Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7778470

LQR CONTROLLER DESIGN BASED IN ABC-WOA ALGORITHM AND MODEL ORDER REDUCTION

Deepak Kumar Mahto[1] and Jasvir Singh Rana[2]
[1]Department of Electronics and Communication Engineering, Research Scholar, Shobhit University, Gangoh, Saharanpur, India
[2]Department of Electronics and Electrical Engineering, Prof. & Head, Shobhit University, Gangoh, Saharanpur, India
E-Mail: deepak.deepak2510@gmail.com, jasvirsingh.rana@shobhituniversity.ac.in

Abstract**—** Complex and high-order systems are used to express the many technical and scientific applications. The complexity of modelling, evaluating, and regulating these systems is where they face their biggest challenges. More physical insights may be gleaned from simpler models more easily than from more complicated models, which also provide lower-ordering controllers that are simpler to use. The high degree of computational complexity associated with such issues was reduced using the model order reduction (MOR), which was subsequently further enhanced for usage with growing amounts of CDS. To develop a simplified representation of the whole system and a controller based on Linear Quadratic Regulators (LQRs), a novel The abac-Whale Algorithm for Optimization of Artificial Bee Colonies (WOA) approach has been developed in this study. The mod makes use of the combined ABC-WOA benefits. When an algorithm has quick an approach to convergence with few control inputs, straightforward execution, and avoids situations that are either rare or harsh in their immediate vicinity, it becomes superb. First, effective parameters of reduced-order models for initial systems with a higher grade of complexity based on the ABC-WOA are derived. Then, a model with fewer degrees of freedom -optimized parameters for the linear quadratic regulator (LQR) controller. A statistical illustration is used to assess the efficacy of the suggested strategy. The experimental findings show that the lower order model of the suggested method features an excellent value for the near rough estimate of the actual system.
Keywords**—**Whale Algorithm; Linear Quadratic Regulator; ABC Algorithm; Model Order Reduction; equation; Optimization

I. INTRODUCTION

As the system's demand increases, the high price and complicated nature of the controller, also increase. By making the simplified model accessible for the first time in the highest possible framework, this issue may be solved. In the closed-loop, initial high-order structure will perform better The ability of a controller to created utilizing the model of lower order complexity. Reduced- Models in the ROM format are models that are built to order. Ideal engineers working in the fields of analysis, synthesis, and simulation because they minimize design costs and time and make implementation easier[1]. There are many ways that are commonly employed in MOR, but using them does not ensure that the ROM will be stable. The limited nonlinear lease-square minimization problem is used in a post-processing phase in order to manage ROM in order to assure its stability while simultaneously reinforcing and preserving its accuracy.

To implement an MSMIB (modified single machine infinite bus) system, a model order reduction (MOR) design method for power system stabilizers (PSS) employing Enhanced Whale Optimization Code (IWOA) is proposed in [2]. In order for the purpose of creating a ROM pertaining to the MSMIB's higher-order system (HOS) utilizing Integrated squared error (IWOA) (ISE)is taken into account as an objective function. Under varied disturbance situations, the suggested design technique's strength and resilience are evaluated using a range of loading scenarios[3].

Reduction in rank modelling to a greater extent than is the case with linear time continuous (LTIC) (LTIC) SISO systems are characterized by just having a single input and a single output. It was done using the Whale Optimization Algorithm (WOA) in [4]. The method has several noteworthy characteristics, including superior performance, quick convergence, trouble-free implementation, and numerical stability. Three different kinds of systems with complicated roots and repeating poles, as well as one realistic Model of Direct Current Excitation (DC) according to the IEEE of fourth order, have all been used to evaluate the strength of WOA. It's called the "integral square error," and it's a common mistake (ISE) is minimized by way of neutral purpose in current study to acquire all the gain parameters for the low order system's polynomials in the numerator and denominator (LOS). Based on results from ISE, IAE, IRE, and different momentary reaction characteristics, a comparison analysis contains a assessment of the suggested approach with certain famous/recent demand decrease strategies already present in the literature[5].
In this latest iteration of MFO algorithms presented in [6] including the idea for improving the present algorithm's performance and exploration pace as well as for addressing the difficult real-world problems. This OMFO's primary objective is to address the converging problem of search space reduction and prevent local optima. By using it to solve a model order reduction issue, the effectiveness of the suggested approach is shown.
The topic of control systems is highly concerned with the control elements for complex networks (models with extremely high order). In most circumstances, the planned controller's order has to be at least as high in the same way that the macro system does. System becomes progressively more complex when the controller's instruction expands the features of control. There are several decrease in model order strategies that lower in a higher-order system, without sacrificing its defining properties. An optimal controller may be found with the use of a linear quadratic regulator-based design by minimizing a cost function utilizing matrixes Q and R for weighting that equally distribute the state vector and the system input.

This paper's primary goal is to:

- Use an innovative blend of ABC and WOA benefits to implement lowering the complexity of a system-wide model [7].
- Develop a controller that makes use of a Linear Quadratic Regulator (LQR) to assess performance indicators for the frequency and temporal domains.

- MatLab simulates While a LQR is in control, the system's step and frequency responses.

II. Problem formulation

Reduced-order model

Consider the function $G_n(s)$ to be the SISO allocation convenience of the linear time-invariant system of order 'n', with the form indicating how it should be written.

$$G_n(s)=\frac{Nu_n(s)}{De_n(s)}=\frac{c_0+c_1s+c_2s^2+...+c_{n-1}s^{n-1}}{d_0+d_1s+d_2s^2+...+d_ns^n} \quad (1)$$

Where, $c,d:0\le i\le n-1$ are identified scalar coefficients. The aim is to find the $r^{th}(r<n)$ order ROM $G_r(s)$ exemplified by the following form:

$$G_r(s)=\frac{Nu_r(s)}{De_r(s)}=\frac{g_0+g_1s+g_2s^2+...+e_{r-1}s^{r-1}}{h_0+h_1s+h_2s^2+...+d_rs^r} \quad (2)$$

Where, $e,f:0\le i\le n-1$ are unidentified scalar constants. To assess quality of ROM, the difference in mean answers between the the GRS and GNS systems is determined.

$$ISE=\sum_{i=0}^{n}\left[y(t_i)-y_r(t_i)\right]^2 \quad (3)$$

$$G_n(s)=\frac{1}{De_n(s)}\begin{bmatrix} c_{11}(s)c_{12}(s)...c_{1p}(s) \\ c_{12}(s)c_{22}(s)...c_{2p}(s) \\ ... \quad ... \quad ... \quad ... \\ c_{m1}(s)c_{m2}(s)...c_{mp}(s) \end{bmatrix} \quad (4)$$

$$g_{ij}(s)=\frac{a_{ij}(s)}{De_n(s)} \quad (5)$$

$$G_r(s)=\frac{1}{De_r(s)}\begin{bmatrix} g_{11}(s)g_{12}(s)\cdots g_{1p}(s) \\ g_{21}(s)g_{22}(s)\cdots g_{2p}(s) \\ \cdots \quad \cdots \quad \cdots \quad \cdots \\ g_{m1}(s)g_{m2}(s)\cdots g_{mp}(s) \end{bmatrix} \quad (6)$$

$$R_{ij}(s)=\frac{e_{ij}(s)}{De_r(s)} \quad (7)$$

Background

Model order reduction

A method for lowering numerical simulations' computing difficulty due to mathematical model complexity is known for model order reduction (MOR). It has disciplines related to mathematical modelling and is therefore strongly tied to the idea of metamodeling. Due to their complexity and scale, many contemporary Theoretical representations of the real - world procedures present difficulties once applied using computer modelling (dimension). When modelling massively parallel dynamical and control systems, for instance, Ordering models seeks to reduce the computing the difficulty of such a issues[8]. A reduced order model, which is close enough of the prototype, is calculated by reducing the related states and their associated spaces size or the amount of leeway available to the actor. Models with reduced complexity include helpful situations a common occurrence impractical to do full-order computerized model runs. This may be as a result of computing resource constraints demands about the virtual worlds environment, such as actual-time modelling environments the multi-query environments where several simulations must be run. Electronics control systems and model results visualization are situations when a simulation is run in real time whereas design exploration and optimization issues are examples of many-query settings. These are the conditions necessary for a lower order model often the following in order to be relevant to actual problems:

- A minor deviation from the full order model due to approximation.
- Conservation of Property and characterization of the complete order model.
- Reduced order modelling approaches that are resilient and efficient in terms of computation.

Whale Optimization Algorithm (WOA)

WOA is a collective knowledge. method suggested for issues involving continuous optimization. It has been shown that this algorithm performs as well as or better than some of the current algorithmic strategies[9]. WOA has drawn inspiration from the humpback whales' hunting techniques. The concept of a whale is applied to every solution in WOA. In this solution, When the best member of the group is mentioned, a whale will try to go to that spot. The whales employ two different techniques to both attack and locate their prey. In the first, the prey is enclosed, while in the second, bubble nets are made. Whales use an optimal strategy for catching their food. by exploring their environment, and they utilize their environment during an attack. Specifically, this process is referred to as the bubble-net feeding mechanism (Figure 1). The whale creates a dense network of bubbles in a nine-shaped path to get to its destination. WOA is capable of simulating the whole assault strategy. In terms of facilitating the creation of code, the WOA is both straightforward and simple to grasp [10]. WOA uses a smaller number of design parameters compared to alternative heuristic techniques Convergence is quick, and optimal solutions can be obtained with minimal simulation time.

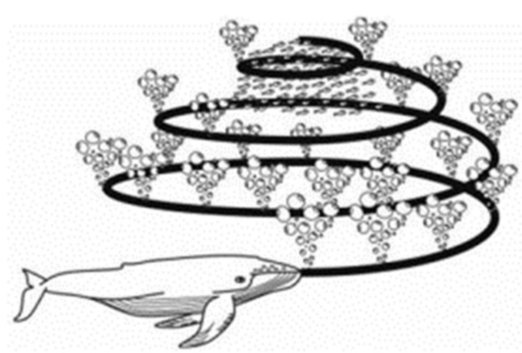

Figure 1

Steps Involved in the WOA Algorithm

[6]Choose the starting limitations for the WOA, such as the the magnitude of the population, as well as the highest possible number of iterations for the algorithm, and any other limitations that are needed. After that, random solutions have been produced to use as a starting point. After then, the WOA's updating will be performed in accordance with the hunting agent's changes. Following is a description of the many different stages that are included in the process of revising the whales in identifying the best possible solutions.

STEP 1 SHRINKING ENCIRCLE MECHANISM FOR THE POSITION UPDATE OF HUNTING AGENT

This current randomly created solutions have been deemed the best answers since the first solutions were generated at random, and the location of the whale is updated using this technique. The whale attacks the target by travelling along a route determined by the equation that is shown below. $\vec{S} = \left| \vec{R} . \vec{P}^{*}(t) - \vec{P}(t) \right|$ (8)

$$\vec{P}(t+1) = \vec{P}^{*}(t) - \vec{A} . \vec{S} \quad (9)$$

Using the equation above, all agents on the search alter their positions. Here, $\vec{S}$ represents the the gap in time and space In the space between both the whale and the prey, $\vec{R}$ and $\vec{A}$ represent those associated with the coefficient vectors, t represents the version being used right now,and P^{*} is to yet, the most effective answer. Orientation scalar is denoted by $\vec{P}$, absolute value is denoted by ||, and one element is multiplied by another using ".". The $\vec{A}$ and $\vec{R}$ vectors are described as

$$\vec{A} = 2 \vec{a} \cdot \vec{r} - \vec{a} \quad (10)$$

$$\vec{R} = 2 \cdot \vec{r} \quad (11)$$

Here, $\vec{r}$ is an arbitrary value that fluctuates between 2 and 0, while $\vec{A}$ is a random integer that fluctuates between 2 and 0. (0,1). During the course of the Through an iterative procedure, the values of a, A, and R for each searching mediator are subject to continuous revision. The active hunting agents are constantly updating their location utilizing Equation (8) if the value of AB is less than 1, & they use the following equation if $\vec{A}$ is more than 1.

$$\vec{S} = \left| \vec{R} \cdot \vec{P}_{rand} - \vec{P} \right| \quad (12)$$

$$\vec{P}(t+1) = \vec{P}^{*}(t) - \vec{A} \cdot \vec{S} \quad (13)$$

This random position vector ($\vec{P}_{rand}$) in this case is selected throughout the procedure from the current populations.

Step 2: Spiral Mechanism for the Position of Updation of Hunting Agent

Hunting agents use both the spiral and a shrinking encircling assault strategy to attack the goal. A spiral equation is developed to approximate the track that takes a spiral shape between the whale and the target. Based on the developed equation stated below, each hunting agent updates their location.

$$\vec{P}(t+1)=\vec{S}\cdot e^{bl}\cdot\cos(2\pi l)+\vec{P}^{*}(t)-\vec{A}\cdot\vec{S} \qquad (14)$$

Where

$$\vec{S}=\left|\vec{P}^{*}(t)-\vec{P}(t)\right| \qquad (15)$$

This stochastic limit "l" in this instance diverges between 0 and 1. Giving each spiral route a 50% chance to revise the locations the people responsible for the hunt so they may find the prey, both spiral itineraries are combined. Finally, every hunting agent proceeds along the route shown by the formula that is shown below.

$$\vec{P}(t+1)=\begin{cases}\vec{P}^{*}(t)-\vec{A}\cdot\vec{S}\, if\ \delta\angle 0.5\\ \vec{S}\cdot e^{bl}\cdot\cos(2\pi l)+\vec{P}^{*}(t)-\vec{A}\cdot\vec{S}\\ if\ \delta\geq\angle 0.5\end{cases} \qquad (16)$$

where δ is a random value differs among 0 and 1.

Artificial Bee Colony (abc) algorithm

ABC model for improvement people as whole that takes its cues from the collective intelligence of a hive of honeybees. The bees that go out to collect food can be broken down into three categories. By the ABC algorithm: workers, tourists, and spies all worked as bees in this operation. Bees who wait for the hive to make a choice about what food to visit are known as Onlookers, whereas bees that proceed to the food source that they have already visited are known as Employed bees. A scout bee is one that searches randomly. The hired bees take use of the food supply, and they also communicate this knowledge to the hive and to bystanders[11]. Scout bees are always looking a search for alternative food supplies close to cluster of bees while viewers bees hang out in the hive at that part of the dance floor for hired bees to provide their knowledge about their found food sources. worker's bees performing a dance specified region within the hive to exchange information about food supplies. What sweet honey they contain the food basis that the dancing bee has recently accessed determines the character of the dance. Spectator bees observe the movement itself Then pick your nutrition supply rendering to the likelihood proportionate to that food source's quality. As a result, superior More people are drawn to sources of food. interested bees than inferior ones[12]. When a food supply is entirely used, all of the bees affiliated with it that are employed leave and turn into scouts. While hired and observer bees might be seen as doing the work It is possible to see the task done by scout bees as one of exploration rather than that of exploitation. Each different source of nourishment is a candidate a remedy for the issue at hand in the ABC algorithm, and the quantity of honey that it contains serves as a stand-in for the effectiveness of the remedy and, via extension, its suitability rate. One worker bee is engaged for each source of nectar or pollen & the total figure of recruited workers is equivalent to total number of nutrition bases.[13].

As a initial stage, the ABC produces a seed population P (C=0) of randomly dispersed SN solutions, also known as nutrition bases location), where SN signifies the population size. A

D-dimension vector represents each nutrition basis (solution) $X_i\left(i=1,2...SN\right)$. D indicates how many optimization parameters are present. Following initialization, the population of the place (solution) is put through several cycles, $C=1,2...C_{\max}$ Throughout the course of the hunt for hired bees, observers, and detectives. A comparison procedure of the place of the food source serves as the foundation for the creation of new positions. The artificial bees in the model, however, do not make use of any comparative data. If the quantity of nectar at the bee will memorize the original place and forget the early place, and they will build a change based on what they can recall from the past as stated in Eq. (18). If not, she remains in her prior position. According to the following equation, the bees belonging to an observer Consider the details of nectar compiled from every source busy bees, and select a nutrition basis with the highest PI value (17)

$$P_i=\frac{fit_i}{\sum_{n=1}^{SN} fit_n} \qquad (17)$$

Where fit_i is the efficiency with which the answer works i as determined by the bee that was used to analyse it, and where fit_i is proportional to the quantity of nectar that the supply of food at site i and SN produces. The knowledge that the worker bees have to provide might then be communicated to the bystanders in this manner. The following expression is used by the ABC in order to generate an innovative food-related role from the previous one (18)

$$v_{ij}=x_{ij}+\phi_{ij}\left(x_{ij}-x_{kl}\right) \qquad (18)$$

Where $k\in\left(1,2,...BN\right)$ and $l\in\left(1,2...D\right)$ are indices that have been picked at random. Even if the k and l are selected at random, they must be distinct from the i and j. A random number between [-1 and 1] is denoted by ϕ_{ij}. It regulates the generation of nearby food supply locations surrounding x_{ij}, and in light of the change is a alignment of neighboring food sources that the bee sees in its field of vision. Equation (18) demonstrates that the disturbance brought by the location of the $x_{i,j}$ also diminishes while comparing the characteristics of the $x_{i,j}$ and $x_{k,l}$ does. As a result, the step length is adaptively shortened as the search gets closer to the search space's best answer. The bee leaves the ancient food basis and goes to the new one if A revised measure of its fitness is higher than the highest possible ability already attained; else, it stays in the old food source. Once every hired bee has completed this procedure, they tell the observers of their fitness, who then Pick a good food source depending on the likelihood of it being available. indicated in Eq (17). With this plan, the excellent The availability of food will increase, Attention than the undesirable ones. Every single bee will look for a well nutrition basis along the surrounding community route Considering a fixed amount of iterations (the limit), and provided that its health benefits does not rise, it turns scout and finds a substitute for the current food supply $x_{i,j}$. It is possible to provide a definition of this process as

$$x_{i,j}=x_j^{\min}+rand\left(0,1\right)*\left(x_j^{\max}-x_j^{\min}\right) \qquad (19)$$

III. PROPOSED METHOD

Detailed description of the proposed abc HAW $_{WOA}$ algorithm

Combining in which application of the whale optimization method's exploiting stage is combined with the stage of startup when changes are made the Achieving optimal performance using ABC method, the suggested HAW optimization algorithm achieves optimal performance. The traditional ABC lacks exploration because to its poor random search strategy and constrained initial food sources. It uses a process known as HAW. Started with an iterative period of mutational inquiry, which allowed it to examine the whole issue space and find new probable locations. The worker bees in this stage of ABC optimization procedure imitate behavior of whales by circling their prey and attacking it with bubbles in order to provide you the most recent data relating to the sites of the nutrition bases. The target prey of WOA is thought to be the finest food basis discovered at each repetition. The HAW has two phases: HAW proposes a mutative initialization phase in the first stage and derives a potential set of diverse solutions from it utilizing various mutations. The another stage proposes an worker bee offensive stage where the starting food source locations are formed by the positions determined by the optimal set of answers from the mutative initialization stage, which imitates whales' manner of attacking their prey. The programme uses the simulated annealing strategy to break out of resident optimal places and prevent looping difficulties during the worker bee attack stage. The HAW algorithm's flowchart is shown in the diagram below. Here is a summary of the suggested HAW optimization:

- In order to increase the pace of the search during the exploration phase, To begin with, we suggest a mutable initialization stage.
- It is proposed that, while foraging, worker bees engage in an assaulting phase, taking a cue from whales' predator trapping/bubble net assaulting strategy. The greatest food supply so far discovered (whales' prey) serves as a guidance for the exploitation of the worker bee offensive stage.
- Simulated Annealing (SA) based worker assaulting stage is projected as a means of escaping from poor position and avoiding looping issues.
- In accordance with the guidelines for the standard ABC optimization, the spectator bee stage and scout bee stage are carried out.

Initialization and fitness calculation

The presence of food provides a partial answer to the optimization issue. The "dim" multitude of different factors, denoting the measurement of the issue space, is used to create each food source. Equation 20 is used to generate the initial population by randomly distributing food sources. A_{kt}^{l} stands for the food source kt^{th} variable with $kt = 1, 2, ...N$, where N is the largest possible magnitude for the food bases.

$$A_{kt}^{l} = A_{mn}^{l} + rand\left(0,1\right) * \left(A_{mx}^{l} - A_{mn}^{l}\right) \qquad (20)$$

$N = 1, 2...\dim$, where "dim" refers to the measurement determined by the quantity of limitations in the primary optimization issue at hand. The random integer created from 0 to 1 is random (0,1). In this case, the upper limit is i^{th} variable of the optimization problem is represented by A_{mx}^{l}, while the lowest bound is provided by A_{mn}^{l}.

Following is the algorithm for the first making new food sources available.

Algorithm 3 : Initialization of the proposed HAW

Generation of Initial population

Form m = 1 to i do

For n = 1 d do

$Y_m^n = Y_{\min}^n + random(0,1) * (Y_{\max}^n - Y_{\min}^n)$

End for n

End for m

Affinity Evaluation and sorting

For m = 1 to i do

Compute fitness (Y_m)

Sort (Y_m) based on fitness

End for

Proposed Mutative exploration phase

During the mutational investigation stage, a great many food bases may be discovered; nevertheless, the number of sources and their quality will vary. We choose the healthiest persons to serve as our food supply. They are then split into three distinct groups using three separate Dependent upon the healthiness gap among each food basis and the ideal nutrition basis for the population, threshold values like limit1, limit2, and limit3 may be calculated. The food sources with the highest fitness levels experience the least mutation, whereas those with the lowest fitness levels experience the most mutation, and this is true across all three food source populations. Therefore, A negative correlation exists between the fitness benefit of a given food supply and the rate of mutation. High-quality, improved food sources are categorized as A_{kt1} food sources since they are as nutritious as the most beneficial diet for the population as a whole. Due to the fact that the A_{kt1} Since the finest food sources may be adjusted by means of Gaussian mutations, a local search process is enabled in their vicinity where equation (21) may be used to sporadically alter the A_{kt1} food bases.

$$A_{kt1}^{'} = A_{kt1} + \mu_g.G(0,1) \qquad (21)$$

A_{kt1} is the original nutrition basis; $A_{kt1}^{'}$ is the altered nutrition basis produced asfter the Gaussian alteration; μ_g alteration rate showing the intensity of the Gaussian noise added; G(0,1) is the random number from the Gaussian circulation, where the mean is 0 and the m change is one.

The best nutrition source for the whole population is compared to intermediate food options with fitness levels in the middle, which are categorized as A_{kt1} food bases. The A_{xt} Because food bases are intermediate, consistent examination procedure made easier when centered on them. The uniform mutations are used to modify the intermediate food sources, and the intermediate food sources that have been modified consistently A_{kt3} food sources are represented by the symbol A'_{kt2} Equation (22) is used to generate the uniformly mutated A_{kt2} food sources, where a value chosen at random selected from a solution, and replaced it with a number that is uniformly random and falls somewhere inside the boundaries of the upper (Ub) and lower bounds that were established by the user (Lb) boundaries.

The lowest food sources are those with low fitness values and whose fitness values deviate significantly from the health benefits of the most reliable source of food in the community. Food sources A_{kt3} are inferior than those A_{kt} and A_{kt1}. As a result, A world-wide search is. made easier for the poorest food bases, which are then altered utilizing Variations on the Levy (LM)utilizing Equation (23), making them more likely to break out of a limiting situation

$$A'_{hk3} = A_{hk3} + \mu_c.C(0,1) \qquad (23)$$

X'_{hk3} is the altered food source produced as a result of the Cauchy alteration, and μ_c is the Cauchy alteration degree, which reveals a measure of how much the mutation has changed.

$$A'_{kt2} = A_{kt2} \qquad (22)$$

The worst food bases A_{xt} have been swapped, along with the altered food bases. The new collection of food sources that are now A_{new} exploitable. The algorithm explains the modified antibody detection step (4)

Algorithm 4: Modified antibody detection phase

Replace the worst 'X' food source by randomly generated food source A_{xt}

For every improved food source (A_{kt})

From the better food sources, choose the $A_{kt1}, A_{kt2}, and\ A_{kt3}$ food sources.

A_{kt1} if $\{|Fitness(Ak_x) - Fitness(A_{best})|\} \leq \text{limit1}$

A_{kt2} $if\ \{|Fitness(A_{kt}) - Fitness(A_{best})|\} \leq \text{limit2}$ and if $\{|Fitness(Ak_x) - Fitness(A_{best})|\} \geq \text{limit1}$

A_{kt3} $if\ \{|Fitness(A_{kt}) - Fitness(A_{best})|\} \geq \text{limit2}$

If A_{kt1} food sources

Mutate using equation (22)

Else if A_{kt2} food sources

Maturate using equation (23)

Set of mutated food sources generated are $\overline{A_{kt}}$

Set $A_{new} = \overline{A_{kt}}$

End for

Generate $A_{new} = A_{new} \cup A_{xt}$

Proposed phase of employee bee attacks

Start locations for food sources in the exploitation phase are a combination of those generated by the random generator and those generated by the mutations discovered in the exploration phase. Each food source has a designated worker bee who hunts for better food sources nearby in a manner similar to how whales hunt for prey. During its quest for a nearby food supply, an employee bee travels in a circle, with the most reliable food supply thus far serving as the circle's center. By using this exploitative mechanism, the most ideal sites are always used to direct the search process. In the early iterations of the circular route, a measure of the magnitude of each step β_1 part of the lookup procedure is maintained large to promote exploration, however to make subsequent iterations more amenable to exploitation, the size of the steps is reduced with time. Adaptive step size β_1 the worker's bees to search the whole issue area so that they may go to far-off places failed to accomplish during this is the looking around part. Because of the variable step size used in the circular route, the issue concerning oscillations and regional peaks may have resolved. When generating Randomness, or the distribution of events, is assumed. Is used, and the output is compared to the control variables C_{1x} and C_{2x}. The location of the food supply is less than C_{1x} determined by utilizing Equation (24).

$$N_{kt}^{l} = A_{kt}^{l} + \beta_1 * (A_{kt}^{l} - A_{dt}^{l}) \qquad (24)$$

Where β_1= The step size, represented by a random number between -1 and 1, fluctuates continually between successive repetitions. N_{kt}^{l} is the new primary source of nourishment. A_{kt}^{l} is the primary source of food at the moment A_{dt}^{l} is a source of food picked at random. After that, if the generated number is smaller than C2 and the likelihood is checked using P_{ix} where if $P_{ix} < 0.5$ The finest nutrition basis (A_{kt}) located so distant is used as the midpoint of a circle to search for a new neighbour hood location utilizing Equation (25).

$$N_{kt}^{l} = \vec{A}_{kt}^{*} - \overrightarrow{M_x}.Y_x \qquad (25)$$

M_x is a symbol for the scalars and vectors of coefficients generated by solving Equation (3 & 4). The value of Y_x in the equation represents the gap between the location of the current food supply and the optimal location (26).

$$Y = | A_{kt}^{*} - A_{kt}^{l} | \qquad (26)$$

Another probability check, if $P_{ix} < 0.5$ Applying Equation (27), a new neighbourhood location is located by searching in a radial direction while maintaining the greatest food source A_{kt} discovered so far at the center of the radial route.

$N_{kt}^{l} = Y_x.et^{aw}.\cos(2\pi l) + A_{kt}^{*}$ (27)

The logarithmic spiral may be represented by the constant a. A random number, denoted by w, is chosen between [-1, 1].

If the fitness of N_{kt}^{l} (food supply in the community) is not as important as physical health A_{kt}^{l} (current food source), worker bees during the swarming phase of their assault N_{kt}^{l} by allowing negative gradients to be part of the Performing a Search, a system may break free of its local fitness maximum and go on to better results. Probability is used as the deciding factor in approving the poorest possible food sources value of $e^{\frac{-\Delta Ex}{t}}$ This is accomplished via the proposed employee bee attacking phase, which utilises a selection method based on simulated annealing in which both the best and worst answers are accepted. The simulated annealing temperature is the governing parameter that determines whether or not the poorest solutions are accepted; as the temperature is lowered by iteration, the likelihood of accepting the worst answers drops. The earliest phases of simulated annealing include a high value for the annealing temperature, denoted by the symbol "T," where the value $\frac{-\Delta Ex}{T}$ likely to be 0, resulting in the possibility value $e^{\frac{-\Delta Ex}{t}}$ towards 1 enabling the resignation to the most undesirable outcomes possible answers. The value increases as iterations are made $\frac{-\Delta Ex}{T}$ tends towards 1 determining the degree of the likelihood $e^{\frac{-\Delta Ex}{t}}$ facilitating the adoption of superior solutions, in the direction of 0. This eliminates the issue of striking at local optimal areas by enabling both incline and decline motions in terms of the terrain of fitness inside the proposed HAW algorithm. Equation shows that as the various repetitions increase, The temperature denoted by the letter 'T' for simulated annealing is falling (28).

$T(t+1) = \phi * T(t)$ (28)

Where T (t=1) represents the current temperature, and T(t) represents the previous temperature. earlier repetition's temperature. This simulated strengthening constant, has a value that is very near to 1. The algorithm describes the suggested worker bee assault phase (5).

Algorithm 5: Proposed Employee bee attacking phase

For K_t =1 to n do

For l_t =1to dim do

If $ran \geq C_{1x}$

Search for the neighbouring food source using equation (24)

Else If $ran \geq C_{2x}$

If $(P_{ix} < 0.5)$

Search for the neighbouring food source using equation (25)

Else if $(P_{ix} \geq 0.5)$

Search for the neighbouring food source using equation (26)

End if

End if

End for *l*

If $fitness(N_{kt}^{l}) > fitness(A_{kt}^{l})$

Accept N_{kt}^{l}

Else

Calculate $\Delta E = fitness(A_{kt}^{l}) - fitness(N_{kt}^{l})$

Accept N_{kt}^{l} with probability $e^{\frac{-\Delta Ex}{t}}$

End if

End for K

Onlooker Bee Phase

When new food sources, denoted by the symbol N_{kt}^{l}, are created, the bees in the area will communicate this information to any nearby observers. In addition, during the assaulting phase of the worker bee population, the spectator bees acquire probability value VS_{ix} the food source from the workers using Equation (29).

$$VS_{kt} = \frac{fitness(A_{kt})}{\sum_{K=1}^{N} fitness(Y_{ix})} \qquad (29)$$

The quality of the food supply, (A_{kt}) correlates with the level of fitness, A_{kt} For each potential dietary basis, a random (0,1) is created and compared with VS_{kt}. Spectator bees choose food sources with VS_{kt} higher than chance (0,1). An algorithmic breakdown of the "observer bee" phase's specifics (6)

Algorithm 6: Onlooker Bee Phase

For k = 1 to N do

Calculate probability using Equation (3)

If random (0,1) < VS_{kt}

Accept N_{kt}^{l}

Else

Reject N_{kt}^{l}

End for

Memorize the best food source A_{best}

Scout bee phase

The foraging scout bees bring back the depleted food supplies and introduce fresh ones. If the food source doesn't get better during an iteration, the associated limit value gets bigger, and if it gets bigger for a specific amount of iterations and crosses the threshold limit price, the scout bees replace those food sources with a new set through a random generation process using Equation. (1). The Algorithm provides a full account pertaining to the scouting phase (7).

Algorithm 7: Scout Bee Phase

While (A_{kt} does not improve)

Count = count +1

If count > Count $_{max}$

Replace A_{kt} with newly generated food source

Else

Count = 0

Iteration = Iteration +1

IV. RESULTS

In this part, the considered systems and suggested controllers are created using MATLAB/Simulink models and simulations. The effectiveness of the plan that was suggested ABCWOA algorithm is measured by means of fixed starting parameters, including Swarm size=50, a Maximum number of generations=100, Acceleration factors (c1=1.2, c2=0.8), and Inertia weight (wm-wM) = 0.4-0.9.

Example 1: In Shamash, consider an eighth-order SISO system.

$$G(s)=\frac{35.2s^7+1086.4s^6+13285.2s^5+82402.1s^4+278376.5s^2+511812.2s^2+482964.1s+194480.4}{s^8+21.3s^7+220.1s^6+1558.4s^5+7669.5s^4+24469.2s^3+46350.3s^2+45952.6s+17760.3}$$

Using the ABCWOA method, the ROM is as follows:

$$G_2(s)=\frac{40.06s+381.4}{s^2+1.808s+35.33}$$

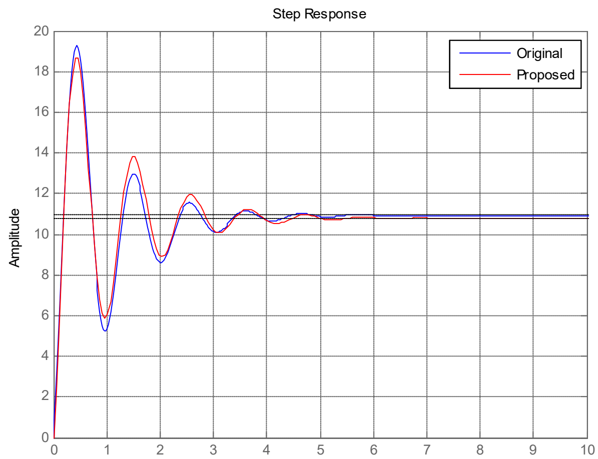

Figure 2 Step responses of the original model and reduced order models for exp-1 open loop

Figure 1 &2 depicts ROMs and higher-order models' (HOM's) step reactions. According to Table 1, When analysing this, both the ISE and the root mean square error (RMS) are computed for comparison. strategy to other well-known approaches that are listed in the literature.

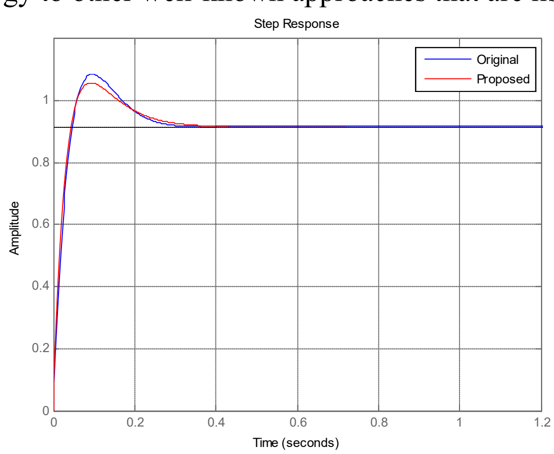

Figure 3 Step responses of the original model and reduced order models for exp-1 closed loop

It is clear from looking at fitness of the best global solution keeps increasing as time passes in the evolutionary algebra, according to this model. Decline until it reaches its lowest possible value of 0.297 after 10 generations for ABCWOA. This value remains stable after this amount of time. Since it has been shown that ABCWOA can converge in a short amount of time, this demonstrates that it is a more practical and effective approach.

Table 1 Comparison of error-index values with existing methods for example 1

Method	Reduced model	RMS error	ISE
ABCWOA	$\frac{40.06s+381.4}{s^2+1.808s+35.33}$	0.299	0.887
Ref. [14]	$\frac{39.518s+388.958}{s^2+1.8378s+35.5198}$	0.339	1.146
Ref. [15]	$\frac{35.1s+401.4}{s^2+1.437s+36.64}$	0.6	2.508

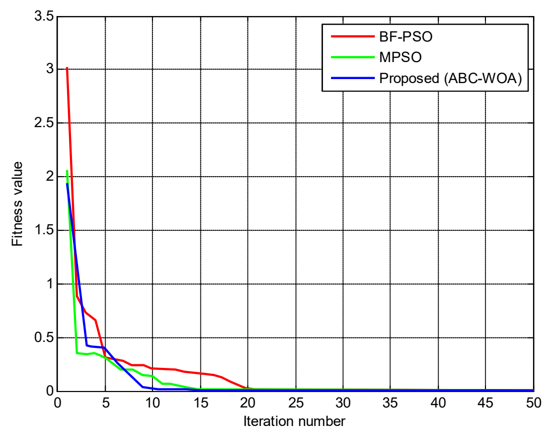

Figure 4 Evolution processes of the ABCWOA strategies

The following are the values of A, B, C, and D after the LQR controllers have been applied to the simplified model:

$$A=\begin{bmatrix}-1.808 & -4.4176\\ 8.1 & 0\end{bmatrix}, B=\begin{bmatrix}8.1\\ 0\end{bmatrix}$$

$$C=\begin{bmatrix}5.007 & 5.959\end{bmatrix}, D=\begin{bmatrix}0\end{bmatrix}$$

The same error reduction method that makes use of ABCWOA is used in the tuning process for the LQR controller's parameter settings. The following are the optimal settings for the LQR controller:

$$Q=\begin{bmatrix}25.577 & 0\\ 0 & 35.6299\end{bmatrix}, R=\begin{bmatrix}1.0125\end{bmatrix}$$

The following constitutes the ideal feedback gain matrix:

$$K1=\begin{bmatrix}5.783786 & 5.505187\end{bmatrix}, K2=\begin{bmatrix}216.091\end{bmatrix}$$

Figure 4 illustrates a measure of how well the controller of the simplified system reacts to sudden changes in input. System performance statistics are collected and compiled in Table 2 in order to provide evidence supporting the controller's observation.

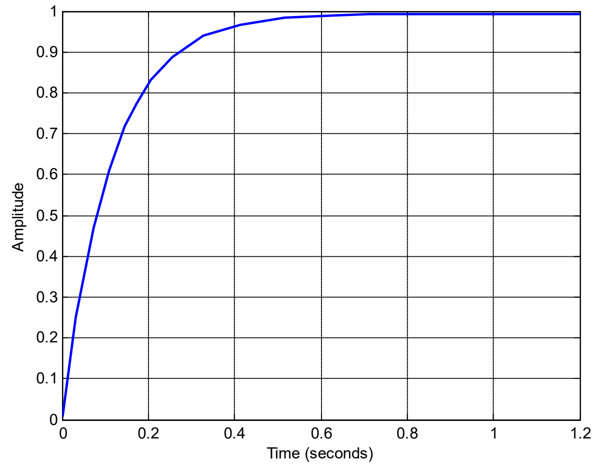

Figure 5 Step responses of reduced-order models for example 1 using the LQR controller.

Table 2 The performance characteristics of the system in example1

Example 2: Take into consideration a sixth-order system transfer function matrix with two inputs and two outputs given:

$$G_6(s)=\begin{bmatrix}\frac{2(s+5)}{(s+1)(s+10)} & \frac{(s+4)}{(s+2)(s+5)}\\ \frac{(s+10)}{(s+1)(s+20)} & \frac{(s+6)}{(s+2)(s+3)}\end{bmatrix}$$

$$G_6(s)=\frac{1}{D(s)}\begin{bmatrix}a_{11}(s) & a_{12}(s)\\ a_{21}(s) & a_{22}(s)\end{bmatrix}$$

Using the ABCWOA method, the ROM is:

$$G_2(s)=\frac{\begin{bmatrix}(1.315s+3) & (1.033s+1.2)\\ (0.5776s+1.5) & (1.8s+3)\end{bmatrix}}{(s+3)(s+1)}$$

Two examples of step reactions, one from the HOM and one from the ROM, are shown in Figure 5. In Table 3, we can see how the proposed ROM stacks up against some alternatives. When After implementing the LQR controllers on the simplified model, the parameters A, B, C, and D are as follows:

$$A = \begin{bmatrix} -4 & -1.5 & 0 & 0 \\ 2 & 0 & 0 & 0 \\ 0 & 0 & -1.5 & -1.5 \\ 0 & 0 & 2 & 0 \end{bmatrix},$$

$$B^{I} = \begin{bmatrix} 2 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 \end{bmatrix}, D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$C = \begin{bmatrix} 0.6585 & 0.7495 & 0.5155 & 0.3005 \\ 0.2891 & 0.3748 & 0.8905 & 0.7535 \end{bmatrix}$$

Using ABCWOA, the optimal LQR controller parameters are as follows:

$$R = \begin{bmatrix} 1000 & 0 \\ 0 & 100 \end{bmatrix}$$

$$Q = \begin{bmatrix} 0.5172 & 0 & 0 & 0 \\ 0 & 0.7022 & 0 & 0 \\ 0 & 0 & 1.0587 & 0 \\ 0 & 0 & 0 & 0.6581 \end{bmatrix}$$

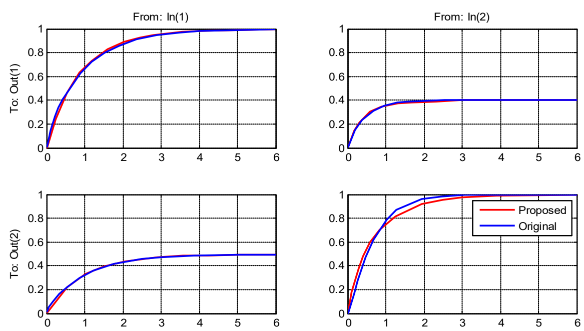

Figure 6 Step responses of the original model and reduced-order models for example 2: open-loop

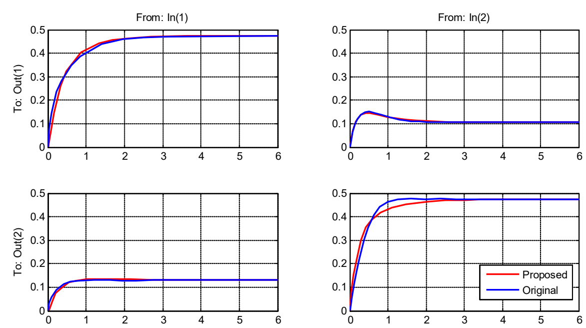

Figure 7 Step responses of the original model and reduced-order models for example 2 Closed Loop

The ideal feedback gain matrix has the following parameters: LQR upgrades.

$$K1 = \begin{bmatrix} 0.0004 & 0.0005 & 0 & 0 \\ 0 & 0 & 0.0048 & 0 \\ & & & 0.0044 \end{bmatrix}$$

K2=65.939

V. CONCLUSION

The investigation of the numerical example leads to the conclusion that the ABCWOA algorithm is a successful optimization method. It converges quickly, has a straightforward implementation, and is able to solve the issue of local extrema. The high-order system model may be made less complicated by this ABCWOA was used. It is said that the ROM that was created by using the suggested ABCWOA technique offers remarkable Irregular verbal taxis to the initial system. The ROM produced using the approach that was suggested and the ROM obtained by other available technologies are compared and contrasted. The outcomes of this comparison are displayed, and they are presented with regard to the incorrect values (ISE and RMS) LQR is a control approach that was developed based on the ABCWOA and decreased system ranking to make the control process more easy. LQR control guarantees that there is no instability and that all operational points are met with appropriate performance.

VI. REFERENCES

[1] R. Genesio and M. Milanese, "A Note on the Derivation and Use of Reduced-Order Models," *IEEE Trans. Automat. Contr.*, vol. 21, no. 1, pp. 118–122, 1976, doi: 10.1109/TAC.1976.1101127.

[2] D. Butti, S. K. Mangipudi, and S. Rayapudi, "Model Order Reduction Based Power System Stabilizer Design Using Improved Whale Optimization Algorithm," *IETE J. Res.*, 2021, doi: 10.1080/03772063.2021.1886875.

[3] F. Chinesta *et al.*, "A Short Review in Model Order Reduction Based on Proper Generalized Decomposition To cite this version : HAL Id : hal-01004940 A Short Review on Model Order Reduction Based on Proper Generalized Decomposition," 2017.

[4] J. Kumar, "WOA based Reduced Order Modeling of LTIC Systems," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 9, no. 4, pp. 4315–4321, 2020, doi: 10.30534/ijatcse/2020/21942020.

[5] Toni Lassila, Andrea Manzoni, Alfio Quarteroni, and Gianluigi Rozza, *Model Order Reduction in Fluid Dynamics : Challenges and Perspectives*, vol. 9. 2014. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-319-02090-7_9

[6] R. Pradhan, S. K. Majhi, and J. Jaypuria, "An orthogonal moth flame optimization for global optimization and application to model order reduction problem," in *Journal of Intelligent and Fuzzy Systems*, 2020, vol. 38, no. 5, pp. 6649–6661. doi: 10.3233/JIFS-179744.

[7] M. M. Mafarja and S. Mirjalili, "Hybrid Whale Optimization Algorithm with simulated annealing for feature selection," *Neurocomputing*, vol. 260, pp. 302–312, 2017, doi: 10.1016/j.neucom.2017.04.053.

[8] E. M. Abdel-Rahman, M. I. Younis, and A. H. Nayfeh, "A nonlinear reduced-order model for electrostatic MEMS," *Proc. ASME Des. Eng. Tech. Conf.*, vol. 5 B, no. January, pp.

1771–1778, 2003, doi: 10.1115/detc2003/vib-48517.

[9] J. Nasiri and F. M. Khiyabani, "A whale optimization algorithm (WOA) approach for clustering," *Cogent Math. Stat.*, vol. 5, no. 1, p. 1483565, 2018, doi: 10.1080/25742558.2018.1483565.

[10] Y. Lang *et al.*, "Process Simulation and Optimization †," no. 3, pp. 1695–1706, 2009.

[11] D. Karaboga and B. Basturk, "On the performance of artificial bee colony (ABC) algorithm," *Appl. Soft Comput. J.*, vol. 8, no. 1, pp. 687–697, 2008, doi: 10.1016/j.asoc.2007.05.007.

[12] D. Karaboga and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm," *J. Glob. Optim.*, vol. 39, no. 3, pp. 459–471, 2007, doi: 10.1007/s10898-007-9149-x.

[13] D. Karaboga, B. Gorkemli, C. Ozturk, and N. Karaboga, "A comprehensive survey: Artificial bee colony (ABC) algorithm and applications," *Artif. Intell. Rev.*, vol. 42, no. 1, pp. 21–57, 2014, doi: 10.1007/s10462-012-9328-0.

[14] H. N. Abdullah, "Reduction of large scale linear dynamic SISO and MIMO systems using modified particle swarm optimization algorithm," *Proc. 2016 IEEE 11th Conf. Ind. Electron. Appl. ICIEA 2016*, pp. 166–171, 2016, doi: 10.1109/ICIEA.2016.7603571.

[15] L. Kumar, R. Prasad, A. K. Gupta, D. Kumar, M. K. Panda, and B. Jha, "Modified Least-Square based Model Reduction using Time Moments and Markov Parameters," *Proc. 2019 IEEE Reg. 10 Symp. TENSYMP 2019*, vol. 7, pp. 441–446, 2019, doi: 10.1109/TENSYMP46218.2019.8971323.