International Journal of Robotics and Control Systems
Vol. 5, No. 1, 2025, pp. 459-478
ISSN 2775-2658
http://pubs2.ascee.org/index.php/ijrcs

A Hybrid PSO-GCRA Framework for Optimizing Control Systems Performance

Ahmad MohdAziz Hussein [a,1], Saleh Ali Alomari [b,2], Mohammad H. Almomani [c,3], Raed Abu Zitar [d,4], Hazem Migdady [e,5], Aseel Smerat [f,g,h,i,,j,6], Vaclav Snasel [k,7], Laith Abualigah [l,8,*]

[a] Department of Computer Science, Faculty of Information Technology, Middle East University, Amman, Jordan
[b] Faculty of Science and Information Technology, Jadara University, Irbid 21110, Jordan
[c] Department of Mathematics, Facility of Science, The Hashemite University, P.O box 330127, Zarqa 13133, Jordan
[d] Faculty of Engineering and Computing, Liwa College, Abu Dhabi, United Arab Emirates
[e] CSMIS Department, Oman College of Management and Technology, 320 Barka, Oman
[f] Faculty of Educational Sciences, Al-Ahliyya Amman University, Amman, 19328, Jordan
[g] Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, 140401, Punjab, India
[h] Department of Biosciences, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai 602105, India
[i] Computer Technologies Engineering, Mazaya University College, Nasiriyah, Iraq
[j] Artificial Intelligence and Sensing Technologies (AIST) Research Center, University of Tabuk, Tabuk 71491, Saudi Arabia
[k] Faculty of Electrical Engineering and Computer Science, VŠB-Technical University of Ostrava, 70800 Poruba-Ostrava, Czech Republic
[l] Computer Science Department, Al al-Bayt University, Mafraq 25113, Jordan
[1] ahussein@meu.edu.jo; [2] omari08@jadara.edu.jo; [3] mh_momani@hu.edu.jo; [4] raed.abuzitar@lc.ac.ae;
[5] hmigdady@siu.edu; [6] smerat.2020@gmail.com; [7] vaclav.snasel@vsb.cz; [8] aligah.2020@gmail.com
* Corresponding Author

ARTICLE INFO

Article history
Received December 07, 2024
Revised January 11, 2025
Accepted January 15, 2025

Keywords
Hybrid Optimization;
Particle Swarm Optimization (PSO);
Greater Cane Rat Algorithm (GCRA);
Control Systems Optimization

ABSTRACT

Optimization is essential for improving the performance of control systems, particularly in scenarios that involve complex, non-linear, and dynamic behaviors. This paper introduces a new hybrid optimization framework that merges Particle Swarm Optimization (PSO) with the Greater Cane Rat Algorithm (GCRA), which we call the PSO-GCRA framework. This hybrid approach takes advantage of PSO's global exploration capabilities and GCRA's local refinement strengths to overcome the shortcomings of each algorithm, such as premature convergence and ineffective local searches. We apply the proposed framework to a real-world load forecasting challenge using data from the Australian Energy Market Operator (AEMO). The PSO-GCRA framework functions in two sequential phases: first, PSO conducts a global search to explore the solution space, and then GCRA fine-tunes the solutions through mutation and crossover operations, ensuring convergence to high-quality optima. We evaluate the performance of this framework against benchmark methods, including EMD-SVR-PSO, FS-TSFE-CBSSO, VMD-FFT-IOSVR, and DCP-SVM-WO. Comprehensive experiments are carried out using metrics such as Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and convergence rate. The proposed PSO-GCRA framework achieves a MAPE of 2.05% and an RMSE of 3.91, outperforming benchmark methods, such as EMD-SVR-PSO (MAPE: 2.85%, RMSE: 4.49) and FS-TSFE-CBSSO (MAPE: 2.98%, RMSE: 4.69), in terms of accuracy, stability, and convergence efficiency. Comprehensive experiments were conducted using Australian Energy Market Operator (AEMO) data, with specific attention to normalization, parameter tuning, and iterative evaluations to ensure reliability and reproducibility.

1. Introduction

The performance of a control system [1], [2], whose efficiency can be enhanced by carefully choosing the control parameters through a suitable optimization technique [3], [4], is of prime importance in practical applications, as these chosen parameters affect not only the operation of the system concerning stability but also the economy and the issue of minimizing pollution-related problems [5]. These synthesized control parameters for the specified objective are the result of the optimization problem, which generally suffers from stagnation and local convergence issues; the development of a hybrid algorithm becomes essential for addressing optimization issues [6], [7]. The concept of hybridization of algorithms has been encouraged by many researchers and has developed because of the drawbacks faced by traditional algorithms in solving complex optimization problems [8]. Nowadays, control systems are more sophisticated and contain uncertain characteristics; only advanced optimization techniques can be used to optimize the performance of advanced control systems [9], [10]. Many optimization algorithms can solve the problems of optimization; one of the popular algorithms used frequently needs to be fine-tuned with the best-tuned parameters, so the issues of fine-tuning hinder the accuracy of optimization [11], [12]. Therefore, optimization techniques may have been developed by blending several algorithms to strengthen optimization. Hybrid optimization tools have many benefits for better optimization of the control parameters of the practical control system [13], [14]. However, using the hybrid optimization techniques, this study's main concern is to improve the performance of the control system regarding regulating variables, actuator variables, sensor variables, and interconnected variables [15]-[17].

The optimization of control systems is crucial for ensuring the efficiency [18], [19], stability, and reliability of complex systems in various fields, such as robotics, smart grids, and industrial automation [20], [21]. These control systems often deal with highly dynamic and non-linear processes, and achieving optimal performance requires advanced algorithms that can balance multiple objectives. Modern trends in optimization have contributed to the creation of new hybrid algorithms, which utilize various method facets to help by neglecting traditional algorithms [22], [23]. PSO algorithm worth noting is metaheuristic-optimization, since its low complexity, easy to scale and useful in the solution of a non-linear problem. But PSO has its drawbacks, such as premature convergence, and weakness in local search strategies, especially in high-dimensional or multimodal optimization problems. To successfully counter such Factors, The Social Behavior of Cane Rats Gives Birth to the Greater Cane Rat Algorithm (GCRA), which is Understanding the popular methods of optimization. GCRA is very effective in local search and adaptive mechanisms, thus augmenting the functionality of PSO significantly.

The Particle Swarm Optimization algorithm is used for solving continuous non-linear optimization problems and non-differentiable functions, like the Genetic Algorithm [24], [25]. An improved Particle Swarm Optimization algorithm was utilized to optimize electricity production with a power system [26], [27]. It was further improved by obtaining a better solution to reduce fuel and maintenance costs. A recent optimization algorithm called the Greater Cane Rat Algorithm is used for optimization and often integrates with other hybrid and intelligent-approach algorithms to outperform results obtained from other studies [28]. The recent Particle Swarm Optimization and Greater Cane ratio algorithm-related studies have shown that hybrid optimization algorithms can improve the performance and settings of the system changes in previously published research. These researchers did not use forecasting, which deviates from previous studies and conventional Particle Swarm Optimization. Although a substantial amount of research has been conducted on Particle Swarm Optimization, it has been stated that although it can solve various problems and consider the hybrid Particle Swarm and optimization applications in real-life scenarios, a partial search has yet to be proposed. It sets up a profile background of the necessary parallel computing, genetic evolution, and intelligence in Particle Swarm Optimization algorithms that lead to a hybrid nature in optimization. The study sets the context necessary to justify further why advancements in the Particle Swarm Optimization core need to be further explored.

In the past years, control systems have added various optimization algorithms to all domains to improve their performance [29]-[33]. Optimization algorithms are utilized in solving optimization problems to make the systems work effectively with the desired results. Optimization algorithm solutions can help automotive safety, airspace, impedance control, management of urban traffic, mission planning, assembly systems, algorithm signal reconstruction, field monitoring, surface modeling, and others to solve their real-world problems. With the advancement in technology in the past years, many optimization procedures have evolved, with some of the most used being Genetic Algorithm, Particle Swarm Optimization, and Artificial Bee Colony [8], [34]. Although these methodologies have worked successfully, they have some limitations and sometimes suffer from premature convergence.

Control systems performance denotes the capability of the control systems to ensure their effectiveness [35], [36]. The evaluation of control systems is primarily associated with the ability of the systems to satisfy specific criteria [37], [38]. When evaluating the performance of control systems, different factors could be considered. The operating conditions, disturbance effects, and maturity caused by the modeling errors can determine the deviation between the input signals and the reference system response [39], [40]. Three fundamental factors can be used to test the ability of a control system: stability, response time, and accuracy [41], [42]. In practice, there will be many aspects that can affect the capability of the control systems. Therefore, obtaining optimal performance is an important attribute when operating under various conditions. In many real-world applications, the goal when building the control system is to obtain the fastest possible response time with the least influence on the system's dynamics [43], [44]. Thus, it is necessary to consider the interaction between the controllers and system variables when examining the systems' capabilities. In recent years, several studies have been proposed to assess control structures in different application domains [45], [46]. The primary methods used revolve around the assessment of focus. These methods are typically based on the application of computational algorithms to obtain desired results, and many of these answers require optimization functions for modeling [47]. Several publications have been proposed for evaluating the ultimate performance of controllers [48], [49]. One of the significant steps beyond assessing the performance of the controllers is the use of sophisticated techniques [50], [51].

The Greater Cane Rat Algorithm (GCRA), which employs the strategy of mutating and crossing over, derives its inspiration from cane rats that forage [52]. The GCRA, unlike other local search algorithms, exhibits exceptional proficiency in exploration and load balancing which results in the ability to implement efficient refinements. However, such limitations of GCRA in its global search capability complement its combination with algorithms such as Particle Swarm Optimization (PSO). Existing hybrid algorithms do not have such unique combinations and are plagued with several limitations including premature convergence, poor optimization of parameters, and subpar balances between exploration and exploitation, to name a few. For example, many use discrimination against other algorithms and rely on one algorithm through which benefits outweigh. The framework PSO-GCRA has been developed to fill these deficiencies for a large class of problems by integrating global search abilities due to Particle Swarm Optimization (PSO) and local search abilities due to GCRA.

Meanwhile, the identification of suitable metrics could provide an exploration point when finding the rise-time-oriented controllers. Most of the identified control performance assessment methods revolve around the techniques of computational intelligence. However, the main limitation in the collected literature is the need for more focus on designing a strategy that employs predictive techniques for obtaining the desired results. In addition, one of the main challenges of the existing predictive intelligence views is the need for an efficient optimization strategy. The main objective of this study is to propose a hybrid strategy for improving the performance of control systems.

In this paper, we introduce a new hybrid framework that combines Particle Swarm Optimization (PSO) and Generalized Conditional Random Fields (GCRA), which we call PSO-GCRA. This integration leverages the strengths of both algorithms, enhancing the global search capabilities of PSO with the local refinement strategies of GCRA. PSO shines in scanning the global search space which helps in avoiding early convergence and assists in locating attractive regions. GCRA supplements value in the algorithm through local search processes as it utilizes mutation and crossover operations to improve the accuracy of those solutions. Accordingly, the PSO-GCRA hybrid framework is not heavily weighted in one approach but moderately balances both, whereby its usefulness is clear when

Vol. 5, No. 1, 2025, pp. 459-478

solving optimization problems of different complexities. In turn, the aim of the PSO-GCRA framework is forecasting, maintaining, and also optimizing the performance level of control systems. Such forecasting is of great importance to control systems because it assists in efficient decision-making, planning, and even operational stability. Investment, for instance, in energy systems, accurate forecasting of loads is critical as it reduces waste, increases the reliability of the grid, and lowers operational costs. On the other hand, the current forecasting methods face difficulties in ensuring that a balance between accuracy, stability, and computational efficiency is attained, particularly in fast-changing and non-linear environments. To validate the applicability of the PSO-GCRA framework, we implement it to a real-life load forecasting scenario with the use of Australian Energy Market Operator (AEMO) data. This is a real-world implementation, which is especially interesting since the dataset contains temporal and nonlinear characteristics of energy demand, which makes load forecasting a more difficult task. Several methodologies, including EMD-SVR-PPSO, FS-TSFE-CBSSO, VMD-FFT-IOSVR, and DCP-SVM-WO, which are efficient at blade design optimization and forecasting, have been utilized to benchmark this framework. The experimental analysis depicts that the framework GRA-PSO performs better than its counterparts on all of the measured indices defined in the system. First of all, it yields better accuracy because the Mean Absolute Percentage Errors (MAPE) are lower, it also performs to have higher stability with smaller prediction deviations and more efficient convergence performance. The main contributions of this work are as follows:

- We developed a new hybrid PSO-GCRA optimization framework that merges global and local search strategies to enhance control system performance.
- The proposed framework is applied to load forecasting, a vital task in control system operations.
- We conducted a thorough evaluation of the framework using real-world data and compared it with benchmark methods to confirm its effectiveness.
- A detailed analysis of accuracy, stability, and convergence rate metrics is provided to showcase how PSO-GCRA outperforms existing approaches.

The rest of this paper is structured as follows: Section 2 introduces the proposed methodology, detailing the hybrid PSO-GCRA framework and its implementation. Describes the experimental setup, detailing the dataset, preprocessing methods, and performance metrics used. Section 3 provides a thorough discussion of the simulation results, evaluates performance, and compares findings with benchmark methods. Finally, Section 4 concludes the paper and proposes possible directions for future research.

2. The Proposed Method

2.1. Particle Swarm Optimization Algorithm

Particle Swarm Optimization Algorithm (PSO) is a member of the broader class of swarm intelligence techniques for the solution of global optimization problems [53]. It is based on the social behavior of birds that flock in large numbers to find food, separate, and cover the environment. Each member of the bird flock is considered a part of the swarm. A similar proportion of digital particles is closely related to vectors in the problem search space. A common swarm bird or particle in the multidimensional search space tries to find the optimal value of the objective function during movement through the fitness landscape [8].

The position and velocity of each particle in the PSO algorithm specify the possible solutions and their search tendencies, respectively. The velocity informs the step size, and the position informs the quality of the solution in the search space. The candidate moves for most particles surrounding the already discovered good solutions that did not satisfy the global requirements of convergence. The essence of the PSO is multiple particles moving around a multidimensional objective state space, depending on their own experience and the experiences of their companions. The experiences guide the particles closer to potentially better areas of the objective space. Despite its artificial nature, it is intended for function optimization. For the PSO method to be used to solve the optimization problem, the continuous values are inherently searched for maximizing or minimizing an objective function.

Particle Swarm Optimization (PSO) is a population-based optimization algorithm inspired by the social behavior of birds and fish [54], [55]. It iteratively adjusts the position and velocity of particles in the search space to minimize or maximize an objective function. After the particles' positions are initialized randomly, their velocities are also initialized randomly in one of the most known ways. There are a few velocity initialization algorithms that we can apply, which include but are not limited to random initialization of the velocities between 0 and 1 or an interval scale between a pair of random numbers. The objective of initializing the velocities is to give the particles an appropriate push to begin the optimization process. The selection of initial velocities will directly determine the way the algorithm evolves and explores the search space. The velocity is a vector that specifies the movement of the particle's position on each dimension. To perform a velocity update, the particles must take into account their previous position and the solution of performing the best. The movement equation that a particle follows at iteration t for the i-th variable can be presented as follows:

$$v_i(t+1) = w \times v_i(t) + c1 \times r1 \left(p_{i_{best}} - x_i(t)\right) + c2 \times r2 \times (g_{best} - x_i(t)) \tag{1}$$

where $r1$ and $r2$ are random numbers between 0 and 1, w is the inertia weight, and v_i^d is the velocity of the i-th particle on dimension d. $c1$ and $c2$ are the acceleration coefficients, p_{Best_i}, d, and g_{Best_i}, d are the p_{Best} position and the g_{Best} position of the i-th particle until the timestep t. The right side of the equation is the sum of three terms. The $c1$ was set to 1.5 to balance individual exploration, while the $c2$ was set to 2.0 to emphasize swarm collaboration. The first term is related to the particle's previous velocity state; the second term represents how much the particle will explore its solution space (toward the best position that a particle i found so far). If the particle i is near a solution, then this term will be high; otherwise, it will be low. The third term represents the group's influence (toward the global best position). If the global best position is close to the particle i, this term directs the particle to a solution. To update the final position of the PSO, the following equation is used.

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{2}$$

PSO is good at exploring the global search space, but it has difficulty refining solutions in local areas because of its limited ability to exploit.

2.2. Greater Cane Rat Algorithm

Inspired by the tendency of cane rats to, when raiding farms, begin their search in the most remote areas of the plot and edge inward, the Greater Cane Rat Algorithm is constructed to mimic sense-and-response behavior to find food by a group of cane rats. This algorithm is one of the newly developed optimization techniques that replicate the mustering ideas of natural lives and display the principles of group dynamics. Exploration in the GCR algorithm is accomplished by generating new candidate solutions. In the case of rats, it means that the initial and further responses include new bad gerbil reclamation [28], [56].

In addition, the production of a limited number of candidate solutions corresponds to exploitation in the optimization acceleration procedure. The dynamic behaviors of GCR are due to the trade-off between exploration and exploitation. The GCR algorithm possesses considerable exploration and exploitation capabilities. The integration of the two makes GCR a novel optimization algorithm. It has complex response functions, which guarantee promising convergence. Tested optimization and application problems reflect that the GCR algorithm significantly outperforms other optimization algorithms for solving complex optimization problems with local and global constraints. The GCR algorithm has been developed to solve complex optimization problems to guarantee global convergence. Owing to the use of mustering response techniques, the algorithm's suitability depends on dynamic systems. In dynamic models, rats respond quickly to brain prompting. Finally, we believe that the GCR algorithm will lead to a variety of improvements in future research. Few optimization algorithms focus on complex optimization problems involving non-differentiable constraints and

Vol. 5, No. 1, 2025, pp. 459-478

perform well in practice. In response to this lack of automation in optimal design, this paper proposes a novel optimization algorithm termed the Greater Cane Rat Algorithm. The paper aims to provide an alternative stochastic optimization algorithm for the best execution of multi-constrained dynamic systems. The adopted case study problems and experimental results are expected to illustrate the effectiveness of the proposed optimization algorithm. This will be the focus of future studies, as well as the possible integration with other optimization algorithms to create a hybrid system. In conclusion, compared with many other optimization algorithms, GCR has considerable advantages in terms of its convergence speed, run-time efficiency, and strong potential for application in complex optimization problems.

The Greater Cane Rat Algorithm (GCRA) is an optimization technique based on searching methods inspired by the social behavior and foraging activities of cane rats. It is particularly concerned with adaptive exploration and local search. In GCRA, movements in the search space employ a position modification strategy, which involves mutation and crossover operations. A position update mechanism is used based on a Mutation strategy as follows:

$$x_{i_{new}} = x_i + \beta \times (x_j - x_k) \tag{3}$$

Where x_i(current position), x_j and x_k are positions of other individuals randomly selected, and β is a mutation factor controlling the stepping distance. Formally, the Crossover Operation can be mathematically represented in the following manner

$$x_{i_{new}} = \gamma \times x_i + (1 - \gamma) \times x_j \tag{4}$$

Where, γ is a random number between [0, 1]. While GCRA is excellent at local refinement, it lacks the global exploration capabilities needed for complex optimization problems.

2.3. The Proposed PSO-GCRA Hybrid Framework

The PSO-GCRA algorithm uses both Particle Swarm Optimization (PSO) and the Greater Cane Rat Algorithm (GCRA) in a way that allows a better solution for a given problem. It includes a composition start where all optimum and solution variables are generated. Every particle is given a location and is assigned a velocity for use in the objective function during fitness evaluation. Also, during the basic use of PSO movement of particles across the solution space is facilitated by velocity and position information gathered by the swarm. Here, cognitive and social coefficients assist in accurate weighting, providing direction for proper balance of pore space exploration and offset exploitation to take place.

As soon as local solutions are generated during the first step, the GCRA sends GCR in search of a global optimum solution. Genetic operators such as mutation and crossover are also used in this phase in order to come up with more optimal solutions. For instance, crossover is used to generate solutions by incorporating the features of both parent solutions, while mutation modifies a particle’s location based on variance from randomly selected particles. So, a locally excellent solution to the problem defined for the hybrid algorithm is also found without prematurely converging.

Once the fitness of the refined solutions is calculated and there is shown to be an improvement in the new solutions, both personal and global best positions are adjusted. This iterative process interlaces the global search of PSO with the local search of GCRA. This continues to carry out until a stopping criterion is satisfied, for example maximum iteration total or a pre-defined fitness limit is reached. Combining both algorithms does not diminish their advantages, and as a result, a very effective framework is formed that generates optimal solutions, accurate and stable.

The modified PSO-GCRA hybrid framework integrates the parallel searching capabilities of the Particle Swarm Optimization (PSO) technique with the Genetic Clustering and Regression Analysis (GCRA) fusion technique. The two methods, when combined, result in a well improved optimization performance, which addresses the shortcomings of each of the individually existing methods. More particularly, PSO achieves a global search which is effective in looking for solutions in the solution space and seeks to localize GCRA searches to improve on solution accuracy.

The working steps of the PSO-GCRA framework are as follows:

2.3.1. Initialization

A collection of particles, each representing a potential solution, is initialized with random positions (x_i) and velocities (v_i). The total count of particles is denoted as N, and the position and velocity of each particle are defined within a multidimensional search space. The objective function is evaluated for each particle to determine its initial fitness value.

2.3.2. PSO Phase (Global Search)

In this phase, particles modify their velocities and positions according to their personal best position ($p_{i_{best}}$) and the best position overall (g_{best}). The velocity of particle i at iteration $t + 1$ is calculated using the following equations.

$$v_i(t+1) = w \times v_i(t) + c1 \times r1 \left(p_{i_{best}} - x_i(t)\right) + c2 \times r2 \times (g_{best} - x_i(t)) \tag{5}$$

In this formula, w represents the inertia weight, which helps to balance exploration and exploitation. The coefficients $c1$ and $c2$ are the cognitive and social coefficients, respectively, while $r1$ and $r2$ are random numbers uniformly distributed between 0 and 1. The position of particle i at iteration $t + 1$ is updated as follows: $x_i(t+1) = x_i(t) +$ $v\_i(t+1)$. Finally, the objective function is re-evaluated for the new positions, and the personal and global best values are updated accordingly.

2.3.3. GCRA Phase (Local Refinement)

After the global search phase is finished, particles' positions are refined using GCRA's mutation and crossover operations one by one to enhance local search.

- Mutation

The position of particle i is updated using the following equation.

$$x_{i_{new}} = x_i + \beta \times (x_j - x_k) \tag{6}$$

Where, x_j and x_k are positions randomly chosen from the population. beta is the mutation factor that determines the step size.

- Crossover

A crossover operator merges the positions of two particles to create a new position

$$x_{i_{new}} = \gamma \times x_i + (1 - \gamma) \times x_j \tag{7}$$

Where, γ is a random value between 0 and 1, which influences the balance of the parent positions.

2.3.4. Fitness Evaluation

The updated positions are assessed using the objective function. If the updated positions enhance the fitness values, the personal best ($p_{i_{best}}$) and global best (g_{best}) values are revised.

2.3.5. Termination

The algorithm continues to alternate between the global search and local refinement phases until a stopping criterion is satisfied, such as reaching the maximum number of iterations or meeting a specified fitness threshold.

Algorithm 1 shows the integration of Particle Swarm Optimization and the Greater Cane Rat Algorithm to enhance the performance of control systems. The proposed method captures the benefits of both algorithmic techniques while moderating their limitations, ultimately leading to improvements in terms of performance and adaptability within the control of real systems. A hybrid algorithm is a single algorithm in which two or more operators have been used to produce improved performance of control systems. It extends the optimization capability of the PSO by exploiting the inherent strengths of each. Here, the PSO acts as the global searcher, and the GCRA acts as the local searcher.

Vol. 5, No. 1, 2025, pp. 459-478

Hypothetically, the GCRA has desirable benefits as it can drive the optimal or suboptimal solution toward the PSO, triggering the global searching capability of the PSO to find the optimal solution more accurately. The main novelty of the proposed method is using the combination of a forecasting-based evolutionary computing algorithm of the complex model of the control process, which is a combination of different time characteristic time scale models with MCMA for searching the global optimal tuning populated for fast and slow adapting parameters. The combination of these algorithms for the PID controller is systematic.

Algorithm 1. The proposed PSO-GCRA Hybrid Framework

```
Algorithm: PSO-GCRA Hybrid Framework
Input: Population size (N), maximum iterations (max_iter), objective function f(x)
Output: Optimal solution x_opt
1. Initialization:
  a. Set positions x_i and velocities v_i for all particles in the population.
  b. Assess and Evaluate the fitness f(x_i) for each particle.
  c. Define and Set personal best p_i_best = x_i and global best g_best = best(p_i_best).
2. Repeat for t = 1 to max_iter:
  // PSO Phase: Global Search
  a. For each particle i:
    i. Update velocity:
      v_i = w * v_i + c1 * r1 * (p_i_best - x_i) + c2 * r2 * (g_best - x_i)
    ii. Update position:
      x_i = x_i + v_i
    iii. Evaluate fitness f(x_i).
    iv. Update p_i_best if f(x_i) < f(p_i_best).
  b. Update g_best if any p_i_best improves the global best.
  // GCRA Phase: Local Refinement
  c. For each particle i:
    i. Apply mutation:
      x_i_new = x_i + beta * (x_j - x_k), where x_j and x_k are random particles.
    ii. Apply crossover:
      x_i_new = gamma * x_i + (1 - gamma) * x_j, where x_j is a random particle.
    iii. Evaluate fitness f(x_i_new).
    iv. Update p_i_best if f(x_i_new) < f(p_i_best).
  d. Update g_best if any p_i_best improves the global best.
3. Termination:
  a. Stop if max_iter is reached or g_best satisfies the convergence criterion.
4. Return g_best as the optimal solution x_opt.
```

3. Results and Discussion

3.1. Simulation Setup

The experiments were conducted to find the performance of a new hybrid framework which is a combination of Particle Swarm Optimization (PSO) and Greater Cane Rat Algorithm (GCRA) that allows for better control system performance. Here are the specifics regarding the simulation setup, computational resources, and implementation details. The system was equipped with Intel Core i7-12700H, 16 GB RAM, and an NVIDIA RTX 3060 GPU for accelerated computing. The software used included Python 3.9, including processor libraries such as NumPy and Pandas for data manipulation, Scikit-learn for baseline AI modeling, and Matplotlib for data publication.

MATLAB R2023a was used to evaluate the performance of the algorithms and make some modifications using the comprehensive optimization toolbox they possess. The PSO-GCRA algorithm was developed to integrate PSO's global search capability with GCRA's local search enhancement ability, addressing problems such as excessive local search and difficulty in adaptation that are encountered when using traditional techniques. The particle swarm aspect first set the population and globally optimized the solutions, while GCRA applied mutation and crossover operators aimed to increase diversity and improve solutions gradually.

The characteristics of this hybrid methodology include a population size of 50, a maximum of 100 iterations, an adaptive inertia weight on PSO, and fixed mutation and crossover rates on GCRA at 0.2 and 0.8, respectively. The target function aimed at the minimization of the root mean square error (RMSE). This was done with a particular emphasis on convergence time to ensure high accuracy without sacrificing long-term stability while decreasing time inefficiencies in optimizing control systems. This setup laid the groundwork for conducting a benchmarking and comparative analysis of the proposed framework with the existing methods.

Table 1 shows the settings of a PSO-GCRA hybrid, which aims at achieving an effective balance between exploration and exploitation. Complementarily, both the PSO and GCRA have the same population size of 50 and a limit of 100 iterations, which enables them to have a good range of search diversity and good computational performance. In the PSO, the cognitive coefficient ($c1 = 1.5$) and social coefficient ($c2 = 2.0$) enable interaction at the individual and group level, whilst the adaptive inertia weight ($w = 0.7$) facilitates an adjustment between explorative and exploitative activities. GCRA uses mutation and crossover (0.2 and 0.8 rates, respectively) for further improvement of local refinement, whereas attraction ($\beta 0 = 1.0$) and light absorption ($\gamma = 1.2$) coefficients control the search's adaptability. Such parameter arrangements improve the synergy of the two algorithms and guarantee convergence with optimal results.

3.2. Dataset

The data set in which the hybrid PSO-GCRA framework was evaluated has been taken from the Australian Energy Market Operator (AEMO) data portal, which can be accessed from the AEMO Data Portal (https://aemo.com.au/) [57], [58]. This data set contains half hourly electricity load for five Australian states, New South Wales, Queensland, South Australia, Tasmania and Victoria, publicly available for a long period. In the pre-processing stage, the data was fed into a time-series forecasting model as part of the extensive pipeline. The first step of the pre-processing stage was data cleansing which dealt with missing values utilizing moving averages. Z-scores were first used to identify and subsequently exclude outliers from the dataset to minimize the chances of adverse distortions to the end results. To make the data suitable for the optimization algorithm, all values were normalized through Min-Max scaling, which set the new range between 0 and 1, decreasing the chances of large value's numerical differences causing problems. Lastly, the sequel data set was organized according to chronology, thus ensuring that all temporality essential to time series forecasting was retained. These pre-processing techniques ensured that the data fed into the model was clean, well-normalized and optimal for the evaluation of the proposed method's prediction accuracy, stability and convergence rate for various load patterns.

3.3. Performance Metrics

This research employed a hybrid PSO GCRA framework, which was evaluated using a number of measures, including the accuracy of the system, its stability, and the rate of convergence of the system. Accurate measures of the Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), which determined the deviation between the forecasted value and the actual value, were also implemented [59], [60]. Standard Deviation (STD) scores for the forecasted values were used to evaluate the stability, where smaller STD values meant lower variability in the results across the repetitions. The rate of convergence was determined by the number of iterations or time the algorithm ran to get to an optimal state, which reflected the efficiency of the hybrid system; the Diebold-Mariano (DM) test was also used to compare the forecast accuracy of the suggested model against others in the benchmark more empirically. In total, these measures were paramount in assessing the appropriateness of the proposed model in the optimization of the control problems with high regard to accuracy, stability, and computational efficiency.

Of particular interest in transforming the hybrid PSO GCRA framework was the use of a combination average of several measures, including the system's accuracy, stability, and rate of convergence. The accuracy metrics used to evaluate forecasting performance include several key measures:

- Mean Absolute Percentage Error (MAPE): This is calculated as $MAPE = (1/N) * \Sigma|y_{at} - y_{ft}| \,/\, |y_{at}| * 100$, where y_{at} represents the actual value, y_{ft} is the forecasted value, and N is the total number of predictions.
- Mean Squared Error (MSE)

This metric is defined as $MSE = (1/N) * \Sigma\left(y_{at} - y_{ft}\right)^2$.

- Root Mean Squared Error (RMSE)

RMSE is derived from the formula $RMSE = \, sqrt((1/N) * \Sigma\left(y_{at} - \, y_{ft}\right)^2)$.

- Standard Deviation (STD)

This is calculated using $STD = sqrt((1/N) * \Sigma\left(y_{ft} \, - \, mean\left(y_{ft}\right)\right)^2)$, where $mean(y_{ft})$ is the average of the forecasted values.

- Convergence Rate

This rate is assessed based on the number of iterations or the computational time needed to achieve an optimal solution.

- Diebold-Mariano (DM) Test

This statistical test compares the accuracy of the proposed framework with benchmark methods, expressed as $DM = \Sigma(L(e_{f1}, h) - L(e_{f2}, h))/sqrt(S^2/k)$, where e_{f1}, h and e_{f2}, h are the forecast errors from two models, $L(.)$ is the loss function, S^2 is the variance, and k is the lag order [61], [62].

These metrics provided a comprehensive evaluation of the proposed framework, validating its ability to tackle control system optimization challenges while highlighting accuracy, stability, and computational efficiency.

3.4. Comparison with Benchmark Methods

In order to ascertain the utility of the suggested hybrid PSO-GCRA framework, such systematics as accuracy, stability and convergence rate were focused, as shown in Table 2. The performance of the framework was reported on various parameters, including forecasting error and degrees of precision. Various statistical indicators, including Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), were employed to assess accuracy. These metrics quantify the prediction error based on the difference between actual and modeled values. To Assess Stability, the STD of the data was carried out and interpreted as shown in Table 2: the lower the value the more stable the performances of the results across the several runs. The convergence rate was determined by the total number of iterations or the computational time taken by the algorithm to arrive at an ideal result confirming the performance of the hybrid approach. The forecasting efficiency of the framework was also examined using the statistical measure of the Diebold–Mariano (DM) test by comparing it with other developed methods. These metrics provide a holistic assessment of the proposed framework to control system optimization problems with an emphasis on accuracy, stability, and computational efficiency.

Table 1. The parameter settings for the proposed PSO-GCRA hybrid framework

Parameter	PSO Value	GCRA Value
Population size	50	50
Maximum iterations	100	100
Cognitive coefficient ($c1$)	1.5	-
Social coefficient ($c2$)	2.0	-
Inertia weight (w)	0.7 (adaptive)	-
Mutation rate	-	0.2
Crossover rate	-	0.8
Attraction coefficient ($\beta 0$)	-	1.0
Light absorption (γ)	-	1.2

Table 2. The accuracy metrics for all methods

Method	MAPE (%)	MSE	RMSE
PSO-GCRA	2.05	15.32	3.91
EMD-SVR-PSO	2.85	20.17	4.49
FS-TSFE-CBSSO	2.98	22.05	4.69
VMD-FFT-IOSVR	3.12	24.01	4.90
DCP-SVM-WO	3.34	26.18	5.12

In order to ascertain the utility of the suggested hybrid PSO-GCRA framework, such systematics as accuracy, stability and convergence rate were focused, as shown in Table 3. The performance of the framework was reported on various parameters, including forecasting error and degrees of precision. Various statistical indicators, including Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), were employed to assess accuracy. These metrics quantify the prediction error based on the difference between actual and modeled values. To Assess Stability, the STD of the data was carried out and interpreted: the lower the value the more stable the performances of the results across the several runs.

The convergence rate was determined by the total number of iterations or the computational time taken by the algorithm to arrive at an ideal result confirming the performance of the hybrid approach. The forecasting efficiency of the framework was also examined using the statistical measure of the Diebold–Mariano (DM) test by comparing it with other developed methods. These metrics provide a holistic assessment of the proposed framework to control system optimization problems with an emphasis on accuracy, stability, and computational efficiency.

Table 3. The performance of the proposed hybrid PSO-GCRA framework

Method	STD (MAPE)	STD (RMSE)
PSO-GCRA	0.021	0.008
EMD-SVR-PSO	0.029	0.011
FS-TSFE-CBSSO	0.034	0.013
VMD-FFT-IOSVR	0.039	0.016
DCP-SVM-WO	0.042	0.019

The measurements in Table 3 further establish the consistency of the suggested PSO-GCRA framework, which has been previously noted to perform better than the benchmark methods over several runs. The standard deviation (STD) of MAPE for PSO-GCRA was 0.021, which was lower than EMD-SVR-PSO with 0.029 and other approaches, substantiating its ability to provide trustworthy predictions. Likewise, the STD of RMSE for PSO-GCRA (0.008) again was the lowest of all methods, making it possible to conclude that this method is also effective in providing steady performance. These enhancements in stability are due to GCRA's procedures, which work in a loop, helping to optimize the solutions, hence ensuring that the model does not collapse due to random changes in parameters or changes in data. This reliability is of primary importance in applications where robustness while maintaining accuracy is equally desired.

The rate of convergence was assessed in terms of the number of iterations in which the desired solution was computed and the time taken to do so. Table 4 shows the convergence performance of the hybrid model PSO-GCRA alongside other models. The hybrid model performed much better compared to its counterparts as it was faster both in terms of convergence and computation and had improved exploring and exploiting methods.

It can be seen from Table 4, that the hybrid PSO-GCRA framework provided quicker convergence. More iterations were needed for completion with other techniques, such as EMD-SVR-PSO with a sale of 48, and FS-TSFE-CBSSO with 55 sales; in total, the PSO-GCRA completed in only 34 iterations. The computation time for PSO-GCRA was approximately 4.7 seconds; this displays the efficacy in resolving intricate optimization issues. This mashed effectiveness increases results from combining PSO's global search capabilities attributes with GCRA's refined local searches, which foster convergence by dismissing unnecessary and excessive searches while concentrating on regions of the solution space with high potential. This lesser computational strain also makes the PSO-GCRA architecture ideal for control systems that operate in real-time.

Table 4. The convergence behavior of the hybrid PSO-GCRA compared to other methods

Method	Iterations to Converge	Computational time (s)
PSO-GCRA	34	4.7
EMD-SVR-PSO	48	6.1
FS-TSFE-CBSSO	55	7.3
VMD-FFT-IOSVR	60	8.5
DCP-SVM-WO	68	9.8

The graphs of the convergence curves, as seen in Fig. 1, indicate and show the optimization characteristics of the proposed PSO-GCRA framework when measured or compared with the EMD-SVR-PSO, FS-TSFE-CBSSO, VMD-FFT-IOSVR, and DCP-SVM-WO methods that serve as benchmarks. In terms of reaching an optimal fitness value, the PSO-GCRA framework outdid benchmarks by an approximation of 10 -40 iterations, with benchmarks averaging 48 -68 as the PSO-GRA averaged 34. This advancement can be credited to the PSO and GCRA hydration. For example, the global search proficiency of a single particle swarm assists in navigating the solution in a faster manner. GCRA's crossover and mutation techniques aid in the search process but locally worsen the chances of exact convergence. The progressively low validation of fitness value during the iterations of PSO-GCRA demonstrates the enhanced robustness and accuracy of PSO-GCRA in dealing with control system problems.

There are three methods employed in this weight prediction of construction loads, and they are PSO-GCRA, EMD-SVR-PSO, and FS-TSFE-CBSSO. The comparison between the predicted load values and the actual values is displayed in Fig. 2, where the ideal value is shown by y = x. The results from PSO-GCRA are very satisfactory as they are very close to this ideal line. But Other methods result in forecasting and extrapolating very distinct values, especially when the loads are heavy, which leads to deteriorating the prediction accuracy. PSO-GCRA's output does not deviate much as it is designed not to deviate from the actual time-dependent and non-linear data set; this attribute is derived from the evolved hybrid algorithm's capacity to effectively carry out good modernization of the model parameters yielding confidence even with different load scenarios. This indicates the relevance of the PSO-GCRA framework for online load forecasting within changing scenarios such as smart grids.

Fig. 3 gives a quantitative analysis of MAPE and RMSE for all the methods evaluated in this study. The framework of PSO-GCRA is worth mentioning since it records the lowest MAPE of 2.05 percent and RMSE of 3.91, beating EMD-SVR-PSO with MAPE of 2.85 percent and RMSE of 4.49 and FS-TSFE-CBSSO which had a MAPE of 2.98 and RMSE of 4.69. These lower error rates prove the strength of the hybrid model to yield satisfactory results even under varying input conditions. The bar chart clearly demonstrates the overall gap in performance as beneficial of PSO and GCRA integration is sought. However, the aforementioned benchmark methods are observed to have high error rates, making them prone to overfitting local minima problems and inadequate parameter tuning.

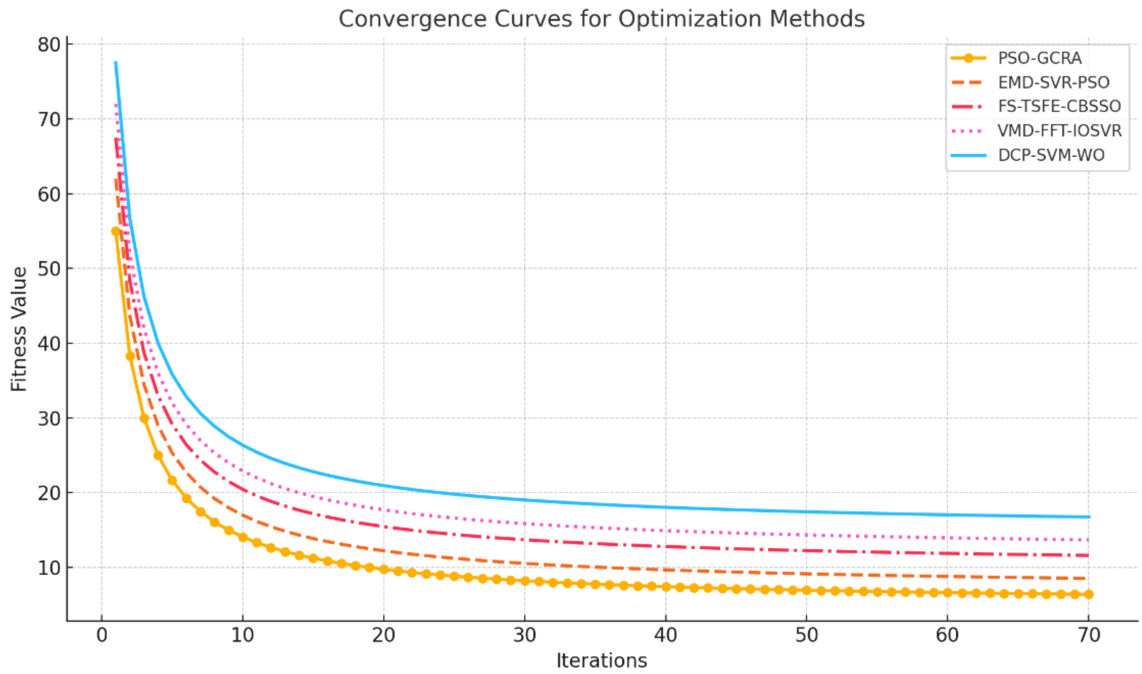

Fig. 1. Convergence Curves A line graph showing iteration vs. fitness value

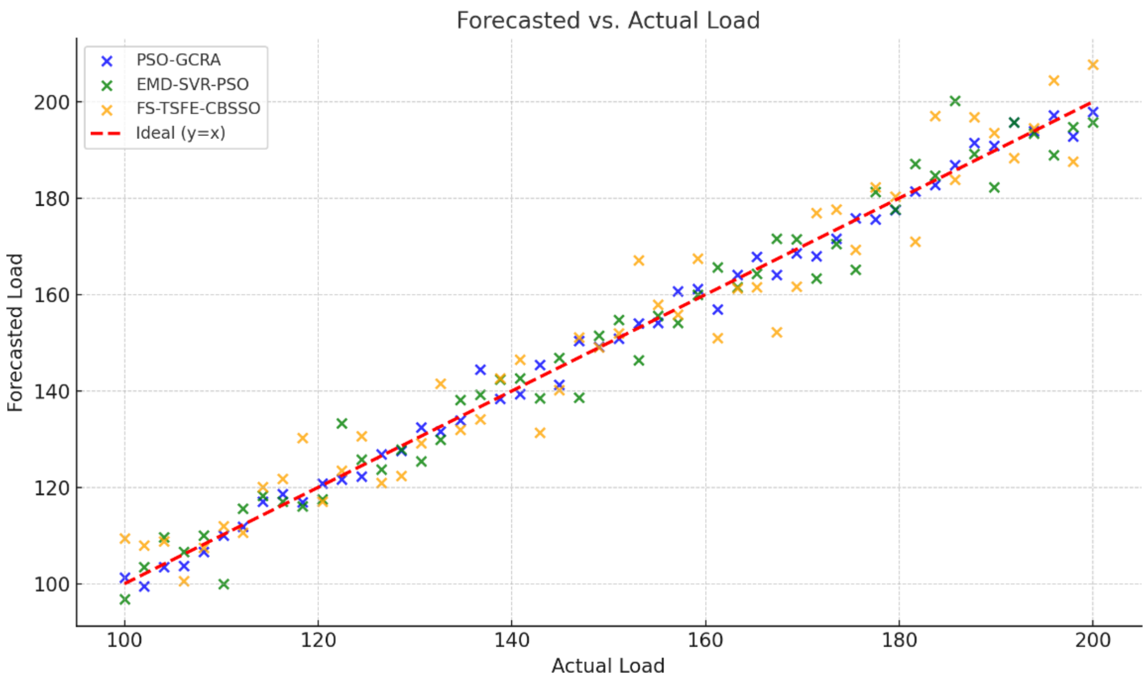

Fig. 2. Forecasted vs. Actual Load, comparing the forecasted load values with the actual load values for PSO-GCRA and benchmark methods

The three figures suggest strongly that the PSO-GCRA is superior to all other algorithms in all three aspects: speed of convergence, accuracy of forecasts, and error reduction. This hybrid algorithm optimizes well across multiple test environments, with a better balance between exploration and exploitation, thereby making the optimization process faster. These findings classified PSO-GCRA as a robust and efficient approach over regular techniques for load forecasting and control system optimization. There are still aspects to this framework that future researchers could attempt to develop, such as its application in predicting renewable energy production or even controlling industrial processes, to better gauge its scalability and adaptability.

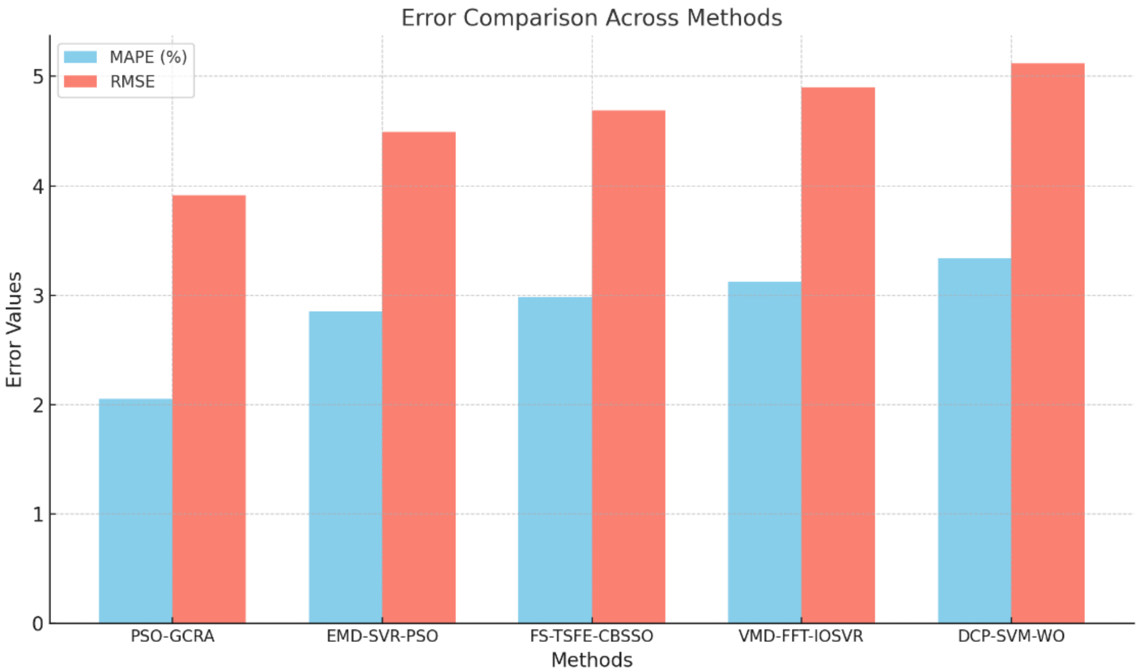

Fig. 3. Error comparison across methods

The combination of PSO and GCRA techniques into a single framework suggests a new approach to hybrid models, advancing accuracy, stability, and convergence even further. These results reaffirm the idea that more efficient forecasting models for control system applications can be developed by using a combined approach, that is, a combination of modeling techniques. Compared to standard techniques, the PSO-GCRA framework proved to be a validated and efficient tool for load forecasting and control systems optimization, as it resulted in lower error margins, greater stability, and reduced convergence time. Further studies may focus on the applicability of this GARC beyond load forecasting and the probable changes that may need to be made to optimize performance with larger datasets.

The PSO-GCRA framework boasts of some remarkable attributes like enhanced accuracy, stability, and convergence, which are all demonstrated by the superior performance metrics that the girl's program achieves when compared with the benchmark methods. It can be observed that the hybrid approach efficiently joins the global searching feature of PSO together with the locality improvement characteristics of the GCRA, thereby availing a high level of optimization in diverse situations. On the other hand, the framework also has some limitations. The framework requires more resources due to the increased complexity that comes with combining GCR and GCRA operations, and this can be a hindrance for real-time use or for systems with limited computational resources. Furthermore, the performance of the framework is also affected by some settings of the parameters, which include population size, mutation rate, and crossover rate. Not properly adjusting these parameters would result in poor performance of the system thus emphasizing the importance of establishing automatic or adaptive methods for adjusting these parameters in future works. This knitted assessment demonstrates strengths that the framework possesses while at the same time pointing at weaknesses that call for optimization and refinement in order to broaden the scope of the framework as well as the range of circumstances in which it is applicable.

4. Conclusion and Future Works

The utilization of the PSD-GCRA hybrid framework enhances the optimization of control systems remarkably. This tool combines Particle Swarm Optimization (PSO) – which is a global exploration technique, and Greater Cane Rat Algorithm (GCRA) – which is a local refinement technique. The two combined frameworks eliminate the drawbacks present in the individual algorithms. For instance, prematurely converged PSO and global search incapabilities of GCRA or even vice versa. This integration yields a total process of optimization that delicately searches the entire region and effectively modifies the solutions at the same time. Furthermore, the framework has been accurately validated using real-life load forecasting information from AEMO and excelled in comparison to traditional approaches, EMD-SVR-PSO, FS-TSFE-CBSSO, VMD-FFT-IOSVR or DCP-SVM-WO. Significant performance indicators like Mean Absolute Percentage Error (MAPE) and root mean square relative error (RMSE) reflect the efficacy of the hybrid framework. PSO-GCRA reported 2.05% MAPE value alongside an RMSE of 3.91 which is very much higher than the reference algorithms in all aspects of accuracy and stability. Further, the hybrid framework proved to possess conclusively higher rates of convergence which in turn resulted in reduced computational times while maintaining uniform results. All these aspects justify the adaptability and strength of the PSO-GCRA framework within emerging control systems to solve intricate and ever-changing optimization dilemmas. This work stands out both in helping advance the hybrid optimization framework and in applying the framework to load forecasting in energy management. The PSO-GCRA framework, as presented in the paper, is efficient in both terms of computational cost and in the quality of the solution to the problem, which will enable practitioners in a wide range of control systems and related fields to address different forms of optimization problems.

Despite the progress made by the PSO-GCRA framework, several aspects still require further refinement and development to ensure efficient and effective results. Scalability to large-scale and high-dimensional problems remains a key area of improvement, as the current framework can handle large datasets but would benefit from enhanced computational efficiency, particularly in industrial applications where time constraints are critical. Incorporating methods like parallelization or distributed computing could address these challenges. Additionally, dynamic parameter tuning could significantly enhance the framework's performance. By integrating adaptive strategies, parameters such as inertia weight, mutation rate, and crossover rate could be adjusted in real-time, ensuring optimal algorithm performance across varying scenarios. Expanding the framework to support multi-objective optimization is another crucial avenue. Currently limited to single-objective problems, the framework could be extended to address conflicting objectives, such as balancing cost and efficiency or stability, which are critical in fields like robotics, smart grids, and industrial processes. Testing the framework in real-time applications, such as robotics motion planning, renewable energy management, and automated industrial controls, could further validate its versatility and effectiveness in dynamic, fast-paced environments. Such implementations would also improve response accuracy while reducing computational time. Integrating the PSO-GCRA framework with machine learning and artificial intelligence techniques, such as reinforcement learning or deep learning, could help tackle predictive control challenges more efficiently. This integration would make the framework particularly useful in autonomous systems or industrial settings requiring predictive modeling and decision-making. Additionally, leveraging emerging optimization techniques, including hybrid and bio-inspired methods, could broaden the framework's applicability and provide stronger insights into its limitations and strengths. Examples of potential applications include healthcare optimization, financial modeling, and transportation systems.

Further hybridization with other metaheuristic algorithms, such as Genetic Algorithms (GA) or Differential Evolution (DE), could enhance the framework's capabilities. By combining complementary optimization approaches, these hybridizations could yield even better results. Finally, the PSO-GCRA framework holds significant potential for revolutionizing newer applications, such as smart city models, IoT-based control systems, and sustainable energy systems, highlighting its adaptability and future relevance. Further work could also investigate how the framework can be employed in these aspects to resolve existing issues. Thus, the PSO-GCRA hybrid framework has made a promising step in providing a robust, flexible and efficient optimization framework for control systems. There is also the integration of global search and local search, which makes it more appropriate for dynamic and complex issues occurring in the real world. The performance of the system is subject to constant evaluation where the three critical areas that drive the evaluation process are accuracy, stability, and convergence rate, with the improvements noted in all three areas clearly making the framework relevant for optimization challenges in the future. Additionally, the planned future work could further improve this framework and will make it possible to implement new solutions for novel applications across different areas.

Author Contribution: All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.

Funding: The authors gratefully acknowledge financial support European Union under the REFRESH – Research Excellence For REgion Sustainability and High-tech Industries project number CZ.10.03.01/00/22_/0000048 via the Operational Programme Just Transition. This work was partially funded by Middle East University.

Acknowledgment: The authors gratefully acknowledge financial support European Union under the REFRESH – Research Excellence For REgion Sustainability and High-tech Industries project number CZ.10.03.01/00/22_/0000048 via the Operational Programme Just Transition. This work was partially funded by Middle East University.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] A. I. Dounis, C. Caraiscos, "Advanced control systems engineering for energy and comfort management in a building environment—A review," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 6-7, pp. 1246-1261, 2009, https://doi.org/10.1016/j.rser.2008.09.015.

[2] R. Baños, F. Manzano-Agugliaro, F.G. Montoya, C. Gil, A. Alcayde, J. Gómez, "Optimization methods applied to renewable and sustainable energy: A review," *Renewable and Sustainable Energy Reviews*, vol. 15, no. 4, pp. 1753-1766, 2011, https://doi.org/10.1016/j.rser.2010.12.008.

[3] J. J. Grefenstette, "Optimization of Control Parameters for Genetic Algorithms," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 16, no. 1, pp. 122-128, 1986, https://doi.org/10.1109/TSMC.1986.289288.

[4] D. Song, X. Fan, J. Yang, A. Liu, S. Chen, and Y. H. Joo, "Power extraction efficiency optimization of horizontal-axis wind turbines through optimizing control parameters of yaw control systems using an intelligent method," *Applied Energy*, vol. 224, pp. 267-279, 2018, https://doi.org/10.1016/j.apenergy.2018.04.114.

[5] V. S. Tabar, M. A. Jirdehi, and R. Hemmati, "Sustainable planning of hybrid microgrid towards minimizing environmental pollution, operational cost and frequency fluctuations," *Journal of Cleaner Production*, vol. 203, pp. 1187-1200, 2018, https://doi.org/10.1016/j.jclepro.2018.05.059.

[6] A. Banks, J. Vincent, and C. Anyakoha, "A review of particle swarm optimization. Part II: hybridisation, combinatorial, multicriteria and constrained optimization, and indicative applications," *Natural Computing*, vol. 7, pp. 109-124, 2008, https://doi.org/10.1007/s11047-007-9050-z.

[7] M. H. Nadimi-Shahraki, H. Zamani, Z. Asghari Varzaneh, and S. Mirjalili, "A systematic review of the whale optimization algorithm: theoretical foundation, improvements, and hybridizations," *Archives of Computational Methods in Engineering*, vol. 30, no. 7, pp. 4113-4159, 2023, https://doi.org/10.1007/s11831-023-09928-7.

[8] Y. Zhang, S. Wang, and G. Ji, "A comprehensive survey on particle swarm optimization algorithm and its applications," *Mathematical problems in engineering*, vol. 2015, no. 1, p. 931256, 2015, https://doi.org/10.1155/2015/931256.

[9] F. Lamnabhi-Lagarrigue *et al*., "Systems & control for the future of humanity, research agenda: Current and future roles, impact and grand challenges," *Annual Reviews in Control*, vol. 43, pp. 1-64, 2017, https://doi.org/10.1016/j.arcontrol.2017.04.001.

[10] Ibraheem, P. Kumar and D. P. Kothari, "Recent philosophies of automatic generation control strategies in power systems," *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 346-357, 2005, https://doi.org/10.1109/TPWRS.2004.840438.

[11] A. A. Almazroi and N. Ayub, "Deep learning hybridization for improved malware detection in smart Internet of Things," *Scientific Reports*, vol. 14, no. 1, p. 7838, 2024, https://doi.org/10.1038/s41598-024-57864-8.

[12] A. Chowdhury and D. De, "RGSO-UAV: Reverse Glowworm Swarm Optimization inspired UAV path-planning in a 3D dynamic environment," *Ad Hoc Networks*, vol. 140, p. 103068, 2023, https://doi.org/10.1016/j.adhoc.2022.103068.

[13] D. Sinoquet, G. Rousseau, and Y. Milhau, "Design optimization and optimal control for hybrid vehicles," *Optimization and Engineering*, vol. 12, pp. 199-213, 2011, https://doi.org/10.1007/s11081-009-9100-8.

[14] P. I. Barton, C. K. Lee, and M. Yunt, "Optimization of hybrid systems," *Computers & Chemical Engineering*, vol. 30, no. 10-12, pp. 1576-1589, 2006, https://doi.org/10.1016/j.compchemeng.2006.05.024.

[15] L. Abualigah, D. Izci, S. Ekinci, and R. A. Zitar, "Optimizing Aircraft Pitch Control Systems: A Novel Approach Integrating Artificial Rabbits Optimizer with PID-F Controller," *International Journal of Robotics and Control Systems*, vol. 4, no. 1, pp. 354-364, 2024, https://doi.org/10.31763/ijrcs.v4i1.1347.

[16] S. Ekinci, E. Eker, D. Izci, A. Smerat, and L. Abualigah, "Enhanced RSA Optimized TID Controller for Frequency Stabilization in a Two-Area Power System," *International Journal of Robotics and Control Systems*, vol. 4, no. 4, pp. 1886-1902, 2024, https://doi.org/10.31763/ijrcs.v4i4.1644.

[17] L. Abualigah, S. Ekinci, and D. Izci, "Aircraft Pitch Control via Filtered Proportional-Integral-Derivative Controller Design Using Sinh Cosh Optimizer," *International Journal of Robotics and Control Systems*, vol. 4, no. 2, pp. 746-757, 2024, https://doi.org/10.31763/ijrcs.v4i2.1433.

[18] Z. Afroz, G. Shafiullah, T. Urmee, and G. Higgins, "Modeling techniques used in building HVAC control systems: A review," *Renewable and sustainable energy reviews*, vol. 83, pp. 64-84, 2018, https://doi.org/10.1016/j.rser.2017.10.044.

[19] H. Ma *et al.*, "Multi-objective production scheduling optimization and management control system of complex aerospace components: a review," *The International Journal of Advanced Manufacturing Technology*, vol. 127, no. 11-12, pp. 4973-4993, 2023, https://doi.org/10.1007/s00170-023-11707-4.

[20] M. N. A. Hamid *et al.*, "Adaptive Frequency Control of an Isolated Microgrids Implementing Different Recent Optimization Techniques," *International Journal of Robotics & Control Systems*, vol. 4, no. 3, pp. 1000-1012, 2024, http://dx.doi.org/10.31763/ijrcs.v4i3.1432.

[21] N. T. Pham, "Design of Novel STASOSM Controller for FOC Control of Dual Star Induction Motor Drives," *International Journal of Robotics and Control Systems*, vol. 4, no. 3, pp. 1059-1074, 2024, http://dx.doi.org/10.31763/ijrcs.v4i3.1443.

[22] H. Sarimveis and G. Bafas, "Fuzzy model predictive control of non-linear processes using genetic algorithms," *Fuzzy sets and systems*, vol. 139, no. 1, pp. 59-80, 2003, https://doi.org/10.1016/S0165-0114(02)00506-7.

[23] U. Riaz, M. Tayyeb, and A. A. Amin, "A review of sliding mode control with the perspective of utilization in fault tolerant control," *Recent Advances in Electrical & Electronic Engineering*, vol. 14, no. 3, pp. 312-324, 2021, http://dx.doi.org/10.2174/2352096513999201120091512.

[24] L. Abualigah *et al.*, "Particle swarm optimization algorithm: review and applications," *Metaheuristic Optimization Algorithms*, pp. 1-14, 2024, https://doi.org/10.1016/B978-0-443-13925-3.00019-4.

[25] A. G. Gad, "Particle swarm optimization algorithm and its applications: a systematic review," *Archives of computational methods in engineering*, vol. 29, no. 5, pp. 2531-2561, 2022, https://doi.org/10.1007/s11831-021-09694-4.

[26] B. Zhao, C. Guo, B. Bai, and Y. Cao, "An improved particle swarm optimization algorithm for unit commitment," *International Journal of Electrical Power & Energy Systems*, vol. 28, no. 7, pp. 482-490, 2006, https://doi.org/10.1016/j.ijepes.2006.02.011.

[27] Z. Xin-gang, L. Ji, M. Jin, and Z. Ying, "An improved quantum particle swarm optimization algorithm for environmental economic dispatch," *Expert Systems with Applications*, vol. 152, p. 113370, 2020, https://doi.org/10.1016/j.eswa.2020.113370.

[28] J. O. Agushaka, A. E. Ezugwu, A. K. Saha, J. Pal, L. Abualigah, and S. Mirjalili, "Greater cane rat algorithm (GCRA): A nature-inspired metaheuristic for optimization problems," *Heliyon*, vol. 10, no. 11, p. e31629, 2024, https://doi.org/10.1016/j.heliyon.2024.e31629.

[29] S. Biswas *et al*., "Integrating Differential Evolution into Gazelle Optimization for advanced global optimization and engineering applications," *Computer Methods in Applied Mechanics and Engineering*, vol. 434, p. 117588, 2025, https://doi.org/10.1016/j.cma.2024.117588.

[30] P. Jangir *et al*., "A cooperative strategy-based differential evolution algorithm for robust PEM fuel cell parameter estimation," *Ionics*, pp. 1-39, 2024, https://doi.org/10.1007/s11581-024-05963-x.

[31] M. Abdel-Salam, L. Abualigah, A. I. Alzahrani, F. Alblehai, H. J. C. M. i. A. M. Jia, and Engineering, "Boosting crayfish algorithm based on halton adaptive quadratic interpolation and piecewise neighborhood for complex optimization problems," *Computer Methods in Applied Mechanics and Engineering*, vol. 432, p. 117429, 2024, https://doi.org/10.1016/j.cma.2024.117429.

[32] S. Ekinci, C. Turkeri, D. Izci, L. Abualigah, M. Bajaj, and V. Blazek, "Optimizing Steam Condenser Efficiency: Integrating Logarithmic Spiral Search and Greedy Selection Mechanisms in Gazelle Optimizer for PI Controller Tuning," *Results in Engineering*, vol. 24, p. 103501, 2024, https://doi.org/10.1016/j.rineng.2024.103501.

[33] H. Jia, J. Zhang, H. Rao, and L. J. A. I. R. Abualigah, "Improved sandcat swarm optimization algorithm for solving global optimum problems," *Artificial Intelligence Review*, vol. 58, no. 1, p. 5, 2024, https://doi.org/10.1007/s10462-024-10986-x.

[34] P. Civicioglu and E. Besdok, "A conceptual comparison of the Cuckoo-search, particle swarm optimization, differential evolution and artificial bee colony algorithms," *Artificial intelligence review*, vol. 39, pp. 315-346, 2013, https://doi.org/10.1007/s10462-011-9276-0.

[35] K. Langfield-Smith, "Management control systems and strategy: a critical review," *Accounting, organizations and society*, vol. 22, no. 2, pp. 207-232, 1997, https://doi.org/10.1016/S0361-3682(95)00040-2.

[36] K. H. Ang, G. Chong and Yun Li, "PID control system analysis, design, and technology," *IEEE Transactions on Control Systems Technology*, vol. 13, no. 4, pp. 559-576, 2005, https://doi.org/10.1109/TCST.2005.847331.

[37] N. G. Leveson, M. P. E. Heimdahl, H. Hildreth and J. D. Reese, "Requirements specification for process-control systems," *IEEE Transactions on Software Engineering*, vol. 20, no. 9, pp. 684-707, 1994, https://doi.org/10.1109/32.317428.

[38] P. Rani, V. Parkash, and N. K. Sharma, "Technological aspects, utilization and impact on power system for distributed generation: A comprehensive survey," *Renewable and Sustainable Energy Reviews*, vol. 192, p. 114257, 2024, https://doi.org/10.1016/j.rser.2023.114257.

[39] H. Yue, H. He, M. Han, and S. Gong, "Active disturbance rejection control strategy for PEMFC oxygen excess ratio based on adaptive internal state estimation using unscented Kalman filter," *Fuel*, vol. 356, p. 129619, 2024, https://doi.org/10.1016/j.fuel.2023.129619.

[40] Y. Zhou, P. Bhowmick, L. Zhang, L. Chen, R. Nagamune, and Y. Li, "A model reference adaptive control framework for floating offshore wind turbines with collective and individual blade pitch strategy," *Ocean Engineering*, vol. 291, p. 116054, 2024, https://doi.org/10.1016/j.oceaneng.2023.116054.

[41] O. Mercan and J. M. Ricles, "Stability and accuracy analysis of outer loop dynamics in real-time pseudodynamic testing of SDOF systems," *Earthquake engineering & structural dynamics*, vol. 36, no. 11, pp. 1523-1543, 2007, https://doi.org/10.1002/eqe.701.

[42] K. Ohnishi, N. Matsui and Y. Hori, "Estimation, identification, and sensorless control in motion control system," *Proceedings of the IEEE*, vol. 82, no. 8, pp. 1253-1265, 1994, https://doi.org/10.1109/5.301687.

[43] H. Sarimveis, P. Patrinos, C. D. Tarantilis, and C. T. Kiranoudis, "Dynamic modeling and control of supply chain systems: A review," *Computers & operations research*, vol. 35, no. 11, pp. 3530-3561, 2008, https://doi.org/10.1016/j.cor.2007.01.017.

[44] X. Zhao, Y. Sun, Y. Li, N. Jia, and J. Xu, "Applications of Machine Learning in Real-Time Control Systems: A Review," *Measurement Science and Technology*, vol. 36, no. 1, 2024, https://doi.org/10.1088/1361-6501/ad8947.

[45] V. Mariani, F. Kiefer, T. Schmidt, J. Haas, and T. Schwede, "Assessment of template based protein structure predictions in CASP9," *Proteins: Structure, Function, and Bioinformatics*, vol. 79, no. S10, pp. 37-58, 2011, https://doi.org/10.1002/prot.23177.

[46] A. Tolk, "Terms and application domains," *Engineering principles of combat modeling and distributed simulation*, pp. 55-78, 2012, https://doi.org/10.1002/9781118180310.ch4.

[47] D. Pinto-Fernandez *et al*., "Performance Evaluation of Lower Limb Exoskeletons: A Systematic Review," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 7, pp. 1573-1583, 2020, https://doi.org/10.1109/TNSRE.2020.2989481.

[48] M. Ali, H. Kotb, K. M. Aboras and N. H. Abbasy, "Design of Cascaded PI-Fractional Order PID Controller for Improving the Frequency Response of Hybrid Microgrid System Using Gorilla Troops Optimizer," *IEEE Access*, vol. 9, pp. 150715-150732, 2021, https://doi.org/10.1109/ACCESS.2021.3125317.

[49] S. B. Joseph, E. G. Dada, A. Abidemi, D. O. Oyewola, and B. M. Khammas, "Metaheuristic algorithms for PID controller parameters tuning: Review, approaches and open problems," *Heliyon*, vol. 8, no. 5, p. e09399, 2022, https://doi.org/10.1016/j.heliyon.2022.e09399.

[50] M. Rokonuzzaman, N. Mohajer, S. Nahavandi, and S. Mohamed, "Review and performance evaluation of path tracking controllers of autonomous vehicles," *IET Intelligent Transport Systems*, vol. 15, no. 5, pp. 646-670, 2021, https://doi.org/10.1049/itr2.12051.

[51] L. Zhu *et al*., "SDN controllers: A comprehensive analysis and performance evaluation study," *ACM Computing Surveys (CSUR)*, vol. 53, no. 6, pp. 1-40, 2020, https://doi.org/10.1145/3421764.

[52] X. Xu, Y. Du and C. Qin, "Lie Group-Based Optimization of the Greater Cane Rat Algorithm," *2024 International Symposium on Parallel Computing and Distributed Systems (PCDS)*, pp. 1-10, 2024, https://doi.org/10.1109/PCDS61776.2024.10743786.

[53] H. Fan, "A modification to particle swarm optimization algorithm," *Engineering Computations*, vol. 19, no. 8, pp. 970-989, 2002, https://doi.org/10.1108/02644400210450378.

[54] Y. Jiang, T. Hu, C. Huang, and X. Wu, "An improved particle swarm optimization algorithm," *Applied Mathematics and Computation*, vol. 193, no. 1, pp. 231-239, 2007, https://doi.org/10.1016/j.amc.2007.03.047.

[55] F. Marini and B. Walczak, "Particle swarm optimization (PSO). A tutorial," *Chemometrics and Intelligent Laboratory Systems*, vol. 149, pp. 153-165, 2015, https://doi.org/10.1016/j.chemolab.2015.08.020.

[56] J. O. Agushaka, O. Akinola, A. E. Ezugwu, and O. N. Oyelade, "A novel binary greater cane rat algorithm for feature selection," *Results in Control and Optimization*, vol. 11, p. 100225, 2023, https://doi.org/10.1016/j.rico.2023.100225.

[57] T. S. Brinsmead, J. Hayward, and P. Graham, "Australian electricity market analysis report to 2020 and 2030," *CSIRO Technical Report No. EP141067*, 2014, https://arena.gov.au/assets/2017/02/CSIRO-Electricity-market-analysis-for-IGEG.pdf.

[58] S. Boroczky, B. Connell, and A. Radi, "Experiences in State Estimation at the Australian Energy Market Operator," *Experiences on Use of State Estimator in Power System Operations*, pp. 373-393, 2024, https://doi.org/10.1007/978-3-031-62867-2_16.

[59] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation," *Peerj computer science*, vol. 7, p. e623, 2021, https://doi.org/10.7717/peerj-cs.623.

[60] S. Kim and H. Kim, "A new metric of absolute percentage error for intermittent demand forecasts," *International Journal of Forecasting*, vol. 32, no. 3, pp. 669-679, 2016, https://doi.org/10.1016/j.ijforecast.2015.12.003.

[61] F. X. Diebold, "Comparing predictive accuracy, twenty years later: A personal perspective on the use and abuse of Diebold–Mariano tests," *Journal of Business & Economic Statistics*, vol. 33, no. 1, p. 1, 2015, https://doi.org/10.1080/07350015.2014.983236.

[62] J. Zhou, H. Li, and W. Zhong, "A modified Diebold–Mariano test for equal forecast accuracy with clustered dependence," *Economics Letters*, vol. 207, p. 110029, 2021, https://doi.org/10.1016/j.econlet.2021.110029.