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TUNED PID CONTROLLER FOR DC MOTOR SPEED CONTROL USING OPTIMIZATION ALGORITHMS

A graduation project is submitted to the Electrical Engineering Department in partial fulfillment of the requirements for the degree of Bachelor of Science in College of Engineering - Electrical Engineering

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SUPERVISOR CERTIFICATION

I certify that the preparation of this project entitled TUNED PID CONTROLLER FOR DC MOTOR SPEED CONTROL USING OPTIMIZATION ALGORITHMS**,** prepared by DUHA SAMI, HUDA MOHAMMED, MALK HASSAN, and KAWTHER LAWAH**,** was made under my supervision at General College of Engineering Electrical Engineering Department in partial fulfillment of the Requirements for the Degree of Bachelor of Science in College of Engineering - Electrical Engineering.

Signature:

Name: (Supervisor)

Date:

DEDICATION

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

دَعْوَاهُمْ فِيهَا سُبْحَانَكَ اللَّهُمَّ وَتَحِيَّتُهُمْ فِيهَا سَلَامٌ

وَآخِرُ دَعْوَاهُمْ أَنِ الْحَمْدُ لِلَّهِ رَبِّ الْعَالَمِينَ)

صدق الله العلي العظيم

مهداة إلى أمامنا صاحب العصر والزمان

الحجة أبن الحسن (عجل الله تعالى فرجه)

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ABSTRACT

The DC motor has been commonly utilized in the industry although its maintenance is costly, more than the induction motor. Consequently, speed control of DC motor has attracted considerable researches and different algorithms have evolved. All the traditional algorithms for the Proportional Integral Derivative (PID) controller provide initial practical values for (kp, ki, and kd) PID parameters, which are manually tuned to achieving the desired performance. The manual tuning is inaccurate and a hard job, which requests comprehensive experience of the problem domain. This research presents the Whale Optimization Algorithm (WOA) and Equilibrium optimizer (EOto optimally tune gain parameters of PID control scheme in order to regulate DC motor's speed. These suggested techniques tune the controller by the minimization of the fitness function represented by the integral of time multiplied by absolute error (ITAE). The modelling and simulation are carried out in MATLAB/Simulink. The results indicate that the PID-WOA controller demonstrates superior performance in terms of step response, minimizing overshoot, settling time, rise time, and peak value in controlling the speed of a DC motor system. However, for steady-state error measured by the ITAE criterion, the EO-PID controller exhibits better performance. This highlights the trade-offs between different control strategies and their impact on specific performance metrics, providing valuable insights for system optimization.

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Chapter one

1.1 Introduction

The motor is device It converts electrical energy into mechanical energy and depends on the type of magnet and has a single armature winding. The motor that works generates a voltage opposite to the input voltage. The electrical circuit is represented by voltage, resistance, and inductance, and the rotor part, the disk, is obstructed by something called a damper. The input of the system is the voltage source. that is applied to the motors armature while the output is the rotational speed of the shift .

The main function of PID controller is to make plant less sensitive to changes The core technology of PID control is how to optimize the three parameters of PID controller to make PID control reach the desired control effect, the optimization of the three important parameters is of great significance for the control performance of the control system. The selection of PID parameters directly affects the control effect of the system, so the optimization of the controller parameters is very important. The algorithm uses repeatedly the model of the object in the process of optimization, and initializes the control parameters which need to be adjusted. Combining with the constraint conditions, we correct the initial value of the parameters, solve the quadratic programming problem and update the Hessian Matrix of Varangian function by line search and when kp equals zero there is on PID.

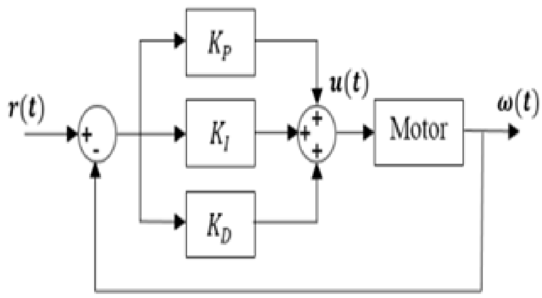

Figure 1.1 The equivalent circuit of the system

The standard PID control configuration is as shown in Figure 1.1 This is a type of feedback controller whose output, a control variable, is generally based on the error between some user-defined set point and some measured process variable. A PID controller attempts to correct the error between a measured process variable and a desired set point by calculating and then outputting a corrective action that can adjust the process accordingly. So by integrating the PID controller to the DC motor were able to correct the error made by the DC motor and control the speed or the position of the motor to the desired point or speed. However, PID controllers cannot be tuned in such way that the optimum step response is achieved for different inertia, load and speed reference, to achieve the desired step response of the system has minimal rise time and without overshoot. For design and tuning of PID controller .

1.2 Problem statement:

When using a PID controller alone, the system may face the following problems:

1. Overshoot: The system may exhibit overshoot, where the control signal causes the system to exceed the desired setpoint before settling down.

2. Oscillations: The system may exhibit oscillations around the setpoint due to the proportional and derivative terms in the PID controller.

3. Steady-state error: The system may have a steady-state error, where it cannot reach the desired setpoint accurately and remains offset from it.

4. Sensitivity to parameter variations: The PID controller's performance may be sensitive to changes in system parameters, leading to instability or poor control.

5. Limited control for complex systems: PID controllers may not be suitable for highly nonlinear or complex systems that require more sophisticated control strategies.

1.3 Aim of project

the goal of this project is to control the speed by making the output signal exactly like the input.

1.4 Objectives

Objectives of using a modified PID controller to control the speed of a DC motor using optimization algorithms include the following:

1. Improve system performance: The main goal of using a modified PID controller is to improve system performance by better and more accurately adjusting the PID parameters using optimization algorithms.

2. Achieve fast and stable response: The use of modified PID control aims to achieve fast and stable response to load changes and various conditions that may affect the motor speed.

3. Reducing deviation from the target value: The modified PID control seeks to reduce the deviation between the target value of the motor speed and the actual value at which the motor is running.

4. Improve system efficiency: By fine-tuning the PID parameters, the system efficiency can be improved and power consumption reduced.

5. Increased motor life: With a properly adjusted PID control, the stress on the motor can be reduced thus increasing its lifespan.

6. Providing a sophisticated and suitable solution: The use of optimization algorithms in adjusting PID parameters aims to provide a sophisticated and suitable solution to achieve the goals of DC motor speed control.

In general, the use of PID control modified by optimization algorithms aims to improve the performance of the control system and achieve specific goals such as effective and accurate DC motor speed control.

1.5 Contribution

Certainly, contributing in this area can be very beneficial. Considering that automatic control is an evolving and complex field, continuous research and development is essential to improve performance and overcome control-related challenges. Here are some ways you can contribute.

Develop new methods to improve the performance of PID units and make them more effective in controlling complex systems.Propose advanced control strategies that use technologies such as advanced control, multiple controllers, or intelligent control. Conduct studies on how to improve systems response and reduce vibrations and bounces using advanced control techniques. Develop advanced mathematical models of dynamic systems to facilitate the design of effective control strategies.Test and evaluate new methods and technologies through simulation or practical application on real systems.

In short, contributions in this field can contribute to the development of new and effective solutions to the challenges facing automatic control and improving systems performance.

1.6 Outline of This Thesis:

In the first chapter, we talked about a general overview of the project, followed by the second chapter Literature review which talks about articles on the subject of the DC motor and controlling its speed, the third chapter is about parameter optimization algorithms PID, the fourth chapter is about the results and discussion of this topic, and last but not least the fifth chapter is About the conclusion, work and future of this project.

Chapter Two

2.1 Literature review

DC motors, renowned for superior speed control, are extensively used in industry despite higher maintenance costs. Research on DC motor speed control has led to the widespread adoption of PID controllers. This survey explores [1] the use of the Artificial Bees Colony (ABC) optimization algorithm to enhance PID controller parameters, aiming to boost DC motor tracking performance. Results indicate that the ABC algorithm outperforms other population-based optimization methods. The study emphasizes the significance of accurate motor position control, contributing insights for PID controller refinement in DC motor applications. The innovative ABC algorithm, known for autonomous adaptation, avoidance of local optima, and parallel exploitation, demonstrates promising results for enhancing time-domain performance in the DC-motor system.

In [2] introduces the Aquila Optimizer (AO) algorithm for determining Proportional Integral Derivative (PID) controller parameters in DC motor speed control. Inspired by a northern hemisphere bird of prey, AO is evaluated on benchmark optimization problems and compared with Seagull Optimization Algorithm (SOA), Marine Predators Algorithm, Giza Pyramids Construction (GPC), and Chimp Optimization Algorithm (ChOA). Results indicate AO's promising and effective performance, showcasing superior outcomes in PID parameter determination. The study highlights the significance of precise parameter adjustment in DC motor control, positioning AO as a robust method with optimal achievements, reducing PID overshoot by an average of 0.023% and improving undershoot by 0.5%.

In [3] use of PID controllers for system control, particularly focusing on the challenge of parameter tuning. It highlights the application of genetic algorithms as a method to optimize PID parameters, using MATLAB simulations and Arduino Uno for implementation on a DC motor system. The genetic algorithm approach offers improved performance compared to traditional trial and error methods, enhancing system response and reducing maximum spikes. The literature survey underscores the continued relevance of PID controllers in industrial settings and mentions alternative tuning methods such as Ziegler-Nichols and Fuzzy logic, which often demand extensive control system expertise.

The paper discusses the challenge of tuning PID controllers, In [4] considering their widespread use in industrial settings. It introduces a flexible and efficient tuning technique based on genetic algorithms (GA) for optimizing PID controller parameters, specifically for a DC motor. A comparison with the Active Set Optimization Algorithm (ASOA) is provided, demonstrating the superiority of GA in meeting a wide range of performance requirements. Both algorithms are applied to speed control of DC motors, with GA-PID enhancing overall system performance and meeting specified requirements effectively.

In the article [5] focus lies on the challenge of tuning PID parameters for optimal system performance. The literature discusses the common use of DC motors in various applications, often controlled using PID The study employs the Particle Swarm Optimization (PSO) method for tuning PID parameters, demonstrating stable results compared to other methods.

Through MATLAB Simulink simulations, optimal PID parameter values are obtained. Hardware testing using Arduino IDE software confirms stable motor speed response, albeit with slightly different parameter values. A comparison between simulation and hardware testing reveals variations in rise time, settling time, and overshoot values, highlighting differences between simulated and real-world performance

A literature survey on PID controllers highlights the challenge of parameter tuning, particularly in systems like DC motors, often relying on trial and error. In [6] genetic algorithms offer a smarter alternative inspired by natural selection, resulting in better system performance. Using MATLAB simulations and Arduino Uno hardware, this research demonstrates that genetic algorithms provide PID parameters with improved steady time and reduced maximum spikes compared to trial-and-error methods. With an overshoot below 10%, the genetic algorithm approach, utilizing 100 generations, mutation at 0.4, and crossover at 0.8, outperforms trial and error methods. Hardware testing confirms the effectiveness of the genetic algorithm in achieving optimal PID parameters, such as KP = 4.2090, KI = 1.2012, and KD = 0.2539, with an overshoot value of 2. Overall, genetic algorithms offer a reliable method for tuning PID controllers in practical applications like DC motor control.

A novel method [7] for optimal control of a DC motor using a PID controller is introduced, employing an enhanced version of the whale optimization algorithm. This approach aims to minimize settling time while ensuring stable and accurate control of the motor speed. Unlike other control algorithms, PID controllers offer precise control by adjusting process outputs based on error signal history and rate of change. The proposed method boasts easy application, stable convergence, and high computational efficiency, modeled using MATLAB. Comparative analysis with the standard whale optimization algorithm demonstrates superior stability and reduced steady-state error, unaffected by disturbances, and ensuring smooth motor operation. The study explores optimal PID controller parameters under varying resistance and K values to strike a balance between optimality and robustness in system control. The proposed method exhibits enhanced convergence through an updated whale optimization algorithm, ensuring optimal control with minimal settling time and overshoot. Simulation results validate the efficacy of the proposed technique in achieving dynamic system performance superior to standard WOA-PID controllers.

In [8] Introduces Archimedes Optimization Algorithm (AOA) and Dispersive Flies Optimization (DFO) for tuning PID control parameters to regulate DC motor speed. The techniques minimize the ITAE fitness function using MATLAB/Simulink simulations. AOA-PID-ITAE and DFO-PID-ITAE outperform Ziegler-Nichols (ZN) and Particle Swarm Optimization (PSO) methods, reducing rise and settling times. DC motors play a crucial role in various applications due to their precision and continuous control. PID controllers, incorporating proportional integral derivative components, are widely used but conventional tuning methods are time-consuming. Metaheuristic techniques like AOA and DFO offer faster convergence and superior performance compared to ZN and PSO, ensuring optimal PID controller performance in diverse applications.

The authors in [9] presents the application of Harris Hawks Optimization (HHO) algorithm to tune a PID controller for DC motor speed regulation, aiming to minimize the integral of time multiplied absolute error (ITAE).

Comparative analyses with other controllers such as Atom Search Optimization (ASO), Grey Wolf Optimization (GWO), and Sine-Cosine Algorithm (SCA) demonstrate the superior effectiveness and robustness of the proposed HHO/PID controller. The study highlights the significance of meta-heuristic algorithms in real-world engineering applications and introduces a novel approach to enhance DC motor speed control. The HHO algorithm, inspired by Harris' hawks' hunting strategies, has been successfully applied in various domains, but its application for tuning PID controller parameters in DC motor speed regulation is novel. Through simulation and analysis, the study showcases the improved performance of the HHO/PID controller compared to existing methods, indicating its potential for enhancing stability and robustness in DC motor speed control systems.

The authors in [10] focuses on optimizing PID controller tuning for DC motor control using Genetic Algorithm (GA). It compares GA-PID with Ziegler & Nichols method, assessing parameters such as Mean Square Error (M.S.E) and Integral of Time multiplied by Absolute Error (I.TA.E). PID controllers are widely used due to their simplicity and reliability, offering robust performance in various system dynamics. GA-based tuning improves transient response, reducing rise time and overshoot. The study demonstrates that GA provides superior results compared to traditional methods, enhancing speed and position control of DC motors effectively. Through simulation and analysis, the paper underscores GA's efficacy in achieving optimized PID parameters for precise control of DC motors.

The paper [11] introduces a novel approach for tuning PID controllers using the Crow Search Algorithm (CSA) to enhance the performance of DC motors. Traditional methods for PID tuning often require manual adjustments and lack accuracy. The proposed method utilizes a hybrid PID-CSA predictive model to optimize PID parameters, offering improved tracking performance and stability. Comparative analyses with various error indicator functions and other tuning techniques like Ziegler-Nichols and PSO Optimization demonstrate the superiority of PID-CSA in terms of steady-state error, stability, overshoot, rise time, and settling time. The study emphasizes the importance of automatic adjustment methods for PID controllers in industrial applications and highlights the effectiveness of CSA in control engineering. The paper is structured to provide an introduction to CSA, an overview of DC motor systems and controllers, detailed discussion on the design and performance of SCA-PID controllers, and concluding remarks on the proposed system's effectiveness. Experimental results confirm the superior performance of CSA-optimized PID controllers compared to conventional methods, showcasing improved transient and static response parameters.

The study [12] explores Genetic Algorithm (GA) optimization for tuning PID controllers in brushed DC motor velocity control, aiming to enhance performance compared to classical tuning methods like Ziegler-Nichols and Skogestad IMC. By modifying the Integral of Time Multiplied by Absolute Error (ITAE) fitness function to include specific weights on performance metrics like rise time, settling time, overshoot percentage, and steady-state error, GA optimization achieves superior outcomes. The modified ITAE fitness function significantly improves rise time and settling time by 76.63% and 78.29%, respectively, compared to traditional methods. Although it may result in slightly larger steady-state error, it remains acceptable for velocity control applications. Further evaluation in real-life applications, comparing simulation with real-time performance, is suggested for future work. This paper highlights the effectiveness of GA optimization in achieving better PID controller performance compared to classical tuning methods.

The [13] presents a speed controller for a DC motor using PID parameters optimized through Genetic Algorithm (GA). Despite its widespread use in various applications, DC motors exhibit nonlinear behavior, necessitating effective control strategies. The study compares optimization techniques such as GA with traditional tuning methods for PID controllers. Results demonstrate the superiority of GA-based optimization in achieving improved performance metrics such as minimal rise time, settling time, overshoot, and steady-state error. The utilization of GA yields enhanced performance compared to conventional PID controllers, highlighting the effectiveness of evolutionary algorithms in tuning control parameters for DC motor speed control.

Chapter Three

3.1 Dc motor

DC motors are actuators that produce angular rotation when supplied with electrical energy. They have significant importance in various electrical systems employed in domestic and industrial applications such as electrical vehicles, industrial mills and cranes, robots, and multiple home appliances. This importance is due to their advantageous characteristics like precision, convenience, and continuous control. In order to drive the DC motor at appropriate speed or torque.

3.1.1 Modelling of Separately Excited D.C Motor

To realize the D.C Motor drive as a control system transfer function, following steps to be done in MATLAB:

First step is to characterize the equivalent DC motor circuit diagram. Then step 2 is to characterize system equations from the circuit diagram. Subsequently, step 3 is to derive transfer function from derived system equations. After that Step 4 is the Realization of the equivalent block diagram of system drive. Finally, in step 5 .m file is created for model simulation and to analyze the results.

3.1.2 DC Motor Equivalent Circuit

To execute the simulation of separately excited DC motor drive,the equivalent circuit diagram of motor's mechanical part and electrical portion must be obtained first as shown in Fig.1. Here left model represents the armature circuit of D.C motor and right model represents the field circuit which is separately excited. Field excitation parameters are assumed to be fixed as it is separately excited. Therefore, to make this model simple to study and execute, here field excitation parameters of motor are not taken into account while analyzing the simulation model of motor.

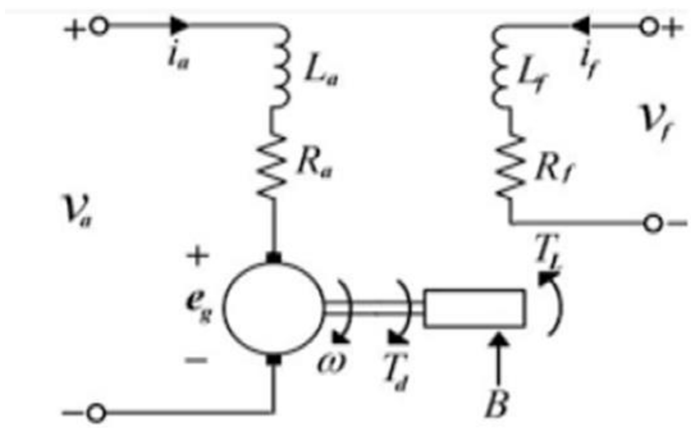

Figure 3.1 Equivalent DC Motor circuit.

In the current research methodology, D.C motor model is modeled in which the rotor is assumed to be a single coil having equivalent inductance expressed as La and equivalent resistance as Ra, therefore representing generated back E.M.F represented as eb. In separately excited dc motor, flux remains constant. The electrical model of separately excited D.C Motor are described by following dynamic equations:

$$\boldsymbol{ea = eb + ia.RaLa.\frac{dia}{dt}} \quad (1)$$

The analogy between generated torque Tm and armature current ia is given by following equation:

$$Tm = Km.\,ia \tag{2}$$

The relation between generated back E.M.F eb and the angular speed is given by the following equation:

$$eb = Kb.\,\omega \tag{3}$$

from equation (1) and (3), we get:

$$ea = Kb.\,\omega + iaRaLa\,\frac{\boldsymbol{dia}}{\boldsymbol{dt}} \tag{4}$$

The equivalent dynamic equation for mechanical system of motor is as follows:

$$Tm = Kmia = J\,\frac{\boldsymbol{dw}}{\boldsymbol{dt}} + Kf\omega + Td \tag{5}$$

3.1.3 Model Block Diagram

Using Laplace transformation technique for equation (4) and (5), following equations are derived:

$$ea(s) = Kb.\,\omega(s) + ia(s).\,Ra + La(s).\,ia \tag{6}$$

and subsequently

$$Tm(s) = Km.\,ia(s) = J.\,\omega(s) + Kf.\,\omega(s) + Td(s) \tag{7}$$

Therefore, from equation (7), armature current is expressed as:

$$ia(s) = [ea(s) - Kb.\omega(s)]\,/\,[Ra + La(s)] \tag{8}$$

and from equation (8), output speed is represented:

$$\omega(s) = [Tm - Td(s)]/[J + Kf] \quad (9)$$

Where,

ea = Armature Voltage (V)

La = Armature Inductance (H)

Ia = Armature Current (A)

Ra = Armature Resistance (ohm)

J = Mechanical Inertia (kg-m2)

eb = Back EMF (V)

Kf = Friction Coefficient (N-m/ rad/ sec)

Td = Torque Disturbance (N-m)

Km = Motor Torque Constant (N-m/ rad)

ω = Angular Speed (rad/sec)

Kb = Back EMF Constant (V/rad/sec)

Tm = Mechanical Torque Developed (N-m)

The block diagram developed from previously stated equivalent circuit equations is as shown in Fig.(3.2)

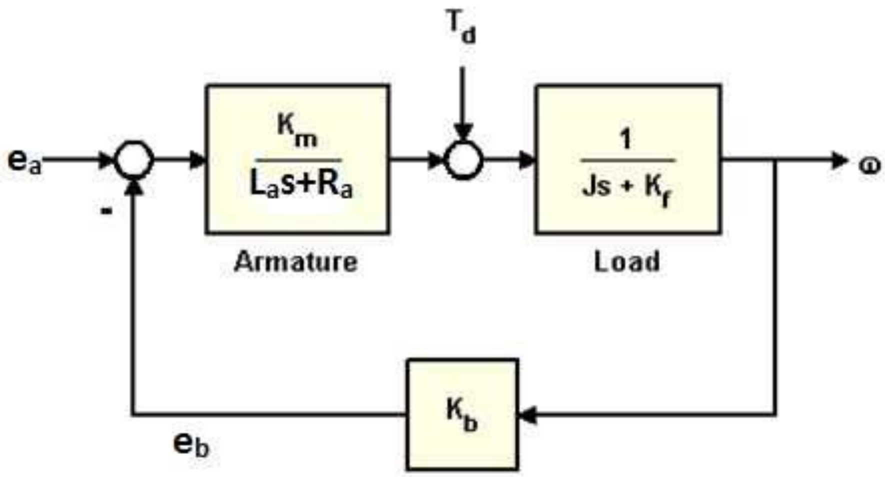

Figure 2.2 Block Diagram of DC Motor.

Control system closed loop system shown in **Fig. 3.2** has the mechanical system Laplace function and electrical system Laplace function stated separately. They are further combined to realize the output motor speed (ω) and from which we can estimate the position of rotor. From this transfer function we can also study about output armature current of motor. Transfer thus obtained is of second order system. Then to control this control system, P.I.D. controller used in forward path From motor equivalent equations and by using specific standard values of parameters, D.C motor model is realized. The D.C motor parameters used in this research paper are defined in equation (10).

Kf = .018,

Km = Kb = 1.4,

Ra = 2 ohms,

La = 16.2 mH

J = 0.117 KgM2,

Va = 220 volts,

Td = 1 N-m,

Thus, the final of transform function is shown in equation (10).

$$\omega = \frac{1.4}{s^3(0.001895) + 0.2349s + 1.996} \tag{10}$$

By equation (10) the expression of rotor position of motor is also calculated. Analyzing the position of rotor of D.C Motor is also a very keen aspect and difficult because the transfer function of position is of third order control

system. Position of rotor is expressed as Ө expressed and its transfer function is expressed in equation (11).

$$\theta = \frac{1.4}{s^3(0.001895) + 0.2349s^2 + 1.996s} \tag{11}$$

Thus, this paper uses the transfer function of rotor position of motor as its plant function and to this PID controller is attached to control the position of motor.

3.2 Optimization algorithm

3.2.1 Equilibrium Optimization (EO):

This section presents the inspiration, mathematical model, and algorithm of the Equilibrium Optimizer (EO).

3.2.1.1 Inspiration:

The inspiration for the EO approach is a simple well-mixed dynamic mass balance on a control volume, in which a mass balance equation is used to describe the concentration of a nonreactive constituent in a control volume as a function of its various source and sink mechanisms. The mass balance equation provides the underlying physics for the conservation of mass entering, leaving, and generated in a control volume. A first-order ordinary differential equation expressing the generic mass-balance equation [14], in which the change in mass in time is equal to the amount of mass that enters the system plus the amount being generated inside minus the amount that leaves the system, is described as:

$$V\frac{\mathrm{dc}}{\mathrm{dt}} = \mathrm{Q\,Ceq} - \mathrm{QC} + \mathrm{G} \tag{12}$$

C is the concentration inside the control volume (V), V $\frac{dc}{dt}$ is the rate of change of mass in the control volume, Q is the volumetric flow rate into and out of the control volume, Ceq represents the concentration at an equilibrium state in which there is no generation inside the control volume, and G is the mass generation rate inside the control volume. When V $\frac{dc}{dt}$ reaches to zero, a steady equilibrium state is reached. A rearrangement of Eq. (12) allows to solve for $\frac{dc}{dt}$ as a function of $\frac{Q}{V}$; where $\frac{Q}{V}$ represents the inverse of the residence time, referred to here as λ, or the turnover rate (i.e., $\lambda = \frac{Q}{V}$). Subsequently, Eq.(12)can also be rearranged to solve for the concentration in the control volume (C) as a function of time (t):

$$\frac{dc}{\lambda\,Ceq - \lambda C + \frac{G}{V}} = dt \tag{13}$$

Eq. (13) shows the integration of Eq. (12) over time:

$$\int_{c0}^{c} \frac{dc}{\lambda\,Ceq - \lambda C + \frac{G}{V}} = \int_{t0}^{t} dt \tag{14}$$

This results in:

$$C = C_{eq} + (C_0 - C_{eq})\,F + \frac{G}{\lambda V}\,(1 - F) \tag{15}$$

In the Eq. (15), F is calculated as follows:

$$F = \exp\,[-\lambda\,(t - t0)] \tag{16}$$

where t_0 and C_0 are the initial start time and concentration, dependent on the integration interval. Eq. (4) can be used to either estimate the concentration in the control volume with a known turnover rate or to calculate the average turnover rate using a simple linear regression with a known generation rate and other conditions.

EO is designed in this sub-section using the above equations as the overall framework. In EO, a particle is analogous to a solution and a concentration is analogous to a particle's position in the PSO algorithm. As Eq. (4) shows, there are three terms presenting the updating rules for a particle, and each particle updates its concentration via three separate terms. The first term is the equilibrium concentration, defined as one of the best-so-far solutions randomly selected from a pool, called the equilibrium pool. The second term is associated with a concentration difference between a particle and the equilibrium state, which acts as a direct search mechanism. This term encourages particles to globally search the domain, acting as explorers. The third term is associated with the generation rate, which mostly plays the role of an exploiter, or solution refiner, particularly with small steps, although it sometimes contributes as an explorer as well. Each term and the way they affect the search pattern is defined in the following.

3.2.1.2 Initialization and function evaluation:

Similar to most meta-heuristic algorithms, EO uses the initial population to start the optimization process. The initial concentrations are constructed based on the number of particles and dimensions with uniform random initialization in the search space as follows:

$$C_{\text{initial } i} = C_{\min} + \text{rand}_i\,(C_{\max} - C_{\min}) \qquad i = 1, 2, \ldots n \tag{17}$$

C initial i is the initial concentration vector of the ith particle, Cmin and Cmax denote the minimum and maximum values for the dimensions, Rand i is a random vector in the interval of [0, 1], and n is the number of particles as the population. Particles are evaluated for their fitness function and then are sorted to determine the equilibrium candidates.

3.2.1.3 Equilibrium pool and candidates (Ceq) :

The equilibrium state is the final convergence state of the algorithm, which is desired to be the global optimum. At the beginning of the optimization process, there is no knowledge about the equilibrium state and only equilibrium candidates are determined to provide a search pattern for the particles. Based on different experiments under different type of case problems, these candidates are the four best-so-far particles identified during the whole optimization process plus another particle, whose concentration is the arithmetic mean of the mentioned four particles. These four candidates help EO to have a better exploration capability, while the average helps in exploitation. The number of candidates is arbitrary and based on type of the optimization problem. One might use other numbers of candidates (e.g. 14 or 16). which is consistent with the literature [14]. For example, GWO uses three best-so-far candidates (alpha, beta, and gamma wolves) to update the positions of the other wolves. However, using less than four candidates degrades the performance of the method in multimodal and composition functions but will improve the results in unimodal functions. More than four candidates will have the opposite effect. These five particles are nominated as equilibrium candidates and are used to construct a vector called the equilibrium pool:

$$\vec{C}_{eq,pool} = \{ \vec{C}_{eq(1)}, \vec{C}_{eq(2)}, \vec{C}_{eq(3)}, \vec{C}_{eq(4)}, \vec{C}_{eq(ave)} \} \quad (18)$$

Each particle in each iteration updates its concentration with random selection among candidates chosen with the same probability. For instance, in the first iteration, the first particle updates all of its concentrations based on $\vec{C}_{eq(1)}$; then, in the second iteration, it may update its concentrations based on $\vec{C}_{eq(ave)}$. Until the end of the optimization process, each particle will experience the updating process with all of the candidate solutions receive approximately the same number of updates for each particle.

3.2.1.4. Exponential term (F)

The next term contributing to the main concentration updating rule is the exponential term (F). An accurate definition of this term will assist EO in having a reasonable balance between exploration and exploitation. Since the turnover rate can vary with time in a real control volume, λ is assumed to be a random vector in the interval of [0, 1].

$$F=e-\vec{\lambda}(t-t0) \tag{19}$$

where time, t, is defined as a function of iteration (Iter) and thus decreases with the number of iterations:

$$F=e-\vec{\lambda}(t-t0) \tag{20}$$

$$t=(1-\frac{Iter}{Max_{iter}})^{(a2\ (Iter\ )/(Max\_iter\ ))} \tag{21}$$

where Iter and Max_iter present the current and the maximum number of iterations, respectively, and a2 is a constant value used to manage exploitation ability. In order to guarantee convergence by slowing down the search speed along with improving the exploration and exploitation ability of the algorithm, this study also considers**:**

$$\vec{t}_0 = \frac{1}{\vec{\lambda}} \ln(-a1 \mathrm{sign}\ (\ \vec{r} - 0.5\ )\ [1 - e^{-\vec{\lambda} t}\ ]) + t \tag{22}$$

where a1 is a constant value that controls exploration ability. The higher the a1, the better the exploration ability and consequently the lower exploitation performance. Similarly, the higher the a2, the better the exploitation ability and the lower the exploration ability. The third component, sign (r − 0.5), effects on the direction of exploration and exploitation. r is a random vector between 0 and 1. For all of the problems subsequently solved in this paper, a1 and a2 are equal to 2 and 1, respectively. These constants are selected through empirical testing of a subset of test functions. However, these parameters can be tuned for other problems as needed. Eq. (23) shows the revised version of Eq. (20) with the substitution of Eq. (22) into Eq. (20):

$$\vec{F} = a1 \text{sign} (\vec{r} - 0.5) [e^{-\vec{\lambda} t} - 1] \tag{23}$$

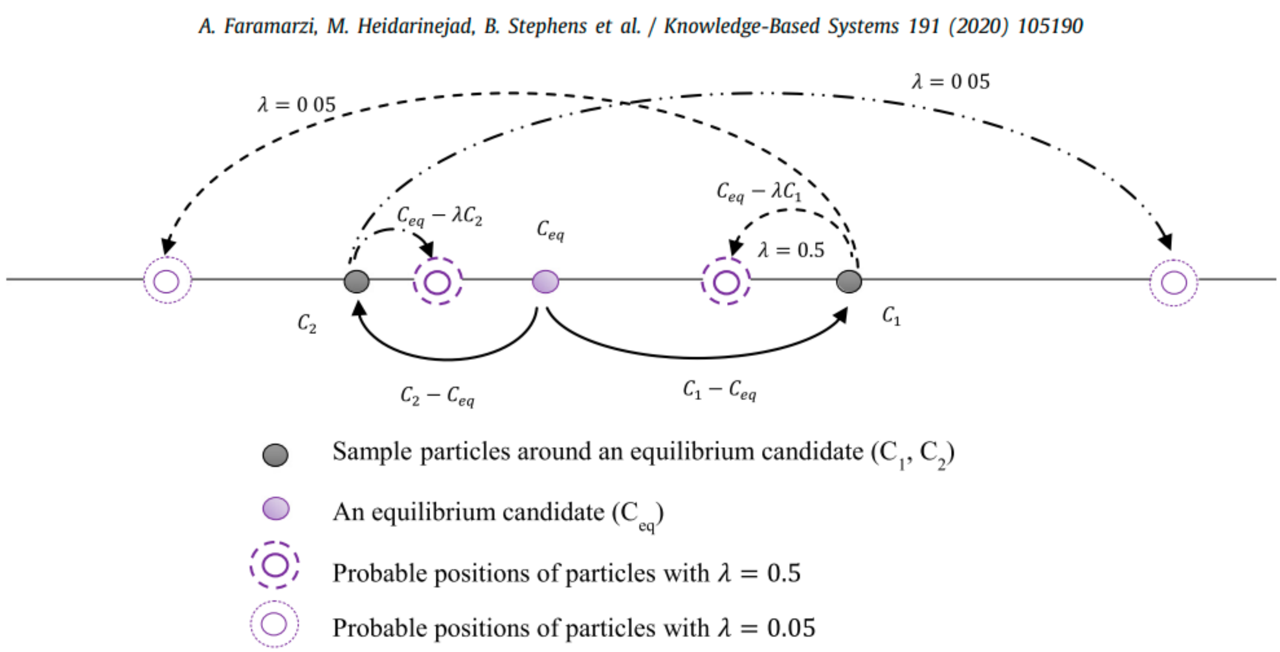

Figure 3.3 presentation of concentrations updating aid in exploration and exploitation.

3.2.1.4. Generation rate (G):

The generation rate is one of the most important terms in the proposed algorithm to provide the exact solution by improving the exploitation phase. In many engineering applications, there are many models that can be used to express the generation rate as a function of time [15]. For example, one multipurpose model that describes generation rates as a first order exponential decay process is defined as:

$$G^{\vec{}} = G_0 e^{-k^{\vec{}}(t-t0)} \tag{24}$$

where G0 is the initial value and k indicates a decay constant. In order to have a more controlled and systematic search pattern and to limit the number of random variables, this study assumes k = λ and uses the previously derived exponential term. Thus, the final set of generation rate equations are as follows:

$$G= G_0 e^{-\lambda(t-t0)} = G_0 F \tag{25}$$

where:

$$G_0= GCP\ (C_{eq} - \lambda C) \tag{27}$$

$$GCP= \begin{cases} 0.5\boldsymbol{r_1} & \boldsymbol{r_2} \geq GP \\ 0 & \boldsymbol{r_2} < GP \end{cases} \tag{28}$$

where $\boldsymbol{r_1}$ and $\boldsymbol{r_2}$ are random numbers in [0, 1] and GCP vector is constructed by the repetition of the same value resulted from Eq. (28). In this equation, GCP is defined as the Generation rate Control Parameter, which includes the possibility of generation term's contribution to the updating process. The probability of this contribution which specifies how many particles use generation term to update their states is determined by another term called Generation Probability (GP). The mechanism of this contribution is determined by Eqs. (27) and (28). Eq. (28) occurs at the level of each particle. For example, if GCP is zero, G is equal to zero and all the dimensions of that specific particle are updated without a generation rate term. A good balance between exploration and exploitation is achieved with GP = 0.5. Finally, the updating rule of EO will be as follows:

$$C = C_{eq} + (C - C_{eq}).F + \frac{G}{\lambda V}(1 - F) \tag{29}$$

where F is defined in Eq. (22), and V is considered as unit. The first term in Eq. (27) is an equilibrium concentration, where the second and third terms represent the variations in concentration. The second term is responsible for globally searching the space to find an optimum point. This term contributes more to exploration, thereby taking advantage of large variations in concentration (i.e., a direct difference between an equilibrium and a sample particle). As it finds a point, the third term contributes to making the solution more accurate. This term thus contributes more to exploitation and benefits from small variations in concentration, which are governed by the generation rate term (Eq. (24)). Depending on parameters such as the concentrations of particles and equilibrium candidates, as well as the turnover rate (λ), the second and third terms might have the same or opposite signs. The same sign makes the variation large, which helps to better search the full domain, and the opposite sign makes the variation small, aiding in local searches. Although the second term attempts to find solutions relatively far from equilibrium candidates and the third term attempts to refine the solutions closer to the candidates, this is not always happening. Small turnover rates (e.g., ≤0.05) in the denominator of the third term increase its variation and helps the exploration in some dimensions as well. Fig. 3.2 demonstrates a 1-D version of how these terms contribute to exploration and exploitation.

$C_1 - Ceq$ is representative of the second term in Eq. (27) while $Ceq - \lambda C1$ represents the third term (G is the function of G_0). The generation rate terms (Eqs. (24)–(25)) control these variations. Because λ changes with each dimension's change, this large variation only happens to those dimensions with small values of λ. It is worth mentioning that this feature works similar to a mutation operator in evolutionary algorithms and greatly helps EO to exploit the solutions. Fig. 3.3 shows a conceptual sketch of the collaboration of all equilibrium candidates on a sample particle and how they affect concentration updating, one after another, in the proposed algorithm. Since the topological positions of equilibrium candidates are diverse in initial iterations, and the exponential term generates large random numbers, this step by step updating process helps the particles to cover the entire domain in their search. An opposite scenario happens in the last iterations, when the candidates surround the optimum point by similar configurations. At these times, the exponential term generates small random numbers, which helps in refining the solutions by providing smaller step sizes. This concept can also be extended to higher dimensions as a hyperspace whereby the concentration will be updated with the particle's movement in n-dimensional space.

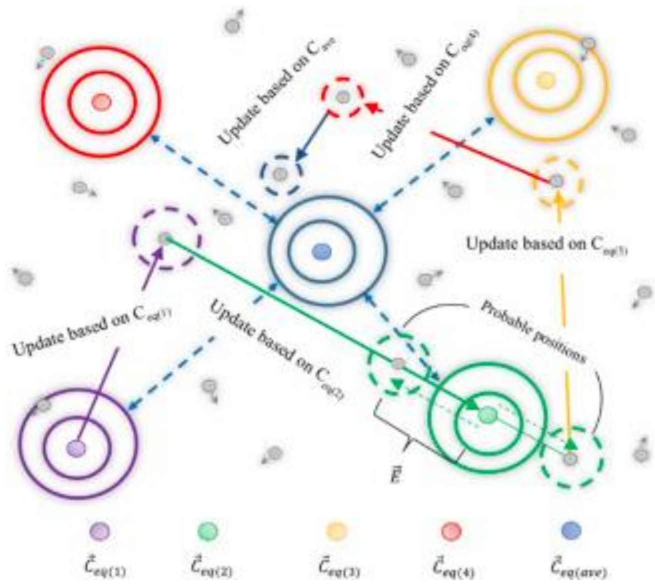

Figure 3.4 Equilibrium candidates' collaboration in updating a particles' concentration in 2D dimensions.

3.2.1.5 Particle's memory saving

Adding memory saving procedures assists each particle in keeping track of its coordinates in the space, which also informs its fitness value. This mechanism resembles the pbest concept in PSO. The fitness value of each particle in the current iteration is compared to that of the previous iteration and will be overwritten if it achieves a better fit. This mechanism aids in exploitation capability but can increase the chance of getting trapped in local minima if the method does not benefit from global exploration ability [16].

3.2.2 The Whale Optimization Algorithm

In this section the inspiration of the proposed method is first discussed. Then, the mathematical model is provided.

3.2.2.1 Inspiration

Whales are fancy creatures. They are considered as the biggest mammals in the world. An adult whale can grow up to 30 m long and 180 t weight. There are 7 different main species of this giant mammal such killer, Minke, Sei, humpback, right, finback, and blue. Whales are mostly considered as predators. They never sleep because they have to breathe from the surface of oceans. In fact, half of the brain only sleeps. The interesting thing about the whales is that they are considered as highly intelligent animals with emotion. According to Hof and Van Der Gucht [17], whales have common cells in certain areas of their brains similar to those of human called spindle cells. These cells are responsible for judgment emotions and social behaviors in humans. In other words the spindle cells make us distinct from other creatures. Whales have twice number of these cells than an adult human which is the main cause of their smartness. It has been proven that whale can think, learn judge communicate, and become even emotional as a human does, but obviously with a much lower level of smartness. It has been observed that whales (mostly killer whales) are able to develop their own dialect as well. Another interesting point is the social behavior of whales. They live alone or in groups. However, they are mostly observed in groups. Some of their species (killer whales for instance) can live in a family over their entire life period. One of the biggest baleen whales is humpback whales (Megaptera novaeangliae). An adult humpback whale is almost as size of a school bus Their favorite prey are krill and small fish herds. Fig. 3.5 shows this mammal.

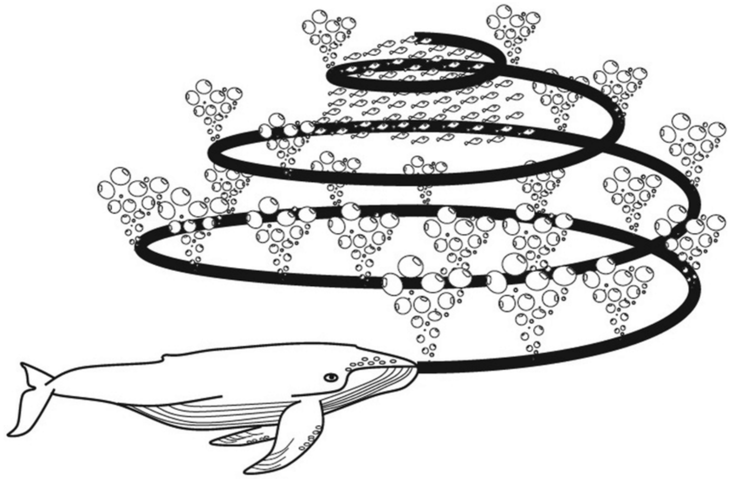

Fig. 3.5. Bubble-net feeding behavior of humpback whales

3.2.2.2 Mathematical model and optimization algorithm

In this section the mathematical model of encircling prey, spiral bubble-net feeding maneuver, and search for prey is first provided. The WOA algorithm is then proposed.

3.2.2.2.1 Encircling prey

Humpback whales can recognize the location of prey and encircle them. Since the position of the optimal design in the search space is not known a priori, the WOA algorithm assumes that the current best candidate solution is the target prey or is close to the optimum. After the best search agent is defined, the other search agents will hence try to update their positions towards the best search agent. This behavior is represented by the following equations:

$$\overrightarrow{D'} = |\ \vec{C}\ \overrightarrow{x^*}(t) - \vec{x}(t)| \tag{30}$$

$$\vec{x}(t+1) = |\overrightarrow{x^*}(t) - \vec{A}.\overrightarrow{D}| \tag{31}$$

where t indicates the current iteration, A and C are coefficient vectors, X^* is the position vector of the best solution obtained so far, X is the position vector, | | is the absolute value, and · is an element-by-element multiplication. It is worth mentioning here that X^* should be updated in each iteration if there is a better solution. The vectors A and C are calculated as follows:

$$\vec{A} = 2\,\vec{a}.\vec{r} - \vec{a} \quad (32)$$

$$\vec{C} = 2.\,\vec{r} \quad (33)$$

where a is linearly decreased from 2 to 0 over the course of iterations (in both exploration and exploitation phases) and r is a random vector in [0,1].

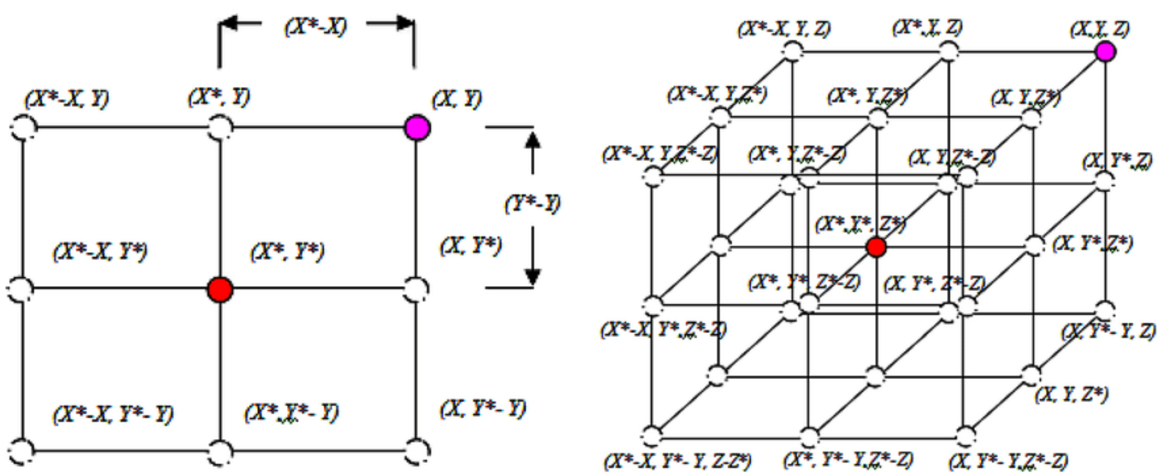

Fig. 3.6 . 2D and 3D position vectors and their possible next locations ($X^*$is the best solution obtained so far)

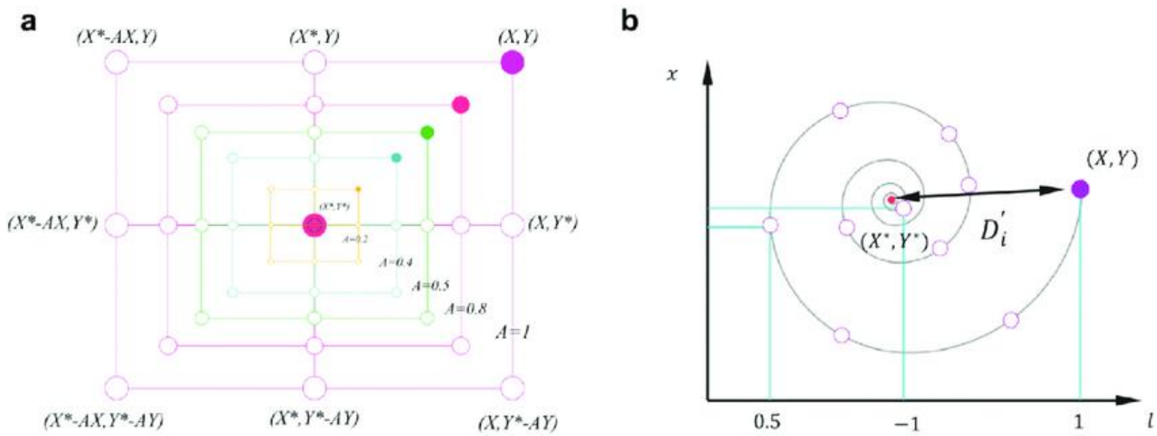

Fig. 3.7. Bubble-net search mechanism implemented in WOA (X^* is the best solution obtained so far): (a) shrinking encircling mechanism and (b) spiral updating position

Fig. 3.7(a) illustrates the rationale behind Eq. (30) for a 2D problem. The position (X,Y) of a search agent can be updated according to the position of the current best record (X^*, Y^*). Different places around the best agent can be achieved with respect to the current position by adjusting the value of A and C vectors. The possible updating position of a search agent in 3D space is also depicted in Fig. 3.7(b). It should be noted that by defining the random vector (r) it is possible to reach any position in the search space located between the key-points shown in Fig. 3.7 Therefore, Eq. (30) allows any search agent to update its position in the neighborhood of the current best solution and simulates encircling the prey. The same concept can be extended to a search space with n dimensions, and the search agents will move in hyper-cubes around the best solution obtained so far. As mentioned in the previous section, the humpback whales also attack the prey with the bubble-net strategy. This method is mathematically formulated as follows:

3.2.2.2.2 Bubble-net attacking method (exploitation phase)

In order to mathematically model the bubble-net behavior of humpback whales, two approaches are designed as follows:

Shrinking encircling mechanism: This behavior is achieved by decreasing the value of a in the Eq. (31). Note that the fluctuation range of A is also decreased by a. In other words A is random value in the interval [−a,a] where a is decreased from 2 to 0 over the course of iterations. Setting random values for A in [−1,1], the new position of a search agent can be defined anywhere in between the original position of the agent and the position of the current best agent. Fig. 3.7(a) shows the possible positions from (X,Y) towards (X^*, Y^*). that can be achieved by 0≤ A ≤1 in a 2D space.

Spiral updating position: As can be seen in Fig. 4(b), this approach first calculates the distance between the whale located at (X,Y) and prey located at (X^*, Y^*). A spiral equation is then created between the position of whale and prey to mimic the helix-shaped movement of humpback whales as follows:

$$\vec{x}(t+1) = \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{x^*}(t) \tag{34}$$

$$\overrightarrow{D'} = |\overrightarrow{x^*}(t) - \vec{x}(t)| \tag{35}$$

and indicates the distance of the it whale to the prey (best solution obtained so far), b is a constant for defining the shape of the logarithmic spiral, l is a random number in [−1,1], and . is an element-by-element multiplication.

Note that humpback whales swim around the prey within a shrinking circle and along a spiral-shaped path simultaneously. To model this simultaneous behavior, we assume that there is a probability of 50% to choose between either the shrinking encircling mechanism or the spiral model to update the position of whales during optimization. The mathematical model is as follows:

$$\vec{x}(t+1) = \begin{cases} \overrightarrow{x^*}(t) - \vec{A}.\overrightarrow{D} & , \quad if \;\; \mathrm{p} < 0.5 \\ \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{x^*}(t), & \quad if \; p \geq 0.5 \end{cases} \tag{36}$$

where p is a random number in [0,1]. In addition to the bubble-net method, the humpback whales search for prey randomly. The mathematical model of the search is as follows.

3.2.2.2.3 Search for prey (exploration phase)

The same approach based on the variation of the A vector can be utilized to search for prey (exploration). In fact, humpback whales search randomly according to the position of each other.

Therefore, we use A with the random values greater than 1 or less than −1 to force search agent to move far away from a reference whale. In contrast to the exploitation phase, we update the position of a search agent in the exploration phase according to a randomly chosen search agent instead of the best search agent found so far. This mechanism and |A| > 1 emphasize exploration and allow the WOA algorithm to perform a global search. The mathematical model is as follows:

$$\begin{gathered} \vec{D} = |\vec{C}.\overrightarrow{X_{rand}} - \vec{X}\,| \\ \vec{x}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \end{gathered} \tag{37}$$

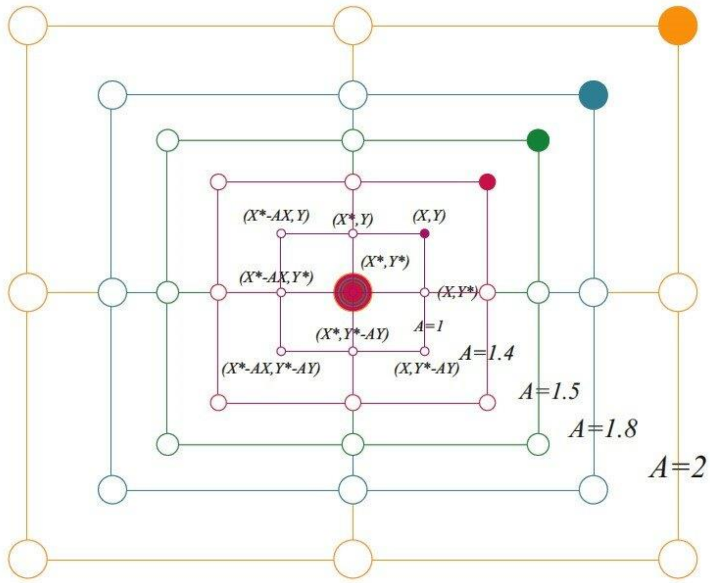

Fig. 3.8. Exploration mechanism implemented in WOA (X* is a randomly chosen search agent)

Chapter Four

RESULTS AND DISCUSSIONS

A set of better PID controller parameters can provide great response which results in the time domain minimizing performance criteria. Such efficiency requirements include minimizing overshoot, rise time, setting time, and steady state error. The proposed PID controller uses a EO and WOA algorithms to identify optimum system parameters for the DC Motor. The most important step in applying proposed algorithms in the control system is to select the cost function, which is utilized to evaluate the fitness of each Crow agent (*Kp, Ki, Kd*). Furthermore, in this work, the proposed cost function depends on different performance indicators to explain clearly how parameters are utilized to highlight how parameters should be addressed in the selection. The system output is also represented by four indices-controlled system: ITAE. These performance indices presented by equations (38) will be used as a part of the cost function as:

$$\boldsymbol{ITAE} = \int_{\mathbf{0}}^{\infty} \boldsymbol{t}|\boldsymbol{e}(\boldsymbol{t})|\, \boldsymbol{dt} \tag{38}$$

The EO-PID and WOA-PID optimizations aim is to achieve a set of PID parameters so that the closed-loop control system has a minimum performance indices. The EO-PID and WOA-PID controller system is implemented using the MATLAB code, which is connected to the Simulink model created. The proposed methodology implements by Intel ® Core TM i7-4700HQ, 2. 4 GHz 16 GB RAM, using the MATLAB framework. The global and specific parameter settings are summarized in Table 1

Table 1 Setting of parameters

Elements	Value
Search Parameter Number	3
Population size	50
Iteration number	100
Search domain	[0,100]

The Fig.(4.1) illustrates the implementation of a PID controller interfaced with the transfer function of a DC motor within a Simulink circuit in MATLAB. This setup allows for the simulation and analysis of the motor's speed control system under the influence of the PID controller. The PID controller is designed to adjust its output based on the error between a desired setpoint and the system's current state, which in this case is the speed of the DC motor. The controller's output then influences the motor's input voltage, effectively controlling its speed.

The transfer function of the DC motor encapsulates the motor's dynamic behavior, representing the relationship between the motor's input voltage and its speed. By connecting the PID controller to the motor's transfer function within the Simulink environment, the overall system's response to various inputs and controller configurations can be simulated and analyzed.

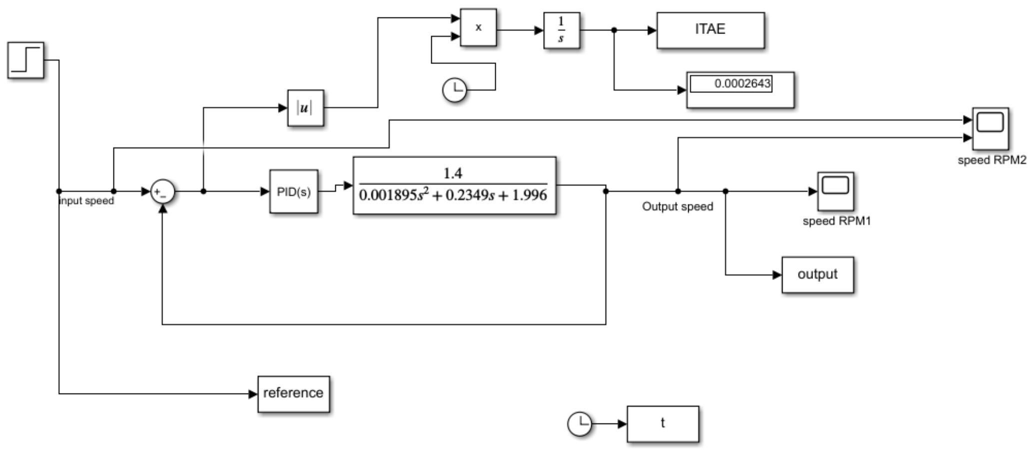

Fig.(4.1) PID-Controlled DC Motor System: Simulink Circuit with Transfer Function.

Table 2 shows the gained PID controller parameters for both metaheuristics-based techniques such as the different versions of proposed EO-PID and WOA-PID controller. In the context of controlling the speed of a DC motor system, a comparative analysis was undertaken between the Proportional-Integral-Derivative (PID) controller enhanced with Whale Optimization Algorithm (WOA) and the Equilibrium Optimization Proportional-Integral-Derivative (EO-PID) controller. As shown in Table 3 the PID-WOA controller demonstrated superior performance in terms of step response criteria. Specifically, the PID-WOA exhibited a minimized overshoot, reduced settling time, shorter rise time, and optimal peak value. These attributes collectively indicate that the PID-WOA controller effectively and rapidly stabilized the motor speed while minimizing overshoot and oscillations.

However, when considering the steady-state error, the EO-PID controller outperformed the PID-WOA. The Integral of Time multiplied by Absolute Error (ITAE) criterion, a common measure of steady-state error, was smaller for the EO-PID controller. This suggests that the EO-PID controller was more effective in eliminating long-term drift and achieving a stable output at steady state.

Interestingly, the value of the derivative gain Kd was determined to be zero in this scenario as shown in Table 2. This implies that a Proportional-Integral (PI) controller could suffice for this system, as the derivative term does not contribute to the system's performance. The elimination of the derivative control could simplify the controller while maintaining satisfactory performance. However, this also indicates that the system does not require a high-frequency noise filter, which is often provided by the derivative term.

Therefore, the choice between the PID-WOA and EO-PID controllers, or even a simpler PI controller, would depend on the specific requirements of the system, such as whether rapid response, steady-state precision, or simplicity and robustness is prioritized.

Table 2. The values of Adjust PID parameters

Methods	**K_p**	**K_i**	**K_d**
PID_WOA ITAE	10.8973413	96.8765	0
PID_EO ITAE	10.8956614	99.9812	0

Table 3. Step response values for PID controllers.

Methods	**Overshoot**	**Settling Time (sec)**	**Rise Time(sec)**	**Peak value**	**ITAE**
PID_WOA ITAE	6.9386	0.0657	0.0219	1.0694	$3.0638*10^{-4}$
PID_EO ITAE	7.3154	0.0669	0.0218	1.0732	$2.6430*10^{-4}$

The figure (4.2) illustrates the system response of the Whale Optimization Algorithm-enhanced Proportional-Integral-Derivative (WOA-PID) controller in comparison with the reference speed and the Equilibrium Optimization Proportional-Integral-Derivative (EO-PID) controller. This comparison provides valuable insights into the performance of the WOA-PID controller in regulating the speed of the system, particularly in relation to the reference speed and the EO-PID controller.

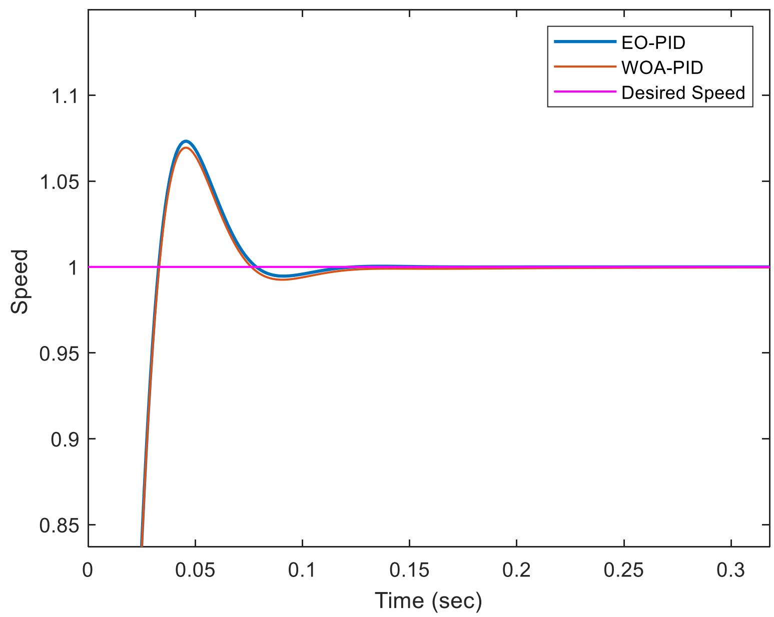

Fig.(4.2) Comparison for step responses of DC motor speed control systems.

Additionally, figure (4.3) showcases the convergence curve of both the WOA-PID and EO-PID algorithms. This convergence curve offers a visual representation of the algorithms' convergence behavior, shedding light on their respective abilities to reach an optimal solution over the course of iterations.

These figures collectively contribute to a comprehensive understanding of the comparative performance and convergence characteristics of the WOA-PID and EO-PID controllers in regulating the system's speed, providing valuable insights for further analysis and optimization of the control system.

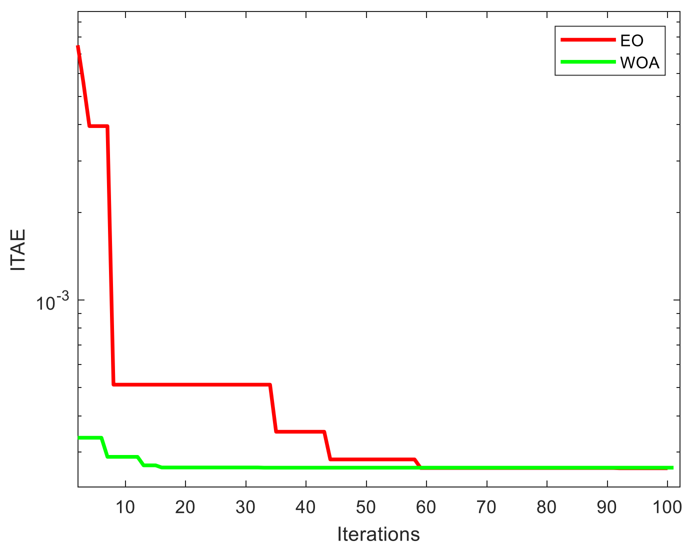

Fig.(4.3) The convergence curve of EO and WOA algorithms.

Chapter Five

Conclusion And Future Work

DC motor control is a very interesting field due to the rapid development of control methods. Weak parameter adjustment will result in dc motor performance. This study, reveals the effectiveness of the PID-WOA controller in minimizing overshoot, settling time, rise time, and peak value in controlling the speed of a DC motor system. However, the EO-PID controller exhibits superior performance in addressing steady-state error as measured by the ITAE criterion. This underscores the significance of considering multiple performance metrics when evaluating control strategies.

Future research could focus on optimizing a hybrid control strategy that leverages the strengths of both PID-WOA and EO-PID controllers to achieve comprehensive performance improvements across various metrics. Additionally, exploring the applicability of these controllers in real-time systems and investigating their robustness under varying operating conditions would be valuable areas for further exploration.

References

[1] El-Telbany, M. E. (2013). Tuning PID controller for DC motor: An artificial bees optimization approach. *International Journal of Computer Applications*, *77*(15).

[2] Aribowo, W., Supari, S., & Suprianto, B. (2022). Optimization of PID parameters for controlling DC motor based on the aquila optimizer algorithm. *International Journal of Power Electronics and Drive Systems*, *13*(1), 216.

[3] Suseno, E. W., & Ma'arif, A. (2021). Tuning of PID controller parameters with genetic algorithm method on DC motor. *International Journal of Robotics and Control Systems*, *1*(1), 41-53.

[4] El-Deen, A. T., Mahmoud, A. H., & El-Sawi, A. R. (2015). Optimal PID tuning for DC motor speed controller based on genetic algorithm. *Int. Rev. Autom. Control*, *8*(1), 80-85.

[5] Rahayu, E. S., Ma'arif, A., & Çakan, A. (2022). Particle Swarm Optimization (PSO) Tuning of PID Control on DC Motor. *International Journal of Robotics & Control Systems*, *2*(2).

[6] Suseno, E. W., & Ma'arif, A. (2021). Tuning of PID controller parameters with genetic algorithm method on DC motor. *International Journal of Robotics and Control Systems*, *1*(1), 41-53.

[7] Razmjooy, N., Vahedi, Z., Estrela, V. V., Padilha, R., & Monteiro, A. C. B. (2020). Speed control of a DC motor using PID controller based on improved whale optimization algorithm. In *Metaheuristics and Optimization in Computer and Electrical Engineering* (pp. 153-167). Cham: Springer International Publishing.

[8] Acharya, B. B., Dhakal, S., Bhattarai, A., & Bhattarai, N. (2021). PID speed control of DC motor using meta-heuristic algorithms. International Journal of Power Electronics and Drive Systems, 12(2), 822.

[9] Ekinci, S., Izci, D., & Hekimoğlu, B. (2020, June). PID speed control of DC motor using Harris hawks optimization algorithm. In 2020 International conference on electrical, communication, and computer engineering (ICECCE) (pp. 1-6). IEEE.

[10] Thomas, N., & Poongodi, D. P. (2009, July). Position control of DC motor using genetic algorithm based PID controller. In Proceedings of the world congress on engineering (Vol. 2, pp. 1-3).

[11] Alkrwy, A., Hussein, A. A., Atyia, T. H., & Khamees, M. (2021, February). Adaptive tuning of PID controller using crow Search algorithm for DC motor. In IOP Conference Series: Materials Science and Engineering (Vol. 1076, No. 1, p. 012001). IOP Publishing.

[12] M. Zahir, A. A., Alhady, S. S. N., Othman, W. A. F. W., & Ahmad, M. F. (2018). Genetic algorithm optimization of PID controller for brushed DC motor. In Intelligent Manufacturing & Mechatronics: Proceedings of Symposium, 29 January 2018, Pekan, Pahang, Malaysia (pp. 427-437). Springer Singapore.

[13] Suman, S. K., & Giri, V. K. (2016, March). Speed control of DC motor using optimization techniques based PID Controller. In 2016 IEEE International Conference on Engineering and Technology (ICETECH) (pp. 581-587). IEEE.

[14]. W.W. Nazaroff, L. Alvarez-Cohen,Environmental Engineering Science, firsted., Wiley,New York, 2000

[15] Z. Guo, Review of indoor emission source models. Part 1. Overview, Environ .Pollut. 120 (2002) 533–549, http://dx.doi.org/10.1016/S0269-7491(02)00187-2.

[16] R.P. Parouha, K.N. Das, A memory based differential evolution algorithm for unconstrained optimization, Appl. Soft Comput. 38 (2016) 501–517, http://dx.doi.org/10.1016/j.asoc.2015.10.022.

[17] Hof PR , Van Der Gucht E . Structure of the cerebral cortex of the humpback whale, Megaptera novaeangliae (Cetacea, Mysticeti, Balaenopteridae). Anat Rec 2007;290:1–31 .