, subtraction, multiplication, and division are used for finding the best solution among the candidate solutions. The following set of random solutions (X) are generated at the beginning of this algorithm:

$$X=\begin{bmatrix} x_{1,1} & \cdots & \cdots & x_{1,j} & x_{1,n-1} & x_{1,n} \\ x_{2,1} & \cdots & \cdots & x_{2,j} & \cdots & x_{2,n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N-1,1} & \cdots & \cdots & x_{N-1,j} & \cdots & x_{N-1,n} \\ x_{N,1} & \cdots & \cdots & x_{N,j} & x_{N,n-1} & x_{N,n} \end{bmatrix} \quad (1)$$

The best candidate solution in each iteration is considered as the best obtained solution so far. A function named Math

Optimizer Accelerated (*MOA*) is used to select the search phases of exploration or exploitation after the initialization step. This function is given as follows:

$$MOA(t_c) = Min + t_c \times \left(\frac{Max - Min}{t_M} \right) \quad (2)$$

where the value of the function at current iteration is denoted by $MOA(t_c)$. The current iteration is represented by t_c and has a range between one and the maximum number of iterations (t_M). The minimum and maximum values of the accelerated function are denoted by Min and Max, respectively. The exploration phase is conditioned by the MOA function for $r_1 > MOA$ where r_1 is a random number.

In terms of exploration, the arithmetic operators of multiplication (*M*) or division (*D*) are used for random search on several regions. Therefore, two different strategies—the multiplication and division search strategies—exist in this algorithm, which are mathematically modeled in (3):

$$x_{i,j}(t_c+1) = \begin{cases} best(x_j) \times MOP \times ((UB_j - LB_j) \times \mu + LB_j), \text{ for } r_2 > 0.5 \\ best(x_j) \div (MOP + \epsilon) \times ((UB_j - LB_j) \times \mu + LB_j), \text{ for } r_2 < 0.5 \end{cases} \quad (3)$$

where the solution of i in the next iteration is represented by $x_i(t_c+1)$, the j^{th} position of solution i for current iteration is denoted by $x_{i,j}(t_c)$ and the j^{th} position of the best solution obtained so far is given by $best(x_j)$. In the respective equation, ε denotes a small integer number whereas μ represents the control parameter for search process adjustment. The upper and lower bounds of position j are represented by UB_j and LB_j, respectively. The MOP function given in the latter equation is used to represent the math optimizer probability. This is a coefficient which is calculated as follows:

$$MOP(t_c) = 1 - \frac{(t_c)^{1/\alpha}}{(t_M)^{1/\alpha}} \quad (4)$$

In (4), $MOP(t_c)$ is used to denote the value of the function for current iteration whereas α is a sensitive parameter which defines the accuracy of the search through iterations. The execution of M or D, given in (3), is decided based on another random number which is denoted by r_2. The M operator is performing the task, as can be seen from (3), for $r_2 > 0.5$. In this stage, the D operator is neglected until the M operator completes the task. In case of $r_2 < 0.5$, the execution of the task occurs vice versa (see (3)). In this way, the position is updated for the exploration phase.

The mathematical operators of addition (*A*) and subtraction (*S*) are used for exploitation. As is the case for exploration, the MOA function is used for conditioning in this phase as well. As opposed to the exploration, this phase is performed for $r_1 < MOA$. The exploitation phase of AOA is modeled using (5) where r_3 is a random number.

$$x_{i,j}(t_c+1) = \begin{cases} best(x_j) + MOP \times ((UB_j - LB_j) \times \mu + LB_j), \text{ for } r_3 > 0.5 \\ best(x_j) - MOP \times ((UB_j - LB_j) \times \mu + LB_j), \text{ for } r_3 < 0.5 \end{cases} \quad (5)$$

The execution of A or S is decided based on the value of r_3. The A operator is executed for $r_3 > 0.5$ and the S operator is neglected until the A operator finishes the task, whereas for $r_3 < 0.5$ the reverse occurs. The flowchart of AOA is given in Fig. 1.

III. OBL

The concept of the OBL [12] has so far successfully been demonstrated to effectively enhance various optimization algorithms. In the OBL, the corresponding opposite solutions of the candidate solutions are simultaneously considered, which increases the possibility of being closer to the global optimum.

The following equation can be used to define the opposite of a candidate solution:

$$\bar{x} = a + b - x \quad (6)$$

where $\bar{x}$ is the opposite of the candidate solution of x which is within $[a, b]$. The latter form can be extended for multiple dimensions using the following definition, where $x_j \in \mathbb{R}$ which is within $[a_j, b_j]$ and $j = 1, 2, \ldots, d$;

$$\bar{x}_j = a_j + b_j - x_j \quad (7)$$

Assuming the following point (P) to be a candidate solution in a d-dimensional space,

$$P = (x_1, x_2, \ldots, x_d) \quad (8)$$

Then, the opposite of the candidate solution, by definition, would be:

$$\bar{P} = (\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_d) \quad (9)$$

Once those points are determined, they are simultaneously evaluated in terms of their fitness values. If the fitness value of the opposite solution is better than that of the candidate solution, then the point P is replaced by $\bar{P}$. Otherwise, point P is retained. The mechanism of the OBL is demonstrated in Fig. 2.

The OBL scheme has so far been integrated with different metaheuristic algorithms to enhance their global search capability. A few such examples can be listed as differential evolution [17], solving high-dimensional continuous optimization problems, gravitational search algorithm [18] for combined economic and emission dispatch problems of power systems, flower

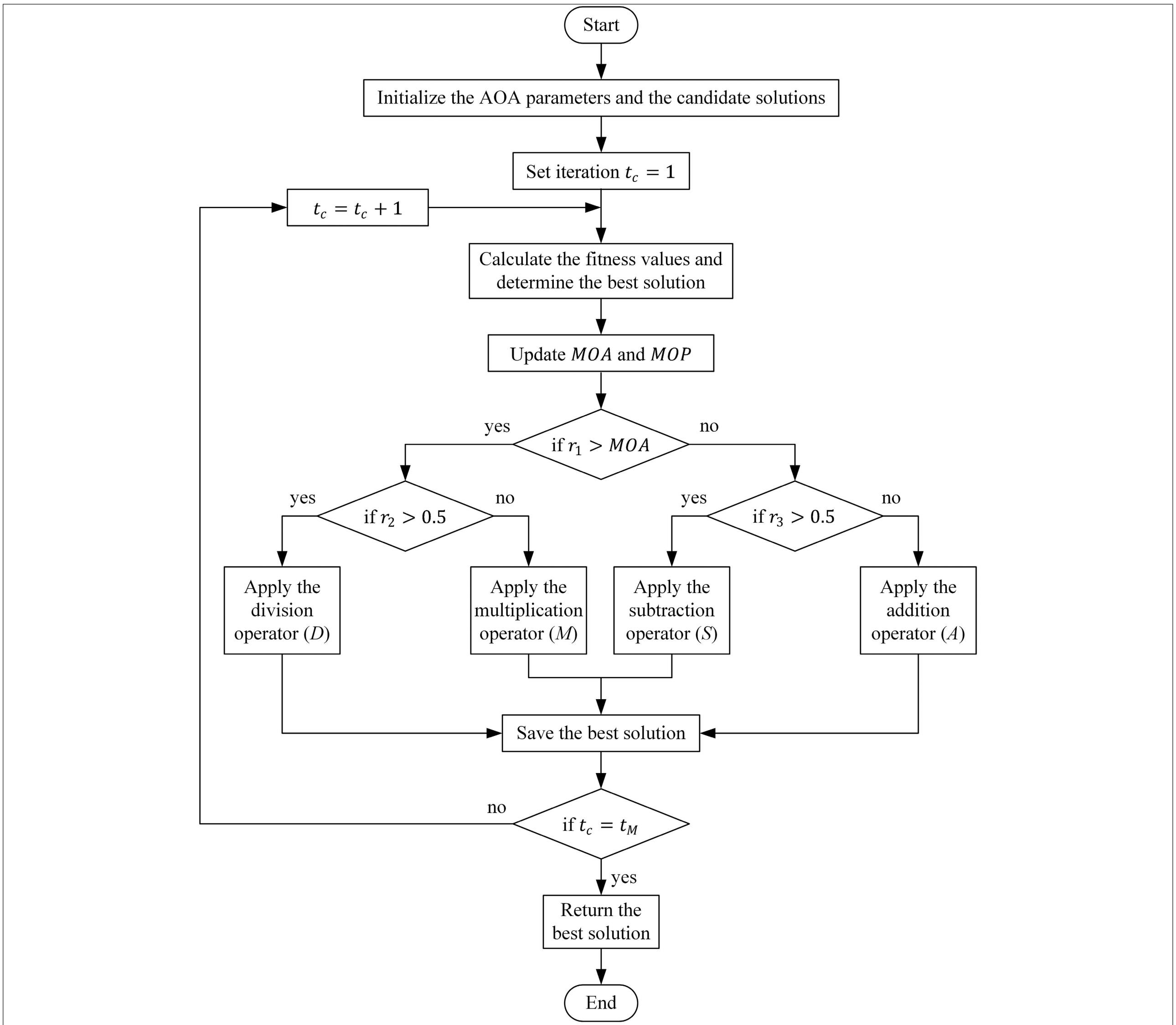

Fig. 1. Flowchart for the original AOA algorithm.

pollination [19], and equilibrium optimizer [20] for engineering design problems, krill herd algorithm [21] for economic load dispatch problems, and Henry gas solubility optimization [22] for DC motor speed control.

IV. NM SIMPLEX METHOD

This algorithm performs gradient-free computations and was developed to solve nonlinear functions as a simplex search method [23]. An optimal vertex (x_1) is identified through generating $d+1$ vertices (x_1, x_2, … x_{d+1}) and evaluating the respective fitness function values ($f(x_1)$, $f(x_2)$, …, $f(x_{d+1})$) which are then sorted in ascending order. Four scalar coefficients (reflection, ρ, expansion, γ, contraction, β, and shrinkage, δ) are used to replace the worst vertex (x_{d+1}). Sorting computed fitness values helps establishing the best (x_1), the worst (x_{d+1}), and the centroid ($\bar{x}$) points. The following is then used to identify the reflection point (x_r):

$$x_r = \bar{x} + \rho\left(\bar{x} - x_{d+1}\right) \tag{10}$$

The reflection point is expanded across the search space as follows:

$$x_e = \bar{x} + \gamma\left(x_r - \bar{x}\right) \tag{11}$$

where the expansion point is denoted by x_e which replaces the worst value if $f\left(x_e\right) < f\left(x_r\right)$. Otherwise, x_r replaces this point. The contraction step is employed if $f\left(x_d\right) \le f\left(x_r\right)$. An outer contraction ($x_{oc}$) is generated by the following

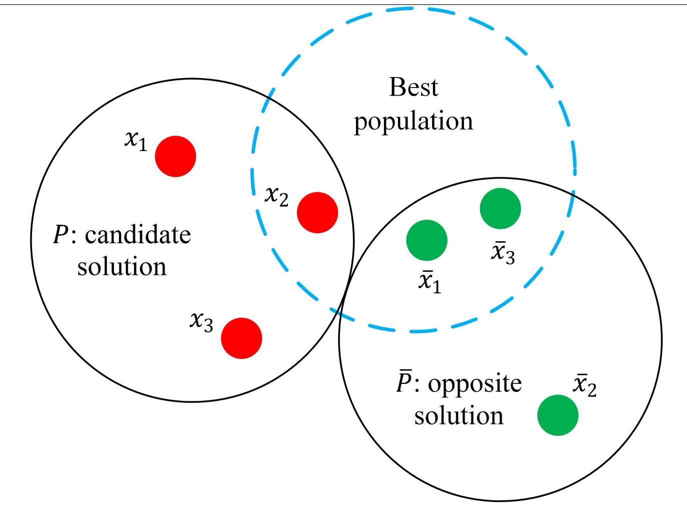

Fig. 2. Main OBL mechanism.

equation to achieve the corresponding fitness value of $f(x_{oc})$ for $f(x_r)<f(x_{d+1})$

$$x_{oc}=\bar{x}+\beta(x_r-\bar{x}) \tag{12}$$

The point of x_{oc} replaces the x_{d+1} point and the iterations are terminated if $f(x_{oc})\le f(x_r)$. Otherwise, the shrinkage occurs in the next action. An inner contraction (x_{ic}), provided as follows, may also be constructed in the contraction step to achieve corresponding fitness of $f(x_{ic})$ for $f(x_{d+1})\le f(x_r)$:

$$x_{ic}=\bar{x}+\beta(x_{d+1}-\bar{x}) \tag{13}$$

The point of x_{ic} replaces the x_{d+1} point and iterations are terminated in case of $f(x_{ic})<f(x_{d+1})$, otherwise, the shrinkage occurs. The shrinkage step is the final operation in the NM algorithm, which uses following equation to construct new points by shrinking them;

$$x_i=x_1+\delta(x_i-x_1), i=2,3,\ldots,d+1 \tag{14}$$

The flowchart of the NM simplex method is provided in Fig. 3.

The NM simplex search method was proposed decades ago to tackle the minimization problems and has so far been utilized as an efficient approach for local search [23]. Examples of hybridizing existing algorithms with the NM simplex search method can be encountered in the literature. A few of those examples can be listed as particle swarm optimization [24] for global optimization of multimodal functions, Harris hawks optimization [25] for solving nonlinear ordinary differential equations, pigeon-inspired optimization [26] for minimization of well-known benchmark functions, spider monkey optimization [27] for global optimization, ant colony optimization [28] for controller tuning of an automatic voltage regulator, and firefly algorithm [29] for optimal reactive power dispatch.

V. PROPOSED NOVEL ENHANCED OBAOANM ALGORITHM

The proposed novel enhanced ObAOANM algorithm aims to construct a better balance between the diversification and intensification stages such that it can perform with greater efficiency. To do so, the algorithm starts with the parameter initialization followed by the generation of a random population that contains N number of candidate solutions. All the solutions are computed to determine the best one. This is followed by performing the AOA algorithm in order to update the current population. At this stage, the inserted OBL scheme simultaneously calculates the modified opposite solutions. An important point to note at this stage is the operation of a modified version of OBL mechanism. Rather than the standard definition of the OBL scheme for determination of the opposite solutions, the following definition was used in this study:

$$\bar{x}_j=r_1a_j+r_2b_j-x_j \tag{15}$$

where r_1 and r_2 are two numbers randomly generated within $[0,1]$. Once the current and the opposite solutions are calculated, the best N solutions are chosen from the union set of current and opposite solutions. After determination of the best solutions with the above steps, the best ones are used as an initial simplex by NM algorithm. Here, the NM algorithm runs for the total number of iterations after every 10 iterations of the AOA algorithm, which consequently helps achieve a better balance between the exploration and exploitation phases. This cycle continues until the termination condition is met. The parameters of the proposed ObAOANM algorithm were chosen to be 5 for sensitive parameter (α), 0.4980 for control parameter (μ), 1 for reflection factor (ρ), 2 for expansion factor (γ), and 0.5 for contraction (β) and shrinkage factors (δ). Fig. 4 illustrates the flowchart of the proposed

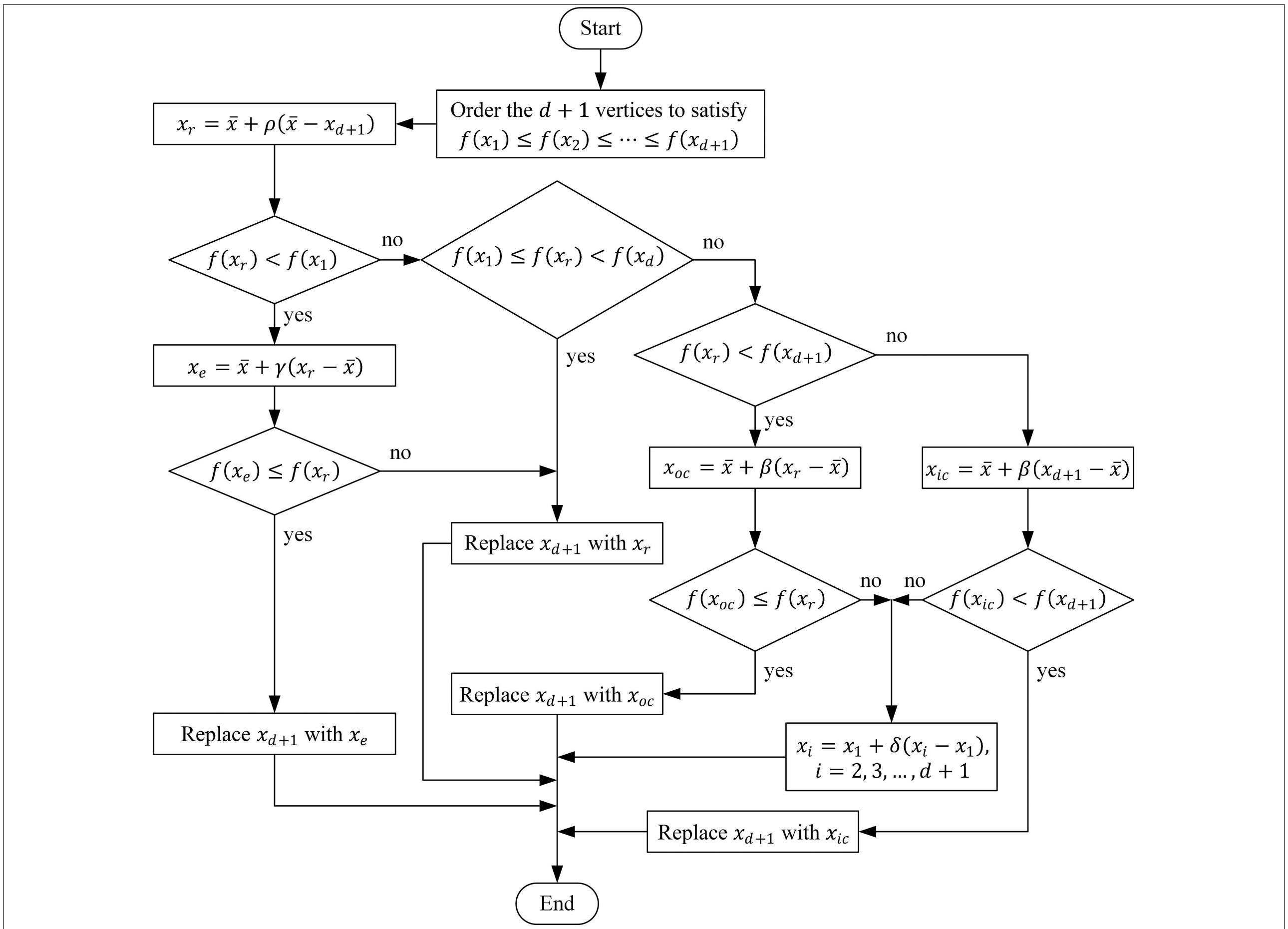

Fig. 3. Flowchart for the NM simplex method.

ObAOANM algorithm for a better demonstration of the proposed approach.

VI. EXPERIMENTAL RESULTS ON BENCHMARK FUNCTIONS

The developed ObAOANM algorithm's performance was tested using well-known benchmark functions listed in Table I [30]. Two-dimensional visualization of the listed test functions is provided in Fig. 5. In this study, performance comparison with the original version of the AOA algorithm was evaluated to be sufficient, as it has already been compared with 11 different efficient algorithms [10]. The respective comparisons, given in [10], have shown the AOA algorithm to be superior in terms of statistical performance.

Bearing the previously performed comparisons in mind, Table II only presents the comparative results of the test functions achieved by the AOA and ObAOANM algorithms by taking the dimension of the problem as 30 and running both algorithms for 40 times, along with adopting a population size of 30 and a maximum iteration number of 500. As can be easily observed, ObAOANM provides far better results in terms of statistical metrics (mean, standard deviation (SD), best and worst), as provided in the table, which indicate its highly competitive performance in finding the best optimal solutions.

VII. IMPLEMENTATION OF THE OBAOANM TO THE PID-CONTROLLED AUTOMOBILE CRUISE CONTROL SYSTEM

A. Automobile Cruise Control System

An automobile cruise control system aims to regulate the speed of a vehicle by considering the reference speed value command from the driver. The system takes into account the command signal, v_{ref}, together with the actual speed signal from the feedback sensor, and then attempts to maintain the speed of the vehicle, v, through adjustment of the engine throttle angle u. In this way, it increases or decreases the drive force (F_d) of the engine. The longitudinal dynamics of a vehicle can be given as [31]:

$$F_d = M\frac{dv}{dt} + F_a + F_g \tag{16}$$

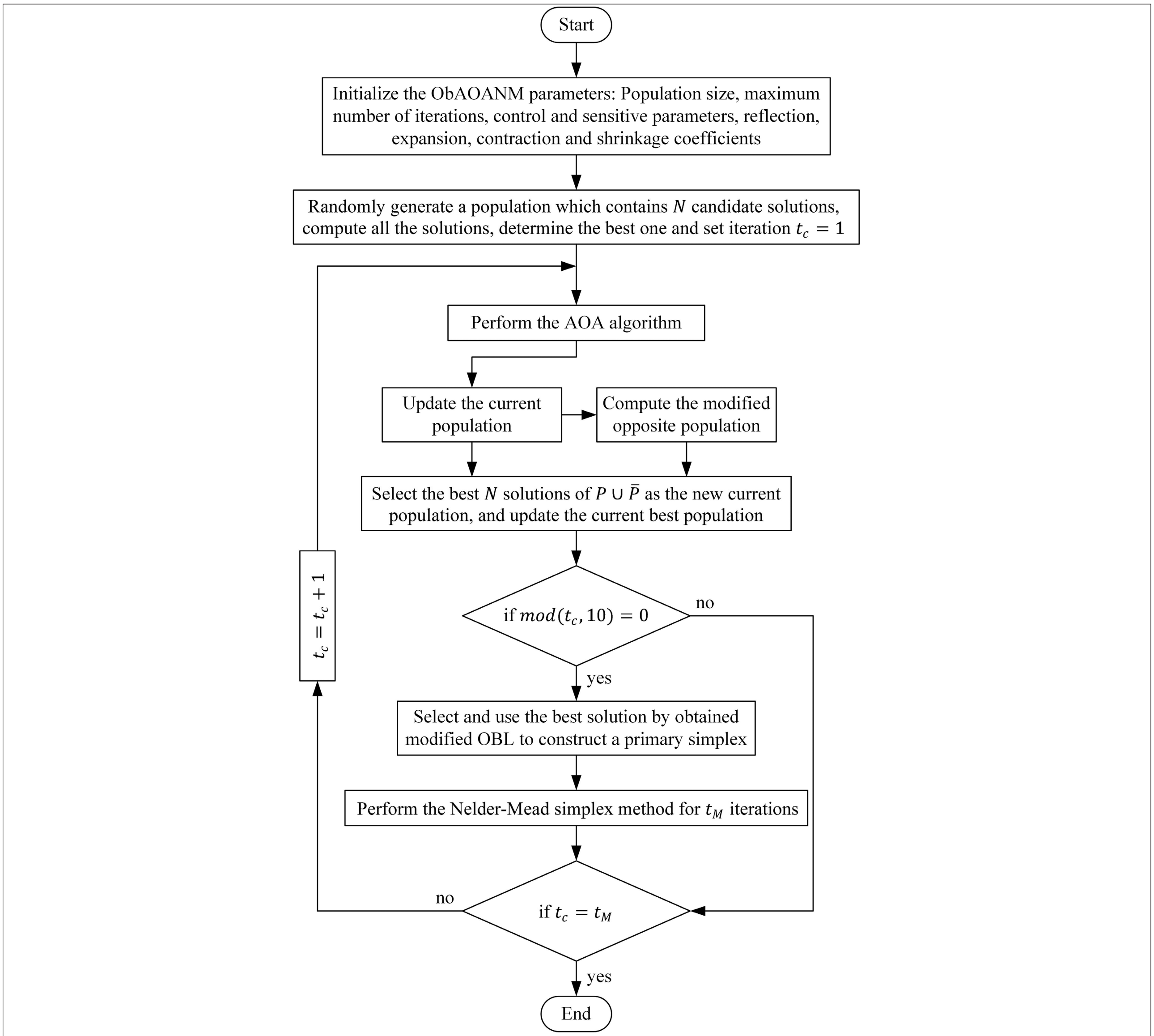

Fig. 4. Flowchart for the proposed ObAOANM algorithm.

where F_a and F_g represent aerodynamic drag and the downgrade force (climbing resistance), respectively, whereas $M\frac{dv}{dt}$ is the inertia force. The forces of F_a, F_g and F_d are all produced as can be seen from the model given in Fig. 6. In the respective model, the total mass of the vehicle and the passenger(s), the aerodynamic drag coefficient, wind gust speed, and the road angle are respectively denoted by M, C_a v_w and θ.

The model of the throttle actuator of the cruise control system is constructed as a first-order lag system with a saturation characteristic. In this study, the parameters provided in Table III were adopted to obtain the mathematical model of the system. In order to design a controller, the related system needs to be simplified. For this purpose, the vehicle was assumed to be operating at a speed of 30 km/h with no climbing resistance and wind gust speed. The drive force will operate without saturating most of the time if an appropriately designed controller is used. Considering the latter nominal situation, the state of model of the plant can then be defined as [31]:

$$\dot{v} = \frac{1}{M}\left(F_d - C_a v^2\right) \tag{17}$$

$$\dot{F}_d = \frac{1}{T}\left(C_1 u\left(t-\tau\right) - F_d\right) \tag{18}$$

Considering an equilibrium state for a nominal operating speed of $v_{ref} = v_0 =$ 30 km/h requires a nominal drive force of $F_{d0} = C_a v_0^2$ with a nominal throttle position of $u_0 = F_{d0} / C_1$.

TABLE I. DETAILS OF BENCHMARK FUNCTIONS USED IN THE EXPERIMENT

Function	Type	Formula	Range	Optimum
Sphere	Unimodal	$f_1(x)=\sum_{i=1}^{n}x_i^2$	$[-100,100]$	0
Rosenbrock	Unimodal	$f_2(x)=\sum_{i=1}^{n-1}\left(100\left(x_{i+1}-x_i^2\right)^2+(x_i-1)^2\right)$	$[-30,30]$	0
Schwefel	Multimodal	$f_3(x)=\sum_{i=1}^{n}\left(-x_i\sin\left(\sqrt{\lvert x_i\rvert}\right)\right)$	$[-500,500]$	$-418.9829\times n$
Griewank	Multimodal	$f_4(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	$[-600,600]$	0

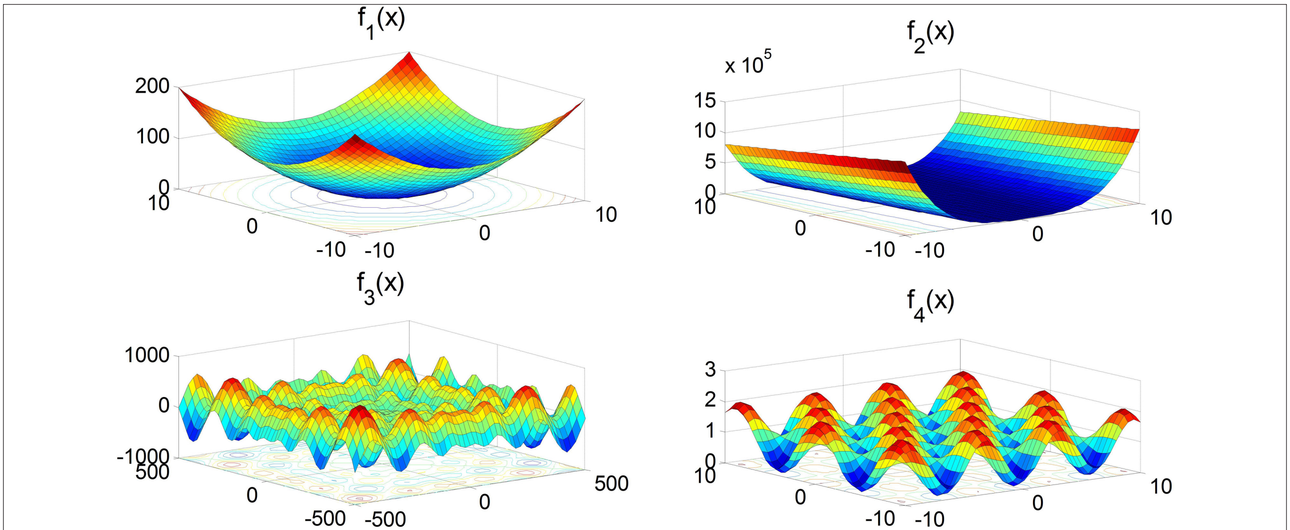

Fig. 5. Two-dimensional versions of the Sphere, Rosenbrock, Schwefel, and Griewank functions.

The following will be produced by linearizing the model around this set of points [31];

$$\delta\dot{v}=-\frac{2C_a v_0}{M}\delta v+\frac{1}{M}\delta F_d \tag{19}$$

$$\delta\dot{F}_d=-\frac{1}{T}\delta F_d+\frac{C_1}{T}\delta u(t-\tau) \tag{20}$$

A transfer function, given in (21), will be obtained with the linearized model with $p_1=-2(C_a v_0)/M$, $p_2=-1/T$, and $C=C_1/MT$:

$$\frac{\Delta V(s)}{\Delta U(s)}=\frac{Ce^{-\tau s}}{(s-p_1)(s-p_2)} \tag{21}$$

The definition can be simplified as in (22) since the effect of the delay is much smaller than that of the lag due to p_1 and p_2:

$$e^{-\tau s}=\frac{1}{e^{-\tau s}}\cong\frac{1}{1+\tau s} \tag{22}$$

Then, the transfer function of the system can be approximated as given in (23) for a nominal operating speed of 30 km/h by substituting the respective values provided in Table III:

$$G(s)=\frac{2.4767}{(s+0.0476)(s+1)(s+5)} \tag{23}$$

B. The Proposed ObAOANM Algorithm-Based PID Tuning

For an appropriately operating system, the PID controller parameters are required to be tuned to their optimal

TABLE II. STATISTICAL RESULTS OF RELEVANT BENCHMARK FUNCTIONS FOR AOA AND PROPOSED OBAOANM ALGORITHMS

Function	Statistical Measure	AOA	ObAOANM (proposed)
Sphere	Mean	8.0975E−09	6.4371E−63
	SD	3.6138E−08	2.8494E−62
	Best	2.5019E−46	1.0605E−70
	Worst	1.6163E−07	1.2749E−61
Rosenbrock	Mean	2.8495E+01	2.1154E−29
	SD	4.7159E−01	4.2498E−29
	Best	2.7014E+01	0
	Worst	2.8944E+01	1.5447E−28
Schwefel	Mean	−8.0163E+03	−9.5013E+03
	SD	7.4057E+02	4.1817E+02
	Best	−9.0566E+03	−1.0371E+04
	Worst	−6.4273E+03	−8.7518E+03
Griewank	Mean	1.0397E+02	1.3917E−14
	SD	5.2206E+01	1.0649E−14
	Best	3.5031E+01	1.9984E−15
	Worst	1.9848E+02	4.8628E−14

values [32]. The transfer function of a PID controlled automobile cruise control system is provided in (24):

$$CLTF_{PID}(s)=\frac{G_{PID}(s)\cdot G(s)}{1+G_{PID}(s)\cdot G(s)}=$$

$$\frac{2.4767\cdot\left(K_d s^2+K_p s+K_i\right)}{s(s+0.0476)(s+1)(s+5)+2.4767\cdot\left(K_d s^2+K_p s+K_i\right)} \tag{24}$$

TABLE III. MODEL PARAMETERS USED [15, 16]

Parameter	Definition	Value
C_1	Actuator constant	743
C_a	Aerodynamic drag coefficient	$1.19\,\mathrm{N}/(\mathrm{m/s})^2$
M	Mass of vehicle and passenger	1500 kg
τ	Driver reaction time	0.2 s
T	Observation time	1 s
F_{dmax}	Maximum saturation limit	3500 N
F_{dmin}	Minimum saturation limit	−3500 N
g	Gravitational acceleration	$9.8\,\mathrm{m/s^2}$

where proportional, integral, and derivative gains are represented by K_p, K_i, and K_d, respectively. In this study, the upper and lower limits for PID controller parameters were chosen to be $3<K_p<5$; $0.10<K_i<0.25$; and $3<K_d<5$. The ObAOANM algorithm was utilized to tune the respective gain parameters to construct an automobile cruise control system with a PID controller. Fig. 7 demonstrates a detailed block diagram of the PID controller implementation in the automobile cruise control system.

As depicted in Fig. 7, the algorithm is inserted into forward path and used to update the parameters of the PID by considering the error signal of $e(t)$ which is the difference between the reference speed ($\delta v_{ref}(t)$) and the actual speed ($\delta v(t)$). The error is specified according to integral of the time-weighted squared error (ITSE) [33] performance index which was adopted as an objective function for this study. The stated objective function is given in (25):

$$ITSE=\int_0^T t\cdot\left[e(t)\right]^2\cdot dt \tag{25}$$

The integration time (T) was taken to be $20s$ for this study.

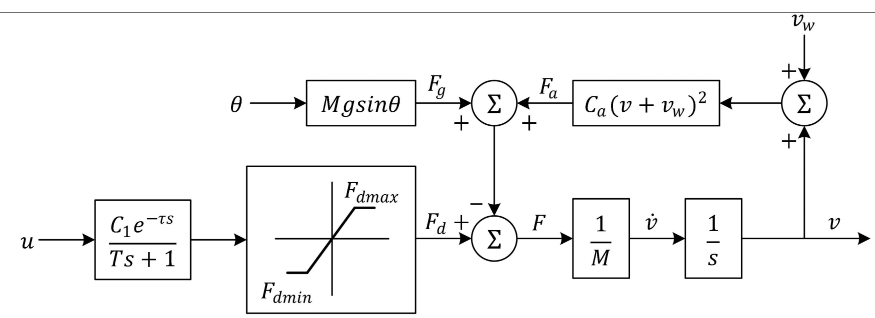

Fig. 6. Dynamic model of cruise control system [31].

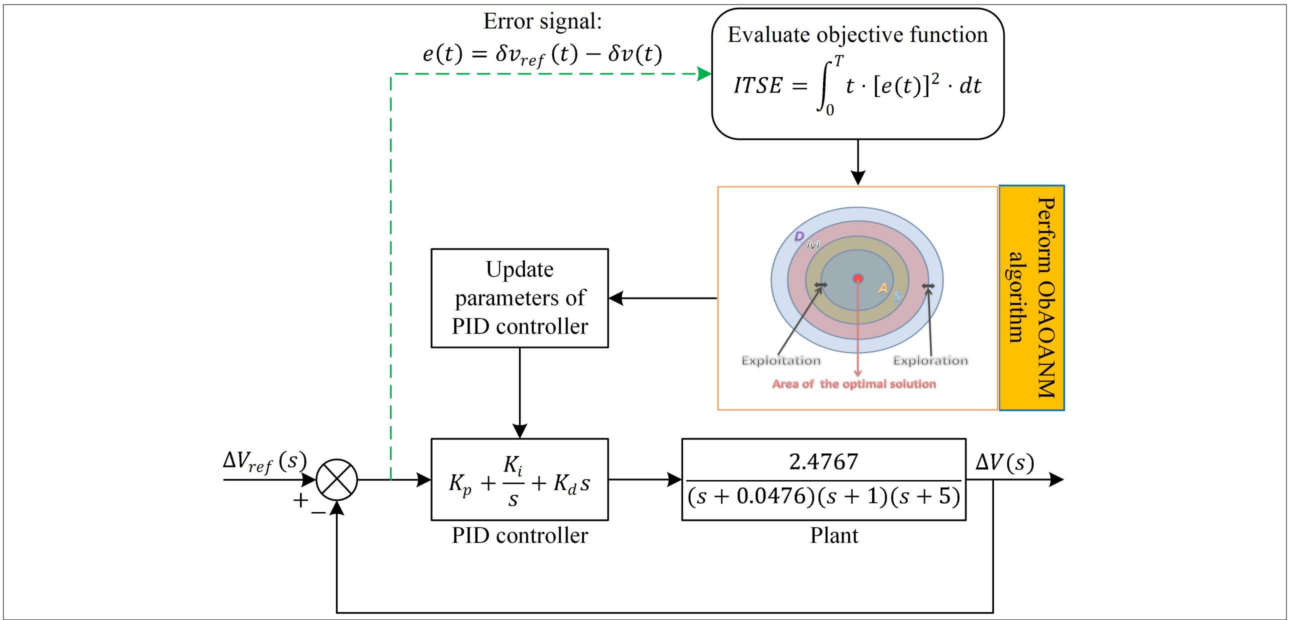

Fig. 7. Detailed block diagram of ObAOANM implementation to optimize the performance of an automobile cruise control system.

C. Statistical Analysis

To observe the performance of the proposed enhanced algorithm, both AOA and ObAOANM algorithms were run comparatively for 40 times using a population size of 30 and maximum iteration number of 50 in order to obtain the statistical values of mean, standard deviation (SD), and best and worst using the ITSE objective function. Table IV provides the respective values. As can be seen, the best values of average, and best and worst, together with standard deviation, are achieved by the proposed ObAOANM algorithm which demonstrates better performance of the developed enhanced approach for the automobile cruise control system.

Further observations were made by constructing a comparative boxplot for both AOA and ObAOANM algorithms. The respective boxplot analysis demonstrating the performance in minimizing the ITSE objective function is provided in Fig. 8. The proposed ObAOANM algorithm has greater capability, as clearly depicted in the related figure, since it provides lower values such that the highest value obtained by ObAOANM is significantly lower than the lowest value obtained by the AOA algorithm.

TABLE IV. STATISTICAL RESULTS OF ITSE OBJECTIVE FUNCTION FOR AOA AND OBAOANM ALGORITHMS

Statistical Measure	AOA	ObAOANM (proposed)
Mean	8.5056E−02	7.7181E−02
SD	2.6665E−03	1.2440E−03
Best	8.2147E−02	7.5680E−02
Worst	9.0608E−02	7.9918E−02

D. Transient Response Analysis

After initial assessment of the proposed algorithm for the automobile cruise control system, the transient response performance was also evaluated. The obtained best PID controller parameters with AOA algorithm are $K_p = 4.0407$; $K_i = 0.2119$; and $K_d = 4.1548$. Substituting the respective values yields the closed-loop transfer function given in (26) for AOA-based PID-controlled automobile cruise control systems

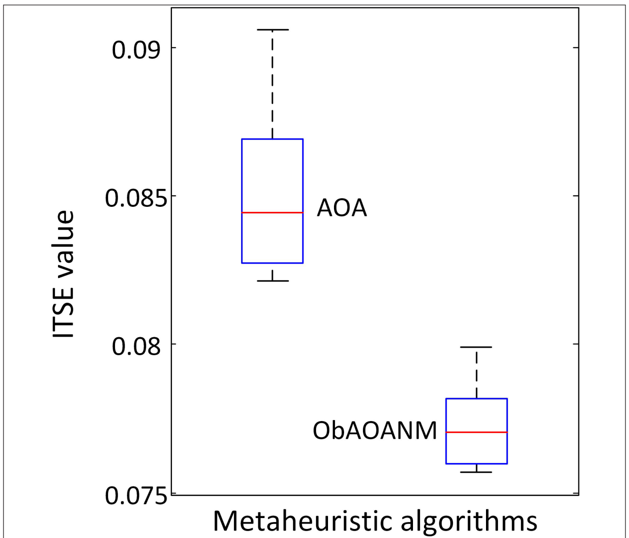

Fig. 8. Boxplot analysis results for AOA and ObAOANM algorithms.

$$CLTF_{AOA-PID}(s)=\frac{\Delta V(s)}{\Delta V_{ref}(s)}=\frac{10.29s^2+10.01s+0.5248}{s^4+6.048s^3+15.58s^2+10.25s+0.5248} \quad (26)$$

Similarly, the obtained best PID controller parameters with the proposed ObAOANM algorithm are $K_p=4.1458$; $K_i=0.1875$; and $K_d=4.3965$. Substituting the respective values yields the closed-loop transfer function given in (27) for the ObAOANM-based PID-controlled automobile cruise control system.

$$CLTF_{ObAOANM-PID}(s)=\frac{\Delta V(s)}{\Delta V_{ref}(s)}=\frac{10.89s^2+10.27s+0.4644}{s^4+6.048s^3+16.17s^2+10.51s+0.4644} \quad (27)$$

The transfer functions obtained in (26) and (27) were used to assess the transient stability of the PID-controlled automobile cruise control system. The comparative step responses regarding the velocity change of the AOA and ObAOANM-based PID-controlled automobile cruise control systems are provided in Fig. 9.

Moreover, time domain performance-related parameters of overshoot ($M_p(\%)$), rise time ($T_r(s)$), settling time ($T_s(s)$), peak time ($T_p(s)$), and steady state error ($E_{ss}(\%)$) are demonstrated in Table V. The related figure and the table provide a clear indication of a better time response profile of the proposed ObAOANM-based PID controller over the original AOA algorithm-based one. Therefore, the proposed enhanced algorithm-based-PID controller has greater capability in terms of providing better time domain performance for automobile cruise control systems.

E. Frequency Response Analysis

Peak gain (P_g), phase margin (P_m), delay margin (D_m), and bandwidth (B_w) are important parameters for the evaluation of the algorithms in the frequency domain. The Bode plot of the automobile cruise control system using the PID controller tuned by the AOA and ObAOANM algorithms is shown in Fig. 10. Table VI demonstrates the performance of both the original AOA and the proposed ObAOANM algorithms in the frequency domain, in terms of the above-listed parameters. It is obvious from the comparative numerical results in the table that the most stable system in terms of frequency response is the proposed ObAOANM-based PID-controlled automobile cruise control system, which also demonstrates the greater capability of the proposed approach.

F. Disturbance Rejection Analysis

The performance of the ObAOANM-based PID-controlled automobile cruise control system was also observed for unexpected disturbance. To perform such an analysis, a disturbing effect was introduced at the controller output, which can be seen in Fig. 11.

Fig. 12 demonstrates the performance of the enhanced algorithm and the original AOA comparatively in terms of disturbance rejection. A disturbing step signal was introduced at $t=0s$. As can be seen from Fig. 12, the proposed approach helps minimizing the overshoot, although it takes a slightly longer time to settle in terms of suppressing the disturbance.

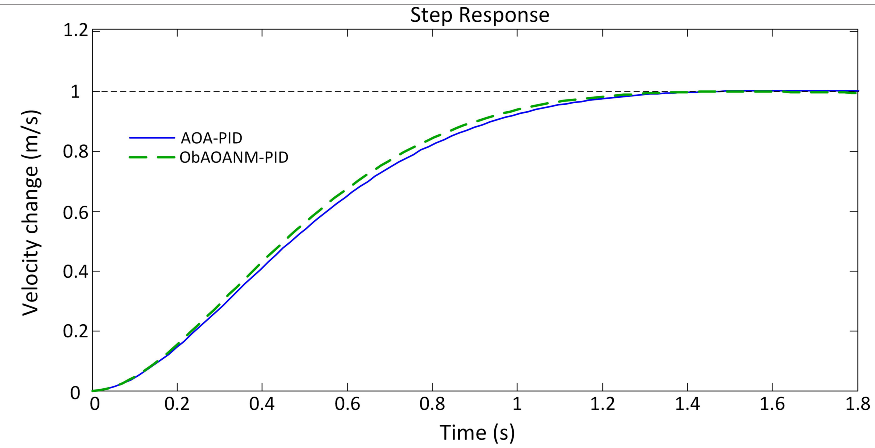

Fig. 9. Velocity step response of the automobile cruise control system.

TABLE V. TIME DOMAIN SIMULATION RESULTS

Algorithm-Controller	$M_p(\%)$	$E_{ss}(\%)$	$T_r(s)$	$T_s(s)$	$T_p(s)$
AOA-PID	0.3625	0	0.7797	1.2201	1.6369
ObAOANM-PID	0.0108	0	0.7457	1.1729	1.5188

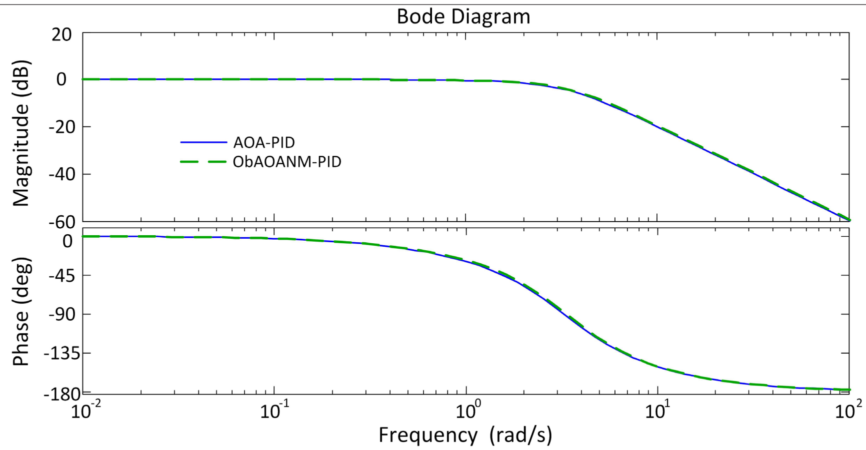

Fig. 10. Bode diagram of automobile cruise control system.

TABLE VI. FREQUENCY DOMAIN SIMULATION RESULTS

Control methods	P_g (dB)	P_m (deg)	D_m (s)	B_w (Hz)
AOA-PID	0.0217	173.1820	13.3181	2.7921
ObAOANM-PID	0	180	infinite	2.9463

G. Comparison with the Existing Approaches

Lastly, other existing approaches of PID [14], fuzzy logic [14], state space [14], genetic algorithm-based PID (GA-PID) [15], and antlion optimizer based on Bode's ideal transfer function for PID (ALO-BODE-PID) [16], were used to comparatively assess the performance of the developed enhanced algorithm for the optimization problem of the automobile cruise control system.

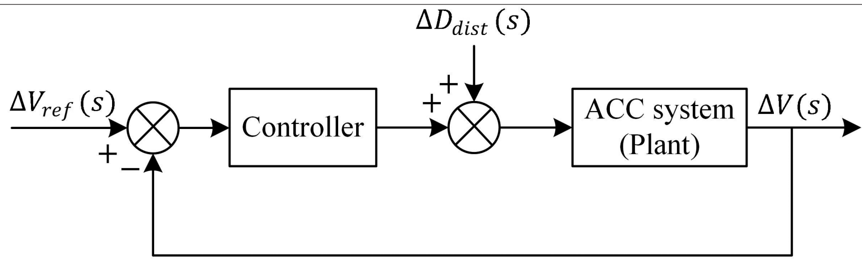

Fig. 11. Block diagram of the PID-controlled automobile cruise control system with disturbing effect.

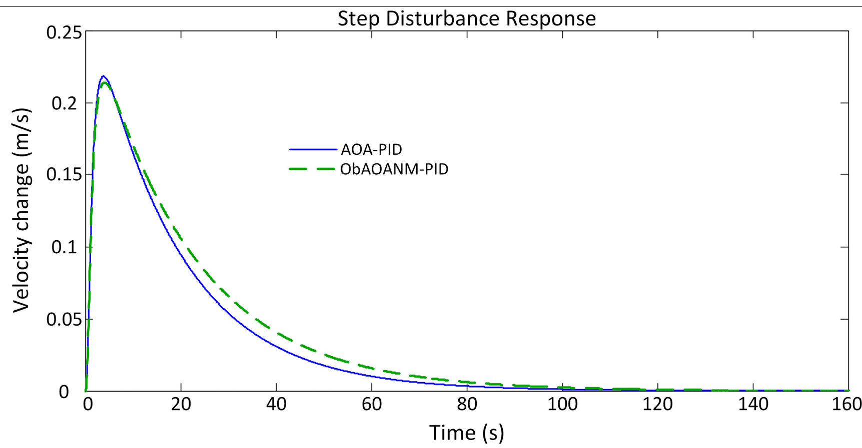

Fig. 12. Comparative step disturbance response for AOA and ObAOANM algorithms.

TABLE VII. COMPARISON OF TRANSIENT RESPONSE RESULTS WITH VARIOUS TUNING APPROACHES

Control methods	$M_p(\%)$	$E_{ss}(\%)$	$T_r(s)$	$T_s(s)$	$T_p(s)$
ObAOANM-PID (proposed)	0.0108	0	0.7457	1.1729	1.5188
ALO-BODE-PID [16]	0.4793	0	0.8336	1.3093	1.8296
GA-PID [15]	1.1456	0	0.9394	1.4559	2.1166
PID [14]	10.2	0.01	1.7	5.5	3.54
Fuzzy logic [14]	1.91	0.01	2.21	3.37	3.16
State space [14]	10	0.01	1.38	5	2.97

All these approaches are listed in Table VII. The corresponding transient response parameters of the terminal velocity change of the automobile cruise control system are also provided in the respective table. As clearly demonstrated, the proposed ObAOANM-tuned PID controller has the best performance characteristics, which further verifies the greater ability of the proposed approach.

VIII. CONCLUSION

This work has investigated a novel enhanced metaheuristic algorithm, the ObAOANM. The respective algorithm was constructed based on the idea of improving the AOA. In this context, the NM simplex method was utilized for better intensification, as it is a good local search algorithm. In terms of diversification, a modified version of the OBL mechanism was used, as the latter has good global search capability. The performance verification was carried out using well-known unimodal and multimodal benchmark functions. The latter has confirmed the greater ability of the constructed algorithm. The developed ObAOANM was also utilized for designing an efficient PID controller for an optimally performing automobile cruise control system. Similar to the case for benchmark functions, the performance of the proposed approach was compared with that of the AOA algorithm in terms of statistical, transient, and frequency responses, along with disturbance rejection, which have shown the greater capability of the ObAOANM for PID-controlled automobile cruise control system. Furthermore, the constructed ObAOANM-based PID-controlled automobile cruise control system was also compared with other available and well performed approaches in the literature (PID [14], fuzzy logic [14], state space [14], GA-PID [15] and ALO-BODE-PID [16]) in terms of time domain analysis. The latter case has also confirmed the greater performance of the proposed ObAOANM-based PID-controlled automobile cruise control system. In terms of future works, the proposed ObAOANM algorithm can be used with different controller structures, for example, fractional order PID, which may increase the performance of an automobile cruise control system further.

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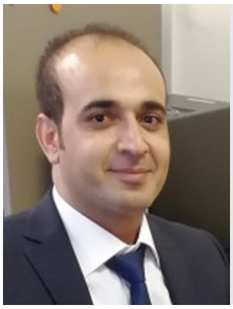

Davut İzci received his B.Sc. degree from Dicle University, Turkey, in Electrical and Electronic Engineering and his M.Sc. and Ph.D. degrees from Newcastle University, England, UK, in Mechatronics and Microsystems, respectively. He is currently an Assistant Professor working at Batman University, Turkey. His research interests are in microsystems development, sensing applications, robotics and optimization techniques along with instrumentation and control systems.

Serdar Ekinci was born in Diyarbakir, TURKEY, in 1984. He received the B.S. degree in Control Engineering, the M.S. and Ph.D degrees in Electrical Engineering all from Istanbul Technical University (ITU), in 2007, 2010, and 2015, respectively. Since 2016, he has been an Assistant Professor with Computer Engineering Department, Batman University, Batman, TURKEY. His areas of interest are electrical power system, stability, control technology and the applications of metaheuristic optimization algorithms to power system control.

MURAT KAYRİ was graduated from Gazi University in Computer Science in 1994. He received his M.Sc. from Yuzuncu Yil University in Electrical and Electronic Engineering and his Ph.D. from Biometry and Genetics. He is currently a Professor at Yuzuncu Yil University and working on Artificial intelligence and control technologies.

ERDAL EKER was born in Van, Turkey, in 1973. He was graduated from Van Yuzuncu Yil University, Turkey, in Mathematics. He received his M.Sc. from Ataturk University, Turkey, in Applied Mathematics and received his Ph.D. from Yuzuncu Yil University in Statistics. He is currently an instructor at Mus Alparslan University, Turkey.