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Performance Optimization of BLDC Motor Control Using Sand Cat Swarm Algorithm and Linear Quadratic Regulator

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***Abstract*—Brushless Direct Current (BLDC) motors are widely utilized in industrial applications due to their precision, efficiency, and ease of control. This study optimizes BLDC motor performance by enhancing the linear quadratic regulator (LQR) using the Matlab program's Sand Cat Swarm Optimization (SCSO) algorithm. The research evaluates key performance metrics, including settling time, overshoot, and cost function, to demonstrate the advantages of the proposed approach. Additionally, a comparative analysis was conducted using the butterfly optimization algorithm (BOA) and conventional LQR to validate the superiority of SCSO. Simulation results show that the LQR-SCSO method significantly improves performance, achieving a 77.2% reduction in settling time, a 91% reduction in overshoot, and a cost function of 0.3376. In comparison, the BOA method achieves reductions of 68.54% in settling time, 67.37% in overshoot, and a cost function of 0.8736, while the conventional LQR achieves reductions of 68% in settling time, 62.3% in overshoot, and a cost function of 1.8393. SCSO has excellent convergence and adaptability; however, the implementation is explored further in terms of computational cost adopted for industrial use in real time. The data are so highly processed that better controls are implemented to repeat simulations across defined parameters. The proposed LQR-SCSO approach is practical and potent in enhancing motor performance, which is a significant advancement and can applied in various fields in the industry, such as robotics and automated systems. However, the proposed method may face obstacles related to the higher computational complexity of higher-order applications, which can be a subject of future studies.**

Keywords—Adaptive Control; Optimization; Brushless DC Motor; Sand Cat Swarm Optimization; Butterfly Optimization Algorithm.

I. INTRODUCTION

Brushless DC (BLDC) motors are essential to applications demanding precision and reliability and are favored in many industries [1], [2]. Although this type of motor has certain advantages, the nonlinear behavior parameters and strong constraints on the operating mode are significant challenges for motor operation—complex control strategies required for optimum performance. One of the most widely utilized control approaches is the linear Quadratic Regulator for BLDC motors. It ensures stability and reduces disturbances by minimizing a quadratic cost function [3]. However, the tuning of the Q and R, which are the weighting matrices of the LQR controller, affects the efficiency of the controller system. These matrices are traditionally adjusted using heuristic or conventional methods, often resulting in high computational demands and suboptimal outcomes [4], [5]. Recently, metaheuristic optimization techniques have shown significant potential in enhancing BLDC motor controls, such as the Whale Optimization Algorithm (WOA,) which has improved dynamic performance, including faster settling times and better robustness against disturbances [6]. Hybrid systems that combine LQR with other techniques, such as PI controllers based on backpropagation neural networks (BPNN), have improved stability and speed control. However, the real-world applicability of these methods is limited since they frequently need precise parameter adjustment and considerable computing complexity [7]. Other optimization techniques, including Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), have made progress in improving system response and stability but face challenges in scalability and implementation due to computational overhead [8]. Different optimization techniques, such as the Artificial Bee Colony (ABC) algorithm, Artificial Neural Networks (ANN), and Newton-Raphson-based approaches, have been explored to improve LQR controllers by reducing overshoot and enhancing response times. However, these techniques face scalability and computational efficiency challenges, particularly in higher-order systems, requiring further validation [9]. The Sand Cat Swarm Optimization (SCSO) algorithm, inspired by the hunting strategies of sand cats, is designed to address complex optimization problems through two primary phases: exploration and exploitation [10]. By dynamically balancing these phases, SCSO ensures a comprehensive search across the solution space while fine-tuning the best solutions to avoid being trapped in local optima, making it particularly effective for optimizing the weighting matrices of the LQR controller, enhancing its capability to enhance the performance of the systems such as BLDC motors. SCSO's computational efficiency in dynamic system conditions makes it a reliable and robust tool for optimization tasks [11]. This research introduced a novel approach to optimizing the LQR controller for BLDC motor systems using the Sand Cat Swarm Optimization (SCSO) algorithm to enhance the performance of BLDC motors. The proposed design was implemented using the Matlab program, and critical performance metrics such as settling time, overshoot, and cost function were evaluated to assess its robustness and efficiency. A compensation analysis with the Butterfly Optimization Algorithm (BOA) highlights the SCSO-LQR system's stability and time response speed superiority. By combining the strength of the LQR controller with the innovative features of the SCSO algorithm, this study presented a robust system for advancing BLDC motor control strategies.

II. Brushless DC Motor Mathematical Model Description

BLDC motors have stator windings embedded in slots on laminated steel cores, with a rotor containing permanent magnets. The latter interacts with the stator's rotating magnetic field, providing motion through electronic commutation. This is enabled either by position sensors or sensorless techniques to detect rotor position [12], [13]. BLDC motors can be designed as in-runner motors, with magnets placed inside the rotor, or out-runner motors optimized for higher torque at lower speeds [14][15]. One of the significant advantages of BLDC motors is that they are brushless, meaning there are no mechanical commutators, resulting in reduced wear and maintenance. Hence, this increases their operation life and reliability. Second, BLDC motors are more efficient and controllable than induction motors. Induction motors may suffer from noise levels, smooth operation, and speed range limitations [16]-[18].

For analyzing dynamic behavior in BLDC motors, one second-order transfer function can be derived based on the motor's electrical and mechanical properties. Electrical dynamics are the first to be considered in this derivation of a model, expressed in (1):

$$V = L\frac{dI}{dt} + R + e_b \tag{1}$$

Where the applied voltage is, the stator inductance is the current; the stator resistance is the back electromotive. The back-EMF is proportional to the rotor's angular velocity ω, given by ω, where is the back-EMF constant. The BLDC motor is defined mechanically in (2):

$$T = J\frac{d\omega}{dt} + B\omega + T_L \tag{2}$$

Here, the generated torque is the moment of inertia of the rotor, the damping coefficient is the load torque, and the generated torque is proportional to the current, expressed as =, where is the torque constant. Combining these two equations, the electrical current I from the first equation is substituted into the second to establish a relationship between the input voltage V and the rotor's angular velocity ω of the rotor [19]. Linearization of the system around a nominal operating point, followed by applying the Laplace transform, yields the transfer function:

$$G(s) = \frac{K}{s^2 + (RJ + LB)s + RBLJ} \tag{3}$$

Where $K=\frac{K_t}{Ke}$ represents the motor gain. Substituting specific parameters in the simplifier transfer function [20]:

$$G(s)= \frac{57.142857}{5.1s^2+4.9s+1} \tag{4}$$

III. Linear Quadratic Regulator

In the field of control theory, which is essential in systems, the linear quadratic regulator (LQR) is a prominent concept in control theory and is particularly relevant to system engineering [21][22]. This methodology is an optimal control approach to determine control inputs that minimize a specific cost function. The main objective of the LQR is to enhance system performance by minimizing a quadratic cost function that optimally balances state variables and control efforts [23][24]. It is heavily dependent on the proper weighting of the variables involved because this directly affects the optimum operation of the system under dynamic conditions [25]-[26].

The effective feedback structure design is crucial for developing a state feedback controller, especially for systems such as Brushless DC (BLDC) motors, where stability is a significant challenge. The LQR framework utilizes a state-feedback control law, expressed as U=KXU, where K represents the gain matrix; this relationship allows the controller to regulate the motor's speed using the measured state variables [27]-[28]. Fig. 1 displayed a detailed model description of the LQR control system, highlighting its integration of state variables, control inputs, and feedback mechanisms for optimal performance and dynamic stability Abbreviations and Acronyms.

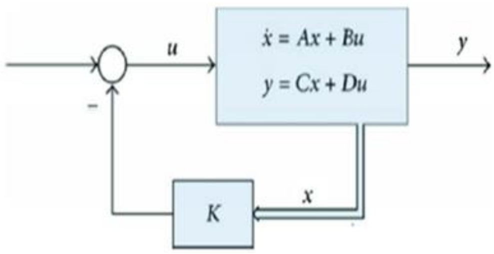

Fig. 1. The LQR control system's model [29]

The dynamics of the LQR-controlled system are described by the four matrices A, B, C, and D. These matrices dictate the system's behavior in the following sense :(A: Captures the relationships between state variables over time, B: Connects the control inputs to changes in the state variables, C: Converts the state variables into measurable system outputs and D: Accounts for the direct feedthrough effects between input and output). The system dynamics are represented by (5) and (6) [30]-[36]:

$$\dot{X}=AX+BU \tag{5}$$

$$\dot{Y}=CX+DU \tag{6}$$

The LQR framework minimizes a quadratic cost function, as defined in (7):

$$J=\int_0^{\infty} X^T QX+U^T RU\, dt \tag{7}$$

The optimal gain matrix K is evaluated using the Algebraic Ricatti Equation (ARE) solution, which assigns relative importance to state variables and control inputs as represented in (8):

$$A^T P+PA-PBR^{-1}B^T P+Q=0 \quad (8)$$

The gain matrix K, which determines the feedback control law, is derived as follows:

$$K=R^{-1}B^T P \quad (9)$$

IV. Sand Cat Swarm Optimization Algorithm

SCSO derives inspiration from the natural hunting strategies of sand cats; this allows it to attain a dynamic balance between exploring new solutions and exploiting promising ones. This adaptability makes the algorithm less vulnerable to getting trapped in a local optimum and enhances its efficiency in navigating complex solution spaces [37]-[42]. During the exploration phase, the algorithm goes through an exhaustive search in the solution space, necessary for maintaining diversity in potential solutions and avoiding an early convergence problem [43]-[46].

The sensitivity range ($\overrightarrow{r_G}$) decreases linearly in each run, taking the search process towards more focused refinement. The mathematical model expressed during this phase is used [47]-[55] in (10), (11), (12) and (13):

$$\overrightarrow{r_G}=S_M\text{-}\left(\frac{2\times S_M\times Iter}{IterMax}\right) \quad (10)$$

$$R=2\times\overrightarrow{r_G}\times rand\text{-}\overrightarrow{r_G} \quad (11)$$

$$\vec{r}=\overrightarrow{r_G}\times rand \quad (12)$$

$$\overrightarrow{pos}(t+1)=\vec{r}\,\overrightarrow{pos_c}(t)\ \text{-}\overrightarrow{pos_{bc}}(t) \quad (13)$$

Where $\overrightarrow{r_G}$ represents sensitivity range decreases linearly, focusing the search over time. S_M represents the random value representing the auditory traits of sand cats ranging between 0 and 1. $\overrightarrow{pos_{bc}}$ is the position of the best candidate solution. $\overrightarrow{pos_c}$ is the current position of the sand cat and r is a randomized sensitivity factor. The exploration phase generates new solutions, whereas the exploitation phase refines them by focusing the search on the most promising areas. This is a converging phase toward an optimal solution [56]-[59] as explained in (14).

$$\overrightarrow{pos_{rnd}}=\left|rand\,\overrightarrow{pos_b}(t)\text{-}\overrightarrow{pos_c}(t)\right|\ \overrightarrow{pos}(t+1)=\overrightarrow{pos_b}(t)\text{-}\vec{r}\ \overrightarrow{pos_{rnd}}\cos\theta \quad (14)$$

Where (θ is A random angle representing the direction of movement, varying between 0 and 360 degrees, $\overrightarrow{pos_{rnd}}$is a randomly adjusted position vector based on the best candidate and current position and $\vec{r}$ represents the sensitivity parameter that adjusts positional changes during this phase).

The sensitivity range, R, effectively controls the transition between exploration and exploitation. While $|R| > 1$ represents the phase of exploration-namely, spread search over the solution space undertaken by the algorithm for $|R| \leq 1$, the algorithm moves to the exploitation phase where the finest prospects are surrounded by more detailed procedures. The sum of these may be used to represent the overall dynamics as [52]-[55].

$$\vec{X}(t+1)=\begin{cases}(\overrightarrow{pos_b}(t)\text{-}\overrightarrow{pos_{rnd}}(t)|R|\leq 1;Explotation\\ \vec{r}(\overrightarrow{pos_{bc}}(t)\text{-}rand\,\overrightarrow{pos_c}(t)|R|>1;Exploration\end{cases} \quad (15)$$

This system makes sure that the focus on refining existing solutions and exploring new areas is dynamically balanced [56]. Fig. 2 illustrates the algorithm's dual-phase structure by showing the change from exploration (|R|>1) to exploitation (|R|≤1) [57].

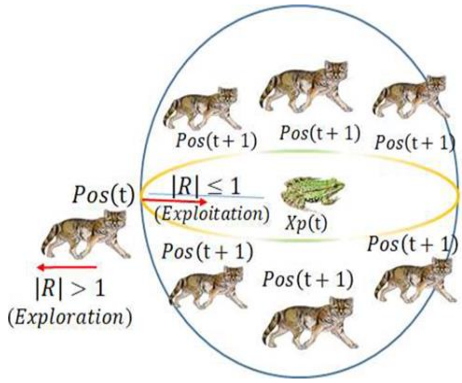

Fig. 2. Exploration and exploitation phase in SCSO [60]

The SCSO algorithm was implemented in MATLAB to optimize the Q and R parameters of the LQR controller. MATLAB provides a reliable platform for simulating the algorithm's performance, allowing precise evaluation of how optimized parameters bettered the control system of the BLDC motor. It enhanced system efficiency through stability without falling into any local optima.

The integration of the Sand Cat Swarm Optimization (SCSO) algorithm with the Linear Quadratic Regulator (LQR) controller is illustrated in Fig. 3. The SCSO optimizes the Q and R matrices by iterating through the exploration and exploitation phases. The optimized parameters are fed into the LQR controller, which adjusts the system's input to enhance stability and performance; it also integrates the optimized result to give effective control of the BLDC motor with minimal error and fast dynamic response. The whole process, from optimization up to implementation in the motor control system, is shown in a flowchart.

V. Butterfly Optimization Algorithm

Butterfly Optimization Algorithm (BFO) is a bio-inspired algorithm based on the foraging behavior of butterflies through sensory stimuli to navigate to the optimal solution. This technique balances the exploration-exploitation dilemma in solving complex optimization problems with a tradeoff between broad search and focused refinement. It mimics the butterflies' sensory modalities, guiding their movement through the search space toward the global best solution [61]-[67]. BOA consists of two main phases: global search and local search, alternating based on a switching probability (p). In the global search phase, butterflies are attracted to the globally best solution, ensuring the exploration of broader solution spaces [68]-[70]. The governs the position update using (16).

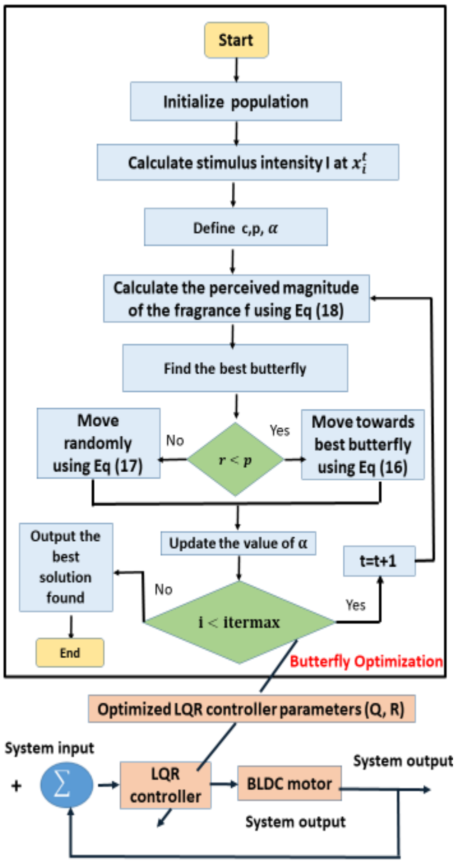

Fig. 3. Integrated LQR with SCSO flowchart

$$x_i^{t+1} = x_i^t + r(g^* - x_i^t)f_i \tag{16}$$

Where x_i^{t+1} is the new position, x_i^t is the current position, g^* is the global best, f is the fragrance of the ith butterfly, and r is a random number between 0, 1. During the local search. The local search refines solutions by moving butterflies toward randomly selected positions within the population [71][75]. The position update is expressed as follows:

$$x_i^{t+1} = x_i^t + r(x_j^t - x_k^t)f_i \tag{17}$$

Where x_j^t,x_k^t are positions of randomly selected butterflies. A switch probability p determines whether each butterfly performs global or local searching. A switching probability (P) determines whether a butterfly engages in global or local searching, enabling a dynamic balance between the two phases.

$$f = cI^{\alpha} \tag{18}$$

Where f represents an attribute of the system, likely associated with the attractor or objective in the algorithm, c refers to how sensory input is processed or perceived, I denote the strength or fitness of the stimuli involved in the algorithm and α is the sensitivity or response intensity of the butterfly (or system) to external stimuli [76]-[80]. This equation ensures that butterflies with higher fitness values exert stronger attraction, guiding the search for optimal solutions. The diagram in Fig. 4 illustrates the implementation of the Butterfly Optimization Algorithm (BOA) to optimize the Linear Quadratic Regulator (LQR) parameters for controlling a Brushless DC (BLDC) motor. The process begins by initializing a population of solutions, where each solution represents a candidate set of Q and R matrices for the LQR. The intensity of each solution is evaluated, and the perceived magnitude of its attractiveness is calculated based on specific parameters (c, p, α) using equation (18). The algorithm then identifies the best-performing solution (best butterfly). It balances exploration and exploitation by renewing the positions of additional solutions randomly using equation (17) or by approaching the best butterfly using equation (16). The ideal Q and R-values are produced when the procedure has completed the maximum number of repetitions. The LQR controller governs the operation of the BLDC motor, which is made to operate by key parameters for efficiency, responsiveness, and stability. It takes these inputs and alters the performance of the motor to provide smoother operations with quicker reaction times. The diagram shows that a feedback loop system continuously monitors and refines the entire process.

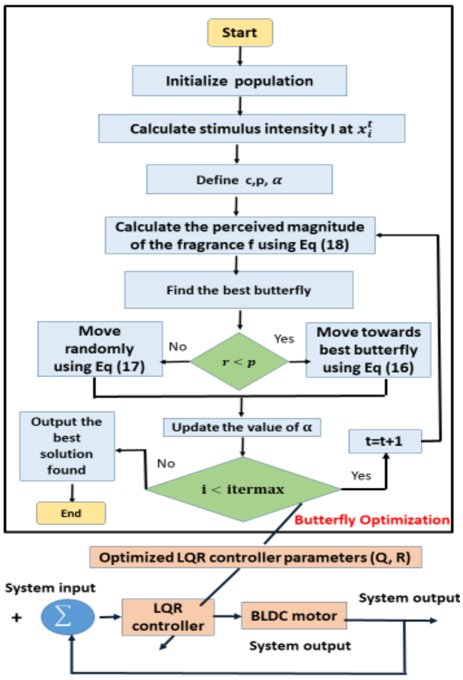

Fig. 4. Integrated LQR with BOA flowchart

VI. SIMULATION AND RESULTS

The system's responses were evaluated using MATLAB software. Fig. 5 and Table I illustrates the performance characteristics of the BLDC motor operating without a controller.

The motor has a high overshoot and long settling time, indicating instability and heavy oscillations. Overshoot means the motor response goes well beyond the set value, which causes mechanical stress on the parts, accelerating wear and reducing the system's life. It is undesirable in applications that require great precision, such as robotic arms or computer numerical control machines, where precise positioning is needed. Additionally, the more the settling time increases, the more these are aggravated since the longer the time taken for a system to reach its steady state involves slower responses, increased energy use, and even vibration that can deteriorate the performance. Combining all these factors renders such a motor unsuitable in systems needing fast and accurate control—for instance, drones, electric vehicles, and high-speed industrial plants. To overcome these limitations, there is a need for a robust control strategy that will assure stability, provide minimum overshoot, and be highly efficient for demanding applications.

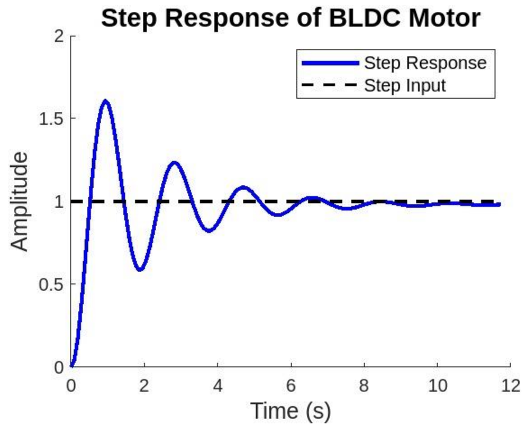

Fig. 5. The response of BLDC motor without controller

TABLE I. RESPONSE PARAMETERS OF BLDC MOTOR WITHOUT CONTROLLER

Parameters	Value
Rise time (sec)	0.3459
Settling time(sec)	7.7440
Overshoot	63.6296

Given instability, an LQR was designed to improve the response of the BLDC motor. The performance of the LQR controller is vastly dependent upon the proper tuning of matrices Q and R. Tuning is a compromise between the minimization of state deviation and the limitation of control effort. Tuning was performed in MATLAB using the iterative method to refine the values for the better response of the BLDC motor. The final parameters used in the design were: $Q=\begin{bmatrix} 10 & 0 \\ 0 & 1 \end{bmatrix}$ and R=1.4583

The corresponding gains derived from these matrices were:

K1=1.8393 and K2=0.0300.

Fig. 6 depicts the impact of incorporating the LQR controller, which significantly enhances the motor's response.

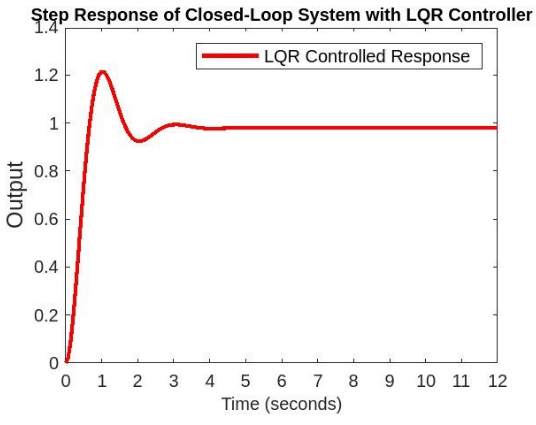

Fig. 6. Step response of LQR controller with BLDC motor

The LQR controller reduced the overshoot from 63.6296 when no controller was used down to 23.9479, an improvement of 62.3%. That will limit the mechanical stress on the motor and improve its reliability, extending its lifetime. The LQR controller reduced the settling time from 7.7440 seconds without control to 2.4857 seconds, which is a good improvement of 68% in the settling time. The system's efficiency is increased with faster stabilization, which is quite helpful for high-speed applications such as robotics and automated processes. The integrated overshoot and settling time improvement alone recorded notable gains in the system's control precision and stability. The response will be much smoother and more reliable in motor functions that fit application requirements, needing consistent and robust performance. Overall, the results have pointed towards the effectiveness of the LQR controller in optimizing the dynamics of a BLDC motor. While substantial improvements are found, the approaches for advanced optimization-employing metaheuristic algorithms such as SCSO can achieve better performance gains to satisfy even more stringent application requirements. Table II summarizes the key metrics achieved with the LQR controller.

TABLE II. RESPONSE PARAMETERS OF LQR CONTROLLER

Parameters	Value
Rise time(sec)	0.4403
Settling time(sec)	2.4857
Overshoot	23.9479
Cost function	1.8393

As illustrated in Fig. 7, integrating SCSO with LQR significantly enhanced the motor's response metrics. The LQR controller, optimized by applying the SCSO algorithm, greatly enhances BLDC motor performance. Within the LQR framework, Q and R matrices were fine-tuned to reach the optimal balance between the state deviations and control effort using the SCSO algorithm. Initial populations are designed, and each solution represents the candidate values of Q and R matrices. It further sets the SCSO parameters: population size 20, maximum iteration 50, and search range from 0 to 360° as settings for guiding the optimization in a proper way. Each candidate solution is measured with respect to a cost function, which incorporates relevant performance metrics, such as overshoot, settling time, and control effort. Candidate positions are updated in the algorithm, balancing the exploration for new solutions and refinement in existing solutions. This iterative process continues to either reach the maximum iterations or an acceptable cost function value as specified by the termination condition. The values of Q and R that are obtained as a result of this procedure are then used to set the gains of the LQR controller. The integration of the SCSO algorithm with the LQR controller, which highly optimizes Q and R matrices, gave a considerably high-performance improvement to BLDC motor performance. The he following optimized derived gains: K1 = 3.6388 and K2 = 0.2843 with optimal value of $Q=\begin{bmatrix} 9.8322 & 0.0347 \\ 0.03180 & 3.2817 \end{bmatrix}$, and R=0.5. This led to the reduction of overshoot from 23.947 to 5.7441, an improvement of 91% over the uncontrolled system. Again, the settling time decreased from 2.4857 seconds to 1.7582 seconds, hence an improvement of 77.2%, while the cost function dropped to 0.3376; hence, a very efficient control system.

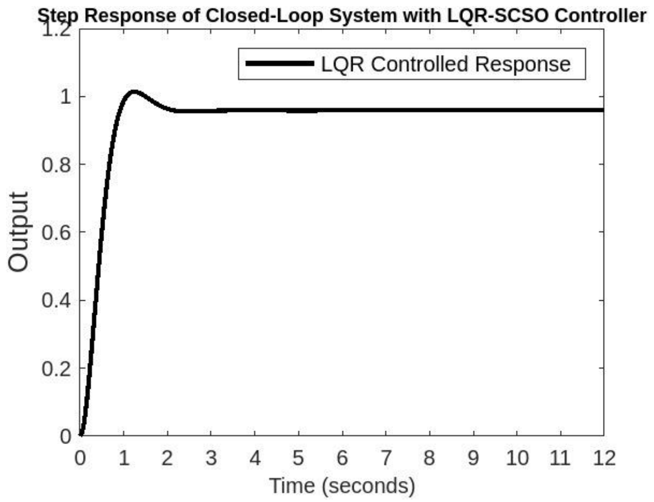

Fig. 7. Step response of tuned LQR controller using the SCSO

These improvements make the LQR-SCSO method suitable for precision and stability applications, including robotics and electric vehicles. The parameter response of the optimal control system detailed in Table III.

TABLE III. RESPONSE PARAMETERS OF LQR CONTROLLER WITH SCSO ALGORITHM

Parameters	Value
Rise time(sec)	0.5988
Settling time(sec)	1.7582
Overshoot	5.7441
Cost function	0.3376

The LQR controller improved with the BOA optimization algorithm, significantly enhancing the performance of the BLDC motor. In the framework of LQR, Q and R matrices were optimized using the Butterfly Optimization Algorithm to achieve an optimal tradeoff between state deviations and control effort. The optimization process began with initializing a population of solutions where each candidate represents the potential values for the Q and R matrices. BOA parameters will be set, including the population size of 20, the maximum number of iterations of 50, and control parameters concerning attraction and navigation.

A cost function has been developed for each solution, which envelops all the important measures: overshoot, settling time, and control effort. The BOA algorithm is a nature-inspired technique that models the foraging behavior of butterflies and strikes a balance between local and global searches in refining the solutions iteratively. It updates candidates' positions based on attraction and fitness values until an optimal solution is obtained. Once the termination criterion—minimal cost or maximum iterations—is satisfied, the LQR controller is configured using the optimum Q and R matrices: The integration of BOA with LQR brought significant enhancements to the motor's response metrics, as illustrated in Fig. 8.

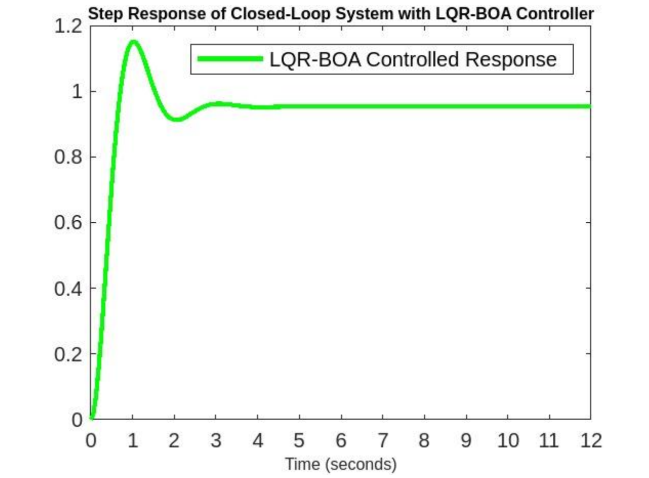

Fig. 8. Step response of tuned LQR controller using the BOA

This demonstrates that with the BOA in combination with the LQR controller, the overshoot has been notably reduced to 8.3% compared to the very high value of 23.9479% for only LQR and shows a marked improvement. Similarly, the settling time, which is reduced from 2.4857 seconds in the case of an LQR controller, goes down to 1.92 seconds, demonstrating much improvement in stability and response for the system. Besides these, the cost function is minimized to 0.4500, proving how efficiently the BOA will work in optimizing the control strategy—the optimized response parameters by using the control systems techniques explained in Table IV and Fig. 9.

TABLE IV. RESPONSE PARAMETERS OF LQR CONTROLLER WITH SCSO ALGORITHM

Parameters	BLDC	LQR	LQR-BOA	LQR-SCSO
Rise time(sec)	0.3954	0.4403	0.4503	0.5988
Settling time(sec)	7.7440	2.4857	2.4361	1.7582
Overshoot	63.6296	23.9479	20.76	5.7441
Cost function	---	1.8393	0.8736	0.3376

Comparing the performance of LQR-BOA to that of LQR-SCSO, it goes without saying that the LQR optimized through SCSO outweighs BOA on those significant metrics. In summary, the SCSO-based design ensured a better overshoot reduction of 5.7441 as opposed to the 8.3 achieved by BOA and thus has an edge over the minimization of transient deviations. Similarly, the settling time achieved with SCSO was 1.7582 seconds, notably faster than the 1.92 seconds recorded with BOA, emphasizing quicker stabilization and responsiveness. Although BOA achieved a slightly higher cost function value of 0.4500 compared to 0.3376 with SCSO, the overall system performance with SCSO is more balanced and better suited for precision-demanding applications. LQR-SCSO emerges as the superior optimization strategy, particularly when prioritizing overshoot and settling time as key factors in system performance, positioning it as the optimal approach for dynamic, high-speed tasks. The results confirm that LQR-SCSO outperforms other optimization strategies when reducing overshoot and settling time, validating its superior performance in dynamic and high-performance scenarios.

Such improvements emphasize the robustness and efficiency of LQR-BOA, making it a promising method for control optimization tasks that demand precision and fast stabilization, including but not limited to autonomous systems and industrial automation. Nevertheless, the efficiency of the algorithm could also be influenced by different scenarios such as the starting configuration and the dynamic behavior of the environment, which may require additional investigations and tuning of the parameters to calibrate it for various operating conditions shown in Table IV.

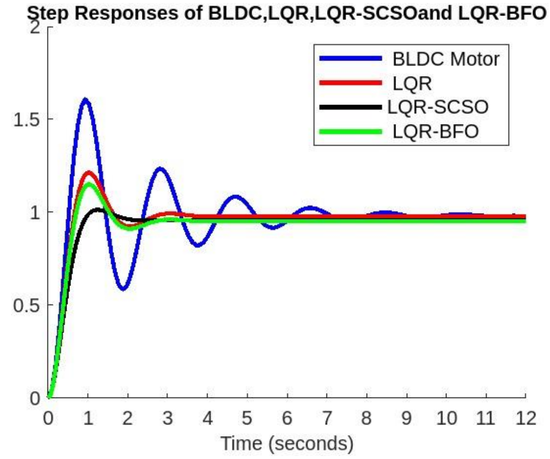

Fig. 9. Step response of BLDC motor, and the optimize control systems responses

VII. Conclusion

In the present study, this research proposes a control system for the BLDC motor that incorporates the SCSO algorithm with modifications of LQR. Further, the results distinctly show the improvement in settling time response preprocessing through the use of SCSO—that is, faster stabilization and finer precision when compared to a traditional LQR controller. Optimized controllers reduced settling time by 77.2% and reduced cost function to 0.3376, while overshoot was reduced by 91%. These improvements underline the practical benefits of the proposed approach and make it a transformative solution for everything from consumer to industrial applications, given its simplicity and efficiency.

A comparative analysis with the Butterfly Optimization Algorithm (BOA) further highlights SCSO's advantages. The SCSO-based LQR achieved a lower overshoot of 5.7441%, compared to 8.3% with BOA, and demonstrated a faster settling time at 1.7582 seconds versus 1.92 seconds for BOA. Although BOA exhibited a slightly higher cost function efficiency (0.4500 compared to 0.3376 for SCSO), the overall performance metrics favor SCSO for applications requiring high precision and rapid response.

The novelty in this work is the integration of SCSO algorithms with LQR for the control of BLDC motors, with significant advances compared to conventional methods and other optimization techniques. These results show the broader impact of improved performance and energy efficiency in advanced robotics, electric vehicles, and automated systems applications. The study does mention some limitations of this study that might give warrant to other potential future research involving the SCSO algorithm computation cost and initial sensitivity, not mentioning robustness for all varieties of environmental or operational conditions regarding the controller in perspective. These will ensure the reliability and adaptability of the method in real situations.

Future research should also focus on the quest for adaptive optimization techniques, such as reinforcement learning or neural networks, in order to render controllers more flexible and fault-hard. Besides, the proposed system needs implementation and testing under real-time conditions in applications like grid-connected systems for the realization of proper implementation features. The research work can be invaluable for further advancements in control system technologies and power system management.

References

[1] N. Nurdamayanti, L. Sartika, and A. M. Prasetia, "Brushless Direct Current (BLDC) Motor Speed Control Using Field Oriented Control (FOC) Method," *Jurnal Edukasi Elektro*, vol. 6, no. 2, Nov. 2022, doi: 10.21831/jee.v6i2.52234.

[2] F. Shafique, M. S. Fakhar, A. Rasool, and S. A. R. Kashif, "Analyzing the performance of metaheuristic algorithms in speed control of brushless DC motor: Implementation and statistical comparison," *PLOS ONE*, vol. 19, no. 10, p. e0310080, Oct. 2024, doi: 10.1371/journal.pone.0310080.

[3] R. Arivalahan, S. Venkatesh, and T. Vinoth, "An effective speed regulation of brushless DC motor using hybrid approach," *Advances in Engineering Software*, vol. 174, p. 103321, Dec. 2022, doi: 10.1016/j.advengsoft.2022.103321

[4] N. X. Chiem and L. T. Thang, "Synthesis of LQR Controller Based on BAT Algorithm for Furuta Pendulum Stabilization," *Journal of Robotics and Control*, vol. 4, no. 5, pp. 662–669, Sep. 2023, doi: 10.18196/jrc.v4i5.19661

[5] Y. Jin, Q. Ouyang, and R. Li, "Research of the LQR algorithm with constraints based on preview control," *Research Square*, 2023, doi: 10.21203/rs.3.rs-2961763/v1.

[6] S. Sharma, N. K. Sharma, M. Bajaj, V. Kumar, F. Jurado, and S. Kamel, "Optimal BLDC Motor Control Using a WOA-based LQR Strategy," in *2022 4th Global Power, Energy and Communication Conference (GPECOM)*, pp. 222–226, Jun. 2022, doi: 10.1109/GPECOM55404.2022.9815609.

[7] T. Wang, H. Wang, H. Hu, and C. Wang, "LQR optimized BP neural network PI controller for speed control of brushless DC motor," *Advances in Mechanical Engineering*, vol. 12, no. 10, p. 168781402096898, Oct. 2020, doi: 10.1177/1687814020968980.

[8] W. Zhao and L. Gu, "Hybrid Particle Swarm Optimization Genetic LQR Controller for Active Suspension," *Applied Sciences*, vol. 13, no. 14, 2023, doi: 10.3390/app13148204.

[9] S. J. Chacko, N. P.c., and R. J. Abraham, "Optimizing LQR controllers: A comparative study," *Results in Control and Optimization*, vol. 14, p. 100387, Mar. 2024, doi: 10.1016/j.rico.2024.100387.

[10] R. Liu *et al*., "A Novel Adaptive Sand Cat Swarm Optimization Algorithm for Feature Selection and Global Optimization," *Biomimetics*, vol. 9, no. 11, Nov. 2024, doi: 10.3390/biomimetics9110701.

[11] Z. Chu and F. Teng, "Managing the Uncertainty in System Dynamics Through Distributionally Robust Stability-Constrained Optimization," in *IEEE Transactions on Power Systems*, vol. 40, no. 1, pp. 449-462, Jan. 2025, doi: 10.1109/TPWRS.2024.3413974.

[12] R. Kristiyono and W. Wiyono, "Autotuning Fuzzy PID Controller for Speed Control of BLDC Motor," *Journal of Robotics and Control (JRC)*, vol. 2, no. 5, 2021, doi: 10.18196/jrc.25114.

[13] H. Maghfiroh, M. Ahmad, A. Ramelan, and F. Adriyanto, "Fuzzy-PID in BLDC Motor Speed Control Using MATLAB/Simulink," *Journal of Robotics and Control*, vol. 3, no. 1, pp. 8–13, Jun. 2021, doi: 10.18196/jrc.v3i1.10964.

[14] D. Kumar and R. a. Gupta, "A comprehensive review on BLDC motor and its control techniques," *International Journal of Power Electronics*, vol. 14, no. 3, pp. 292–335, Jan. 2021, doi: 10.1504/IJPELEC.2021.117523.

[15] D. M. Harfina, Z. Zaini, and W. J. Wulung, "Disinfectant Spraying System with Quadcopter Type Unmanned Aerial Vehicle (UAV) Technology as an Effort to Break the Chain of the COVID-19 Virus," *Journal of Robotics and Control (JRC)*, vol. 2, no. 6, Nov. 2021, doi: 10.18196/jrc.26129.

[16] H. Jawad Ali, D. Kammel Shary, and H. Dawood Abbood, "A Review of Intelligent Techniques Based Speed Control of Brushless DC Motor (BLDC)," *BJES*, vol. 24, no. 1, pp. 109–119, Feb. 2024, doi: 10.33971/bjes.24.1.12

[17] M. Akrami, E. Jamshidpour, B. Nahid-Mobarakeh, S. Pierfederici, and V. Frick, "Sensorless Control Methods for BLDC Motor Drives: A Review," *IEEE Transactions on Transportation Electrification*, 2024, doi: 10.1109/TTE.2024.3387371.

[18] P. N, R. Thirumalaivasan, and B. Ashok, "Design of sliding mode controller with improved reaching law through self-learning strategy to mitigate the torque ripple in BLDC motor for electric vehicles," *Computers and Electrical Engineering*, vol. 118, p. 109438, Sep. 2024, doi: 10.1016/j.compeleceng.2024.109438.

[19] D. Mohanraj *et al*., "A Review of BLDC Motor: State of Art, Advanced Control Techniques, and Applications," *IEEE Access*, vol. 10, pp. 54833–54869, 2022, doi: 10.1109/ACCESS.2022.3175011.

[20] S. Kaul, N. Tiwari, S. Yadav, and A. Kumar, "Comparative Analysis and Controller Design for BLDC Motor Using PID and Adaptive PID Controller," *Recent Advances in Electrical & Electronic Engineering*, vol. 14, no. 6, pp. 671–682, Sep. 2021, doi: 10.2174/2352096514666210823152446.

[21] N. X. Chiem and L. T. Thang, "Synthesis of LQR Controller Based on BAT Algorithm for Furuta Pendulum Stabilization," *Journal of Robotics and Control*, vol. 4, no. 5, pp. 662–669, Sep. 2023, doi: 10.18196/jrc.v4i5.19661.

[22] D. T. Tran, N. M. Hoang, N. H. Loc, Q. T. Truong, and N. T. Nha, "A Fuzzy LQR PID Control for a Two-Legged Wheel Robot with Uncertainties and Variant Height," *Journal of Robotics and Control*, vol. 4, no. 5, pp. 612–620, Sep. 2023, doi: 10.18196/jrc.v4i5.19448.

[23] D. Handaya and R. Fauziah, "Proportional-Integral-Derivative and Linear Quadratic Regulator Control of Direct Current Motor Position using Multi-Turn Based on LabView," *Journal of Robotics and Control (JRC)*, vol. 2, no. 4, Jul. 2021, doi: 10.18196/jrc.24102.

[24] M.-T. Vo, V.-D.-H. Nguyen, H.-N. Duong, and V.-H. Nguyen, "Combining Passivity-Based Control and Linear Quadratic Regulator to Control a Rotary Inverted Pendulum," *Journal of Robotics and Control*, vol. 4, no. 4, pp. 479–490, Jul. 2023, doi: 10.18196/jrc.v4i4.18498.

[25] S. Zarghoon *et al*., "Full-state feedback LQR with integral gain for control of induction heating of steel billet," *Engineering Science and Technology, an International Journal*, vol. 55, p. 101721, Jul. 2024, doi: 10.1016/j.jestch.2024.101721.

[26] A. C. B. de Oliveira, M. Siami, and E. D. Sontag, "Convergence Analysis of Overparametrized LQR Formulations," *arXiv preprint arXiv:2408.15456*, 2024, doi: 10.48550/arXiv.2408.15456.

[27] K. Nosrati, J. Belikov, A. Tepljakov, and E. Petlenkov, "Revisiting the LQR Problem of Singular Systems," *IEEE/CAA Journal of Automatica Sinica*, vol. 11, no. 11, pp. 2236–2252, Nov. 2024, doi: 10.1109/JAS.2024.124665.

[28] H. Jawad Ali and H. Dawood Abbood, "A Review of Intelligent Techniques Based Speed Control of Brushless DC Motor (BLDC)," *Basrah Journal for Engineering Sciences*, vol. 24, no. 1, pp. 109–119, Feb. 2024, doi: 10.33971/bjes.24.1.12

[29] U. Mohammed, S. U. Hussein, M. Usman, and S. Thomas, "Design of an Optimal Linear Quadratic Regulator (LQR) Controller for the Ball-On-Sphere System," *International Journal of Engineering and Manufacturing (IJEM)*, vol. 10, no. 3, pp. 56-70, June 2020, doi: 10.5815/ijem.2020.03.05.

[30] X. Zhang and T. Başar, "Revisiting LQR Control From the Perspective of Receding-Horizon Policy Gradient," *IEEE Control Systems Letters*, vol. 7, pp. 1664–1669, 2023, doi: 10.1109/LCSYS.2023.3271594.

[31] T. Dai and M. Sznaier, "Data-driven quadratic stabilization and LQR control of LTI systems," *Automatica*, vol. 153, p. 111041, Jul. 2023, doi: 10.1016/j.automatica.2023.111041.

[32] G. Kaczmarczyk, M. Malarczyk, D. D. Ferreira, and M. Kaminski, "Stable Rules Definition for Fuzzy TS Speed Controller Implemented for BLDC Motor," *Applied Sciences*, vol. 14, no. 3, p. 982, Jan. 2024, doi: 10.3390/app14030982.

[33] K. Sayed, H. H. El-Zohri, A. Ahmed, and M. Khamies, "Application of Tilt Integral Derivative for Efficient Speed Control and Operation of BLDC Motor Drive for Electric Vehicles," *Fractal Fract*, vol. 8, no. 1, p. 61, Jan. 2024, doi: 10.3390/fractalfract8010061

[34] E. Vinodh Kumar and J. Jerome, "LQR based Optimal Tuning of PID Controller for Trajectory Tracking of Magnetic Levitation System," *Procedia Engineering*, vol. 64, pp. 254–264, Jan. 2013, doi: 10.1016/j.proeng.2013.09.097.

[35] L. B. Prasad, B. Tyagi, and H. O. Gupta, "Modelling and Simulation for Optimal Control of Nonlinear Inverted Pendulum Dynamical System Using PID Controller and LQR," in *2012 Sixth Asia Modelling Symposium*, pp. 138–143, May 2012, doi: 10.1109/AMS.2012.21.

[36] S. Kumar and L. Dewan, "A Comparative Analysis of LQR and SMC for Quanser AERO," in *Control and Measurement Applications for Smart Grid*, pp. 453–463, 2022, doi: 10.1007/978-981-16-7664-2_37.

[37] Y. Niu, X. Yan, Y. Wang, and Y. Niu, "An improved sand cat swarm optimization for moving target search by UAV," *Expert Systems with Applications*, vol. 238, p. 122189, Mar. 2024, doi: 10.1016/j.eswa.2023.122189.

[38] O. R. Adegboye, A. K. Feda, O. R. Ojekemi, E. B. Agyekum, B. Khan, and S. Kamel, "DGS-SCSO: Enhancing Sand Cat Swarm Optimization with Dynamic Pinhole Imaging and Golden Sine Algorithm for improved numerical optimization performance," *Sci Rep*, vol. 14, no. 1, p. 1491, Jan. 2024, doi: 10.1038/s41598-023-50910-x.

[39] Y. Cai, C. Guo, and X. Chen, "An improved sand cat swarm optimization with lens opposition-based learning and sparrow search algorithm," *Sci Rep*, vol. 14, no. 1, p. 20690, Sep. 2024, doi: 10.1038/s41598-024-71581-2.

[40] A. Ali Hameed, A. Jamil, and A. Seyyedabbasi, "An optimized feature selection approach using sand Cat Swarm optimization for hyperspectral image classification," *Infrared Physics & Technology*, vol. 141, p. 105449, Sep. 2024, doi: 10.1016/j.infrared.2024.105449.

[41] Y. Li, Q. Yu, and Z. Du, "Sand cat swarm optimization algorithm and its application integrating elite decentralization and crossbar strategy," *Sci Rep*, vol. 14, no. 1, p. 8927, Apr. 2024, doi: 10.1038/s41598-024-59597-0.

[42] K. H. Thanoon, S. Q. Hasan, and O. I. Alsaif, "Biometric information based on distribution of arabic letters according to their outlet," *International Journal of Computing and Digital Systems*, vol. 90, no. 5, pp. 981–991, 2020.

[43] F. Kiani, F. A. Anka, and F. Erenel, "PSCSO: Enhanced sand cat swarm optimization inspired by the political system to solve complex problems," *Advances in Engineering Software*, vol. 178, p. 103423, Apr. 2023, doi: 10.1016/j.advengsoft.2023.103423.

[44] X. Li, Y. Qi, Q. Xing, and Y. Hu, "IMSCSO: An Intensified Sand Cat Swarm Optimization With Multi-Strategy for Solving Global and Engineering Optimization Problems," *IEEE Access*, vol. 11, pp. 122315–122344, 2023, doi: 10.1109/ACCESS.2023.3327732.

[45] H. Jia, J. Zhang, H. Rao, and L. Abualigah, "Improved sandcat swarm optimization algorithm for solving global optimum problems," *Artif Intell Rev*, vol. 58, no. 1, p. 5, Nov. 2024, doi: 10.1007/s10462-024-10986-x.

[46] A. Bouchahed, M. Assabaa, A. Draidi, F. Makhloufi, and A. Belhani, "Improvement of the linear quadratic regulator control applied to a DC-DC boost converter driving a permanent magnet direct current motor," *IJECE*, vol. 13, no. 6, p. 6131, Dec. 2023.

[47] D. Wu, H. Rao, C. Wen, H. Jia, Q. Liu, and L. Abualigah, "Modified Sand Cat Swarm Optimization Algorithm for Solving Constrained Engineering Optimization Problems," *Mathematics*, vol. 10, no. 22, 2022, doi: 10.3390/math10224350.

[48] W. Wang, Z. Han, Z. Zhang, and J. Wang, "Enhancing sand cat swarm optimization based on multi-strategy mixing for solving

engineering optimization problems," *Evol. Intel*., vol. 18, no. 1, p. 7, Nov. 2024, doi: 10.1007/s12065-024-00996-7.

[49] A. Seyyedabbasi, "Solve the Inverse Kinematics of Robot Arms using Sand Cat Swarm Optimization (SCSO) Algorithm," in *2022 International Conference on Theoretical and Applied Computer Science and Engineering (ICTASCE)*, pp. 127–131, Sep. 2022, doi: 10.1109/ICTACSE50438.2022.10009772.

[50] E. Pashaei, "An Efficient Binary Sand Cat Swarm Optimization for Feature Selection in High-Dimensional Biomedical Data," *Bioengineering*, vol. 10, no. 10, Oct. 2023, doi: 10.3390/bioengineering10101123.

[51] J. D. S. Kumar, M. V. Subramanyam, and A. P. S. Kumar, "Hybrid Sand Cat Swarm Optimization Algorithm-based reliable coverage optimization strategy for heterogeneous wireless sensor networks," *Int. j. inf. tecnol*., Sep. 2024, doi: 10.1007/s41870-024-02163-8.

[52] Y. Li and G. Wang, "Sand Cat Swarm Optimization Based on Stochastic Variation With Elite Collaboration," *IEEE Access*, vol. 10, pp. 89989–90003, 2022, doi: 10.1109/ACCESS.2022.3201147

[53] R. R. Ihsan, S. M. Almufti, B. M. S. Ormani, R. R. Asaad, and R. B. Marqas, "A Survey on Cat Swarm Optimization Algorithm," *AJRCoS*, pp. 22–32, Jun. 2021 doi: 10.9734/ajrcos/2021/v10i230237

[54] F. Kiani, S. Nematzadeh, F. A. Anka, and M. A. Findikli, "Chaotic Sand Cat Swarm Optimization," *Mathematics*, vol. 11, no. 10, 2023, doi: 10.3390/math11102340.

[55] A. Seyyedabbasi, "Binary Sand Cat Swarm Optimization Algorithm for Wrapper Feature Selection on Biological Data," *Biomimetics*, vol. 8, no. 3, Art. no. 3, Jul. 2023, doi: 10.3390/biomimetics8030310.

[56] K. Zhang, Y. He, Y. Wang, and C. Sun, "Improved Multi-Strategy Sand Cat Swarm Optimization for Solving Global Optimization," *Biomimetics*, vol. 9, no. 5, May 2024, doi: 10.3390/biomimetics9050280.

[57] A. Qtaish, D. Albashish, M. Braik, M. T. Alshammari, A. Alreshidi, and E. J. Alreshidi, "Memory-Based Sand Cat Swarm Optimization for Feature Selection in Medical Diagnosis," *Electronics*, vol. 12, no. 9, 2023, doi: 10.3390/electronics12092042.

[58] Li, Y. Hu, B. Ma, and D. Wang, "MBSCSO: Multi-Strategy Boosted Sand Cat Swarm Optimization for Engineering Applications," *IEEE Access*, vol. 12, pp. 153743–153782, 2024, doi: 10.1109/ACCESS.2024.3483457.

[59] Y. Hu, R. Xiong, J. Li, C. Zhou, and Q. Wu, "An Improved Sand Cat Swarm Operation and Its Application in Engineering," *IEEE Access*, vol. 11, pp. 68664–68681, 2023, doi: 10.1109/ACCESS.2023.3292338.

[60] A. Seyyedabbasi and F. Kiani, "Sand Cat Swarm Optimization: A Nature-Inspired Algorithm to Solve Global Optimization Problems," *Engineering with Computers*, vol. 39, 2022, doi: 10.1007/s00366-022-01604-x.

[61] O. I. Alsaif, K. H. Thanoon, and A. H. Al Bayati, "Auto electronic recognition of the Arabic letters sound," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 28, no. 2, pp. 769–776, 2022.

[62] C. B. Kaya and E. Kaya, "Evaluation of The Performance of Butterfly Optimization Algorithm in Solving High-Dimensional Numerical Optimization Problems," *Mühendislik bilimleri ve araştırmaları dergisi*, vol. 4, no. 2, 2022, doi: 10.46387/bjesr.1170933.

[63] M. Zhang, D. Wang, and J. Yang, "Hybrid-Flash Butterfly Optimization Algorithm with Logistic Mapping for Solving the Engineering Constrained Optimization Problems," *Entropy*, vol. 24, no. 4, p. 525, Apr. 2022, doi: 10.3390/e24040525.

[64] S. S. Abd-Aljabar, N. M. Basheer, and O. I. Alsaif, "Alzheimer's diseases classification using YOLOv2 object detection technique," *International Journal of Reconfigurable and Embedded Systems*, vol. 11, no. 3, pp. 240–248, 2022.

[65] R. Zhai, P. Xiao, D. Shu, Y. Sun, and M. Jiang, "Application of Improved Butterfly Optimization Algorithm in Mobile Robot Path Planning," *Electronics*, vol. 12, no. 16, Jan. 2023, doi: 10.3390/electronics12163424.

[66] C. Li, X. Huang, J. Ding, K. Song, and S. Lu, "Global path planning based on a bidirectional alternating search A* algorithm for mobile robots," *Computers & Industrial Engineering*, vol. 168, p. 108123, 2022.

[67] Y. Ma, X. Liu, and P. Shao, "A Multi-Strategy Improved Butterfly Optimization Algorithm," in *2023 International Conference on New Trends in Computational Intelligence (NTCI)*, pp. 324–328, Nov. 2023, doi: 10.1109/NTCI60157.2023.10403745.

[68] E. N. Dragoi and V. Dafinescu, "Review of Metaheuristics Inspired from the Animal Kingdom," *Mathematics*, vol. 9, no. 18, Jan. 2021, doi: 10.3390/math9182335.

[69] A. Arya, K. Pahwa, and Gunjan, "A butterfly optimization approach for improving the performance of futuristic internet-of-things," *Evolving Systems*, vol. 15, no. 3, pp. 1057–1071, Jun. 2024, doi: 10.1007/s12530-023-09539-4.

[70] Y. Li, X. Yu, and J. Liu, "Enhanced Butterfly Optimization Algorithm for Large-Scale Optimization Problems," *J Bionic Eng*, vol. 19, no. 2, pp. 554–570, Mar. 2022, doi: 10.1007/s42235-021-00143-3.

[71] S. N. Makhadmeh *et al*., "Recent Advances in Butterfly Optimization Algorithm, Its Versions and Applications," *Arch Computat Methods Eng*, vol. 30, no. 2, pp. 1399–1420, Mar. 2023, doi: 10.1007/s11831-022-09843-3.

[72] A. Mortazavi and M. Moloodpoor, "Enhanced Butterfly Optimization Algorithm with a New fuzzy Regulator Strategy and Virtual Butterfly Concept," *Knowledge-Based Systems*, vol. 228, p. 107291, Sep. 2021, doi: 10.1016/j.knosys.2021.107291.

[73] K. G. Abdulhussein, N. M. Yasin, and I. J. Hasan, "Comparison between butterfly optimization algorithm and particle swarm optimization for tuning cascade PID control system of PMDC motor," *IJPEDS*, vol. 12, no. 2, p. 736, Jun. 2021, doi: 10.11591/ijpeds.v12.i2.pp736-744.

[74] Y. He, Y. Zhou, Y. Wei, Q. Luo, and W. Deng, "Wind Driven Butterfly Optimization Algorithm with Hybrid Mechanism Avoiding Natural Enemies for Global Optimization and PID Controller Design," *J Bionic Eng*, vol. 20, no. 6, pp. 2935–2972, Nov. 2023, doi: 10.1007/s42235-023-00416-z.

[75] A. Mondal, A. Latif, D. C. Das, S. M. S. Hussain, and A. Al-Durra, "Frequency regulation of hybrid shipboard microgrid system using butterfly optimization algorithm synthesis fractional-order controller," *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, vol. 36, no. 5, p. e3058, 2023, doi: 10.1002/jnm.3058.

[76] T. K. Sharma, "Enhanced butterfly optimization algorithm for reliability optimization problems," *J Ambient Intell Human Comput*, vol. 12, no. 7, pp. 7595–7619, Jul. 2021, doi: 10.1007/s12652-020-02481-2.

[77] K. A. K. Khalaf and M. Teke, "Controlling the operation of the dc motor by using pid with metaheuristic technology," *Journal of Computer & Electrical and Electronics Engineering Sciences*, vol. 1, no. 2, pp. 34–40, Oct. 2023.

[78] B. Jegajothi, G. Geethamahalakshmi, A. Raja, and N. Mahendran, "An efficient metaheuristic optimization based fuzzy controller for brushless DC drives lifetime expansion," *Materials Today: Proceedings*, vol. 56, pp. 3343–3348, Jan. 2022, doi: 10.1016/j.matpr.2021.10.176.

[79] K. Warnakulasooriya and A. Segev, "Comparative analysis of accuracy and computational complexity across 21 swarm intelligence algorithms," *Evol. Intel*., vol. 18, no. 1, p. 18, Dec. 2024, doi: 10.1007/s12065-024-00997-6.

[80] A. H. Maray, O. I. Alsaif, and K. H. Tanoon, "Design And Implementation Of Low-Cost Medical Auditory System Of Distortion Otoacoustic Using Microcontroller," *Journal of Engineering Science and Technology*, vol. 17, no. 2, pp. 1068–1077, 2022.