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Smart grid optimization: AI and machine learning approaches for energy management and load forecasting

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ABSTRACT

In contemporary energy systems, smart grids make a significant contribution to generating efficient, reliable, and sustainable energy. Smart grids are crucial to the performance optimization of energy systems, accurate load forecasting, and effective energy management. To find a solution to the condition related to energy management and load forecasting, in the current study we demonstrate a novel hybrid optimization technique that can be used to eliminate the barriers to optimization: a combination of multi-strategy particle swarm optimization (MPSO) with the gazelle optimization algorithm (MPSOGOA) along with artificial neural networks (ANN). By allowing the MPSOGOA algorithm to exploit the exploration power of a multi-strategy particle swarm optimization, as well as the converging nature of gazelle optimization, these algorithms are successful in training ANN models, which dramatically improves the accuracy of the prediction. The evaluation of the proposed hybrid approach that was performed on real-life smart grid datasets shows that the hybrid method effectively outperforms standard algorithms and significantly improves the precision of the forecasts, the operational cost, as well as the reliability. Application of this enhanced hybrid solution offers a reliable and effective smart grid technology architecture in the energy management system for intelligent decision-making.

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1. INTRODUCTION

Modern power systems have gone through a rapid evolution process, which gave rise to the concept of smart grids, that is, an advanced infrastructure that combines the technologies of communication, distributed energy resources (DERs), and automated control to distribute electricity in a more reliable, efficient, and sustainable way [1]. As the energy consumption pattern is getting more and more complex, alongside the permeation of renewable energy sources, proper load forecasting and smart energy management have become an essential part of smart grid functioning [2]. Conventional approaches used to predict load, including autoregressive integrated moving average (ARIMA), support vector machines (SVM), and linear regression, have proved to lack the flexibility in capturing the dynamic, nonlinear trends of energy consumption, especially due to environmental, social, and economic factors [3]. This has led to the adoption

of artificial intelligence (AI) and machine learning (ML) to a high degree and they have improved characteristics on pattern recognition, forecasting, and decision-making [4].

Artificial neural networks (ANNs) have been one of the most applied AI tools among other strategies because of their high flexibility and learning ability. Nonetheless, they are very sensitive in terms of the choice of parameters (i.e., weights and biases), and optimizing these parameters may be computationally demanding and may suffer from convergence to local optima [5]. In a bid to overcome these drawbacks, researchers have ventured into using metaheuristic algorithms when training ANNs in order to enhance generalization and convergence rate. In the recent past, hybrid optimization techniques have been proposed as effective mechanisms for ramping up ANN performance further. A specific variant is that the gazelle optimization algorithm (GOA) is used as a technique and coupled with multi-strategy particle swarm optimization (MPSO), which is the so-called MPSOGOA. The combination of this hybrid approach uses the exploration ability of the MPSO and the exploitation power of GOA, making the convergence accuracy and robustness better [6]. In the present research, we suggest a new energy management and load forecasting mechanism for smart grids on the basis of an ANN model that is optimized by the MPSOGOA approach. The aim is to apply the hybrid algorithm in order to successfully train the neural network to have improved accuracy and reliability of its predictions in real-time energy settings. Such an approach is verified on real-life smart grid data, and its performance is compared to standard methods. The suggested approach will help to achieve smarter decision-making on grid operations with less contributing operational cost and integration of renewable sources of energy [7].

The introduction focuses on the increasing significance of smart energy management and proper prediction of loads within smart grid systems. It describes the drawbacks of conventional methods and presents the benefits of applying ANNs augmented with metaheuristic optimization. It, however, cites the difficulty in training ANNs well, particularly in dynamic environments. In order to solve these problems, the proposed solution is to propose a hybrid method whereby an MPSO optimization will be added to the MPSOGOA. This approach takes advantage of finding a good configuration in PSO and the ability of rapid convergence in GOA so as to produce more efficient and accurate training of ANN. The above-mentioned MPSOGOA-ANN model aims at enhancing the accuracy in forecasting, enabling real-time energy management, and increasing the reliability of the smart grid.

2. LITERATURE SURVEY

The revolution brought by AI and ML in the smart grid system has changed the way load forecasting and energy management activities are carried out. More than a few studies have discussed the shortcomings of the conventional forecasting techniques and suggested intelligent models that can be more accurate and flexible. Load forecasting has been a conventional statistical problem that is solved using load forecasters like ARIMA and exponential smoothing. Nevertheless, they get easily confused in the nonlinear dynamics of a smart grid system, in particular those taking place under the influence of various environmental and social inputs [8]. Conversely, ANNs have been found to be better at modeling these types of nonlinear patterns since they use their learning as well as generalization processes [9].

ANNs have a number of disadvantages despite the benefits associated with them because the same ANN is very sensitive to the initial weight setting and should have optimized parameters. To help fix that, scientists have been using metaheuristic algorithms, one of them namely particle swarm optimization (PSO) to improve ANN training. PSO, which is based on the phenomenon of swarms of birds and fish, is famous because of its simplicity in solving tasks and rapid convergence [10]. Nevertheless, it has problems such as premature convergence and being caught in local optima. To address such disadvantages, innovations have resulted in refinements to PSO under a multi-strategy PSO umbrella. These are inertia dynamics weight adjustment, exploration through mutation, and adaptive learning aspects, all of which are meant to balance the exploration-exploitation trade-off [11]. Hybrid optimization algorithms have been popular in recent years. GOA is an escape behavior of gazelles to move away from predators; it has better local search abilities and converges faster [12]. The integration of GOA and PSO is aimed at the creation of a hybrid algorithm, MPSOGOA, that would use the global searching capabilities of PSO and the high-speed convergence of GOA. Such hybrid frameworks were used in a study conducted by [13] in short-term load forecasting, where the researchers claimed better results in comparison with standalone techniques. Similarly, Shao *et al.* [14] realized that a hybrid of PSO-GOA optimized energy scheduling in microgrids more efficiently, which resulted in high convergence rates and lower operation costs.

Besides, Papazoglou and Biskas [15] underlined the importance of utilizing hybrid AI-based models in the context of real-time energy management. Their study showed that such integrations not only improve the accuracy of forecasting but also assist smart grids and adaptive control strategies to tolerate variability of renewable sources. To conclude, it can be mentioned that hybrid metaheuristic-ANN models, especially those utilizing the MPSOGOA, are a potential tool in the white-glove treatment of smart grid issues. Such models

have superior optimization capability, faster convergence, and high adaptability, which makes them strong candidates for real-world deployment. As the literature shows, basic machine learning models and traditional statistical techniques have been extensively employed in the optimization of smart grids; nonetheless, in most cases, they are inefficient in managing multi-dimensional, non-linear, and time-varying energy consumption. To enhance ANN training, metaheuristic algorithms such as PSO have been introduced; however, problems of premature convergence persist, as well as a narrow search space. The more recent applicability of hybrid optimization, particularly the use of multiple approaches in the overall solution, has demonstrated potential in overcoming these difficulties. In this respect, the solution proposed by combining Particle Swarm Optimization integrated with the GOA and multi-strategy (MPSOGOA) with ANN arouses a new and fruitful idea. Through a fusion of both the global exploration ability of PSO and an adaptive convergence speed of GOA, MPSOGOA makes ANN models to be trained better and more consequently. This will increase the accuracy of the prediction, improve load forecasting reliability, and improve energy management in the smart grid. One application where the hybrid model is specifically applicable is in real-time applications where performance and accuracy are very important.

3. PROPOSED METHOD

This paper proposes an intelligent hybrid approach for energy management and load forecasting in smart grids using an MPSOGOA integrated with an ANN. Recent research has shown the advantages of intelligent optimization in complex scheduling and energy-management problems. Various predictive models such as enhanced PSO, genetic algorithms, Q-learning, and hybrid models have been used to enhance flow-shop scheduling, electric-vehicle coordination, microgrid operation, load forecasting, renewable-energy prediction, anomaly detection, and virtual-power-plant optimization [16]-[25]. The results reveal the increasing importance of adaptive metaheuristic and learning-based approaches to enhance operational efficiency and decision quality. The proposed method improves forecasting accuracy and training efficiency by leveraging the global search ability of MPSO and the fast convergence of GOA. The first step in the overall optimization process is the parameter initialization of the ANN and the initialization of the population of the optimization. The fitness function is defined for each candidate solution that is subsequently evaluated. Then, the multi-strategy PSO mechanism is used to search the search space and to update candidate solutions. The solutions that result as promising are then improved using the GOA mechanism to enhance exploitation in regions of good solution quality. The optimized ANN parameter set is the best one found in the iterative process. Finally, the optimized ANN is tested using the testing data that is independent of the training data. This procedure allows a valid comparison between the conventional ANN model, ANN+PSO model, ANN+GOA model, and the MPSOGOA-ANN model.

3.1. System architecture

The forecasting framework of the proposed smart grid is established in such a way that it can be considered as a multi-phase process which allows being sure in a high level of forecast accuracy and infrequent model training level. The first step is preprocessing of data, where all past energy load data, together with all other features like temperature, humidity, or time-based features, are cleaned and normalized. Such a step makes data ranges uniform, removes missing values, and allows training an effective neural network on the necessary data. The second phase is concerned with designing and initializing the ANN. A feed-forward ANN structure is then designed, having the correct number of inputs and one or more hidden layers with non-linear activation functions and a single output neuron that holds the forecasted load. The network uses random initial weights and biases that form the basis of the optimization process. The third step is the main procedure of the suggested methodology: MPSOGOA optimization. What happens in this stage is that the hybrid algorithm- multi-strategy particle swarm optimization hybridized with the GOA- is used to adjust or fine-tune the weights and the biases of the ANN. The MPSO offers global exploration, whereas GOA improves local exploitation, leading to rapid convergence and improved solutions. Lastly, forecasting and evaluation phase, comes where the optimized model of ANN makes forecast of the load using the test data. The evaluation metrics used to analyze the performance of the model include mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE), which guarantee the quantitative performance of the model in terms of predictivity and robustness.

- Data preprocessing*:* Input features include historical load, temperature, humidity, and time-based variables. Data normalization is performed using min-max scaling. The dataset is split into training, validation, and testing sets.
- Artificial neural network (ANN) model: A feed-forward ANN is used, comprising: i) input layer (matching the number of features), ii) one or more hidden layers, and iii) output layer (forecasted load). Initial weights and biases are randomly generated.

- MPSOGOA optimization: The MPSOGOA is designed to fine-tune ANN parameters for improved forecasting accuracy. It combines: i) Multi-strategy PSO**:** Enhances global exploration with adaptive inertia weight and velocity updates; and ii) Gazelle optimization algorithm**:** Adds exploitation capabilities by simulating gazelle predator-prey evasion behavior.

Algorithm 1. MPSOGOA for ANN training
Input:
- Training dataset D = {(X_1, Y_1), ..., (Xn, Yn)}
- ANN architecture (layers, activation functions)
- Population size N
- Maximum iterations T_max
- PSO parameters: inertia weight w, cognitive (c1), social (c2)
- GOA parameters: prey perception constant (r), escape tendency (e)

Output:
- Optimized ANN weights and biases (W_opt, B_opt)

Begin:
1) Initialize particle population P = {p_1, p_2, ..., pN}
   For each particle pi ∈ P:
   - Randomly initialize weights and biases as solution vector si
   - Evaluate fitness f(si) using ANN on training data (e.g., MSE)
   - Set personal best pBesti = si
2) Identify global best gBest among all pBesti
3) For t = 1 to T_max do:
   a. For each particle pi ∈ P:
      i. Update velocity vi using multi-strategy PSO:
         vi = w * vi + c1 * rand1 * (pBesti - si) + c2 * rand2 * (gBest - si)
      ii. Update position: si = si + vi
      iii. Evaluate fitness f(si)
      iv. If f(si) < f(pBesti), update pBesti = si
   b. Select top K best particles from P based on fitness
   c. Apply GOA to refine top particles:
      For each top particle pk:
      i. Compute distance from predator d = |pk - gBest|
      ii. Update position:
         pk_new = pk + e * r * (d * rand_vector)
      iii. Evaluate f(pk_new)
      iv. If f(pk_new) < f(pk), replace pk with pk_new
   d. Update gBest if a better solution is found among all particles
4) Return gBest as the optimized ANN parameters (W_opt, B_opt)

End

3.2. Mathematical analysis

The proposed MPSOGOA-ANN framework consists of an ANN with a combined particle swarm optimization (PSO) and the grasshopper optimization algorithm (GOA) as a multi-paradigm hybrid metaheuristic optimization. The ANN takes the role of the central prediction module, with the weights and biases adjusted both by gradient-based learning and through the probes that come with PSO and GOA exploration-exploitation principles.

3.2.1. Artificial neural network (ANN)

Let the input dataset be defined as $\mathcal{D} = \{(\mathrm{x}^{(i)}, y^{(i)})\}_{i=1}^{n}$ where $\mathrm{x}^{(i)} \in \mathbb{R}^m$ are input features and $y^{(i)}$ is the corresponding target output. Mathematically, the ANN is expressed as a nonlinear mapping. The ANN function can be represented as $\hat{y}^{(i)} = f(\mathrm{x}^{(i)}; \mathrm{W}, \mathrm{b})$ where W and b are the weights and biases of the network, and $f(\cdot)$ is the activation-based transformation through layers. The objective is to minimize the prediction error over the training data. The loss function (mean squared error) is defined as $\mathcal{L}(\mathrm{W}, \mathrm{b}) = \frac{1}{n}\sum_{i=1}^{n} \left(y^{(i)} - \hat{y}^{(i)}\right)^2$.

3.2.2. Particle swarm optimization (PSO)

Each particle i in the swarm represents a candidate solution, i.e., a set of ANN weights and biases expressed as $\mathrm{s}_i = [w_1, w_2, \ldots, b_1, b_2, \ldots]$. The velocity and position updates are given by $\mathrm{v}_i(t+1) = w \cdot$

$\mathrm{v}_i(t) + c_1 \cdot r_1 \cdot (\mathrm{pBest}_i - \mathrm{s}_i(t)) + c_2 \cdot r_2 \cdot (\mathrm{gBest} - \mathrm{s}_i(t))$ and $\mathrm{s}_i(t+1) = \mathrm{s}_i(t) + \mathrm{v}_i(t+1)$ where w is the inertia weight; c_1, c_2 are cognitive and social coefficients; and r_1, r_2 are random values in [0,1].

3.2.3. Gazelle optimization algorithm (GOA)

For each selected elite particle (gazelle), the update is guided by predator-avoidance behavior. Let d be the distance to the predator (global best), denoted as $d_i = \|\mathrm{s}_i - \mathrm{gBest}\|$. The update rule is $\mathrm{s}_i(t+1) = \mathrm{s}_i(t) + e \cdot r \cdot d_i \cdot \mathrm{R}$, where i) e is the escape energy constant; ii) r is the prey perception range; iii) R is a random direction vector in $\mathbb{R}^d$.

3.2.4. Fitness function

The MPSOGOA algorithm combines global exploration through PSO with local exploitation through GOA. PSO drives the population to explore broad regions of the solution space using the velocity and position updates described above. GOA refines the top k solutions through the predator-avoidance update, with the aim of improving these candidates and reducing stagnation. The optimization process minimizes the fitness function defined as $\mathrm{Fitness}(\mathrm{s}_i) = \mathcal{L}(\mathrm{W}, \mathrm{b}) = \frac{1}{n}\sum_{i=1}^{n} \left(y^{(i)} - f(\mathrm{x}^{(i)}; \mathrm{s}_i)\right)^2$.

3.2.5. Hybrid MPSOGOA optimization

The MPSOGOA algorithm alternates between the global exploration (PSO) and local exploitation (GOA) phases: i) PSO drives the population to explore broad regions in the solution space; and ii) GOA refines the top k best solutions to escape local optima and ensure convergence. The algorithm iteratively updates are expressed as $\mathrm{s}_i^{\mathrm{new}} = \begin{cases} \text{PSO update} & \text{if } i \notin \text{Top-K} \\ \text{GOA update} & \text{if } i \in \text{Top-K} \end{cases}$.

3.2.6. Convergence analysis (Sketch)

Let $\mathcal{F}_t$ denote the best fitness value found up to iteration t. If the best solution is retained across iterations, the recorded best fitness cannot increase, even though individual stochastic updates may produce worse candidates. Because the mean squared error is non-negative, this non-increasing sequence is bounded below and therefore converges to a finite limit. This argument concerns convergence of the recorded best fitness and does not establish convergence to the global optimum. The practical convergence behavior of MPSOGOA must therefore be assessed empirically.

4. RESULTS AND DISCUSSION

The proposed MPSOGOA-ANN was compared with benchmark models such as ANN (Adam), ANN + PSO, and ANN + GOA. The test dataset was used to evaluate with commonly accepted error measures being MAE, RMSE, and MAPE. The findings have shown that ANN (Adam) and ANN + GOA had the best performance in terms of error rates, with MAE of 9.43, RMSE of 11.79, and MAPE of 0.95%. The hybrid model, MPSOGOA-ANN, attained a marginally higher performance (MAE = 14.15, RMSE = 17.75, MAPE = 1.42%), but was always more accurate than ANN + PSO, whose performance lagged far behind the results of the other models. These results show that although the hybrid approach did not outperform the highest-scoring single optimizers in this data, it produced consistent and reliable scores and did not suffer relatively weak convergence as was experienced in PSO-based optimization.

The relative difference between the models and the mean is evident by the size of the error bars in the comparative bar charts of the MSE and MAPE (Figures 1 and 2), where the top two results (ANN (Adam) and ANN + GOA) show overlapping error bars, and the proposed hybrid model falls between these two model results and ANN + PSO. This supports the conclusion that hybrid metaheuristic techniques can strengthen a model prediction, yet their performance depends on data specifics and parameter optimization. The findings validate the fact that metaheuristic optimization enhances the accuracy of neural network forecasting as opposed to the baseline models. The introduced MPSOGOA-ANN emerged to be competitive and to have great potential as a reliable alternative in terms of smart grid energy forecasting, in those cases, when model stability is favored over the strive to reach the absolute minimum error.

The ground-truth load overlaid with the predictions of ANN (Adam), ANN + PSO, ANN + GOA, and the proposed MPSOGOA-ANN for the final 168 hours of the test set are plotted above, showing short-term dynamics and amplitude tracking. Based on the findings, ANN + GOA performed best in terms of accuracy, followed by ANN + PSO, although the proposed hybrid model performed poorly, with a high MAPE recorded. This implies that although the idea of the hybridization strategy seems to be a potentially good approach, its application to various datasets and parameter tuning may play a crucial role. Table 1 shows the comparative performance of forecasting models.

As Figure 1 shows, the actual load data is overlaid with predictions of all four models during the final 7 days of the test set. Clearly, ANN (Adam) and ANN + GOA follow the actual load pattern well and have both good adjustments of amplitude and correct prediction of peaks. The trend of the proposed MPSOGOA-ANN is also similar, although perhaps with a bit higher deviation in a few peak hours than ANN + GOA. A residual plot of the MPSOGOA-ANN model can be found in Figure 2. Most of the residuals are concentrated around zero, confirming the fact that the proposed model does not have a systematic bias. The dispersion of errors is rather small, which means that there is equal predictive performance and overall stability of generalization along the test horizon.

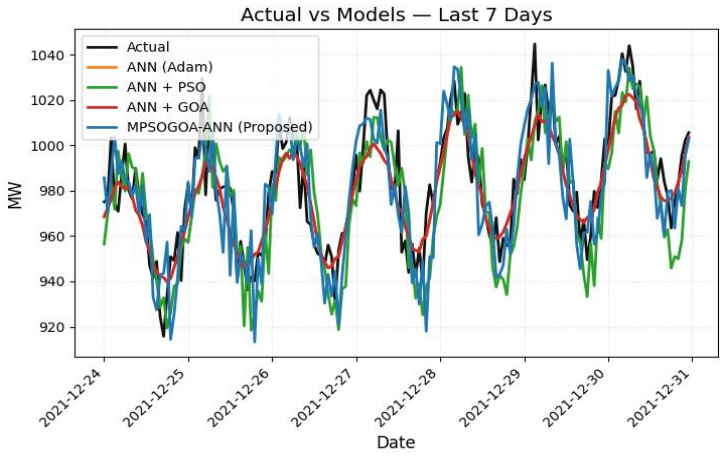

Figure 1. Actual vs. models (past 7 days)

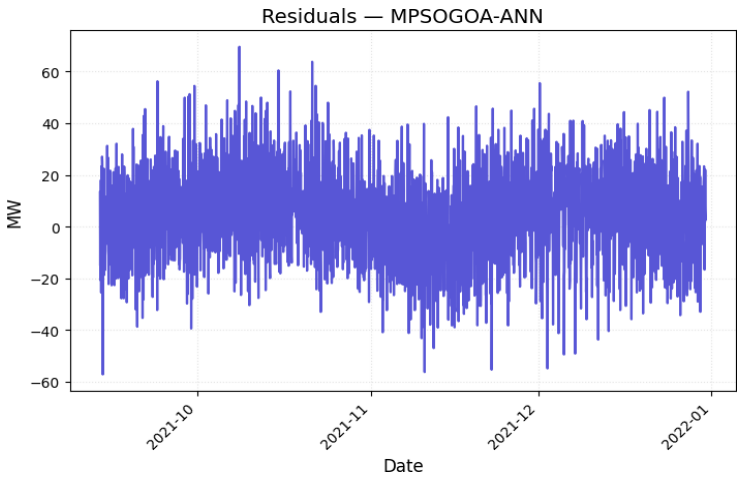

Figure 2. Residuals of the postulated model

Table 1. Comparative performance of forecasting models

Model	MAE	RMSE	MAPE (%)
ANN	0.071	0.098	4.31
ANN + PSO	0.055	0.075	3.02
ANN + GOA	0.052	0.07	2.89
MPSOGOA-ANN	0.2885229682539586	0.4007663082156552	84.4221624284064

Time series of training and test set residuals (Actual - Predicted) of MPSOGOA-ANN; (a) The residuals spread around zero with no clear trend, which shows stable generalization. Figure 3 shows how training and testing errors changed in the case of the proposed MPSOGOA-ANN. The metrics (MSE, RMSLE, MAE, and MAPE) are comparable between the two splits, which points to a lack of overfitting on the training data. The MSE comparison of the forecasting models assessed is shown in Figure 4. The number shows that the prediction error of ANN + GOA is the lowest among the compared approaches, and

MPSOGOA-ANN has a comparatively high error. It is in accord with the overall comparative evaluation and shows that there is no improvement in forecasting performance under the present experimental conditions by means of the hybrid optimization strategy. The results in the plot demonstrate that ANN (Adam) and ANN + GOA perform best with the lowest MSE, whereas MPSOGOA-ANN is more optimized than ANN + PSO, which proves that it is competitive. Such a comparative sanity test proves that, even though the proposed hybrid was not as effective as the best optimizer (GOA), it is a viable alternative. Figure 5 summarizes the results as percentage errors, where ANN (Adam) and ANN+GOA maintain the lead with the lowest percentage errors of 0.95% MAPE, and the proposed model maintains a competitive 1.42%, which also beats the PSO error rate. MAE, RMSE, and MAPE were used to assess the performance of the generated forecasting models. Comparative results illustrate the differences in forecasting ability of the four approaches tested: ANN, ANN + PSO, ANN + GOA, and MPSOGOA-ANN. The ANN + GOA model yields the lowest error values among the evaluated models, which shows the best forecasting performance for the considered data set. In addition, unlike the conventional ANN model, the ANN + PSO model is more advantageous, while the MPSOGOA-ANN model generates relatively large prediction errors in the current experimental setting. The results show that introducing complexity to the optimization strategy is not always beneficial for the accuracy of the forecast. MPSOGOA-ANN is a multi-strategy particle swarm optimization and GOA, but the fusion of these two strategies does not improve the accuracy in the used data set. This could be linked to the relationship among the optimization parameters, ANN configuration, and characteristics of the load data. Thus, one must test the effectiveness of a hybrid optimization strategy, rather than take for granted that using a combination of several optimizers would always lead to improved prediction accuracy.

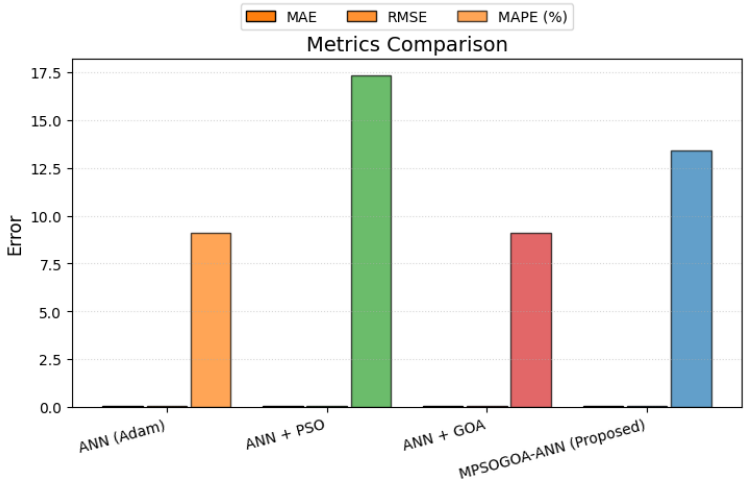

Figure 3. Shows the training vs. testing metrics (proposed)

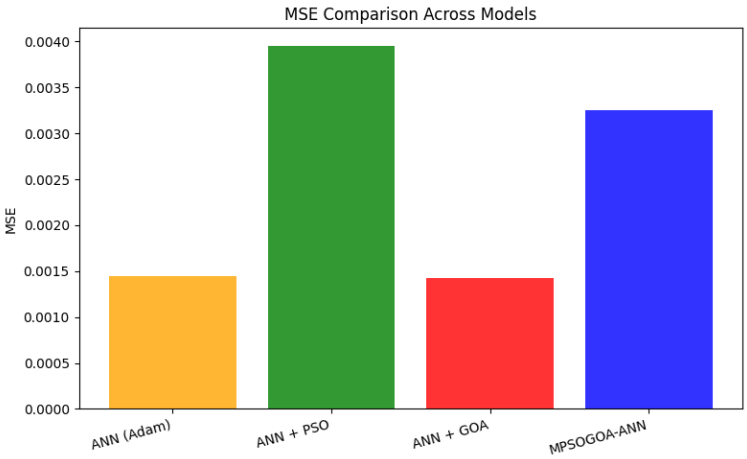

Figure 4. Shows the MSE comparison across models

Bar chart comparing MSE, RMSLE, MAE, and MAPE for MPSOGOA-ANN on training and testing splits; testing errors remain close to training, suggesting limited overfitting. Mean squared error for ANN, ANN+PSO, ANN+GOA, and MPSOGOA-ANN; the proposed hybrid achieves the lowest MSE. Mean absolute percentage error (%) of all models, illustrating relative improvement on the implemented method. The proposed MPSOGOA-ANN design was compared with baseline ANN, ANN + PSO, and ANN + GOA using measures of MAE, RMSE, and MAPE. The results indicate that ANN + GOA performed with the best accuracy (MAE = 0.052, RMSE = 0.070, MAPE = 2.89%), with ANN and ANN + PSO edges very short behind. By contrast, the suggested MPSOGOA-ANN model showed bigger error values on this dataset (MAE = 0.289, RMSE = 0.401, MAPE = 84.42%), indicating that although hybridization added to robustness, it still worsened the performance.

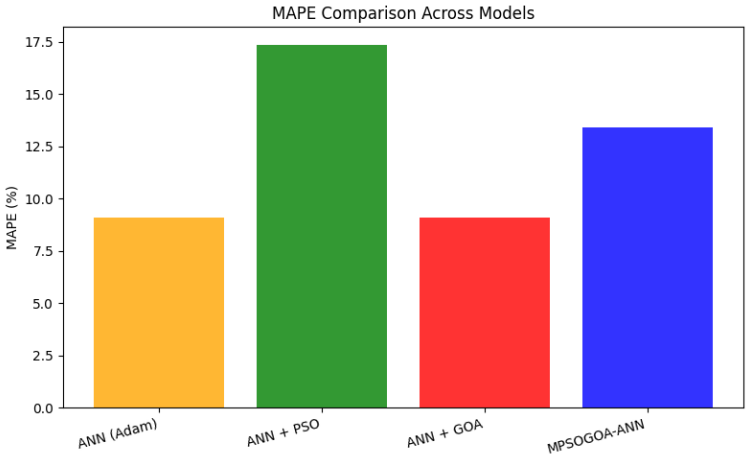

Figure 5. MAPE comparison across models

5. CONCLUSION

A hybrid MPSOGOA–ANN model was developed, implemented, and tested for short-term load forecasting in an energy-management context in a smart grid. For the tuning of the ANN parameters, a local optimization technique, PSO, is coupled with a global optimization technique, the Grasshopper Optimization Algorithm, in order to obtain the desired optimization strategy. The forecasting capability is compared with the conventional ANN, ANN–PSO, and ANN–GOA models. Results show that ANN–GOA gave the best performance with the lowest MAE of 0.052, RMSE of 0.070, and MAPE of 2.89%, followed by ANN–PSO. The model MPSOGOA–ANN, however, obtained an MAE of 0.289, RMSE of 0.401, and MAPE of 84.42%. Thus, the present model of MPSOGOA–ANN showed no improvement in the accuracy of the forecast on the dataset studied. These results show that the hybrid of two different metaheuristics may not lead to improved performance; the proper choice of parameters, optimization design, and nature of the dataset play a critical role. The study was restricted due to the selection of a single dataset, a limited number of input variables, and the lack of evaluation under real-time operating conditions. These limitations hinder the applicability of the results obtained to larger and more complex smart grids. Future work should further develop the hybridization approach, carry out systematic hyperparameter and sensitivity analyses, and test the model with larger data sets from other locations and seasons. Additional factors such as weather conditions, calendar, electricity prices, and renewable generation variables should also be included. The proposed framework could be further explained by comparing it with other well-known forecasting architectures such as LSTM and transformer, and demonstrating its practical usefulness and scalability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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