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Optimization of Proportional-Integral-Derivative Parameters for Speed Control of Squirrel-Cage Motors with Seahorse Optimization

Yunus Emre Ekici[1], Ozan Akdağ[2], Ahmet Arif Aydın[3], Teoman Karadağ[4]

[1]Department of Electric Vehicle Technologies, İnönü University, OSB Vocational School, Malatya, Türkiye
[2]Department of Computer Engineering, Malatya Turgut Özal University, Faculty of Engineering and Natural Sciences, Malatya, Türkiye
[3]Department of Computer Engineering, İnönü University, Faculty of Engineering, Malatya, Türkiye
[4]Department of Electric Electronic Engineering, İnönü University, Faculty of Engineering, Malatya, Türkiye

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ABSTRACT

The two different motion behaviors of seahorses in nature served as inspiration for the seahorse optimization (SHO) method, which is a new metaheuristic swarm intelligence-based approach to solving fundamental engineering problems. In this study, the proportional-integral-derivative (PID) parameters for the simplified speed control of the manipulator joint using squirrel-cage induction motors were calculated with the SHO algorithm. As a result of these calculations, Kp, Ki, and Kd values were obtained as 0.0430, 0.00474, and 0.03254, respectively. Then, the time for the squirrel-cage motor to reach 50 rpm (revolutions per minute) and 90 rpm was calculated with the help of SHO. In PID + SHO operation, the squirrel-cage electric motor reached 50 rpm in 3 seconds and 90 rpm in 8 seconds. In this study, in which the SHO optimization method was used, it was calculated that the acceleration of the squirrel-cage motor and reaching the desired value gave 50% better results compared to the particle swarm optimization algorithm.

Index Terms— Optimization, proportional-integral-derivative (PID), particle swarm optimization (PSO), seahorse, squirrel cage motors

I. INTRODUCTION

In 2022, S. Zhao, T. Zhang, S. Ma, and M. Wang were first to propose the seahorse optimization (SHO) method [1]. Seahorse optimization is a new herd intelligence-based meta-heuristic technique called seahorse optimizer that is modeled after seahorses' movement, hunting, and breeding behavior in nature. It also obtains the best solution to the problems at the optimal value under certain constraints. In comparison to conventional techniques of optimization, it does not claim that every solution will be more optimal but helps improve results in global solutions.

Seahorse optimization can also be used to solve fundamental engineering problems such as the design problem for compression springs, design based problems for reducers, solutions for design problem of expansion vessel, beam-console design problem, and design problem for welded beams [2]. In addition, it gives good results in evaluations on 23 functions and CEC2014 benchmarking standard accepted in the literature. The CEC2014 suite is the generic name for modern algorithms with strong testing capabilities for all types of algorithms. Due to the complexity and dynamics of these benchmark functions, the proposed SHO is extremely suitable for improving the optimization performance [3].

Convergence analysis, statistical analysis, Friedman and Wilcoxon tests were used to calculate and evaluate the optimization performance of SHO, and empirical results show that SHO gives better results than the six most advanced meta-heuristic algorithms [4]. Moreover, SHO can also be applied to higher-dimensional problems. Optimizing at higher dimensions is more difficult due to the complexity of the functions. To cope with these problems, the performance of the algorithm has a more stable structure from 100 dimensions to 500 dimensions when evaluated according to CEC2014 standards [5]. Furthermore, SHO is used to solve real world problems of optimization and engineering problems such as particle swarm optimization (PSO) problem for cloud scheduling in computing field, design optimization for performance in buildings, boxing design problem, and parameter optimization in PID controllers [6-10].

Corresponding author:
Yunus Emre Ekici

E-mail:
emre.ekici@inonu.edu.tr

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In recent years, advances have been made in many techniques for process control in industry [11-13]. Studies have been carried out by considering many control methods such as adaptive-fuzzy control and neural control [14]. In industry, proportional-integral-derivative (PID) controllers are more preferred for process controls with their most common and robust performance [15-17]. However, it is extremely difficult to adjust the gains of PID controllers [18]. This difficulty arises from problems such as high order, time delays, and nonlinearity in many engineering problems [19-22].

Proportional-integral-derivative controller is widely used in control engineering. The reason for this is the simplicity in architecture, mature theoretical analysis, and simple application methods [23]. Until now, a new control approach has been developed so far, it is still widely used as a result in industry and control systems. There are three different adjustable gain parameters for the PID controller; proportional gain Kp, integral gain Ki, and derivative gain Kd, respectively. Adjusting the gain parameters appropriately is one of the factors that increase the efficiency of the system [24].

Proportional-integral-derivative control mechanisms are also used in the industrial field and robotics and autonomous driving systems. Proportional-integral-derivative has a say in more than 90% of these applications [25]. Proportional-integral-derivative measures the difference between the output and the input, and the value it measures is called the error rate. The error rate is denoted by e (t). It then applies a proportional correction. Then the integral and derivative operations are done. These fix steps are called P, I, and D [26].

In the last 20 years, a well-known method has been proposed to set the parameters of PID controllers to appropriate values. Ziegler–Nichols method and frequency and time domain method are the early solutions [27]. Later, with the development of computer and artificial intelligence (AI), intellectual algorithms were developed to optimally tune PID controllers such as PSO and genetic algorithm (GA) [28]. These algorithms are extremely important in terms of giving more useful and realistic results compared to other solutions [29].

In this context, it is aimed to optimally analyze the coefficients of PID parameters and to reach the desired stability region of the electric motor in a less time than other approaches. From the literature review, it has been observed that the error rates of classical optimization methods in PID control are high and delays are experienced in reaching the desired stability region. This problem shows that logistics and production-oriented companies experience delays in process control and process operation times. Delays affect the number of input and output products. In these production-oriented places, PID control should be performed appropriately to ensure efficient operation and increase production. In this context, PID parameters are reconsidered with eahorse algorithm with the purpose of minimizing the error rate. When the results of classical algorithms such as PSO and GA are examined in the literature, it has been examined that the process error rates are higher than the work done with seahorse and an effective speed in production is not revealed. In order to overcome this deficiency in the studies, it was necessary to recalculate the PID parameters with SHO method. The calculation of PID parameters for the simplified speed control of the manipulator joint using squirrel-cage induction motors, on which different algorithms are currently being worked on, uses the SHO algorithm instead of the PSO algorithm for tuning the PID controller. Then, 50 and 90 rpm acceleration times of the motor were investigated with the PID controller and calculated with PSO and SHO algorithms. The objectives and innovative aspects of the proposed SHO method are highlighted as follows:

(i) In the calculation of PID parameters, a different optimization approach is used to ensure that the results are handled comparatively.
(ii) Contrary to known classical methods, a new meta-heuristic technique provides a better global PID solution.
(iii) It is provided to examine the results of new optimization methods, such as SHO, against basic engineering problems.
(iv) In industry, PID controllers ensure that the motors operate at rated power and rated rotation value. Setting the parameters of PID controllers is still done by trial and error methods. These methods increase the error rates. In the literature, classical PSO, GA, and AI algorithms are used to minimize error rates. On the contrary, our study implemented the seahorse algorithm, which successfully minimized error rates in industrial processes to an acceptable extent than other existing algorithms, and also contributed to the existing literature by achieving lower error rates.
(v) Electric motor control with seahorse has lower computational cost compared to other optimization methods in the literature.
(vi) This work with seahorse can be extended to more degrees of freedom.
(vii) In process control, settling time has a very important place in terms of saving time. This study reduces the settling time by 50%, enabling more product input and more output to be obtained with minimum error. A faster settling time than classical optimization methods was achieved with seahorse.

This study is aims to present an alternative method for calculating the parameters of the PID controller, which is one of the basic engineering problems. The main purpose here is to alleviate the difficulties in the solution process. The method proposed in this study aims to address these barriers in the following ways:

(i) To ensure that fundamental engineering problems are reconsidered with an up-to-date optimization algorithm and to alleviate solution process difficulties
(ii) To reduce the error rate by enabling the parameters of the PID controller to be calculated more closely to the real

The remainder of the work is organized as follows: Section II provides a background for the SHO algorithm and covers the steps of the work, Section III contains PID implementations of the SHO algorithm. Experimental results and discussion are presented in Section IV and the Section V provides the conclusion.

II. BACKGROUND

In this section, an overview of SHO is provided, and then SHO installation and movement behaviors of seahorses for this research are presented. Each one is presented next.

A. Seahorse Optimizer

Seahorses belong to the genus *Hippocampus*. These creatures, which like to live in warm waters, belong to the small fish family. Seahorses live widely in subtropical, tropical, and temperate shallow waters [30]. There are about 80 species of seahorses. Some of these have not yet been discovered and named. The seahorse presented in Fig. 1 got this name because its head resembles that of a horse. In general, the length of the seahorse is known as a maximum of 30 cm and a minimum of 2 cm [31]. The shortest of the seahorse species,

Fig. 1. Seahorse.

the pygmy seahorse is only 2 cm tall when it reaches adulthood, but the adult *Hippocampus abdominalis* can be up to 30 cm long. The nose of seahorses is like a pipe [32]. The fact that its nose is this long affects the rotation of its head and is considered to be closely related to nutrition [33].

Seahorses feed mainly on small brine shrimp and zooplanktons and small crustaceans. During feeding, it uses its tubular nose to reach for food and puffs up its cheeks. In order to take the food, it is enough to just open its mouth [34]. A seahorse needs fins on its back to be able to move. These fins are located between the tail and the body. Also, the seahorse does not have a ventral or caudal fin. Its entire body is covered with a specialized bone structure [35].

B. Installation

In this study, the SHO algorithm consists of two important components: Spiral and Brownian motion. The mathematical models that emerged with these components were applied to the PID controller, and the necessary parameter values were obtained. In the SHO method, the studies start with the initialization first. Equation 1 expresses the entire population of seahorses.

$$Seahorse = \begin{matrix} x_1^1 & \cdots & x_1^{Dim} \\ \vdots & \ddots & \vdots \\ x_{pop}^1 & \cdots & x_{pop}^{Dim} \end{matrix} \quad (1)$$

Here, pop refers to the size of the population, and Dim refers to the size of the variable. Resolutions occur between LB and UB. Here UB is the upper limit and LB is the lower limit. The expression of the ith individual Xi in the search space LB and UB is as follows:

$$X_i = \left[x_i^1, \ldots\ldots, x_i^{Dim}\right] \quad (2)$$

$$x_i^j = rand\ x\left(UB^j - LB^j\right) + LB^j \quad (3)$$

Where rand denotes the random value in [0, 1]. X_i^j denotes the jth dimension in the ith individual. i is a positive integer ranging from 1 to pop and j is a positive integer in the range [1, Dim]. x_i^j Both values are included in the calculation in integer format. UB^j and LB^j indicate that the optimized problem is *j*. expresses the upper and lower bounds of the variable. Xelite here is the minimum fit individual, taking the problem as an example. Equation 4 allows to obtain Xelite.

$$X_{elite} = argmin(f(Xi)) \quad (4)$$

Here f (x) is the objective function of the problem.

C. Movement Behaviors of Seahorses

Seahorses have two distinct behaviors. The first behavior is the movement behavior against the whirlpool in the sea. it is known as a Levy flight [36]. The second behavior is Brownian movement against waves [37]. Equation 5 is used for the first movement.

$$X_{new}^1(t+1) = (t) + Levy(\lambda)\left(\left(X_{elite}(t) - (t)\right)xyz + X_{elite}(t)\right) \quad (5)$$

Here, $x=\rho \times \cos(\theta)$, $y=\rho \times \sin(\theta)$, and $z=\rho \times \theta$, show the components of the positions of the three-dimensional search agents, which helps to update the coordinates (*x*, *y*, *z*) under helical motion respectively. Spiral constants given as $\rho = u \times e\theta v$ vary logarithmically and represent the length of the stems defined by *u* and *v* (*u* value set to 0.05 and *v* value 0.05). θ is a random value between 0 and 2π. The Levy (*z*) function belongs to the Lévy distribution and is calculated by Equation 6.

$$Levy(z) = s \times \frac{w \times \sigma}{|k|\frac{1}{\lambda}} \quad (6)$$

The value of λ in Equation 6 is a random number chosen between 0 and 2. In this study, λ was determined as 1.5. s is taken as a coefficient with a value of 0.01. The *w* and *k* values are also random numbers chosen between 0 and 1. σ can be calculated by the equation given below.

$$\sigma = \left(\frac{\Gamma(l+\lambda) \times sin\left(\frac{\pi\lambda}{1}\right)}{\Gamma\left(\frac{l+\lambda}{2}\right) \times \lambda \times 2^{\left(\frac{\lambda - l}{2}\right)}} \right) \quad (7)$$

In the second movement, the Brownian behavior is presented with Equation 8.

$$X_{new}^1(t+1) = X_i(t) + rand * l * \beta_t * ((t) - \beta_t * X_{elite} \quad (8)$$

In Equation 8, *1* is the constant coefficient (in this paper it is set to *1* = 0.05). βt is the random walk coefficient of the Brownian movement and takes a random value. Equation 9 expresses the computation of this random walk.

$$\beta t = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \quad (9)$$

These two states are added together to obtain the new position of the seahorse at the end of iteration *t* and can be formulated as follows.

$$X_{new}^1(t+1) = \begin{matrix} X_i(t) + Levy(\lambda)((X_{elite}(t) - X_i(t) \times x \times y \times z + X_{elite}(t) & r_1 > 0 \\ X_i(t) + rand * l * \beta_t * \left(-\beta_t * X_{elite}\right) & r_1 \leq 0 \end{matrix} \quad (10)$$

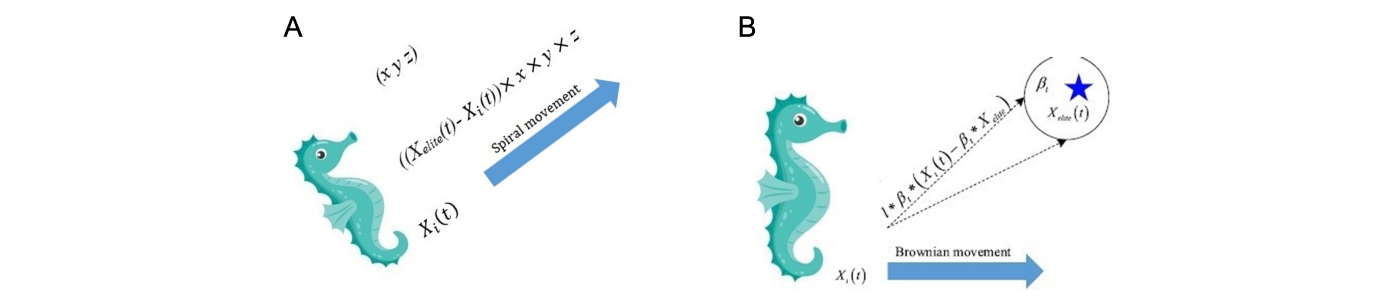

Fig. 2. (a) Seahorse spiral movement. (b) Seahorse Brownian movement.

Here $r1$ is assigned as randn () and it is a random value. Fig. 2 shows the position update diagram of the seahorse following two types of different styles of movement, Brownian or spiral movement, and both show the random movement of the seahorse.

III. THE IMPLEMENTATION PROCESS OF SHO

Seahorse optimization was preferred as the main optimization method of this article because it was more stable and gave good results in the tests made with CEC2014 standards [3]. In addition, the successful results in studies on stability analysis such as Wilcoxon and Friedman test, convergence analysis and statistical analysis [38] made it preferred in this article.

This part of the study includes how the SHO optimization algorithm is used in the calculation of PID parameters. Firstly, the PID transfer function of the simplified speed control of the manipulator joint using squirrel-cage induction motors was recompiled in the MATLAB R2021b. This transfer function is inserted into the SHO algorithm as a new equation. This equation has been added among other equations called Benchmark function. The transfer function is given by algorithm 1 presented below.

Algorithm 1. PID transfer function

```
% f(x) PID transfer function
function o = F(x)
num = x (1), x (2), x (3);
den = 1;
o = tf(num, den)
end
```

In the SHO algorithm, LB is 0 for x (1), x (2) and x (3). UB is 1 for three variables. These values selected with Algorithm 2 have been added to the SHO software.

Algorithm 2. LB and UB value assignment

```
% f(obj) PID transfer function
function [LB, UB, Dim, fobj] = BenchmarkFunctions(F)
Case f(x)
  fobj= @f(x);
  LB =[ 0, 0, 0];
  UB = [1, 1, 1,];
  UB=UB;
  LB=LB;
  Dim= 3;
  end
```

In order to start the SHO optimization, the population and iteration (number of repetitions) values must also be selected. In this study, the population was determined to be 100, and the maximum iteration was determined to be 1500. When the optimization was started with the MATLAB software, the optimal output was presented in Fig. 3 after a total of 1500 iterations.

In Fig. 3, the best score was obtained as 0.032 after the maximum iteration. Kp, Ki, and Kd values were calculated as 0.0430, 0.00474, and 0.03254, respectively.

IV. RESULTS AND DISCUSSION

In this study, the parameters of the PID controller, which are included in the engineering problems, are calculated. The parameters of the PID controller for the simplified speed control of the manipulator joint using squirrel-cage induction motors in the study in [12] are reconsidered with the SHO optimization algorithm. In the reference study [12], the transfer function of the squirrel-cage electric motor, whose speed control will be made, was first calculated. Then, a new block diagram specific to the PSO algorithm was developed. With this block diagram, the Kp, Ki, and Kd values of the PID parameters were calculated. Then, the acceleration times of the squirrel-cage motor were investigated with the PSO algorithm. The PID parameters, squirrel-cage motor parameters, and optimization initialization criteria in the referenced study were chosen similarly to avoid a different outcome in the seahorse study. Commonly selected parameters are presented below.

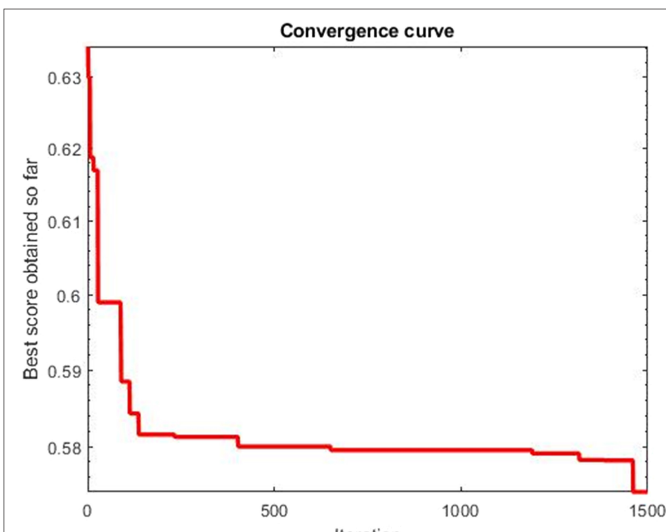

Fig. 3. SHO optimization best score value.

TABLE I. COMPARISON OF CALCULATION RESULTS WITH PID PARAMETERS SHO AND PSO

Optimizer	Kp	Ki	Kd
PID + SHO	0.0430	0.00474	0.03254
PID + PSO	0.04200	0.00504	0.03360

PID, proportional-integral-derivative; PSO, particle swarm optimization; SHO, seahorse optimization.

- In the PSO algorithm used in the referenced study, the lower bound and upper bound values of Kp, Ki, and Kd are between 0 and 1. These values were chosen the same in seahorse algorithm.
- Population and iteration numbers were set as 100 and 1500 for both studies.
- The parameters of the squirrel-cage motor are chosen to be identical in transfer function form. In the study carried out in the article, parametric differences in the electric motor reaching 50 and 90 rpm values were avoided.
- The total duration of the simulation was set as 20 seconds in both studies.
- The stabilization parameter was determined as the rpm number of the squirrel-cage motor and 50 rpm and 90 rpm were taken as the basis in both studies.

The results obtained in the study with the PSO and SHO algorithms are presented in Table I.

According to the results in Table I, the Kp value was obtained as 0.0430 in the SHO application. The Ki value was calculated as 0.00474, and the Kd value was calculated as 0.03254. These values of the PID parameters were recalculated with the help of the transfer function in the MATLAB Simulink program. The transfer function of speed control is given by Equation 11.

$$G(s) = \frac{73.15}{15.25s^2 + 9.706s + 1} \tag{11}$$

The Simulink circuit given in Fig. 4 was created to calculate the rpm of the squirrel-cage electric motor. The Matlab Simulink solver chosen for this application is Code 45. The maximum step size is set to 0.4. Stop time is set to 20.

The Kp, Ki, and Kd values obtained by the SHO method are integrated into the PID controller block diagram. In Fig. 5, the block diagram settings are shown.

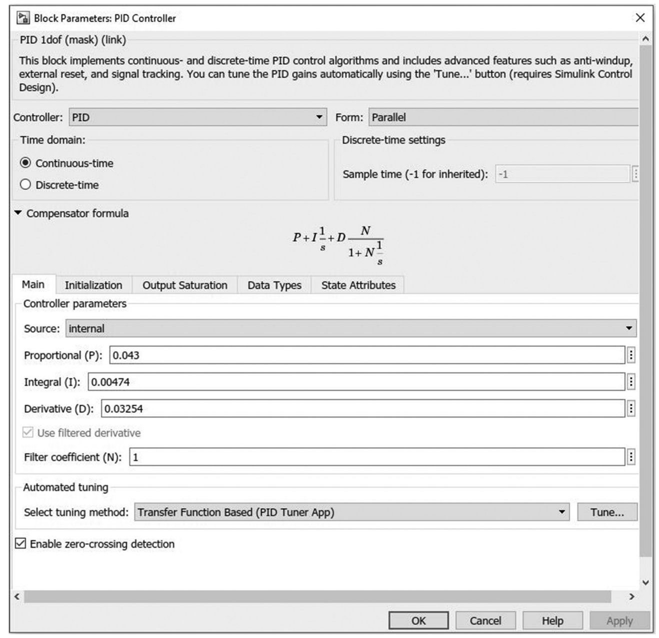

Fig. 5. PID parameter block diagram settings. PID, proportional-integral-derivative.

Instead of the P, I, and D values shown in Fig. 5, the Kp, Ki, and Kd values obtained from the seahorse algorithm were entered. When the Simulink circuit was started, the engine reached 90 rpm in approximately 8 seconds. In the third second, it reached a speed of 50 rpm. The PID setting graph is presented in Fig. 6.

In the study referenced [12], adjustments of PID parameters were made using PSO, and when the result graph was examined, it was observed that the electric motor reached 50 rpm in 5 seconds and 90 rpm in 12 seconds. In our study using SHO, it was observed that the time to reach 50 and 90 rpm was shorter. The results of the PID + PSO and PID + SHO applications are presented in Table II.

Regarding the results presented in Table II, SHO has brought the PID parameters to a more stable range compared to other algorithms. Working in this range, the PID controller made the squirrel-cage electric motor move faster. Therefore, using the PID controller with the SHO algorithm enables the squirrel-cage electric motor to reach the desired stable speed in a shorter time.

Reaching the desired stable range in approximately 50% shorter time than the application using the PSO algorithm reveals the potential

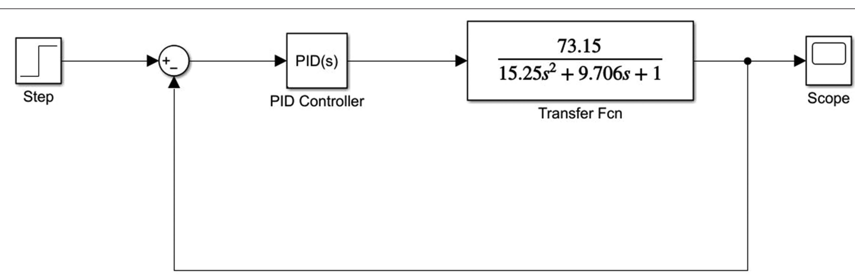

Fig. 4. PID circuit graph of engine rpm calculation. PID, proportional-integral-derivative.

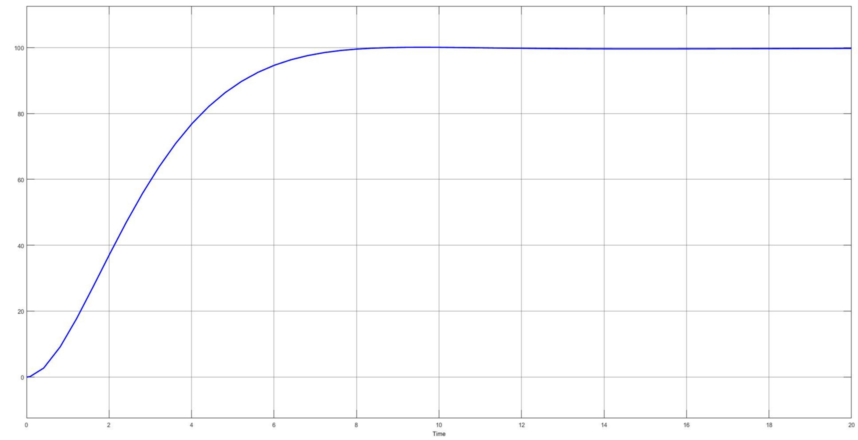

Fig. 6. PID tuning results using SHO.

TABLE II. THE ACCELERATION TIMES OF THE ELECTRIC MOTOR OPERATED WITH SHO AND PSO ALGORITHMS TO 50 RPM AND 90 RPM

Solver	50 RPM	90 RPM
PID + SHO	3 seconds	8 seconds
PID + PSO	5 seconds	12 seconds

PID, proportional-integral-derivative; PSO, particle swarm optimization; SHO, seahorse optimization.

to increase the production speed of industrial establishments. Faster process checks depend on an optimal operating interval. Seahorse optimization has accelerated the process by bringing this optimal working time to a more stable and faster structure.

V. CONCLUSION

This research focuses on the effect of the seahorse algorithm on fundamental engineering problems. In particular, based on reference [12], a new approach with SHO was developed and evaluated. This study is carried out on the example of simplified speed control of a manipulator joint using squirrel-cage induction motors.

First of all, the transfer function of the squirrel-cage motor was integrated into the seahorse algorithm and used as a new optimized function in [12]. Then, the transfer function of the induction motor is optimized using the seahorse algorithm within the determined upper and lower limits.

Using SHO, Kp, Ki, and Kd values were calculated to be 0.0430, 0.00474, and 0.03254, respectively, based on the obtained results. Then, a special circuit was designed in the Simulink environment to evaluate the time it takes for the motor to reach the determined 50 rpm and 90 rpm speed values. As a result of the circuit simulations, it was seen that the time for the motor to reach 50 rpm was 3 seconds, and the time to reach 90 rpm was 8 seconds, using the seahorse algorithm. Compared with the other approach (PID + PSO), it was concluded that it is possible to reach the desired speed in a shorter time with the seahorse algorithm.

This study can be used to optimize the coefficients of PID controllers of MA2000 manipulator joints. The most important problem of MA2000 manipulator joints is that PID control parameters cannot be properly tuned, and their coefficients cannot be optimized. For these systems where PSO and GA algorithms are generally used, coefficient tuning can be done by obtaining the minimum error rate with the SHO algorithm. The study can also make parametric adjustments on different types of motors. SeaHorse algorithm can also be used in optimally tuned fractional PID controller design problems for direct current (DC) motor speed control. During the speed control of the DC motor, it will reach the nominal speed faster than other optimization algorithms. In this way, the time for the DC motor to reach 50 rpm speed can be reduced from 5 seconds to 3 seconds. In DC motors, approximately 60% of the settling time can be saved. In addition, PID parameters tuned with the seaHorse algorithm can also be used in grid-connected hybrid renewable energy systems. Here the PID parameters can be tuned with minimum error and maximum gain, and a time domain objective function can be formulated in terms of voltage and current errors to obtain efficiency. As a result, the seahorse algorithm can provide better results compared to conventional PSO for input and output current, voltage, and power parameters.

The seahorse algorithm has not yet been used to solve multi-objective and discrete optimization problems. It also does not have a sufficient structure for intelligent solutions of complex optimization problems. Among the constraints of our study, sufficient results have not yet been obtained for solving such engineering problems, but seahorse can be used as an alternative to solve problems where classical optimization methods are applied. Multi-objective optimization problems try to minimize or maximize multiple objectives with multiple constraints. In these problems, fixed values are generally not used, but the values of L and λ in the seahorse algorithm, especially in the motion functions (Brownian behavior), are chosen as fixed. The results obtained with variable values will be used in future studies. The constant value used is among the most important constraints of our study. On the other hand, optimization problems are defined as continuous or discrete problems according to the values of the decision variables. Some of the problems are continuous since the function can take infinite values in the range of definition. Discrete optimization problems, unlike continuous optimization, take integer values in the range of definition. Seahorse has a structure suitable for infinite value input in the range defined in the study. However, with the development of the algorithm in future studies, it can be ensured to take integer values in certain definition ranges.

The limitations of our current study are explained in detail. In future studies, it is aimed to reconsider these constraints and to improve the optimization algorithm and apply it to all engineering problems.

In our future research, we intend to investigate how the seahorse algorithm can be applied to variety of engineering problems and compare it with the most prominent optimization methods known in the literature. In this way, the overall applicability and performance of the algorithm will be evaluated more comprehensively.

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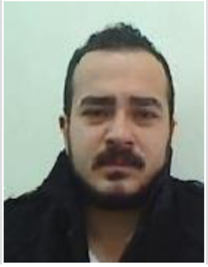
Yunus Emre Ekici (Member, IEEE) received the B.Sc. and M.S. degrees in electrical and electronics engineering. He is currently a Lecturer and a Researcher with the Electric Vehicle Technologies Program, OSB Vocational School, Inonu University. Also, he worked as the Eastern and Southeastern Anatolia Regional Manager of Bozankaya Automotive After Sales Services, a local company that has been producing electric buses for many years. His research interests include electric vehicles, optimization methods, regression methods and battery management systems.



Ozan Akdağ received his B.Sc. degree in Electrical and Electronics Engineering from Inonu University in 2010. He received his master's degree in Electrical and Electronics Engineering from Kahramanmaras Sutcu Imam University in 2013. He received his PHD degree in Computer Engineering Inonu University in 2020. He has also been working as a field/ protection systems engineer at the Ministry of Energy since 2010. His research interests include analysis of power systems, modeling of power systems, optimization, big data, energy efficiency, distributed generation system, smart networks, wind power, relay coordination, greenhouse control.

Ahmet Arif Aydin received the B.S., M.S., and Ph.D. degrees in Department of Computer Science and Engineering. He is currently a Lecturer and a Researcher with the Computer Engineering Department, Engineering Faculty, Inonu University. His research interests include computer sciences, data representation and storage, data modeling, database systems, software engineering, big data analytics, machine learning, engineering and technology.

Teoman Karadağ (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in electrical and electronics engineering. He is currently a Lecturer and a Researcher with the Electrical and Electronics Engineering Department, Engineering Faculty, Inonu University. He worked as an Engineer in the telecommunications industry for more than seven years. His research interests include extremely high and low frequency electromagnetic fields and applications, electric vehicles, and battery management systems.