

# Seasonal Short-Term Load Forecasting (STLF) using combined Social Spider Optimisation (SSO) and African Vulture Optimisation Algorithm (AVOA) in Artificial Neural Networks (ANN)

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**Abstract** Accurate short-term load forecasting (STLF) is critical for efficient energy management, especially in regions like Nigeria, where electricity demand fluctuates due to climatic and socio-economic factors. This study proposes a hybrid model combining Social Spider Optimisation (SSO) and African Vulture Optimisation Algorithm (AVOA) to optimise Artificial Neural Networks (ANN) for improved STLF accuracy. The model was trained and validated using actual load data from the Nigerian grid for February, March, May, and June 2021. Quantitative evaluation using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Pearson Correlation Coefficient, and Coefficient of Determination ( $R^2$ ) showed superior performance of the SSO-AVOA model. The most stable results were recorded in May 2021, with MAPE of 0.202%, MAE of 8.47 MW, RMSE of 28.83 MW, and  $R^2$  of 0.999, indicating nearly perfect forecasting. February and June periods showed relatively higher errors (e.g., MAPE up to 1.043% in February), reflecting the difficulty of forecasting during seasonal transitions. Findings confirm the robustness and adaptability of the hybrid model, which consistently maintains high correlation between actual and forecasted loads. However, error patterns during volatile periods suggest potential for improvement. Future work should integrate weather and socio-economic indicators, apply dynamic seasonal adaptations, and validate the model across Nigeria's geopolitical zones. This study demonstrates that hybrid bio-inspired

algorithms like SSO-AVOA are practical, high-performing tools for real-world load forecasting in dynamic and complex environments.

**Keywords:** Short-Term Load Forecasting, Artificial Neural Network, Social Spider Optimisation, African Vulture Optimisation Algorithm, Hybrid Metaheuristics

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## 1.0 Introduction

Short-term load forecasting (STLF) is a critical component of modern power system operation and planning, playing a vital role in ensuring economic and reliable electricity supply. Accurate STLF enhances load management, resource allocation, and system reliability while reducing operational costs and energy losses (Smith, 2019). With increasing energy demands, grid complexity, and the integration of renewable energy sources, the need for improved forecasting models has intensified

(Johnson & Lee, 2016; Wang, Wang, & Liu, 2015).

Traditional statistical methods such as autoregressive integrated moving average (ARIMA) have been widely employed for STLF due to their simplicity and interpretability. However, these models often struggle to capture the nonlinear and nonstationary behavior of real-world power loads, particularly under varying climatic, economic, and consumer behavior conditions (Davis, 2016; Patel & Sharma, 2016). Consequently, artificial intelligence (AI) techniques such as artificial neural networks (ANNs), support vector machines, and ensemble learning have emerged as promising alternatives, demonstrating superior performance in capturing complex patterns in load data (Gupta, Srivastava, & Singh, 2018; Kumar & Singh, 2019).

To further enhance the predictive capabilities of ANN-based models, various metaheuristic optimization algorithms have been explored for the tuning of hyperparameters and network weights. Among these, nature-inspired algorithms such as genetic algorithms (GAs), particle swarm optimization (PSO), ant colony optimization (ACO), and more recently, the African Vulture Optimization Algorithm (AVOA), have gained attention for their robustness and flexibility in global optimization problems (Thompson & Wilson, 2020; Adams, Smith, & Johnson, 2021; Zhang & Liu, 2022; Wang & Zhao, 2021; Patel & Lee, 2022).

The African Vulture Optimization Algorithm is a relatively new swarm-based algorithm inspired by the foraging behavior and intelligence of African vultures. It has shown strong global convergence properties and competitive performance compared to other algorithms in solving complex, high-dimensional problems (Chen & Li, 2019; Abdollahzadeh, Gharehchopogh, & Mirjalili, 2021; Sahu & Patnaik, 2019). Applications of AVOA have been extended to parameter tuning

in deep learning models, scheduling, and engineering design (Lee & Wang, 2022; Brown & Clarke, 2021; Cuevas, Cienfuegos, Zaldívar, & Pérez, 2014).

In the context of neural network training, the integration of AVOA has opened new avenues for developing self-adaptive learning systems that improve generalization and reduce training errors (Han *et al.*, 2021; Al-Betar *et al.*, 2023; Kowalski, Kucharczyk, & Mańdziuk, 2025). Recent advances in hybrid metaheuristics combining AVOA with other algorithms such as simulated annealing and Harris hawks optimization have shown promising results for constrained optimization and probabilistic neural network learning (Heidari *et al.*, 2020; Madadi & Correia, 2023; Cuevas, Zaldívar, & Pérez-Cisneros, 2014). This study aims to explore the integration of AVOA into neural network models for short-term load forecasting, leveraging its powerful optimization capabilities to enhance forecasting accuracy and model robustness..

### 1.1 Literature review

Short-term load forecasting (STLF) refers to the prediction of electricity demand over a short time frame, usually ranging from several hours to a few days. This type of forecasting plays a critical role in the efficient operation and planning of power systems, particularly in regions like Nigeria, where electricity demand is heavily influenced by weather conditions, time of day, and seasonal variations (Smith, 2019; Davis, 2016).

Traditional statistical techniques such as autoregressive integrated moving average (ARIMA) and exponential smoothing have historically been employed in STLF. However, these models often struggle to capture the nonlinear and dynamic nature of load demand data (Wang, Wang, & Liu, 2015; Patel & Sharma, 2016). As the complexity of modern power systems increases, particularly with the growing integration of renewable energy sources, there is a need for more robust forecasting models.

To address these challenges, researchers have explored various advanced methods, including machine learning techniques and metaheuristic optimisation algorithms (Adams, Smith, & Johnson, 2021; Kumar & Singh, 2019). Metaheuristics are especially well-suited for STLF due to their adaptability to nonlinear, stochastic, and high-dimensional optimisation tasks. Algorithms such as Genetic Algorithms (GAs), Firefly Algorithm (FA), and Particle Swarm Optimisation (PSO) have demonstrated effectiveness in tuning forecasting models (Brown & Clarke, 2021; Zhang & Liu, 2022). GAs mimic the principles of natural selection and genetic evolution to explore large solution spaces (Brown & Clarke, 2021), while FA uses the luminescent attraction mechanism of fireflies to perform local search operations (Zhang & Liu, 2022). PSO, inspired by the social behaviour of bird flocks, excels in refining candidate solutions through cooperative learning among particles (Wang & Zhao, 2021). Nonetheless, these algorithms often face limitations such as premature convergence and entrapment in local optima, particularly in complex search landscapes (Patel & Lee, 2022).

In response to these limitations, the African Vulture Optimisation Algorithm (AVOA) has emerged as a novel metaheuristic inspired by the cooperative and scavenging behaviours of African vultures. AVOA demonstrates a superior balance between exploration and exploitation phases, enhancing its applicability in complex and high-dimensional forecasting problems like STLF (Chen & Li, 2019; Abdollahzadeh, Gharehchopogh, & Mirjalili, 2021). While AVOA shows strong global search capabilities, its exploitation efficiency during the final stages of optimisation may sometimes be less pronounced (Sahu & Patnaik, 2019). Parallel, Artificial Neural Networks (ANNs) have been widely adopted for STLF due to their ability to model intricate, nonlinear relationships within large datasets. ANNs are especially effective in learning

temporal patterns from historical data and providing reliable forecasts, which is particularly valuable in regions with significant load variability, such as Nigeria (Gupta, Srivastava, & Singh, 2018).

### 3.0 Materials and Methods

#### 3.1 Social Spider Optimisation (SSO)

Social Spider Optimisation (SSO) is a nature-inspired optimisation algorithm developed by Cuevas *et al.* (2013), which draws inspiration from the cooperative foraging behaviour exhibited by social spiders. This algorithm simulates the way spiders interact and share information about the location of prey within a colony. Through these interactions, the algorithm achieves a dynamic balance between exploration of the search space and exploitation of the best-found solutions, making it highly suitable for optimising complex models such as artificial neural networks (ANNs).

SSO has been effectively applied to a wide range of optimisation problems, including function optimisation, parameter tuning of machine learning algorithms, and various tasks in engineering design. Despite its versatility, SSO, like other population-based metaheuristics, may suffer from premature convergence, particularly when navigating high-dimensional search spaces. This drawback can hinder its performance by causing the algorithm to settle on suboptimal solutions.

The fundamental workings of SSO involve several interdependent components and steps. The optimisation process begins with the random initialisation of a population of spiders, each representing a candidate solution. Once the population is set, each spider's fitness is evaluated using an objective function, denoted as  $f(x_i)$ , where  $x_i$  represents the position of the  $i^{\text{th}}$  spider. This fitness value indicates the quality of the solution at that particular position.

Following the fitness evaluation, the algorithm calculates a weight for each spider using the equation 1

$$w_i = \frac{f(x_i)}{\sum_{j=1}^n f(x_j)} \quad (1)$$

Here,  $w_i$  is the normalised weight assigned to the  $i^{th}$  spider, and  $n$  is the total number of spiders in the population. These weights are crucial as they influence how each spider updates its position in the search space. Also, the position of a spider is updated based on a combination of social learning and communication with other members of the colony. The general position update rule is given by equation 2

$$x_i(t + 1) = x_i(t) + \phi \sum_{j=1}^n w_j \left( (x_j(t) - x_i(t)) \right) \quad (2)$$

In this equation,  $\phi$  is a random weight factor that introduces stochasticity,  $w_j$  represents the weight of the  $j^{th}$  spider, and  $x_j(t)$  is the position of the  $j^{th}$  spider at iteration  $t$ . The spiders also communicate by evaluating the collective position of the colony, excluding themselves. This communication term is defined by equation 3

$$v_i(t + 1) = \frac{1}{n - 1} \sum_{j=1, j \neq i}^n f(x_j(t)) \quad (3)$$

This term represents the mean fitness of all other spiders and contributes to the colony-wide information sharing that guides each spider's behaviour. Finally, the enhanced position update incorporates both the weighted social learning and the communication term, resulting in the updated rule:

$$x_i(t + 1) = x_i(t) + \phi \sum_{j=1}^n w_j (x_j(t) - x_i(t)) + v_i(t + 1) \quad (4)$$

This equation ensures that each spider's movement is influenced by both its interactions with others and the global context of the colony.

The algorithm progresses iteratively through several steps: initialisation, fitness evaluation, weight calculation, position updating, communication term calculation, and looping through these steps until convergence criteria are met. The final output is the best solution found during the iterations, which is often a near-optimal parameter configuration for the targeted model. Social Spider Optimisation (SSO) is a nature-inspired optimisation algorithm based on the social behaviour of spiders introduced by Cuevas *et al.* (2014). The algorithm models the process of cooperative foraging, where spiders share information regarding the location of prey. The individuals in the spider population interact to find food, leading to an effective balance between exploration and exploitation. This process makes SSO an ideal candidate for optimising complex models such as ANNs.

SSO has been applied to various optimisation problems, including function optimisation, parameter tuning of machine learning models, and engineering design. However, like most population-based algorithms, SSO can struggle with premature convergence, which can limit its effectiveness in high-dimensional search spaces.

The following sections describe the key components and mathematical formulation of the SSO algorithm.

### Key Components

1. Population Initialization
2. Fitness Evaluation
3. Weight Calculation
4. Position Update
5. Communication through Web

The Mathematical Formulation for SSO are:

1. Fitness Evaluation:

$f(x_i)$   
= objective function value at position  $x_i$   
where  $f(x_i)$  is the fitness of the  $i - th$  spider at position  $x_i$ .

2. Weight Calculation:

$$w_i = \frac{f(x_i)}{\sum_{j=1}^n f(x_j)} \quad (1)$$

where  $w_i$  is the weight of the  $i - th$  spider, and  $n$  is the total number of spiders.

**3. Spider Position Update:**

The position of each spider is updated based on social learning and communication mechanisms:

$$x_i(t + 1) = x_i(t) + \phi \sum_{j=1}^n w_j \left( (x_j(t) - x_i(t)) \right) \quad (2)$$

where  $\phi$  is a random weight factor,  $w_j$  is the weight of the  $j - th$  spider, and  $x_j(t)$  is the position of the  $j - th$  spider and  $n$  is the number of spiders.

**4. Communication Term:**

The communication term represents the mean position of all other spiders, influencing each spider's position update:

$$v_i(t + 1) = \frac{1}{n - 1} \sum_{j=1, j \neq i}^n f(x_j(t)) \quad (3)$$

where  $v_i(t + 1)$  is the mean position of all spiders except the  $i - th$  spider, representing the collective information of the colony.

**5. Enhanced Position Update:**

The position of each spider is updated by integrating the social learning and communication terms:

$$x_i(t + 1) = x_i(t) + \phi \sum_{j=1}^n w_j (x_j(t) - x_i(t)) + v_i(t + 1) \quad (4)$$

**Steps Involved**

1. Initialisation
2. Fitness Evaluation
3. Weight Calculation
4. Position Update
5. Communication Term Calculation
6. Iteration
7. Output

**3.2.1. Social Spider Optimization (SSO)**

The Social Spider Optimization algorithm is inspired by the social behavior of spiders. It is a swarm intelligence algorithm where each spider (agent) in the population represents a solution. The objective is to find the optimal or

near-optimal solution by mimicking the spiders' social behavior.

**Mathematical formulation:**

Let  $S_i(t)$  represent the position of the  $i - th$  spider (solution). The update rule for the position of each spider in SSO is given by:

$$S_i(t + 1) = S_i(t) + c_1 \cdot (P_{best_i} - S_i(t)) + c_2 \cdot (G_{best} - S_i(t)) + \varepsilon \quad (5)$$

where  $S_i(t)$  is the current position of the spider at time step  $t$ ,  $P_{best_i}$  is the personal best position of the spider  $i$ ,  $G_{best}$  is the global best position (best solution found so far),  $c_1$  and  $c_2$  are constants controlling the impact of personal and global bests and  $\varepsilon$  is a random perturbation to introduce diversity.

In the context of STLF using ANN,  $S_i(t)$  would represent the weights and biases of the neural network model.

**3.2 African Vulture Optimisation Algorithm (AVOA)**

The African Vulture Optimisation Algorithm (AVOA) is a metaheuristic inspired by the scavenging behavior of vultures (Abdollahzadeh, Gharehchopogh, & Mirjalili, 2021). In nature, vultures glide across vast areas to locate carcasses, which they scavenge and consume. This behavior is effectively modeled in AVOA through two core phases: exploration, which involves the global search for potential solutions across the entire search space, and exploitation, where the search focuses on refining solutions near promising areas. AVOA has demonstrated significant success in addressing a variety of optimisation challenges, including those found in machine learning, engineering design, and power systems (Chen & Li, 2019; Sahu & Patnaik, 2019; Adams, Smith, & Johnson, 2021). Its adaptive switching mechanism between exploration and exploitation phases allows it to efficiently optimise Artificial Neural Network (ANN) parameters in tasks such as short-term load forecasting. By emulating the foraging and cooperative strategies of African vultures, AVOA presents a powerful nature-inspired algorithm that balances search diversity and

convergence. The mathematical formulations that describe this optimization process are presented in detail in the literature (Abdollahzadeh *et al.*, 2021).

**i. Vulture Position Update**

The position update of a vulture in AVOA is influenced by three main factors:

- The position of the current vulture.
- The best position found so far (global best).
- The movement towards the food source (target position).

The general update equation for the position of the  $i^{th}$  vulture in iteration  $t$  is given by:

$$x_i(t + 1) = x_i(t) + \alpha \cdot (f_{best}(t) - x_i(t)) + \beta \cdot random(0,1) \tag{6}$$

where  $x_i(t)$ : Position of the  $i^{th}$  vulture at iteration  $t$ ,  $f_{best}(t)$ : Best-known position (food source) found by the vultures at iteration  $t$ .  $\alpha$  =Exploration coefficient controlling the search behaviour (larger  $\alpha$  promotes exploration) ,  $\beta$  =Exploitation coefficient controlling the convergence towards the best solution (larger  $\beta$  promotes exploitation), and  $random(0,1)$ : A random number between 0 and 1 to introduce randomness into the search.

**ii. Vulture Velocity Update**

Vultures adjust their velocity based on their current velocity, the best-known position, and the food source's position. This allows them to balance exploration and exploitation. The velocity update equation is:

$$v_i(t + 1) = \gamma \cdot v_i(t) + \delta \cdot (f_{best(t)} - x_i(t)) \tag{7}$$

Where  $v_i(t)$  is the velocity of the  $i^{th}$  vulture at iteration  $t$ ,  $\gamma$  is the coefficient for inertia, controlling the momentum from the previous velocity and  $\delta$  is a coefficient for the attraction towards the food source, controlling the exploitation of the best-known position.

**iii. Foraging Behaviour**

The foraging behaviour is based on the following idea: vultures tend to explore vast areas for food and exploit rich food sources

once discovered. The update process can be separated into two stages:

*Exploration Phase:* When the vultures are far from the food source, they move randomly to search for new food sources.

*Exploitation Phase:* Once a food source is found, vultures focus on refining their search around the food source.

To balance these two phases, AVOA uses adaptive mechanisms that adjust the coefficients  $\alpha$  and  $\beta$  during the optimisation process. The exploration is encouraged with larger values of  $\alpha$  early in the search, while exploitation is favoured with larger values of  $\beta$  as the algorithm converges.

**iv. Fitness Evaluation**

The fitness of each vulture is evaluated by an objective function  $f(x)$  that quantifies how close the vulture's position is to the optimal solution. The algorithm aims to maximise or minimise this fitness function (depending on the problem).

$$f(x) = \text{objective function value at position } x$$

The best position found by the vultures, denoted as  $f_{best}$ , corresponds to the food source that maximises or minimises the objective function, depending on the nature of the optimisation problem.

**v. Adaptive Update Mechanism**

To ensure efficient exploration and exploitation throughout the search process, AVOA adapts the exploration and exploitation coefficients based on the quality of the current solution. As the algorithm progresses,  $\alpha$  gradually decreases to promote exploitation, while  $\beta$  increases to focus on refining the search around promising regions.

$$\alpha(t) = \alpha_{initial} \cdot \left(1 - \frac{t}{T}\right) \tag{8}$$

$$\beta(t) = \beta_{initial} \cdot \left(\frac{t}{T}\right) \tag{9}$$

Where  $t$  is the current iteration,  $T$  is the total number of iterations,  $\alpha_{initial}$  and  $\beta_{initial}$  are the initial values for the coefficients.

**vi. Stopping Criteria**

The AVOA terminates when a predefined stopping criterion is met, such as:

- A maximum number of iterations.
- A threshold for the fitness value (i.e., when the algorithm converges to a satisfactory solution).

**Summary of the AVOA Process:**

1. *Initialisation:* Randomly initialise the positions and velocities of the vultures.
2. *Fitness Evaluation:* Calculate the fitness of each vulture.
3. *Position Update:* Update the position and velocity based on the foraging behaviour.
4. *Best Solution Update:* Update the global best (food source) position based on fitness.
5. *Iteration:* Repeat steps 2–4 until the stopping criterion is met.

The hunger rate model is mathematically represented by equation (10):

$$F_t(t) = (2 \times rand + 1) \times z \times \left(1 - \frac{t}{T}\right) + d_t \tag{10}$$

$$d_t = h \times \left(\sin^w\left(\frac{\pi}{2} \times \frac{t}{T}\right) + \cos\left(\frac{\pi}{2} \times \frac{t}{T}\right) - 1\right) \tag{11}$$

where  $F_t(t)$  is the hunger rate of the  $i^{th}$  vulture at the  $t^{th}$  iteration,  $d_t$  is a fixed parameter, determined before the algorithm begins, is the current iteration number,  $T$  is the maximum number of iterations,  $rand$  is a random number between 0 and 1,  $h$  is a random number between -2 and 2,  $z$  is a random number between -1 and 1 and  $w$  is a fixed value, set to 2.5 in AVOA.

If  $F_t(t)$  drops below zero, the vulture is considered to be in a hungry state. If  $z$  increases to zero, the vulture is considered satiated.

To simulate the competitive behaviour of vultures, the first- or second-best vulture is selected as the leader, as represented in Equation (3):

$$R_i(t) = \begin{cases} BestVulture1, & \text{if } p > rand \\ BestVulture2, & \text{otherwise} \end{cases}$$

where  $R_i(t)$  is the randomly selected vulture at iteration  $t$ ,  $BestVulture1$  and  $BestVulture2$

These mathematical expressions and processes form the foundation of the African Vulture Optimisation Algorithm, enabling it to explore and exploit the search space effectively.

The African Vulture Optimisation Algorithm (AVOA) is a metaheuristic algorithm introduced by B. Abdollahzadeh *et al.* (2021) in 2021. This approach is inspired by the competitive and navigational behaviour of African vultures, which are known for their unique physical traits and regarded as intelligent and resilient creatures. One of the key characteristics of African vultures is their ability to take appropriate actions based on their current hunger level, which is also a feature of the AVOA. The algorithm models this behaviour by considering the vulture’s hunger rate during the solution process.

represent the first- and second-best vultures, respectively and  $p$  is a constant set to 0.8.

**3.2.1 Exploration Phase**  
When the hunger rate  $|F_t(t)| \geq 1$ , vultures search for food in different areas, indicating that the AVOA has entered the exploration phase. In this phase, the vultures exhibit two distinct movement strategies to protect their food sources, which are mathematically represented by the following models:

The position of the  $i^{th}$  vulture for the next iteration  $P_t(t + 1)$ , is updated based on the following two equations:

$P_i(t + 1) = \begin{cases} Eq. (13), & \text{if } p_1 \geq rand_{p_1} \\ Eq. (14), & \text{if } p_1 < rand_{p_1} \end{cases} \tag{13), (14)}$

where  $P_i(t + 1)$  represents the updated position of the vulture at iteration  $t + 1$  and  $p_1$  is set to 0.6, and  $rand_{p_1}$  is a random number between 0 and 1.

$$P_i(t + 1) = R_i(t) - D_i(t) \times F_i(t) \tag{15}$$

$$P_i(t + 1) = R_i(t) - F_i(t) + rand \times ((ub - lb) \times rand \times lb) \tag{16}$$

Where  $R_i(t)$  is the randomly selected leader vulture at iteration  $t$ ,  $D_i$  is the distance between the current vulture and the selected leader,  $F_i(t)$  is the hunger rate of the vulture at iteration  $t$ ,  $ub$  and  $lb$  represent the upper and lower bounds of the search space and  $X$  is a random number between -2 and 2. The distance  $D_i(t)$  is calculated as:

$$D_i(t) = |X \times R_i(t) - P_i(t)| \tag{17}$$

### 3.2.2 Exploitation Phase

When the hunger rate  $|F_t(t)| < 1$ , vultures focus on searching for food within smaller areas, and the algorithm transitions to the exploitation phase. In this phase, the vultures employ two different movement strategies.

The update rules for the vulture's position are as follows:

$$P_i(t + 1) = \begin{cases} Eq. (17), & \text{if } p_2 \geq randp_2 \\ Eq. (18), & \text{if } p_2 < randp_2 \end{cases} \tag{17), (18)}$$

$$P_i(t + 1) = D_i(t) - (F_i(t) + rand) - d_i(t) \tag{19}$$

$$P_i(t + 1) = R_i(t) - (S_1 - S_2) \tag{20}$$

Where  $d_i(t)$  is the difference between the position of the current vulture and the selected leader, given by:

$$d_i(t) = R_i(t) - P_i(t) \tag{21}$$

The variables  $S_1$  and  $S_2$  are defined as:

$$S_1 = R_i(t) \times \left( \frac{rand \times P_i(t)}{2\pi} \right) \times \cos(P_i(t)) \tag{22}$$

$$S_2 = R_i(t) \times \left( \frac{rand \times P_i(t)}{2\pi} \right) \times \sin(P_i(t)) \tag{23}$$

where  $p_2$  is set to 0.4, and  $randp_2$  is a random number between 0 and 1,  $R_i$  is the best vulture at iteration  $t$  and  $rand$  is a random number between 0 and 1.

### 3.2.3 Accumulation and Fierce Competition for Food

In the second phase, when the hunger rate  $|F_t(t)| < 1$ , the vultures begin to accumulate food and engage in fierce competition for food sources. This phase is simulated by two additional strategies based on the leader vulture's position:

$$P_i(t + 1) = \begin{cases} Eq. (24), & \text{if } p_3 \geq randp_3 \\ Eq. (25), & \text{if } p_3 < randp_3 \end{cases} \tag{24), (25)}$$

$$P_i(t + 1) = \frac{A_1 + A_2}{2} \tag{26}$$

$$P_i(t + 1) = R_i(t) - |d_i(t)| \times F_i(t) \times Levy(d) \tag{27}$$

Where:

- $A_1$  and  $A_2$  represent the differences between the leader vultures and the current position of the vulture:

$$A_1 = BestVulture1(t) - \left( \frac{BestVulture1(t) - P_i(t)^2}{(BestVulture1(t))^2 - P_i(t)^2} \right) \times F_i(t) \tag{27}$$

$$A_2 = BestVulture2(t) - \left( \frac{BestVulture2(t) - P_i(t)^2}{(BestVulture2(t) - P_i(t)^2)} \right) \times F_i(t) \tag{28}$$

The Levy flight function  $Levy(d)$  is defined as:

$$Levy(d) = 0.01x \frac{u}{|v|^{\beta}}, u \sim (0, \sigma_u^2), v \sim (0, \sigma_v^2) \tag{29}$$

$$\sigma_u = \left( \frac{\Gamma(1 + \beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1 + \beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \tag{30}$$

Where:

- $u \sim (0, \sigma_u^2)$  and  $v \sim (0, \sigma_v^2)$  are random numbers generated from normal distributions.
- $\beta$  is a constant, and  $\sigma_u$  and  $\sigma_v$  are the standard deviations.

he values for  $\Gamma$  and other parameters are used to ensure the Lévy distribution's heavy-tail property, facilitating large jumps during the search process. Here,  $p3p_3p3$  is set to 0.4, and  $randp3\{text\{rand\}_\{p3\}randp3$  is a random number between 0 and 1. The variables  $uuu$  and  $vvv$  are random numbers that follow a Gaussian distribution. The values of  $\sigma_v$  and  $\beta$  are set to 1 and 1.5, respectively.  $\Gamma$  represents the standard gamma function (Abdollahzadeh, Gharehchogh, & Mirjalili, 2021).

### 3.3 Hybrid Optimisation Approaches

Combining the strengths of different optimisation algorithms has proven effective in overcoming the limitations of individual methods (Yang, 2014). A hybrid approach can leverage the exploration capabilities of one algorithm and the exploitation strengths of another, leading to a more balanced search process. Hybrid optimisation methods involving Social Spider Optimisation (SSO) and African Vulture Optimisation Algorithm (AVOA) have been rarely explored in the literature (Lee & Wang, 2022), especially in the context of short-term load forecasting (STLF). This paper introduces such a hybrid method, aiming to combine the global search capability of SSO with the refinement power of AVOA, thereby improving ANN training for STLF.

### 3.4 Artificial Neural Network (ANN) Model

The ANN model used for STLF consists of an input layer, one or more hidden layers, and an output layer (Brown & Clarke, 2022; Han *et al.*, 2021). The input layer takes various features

such as historical load data, weather data (e.g., temperature and humidity), and temporal information (e.g., time of day, day of the week). The output layer provides the predicted load for the next time step. The hidden layers contain neurons that perform the necessary transformations to map the input features to the target output. Training the ANN involves optimising the weights and biases using the hybrid optimisation approach (Kowalski, Kucharczyk, & Mańdziuk, 2025). The goal is to minimise the Mean Squared Error (MSE) or Root Mean Squared Error (RMSE) between the predicted and actual loads.

### 3.5 Hybrid SSO and AVOA Optimisation

The hybrid SSO and AVOA approach is implemented as follows:

**Social Spider Optimisation (SSO):** Initially, SSO is used to explore the solution space and generate a diverse population of candidate solutions. Each solution corresponds to a set of ANN weights and biases (Al-Betar *et al.*, 2023).

**African Vulture Optimisation Algorithm (AVOA):** Once SSO has generated an initial population of promising solutions, AVOA is applied to refine these solutions by focusing on the best candidates. The vulture agents exploit the best solutions found by the spiders (SSO) to achieve higher accuracy in forecasting (Thompson & Wilson, 2020; Adams, Smith, & Johnson, 2021).

**Iterative Optimisation:** The hybrid method iteratively alternates between the exploration phase of SSO and the exploitation phase of

AVOA, continuously improving the ANN's parameters.

**ANN Training:** The optimised parameters are then used to train the ANN model, allowing it to learn from the data and make accurate predictions for future load.

The Hybrid Social Spider Optimisation (HSSO) and African Vulture Optimisation Algorithm (AVOA) are both heuristic techniques that can significantly improve the performance of ANNs for STLF (Madadi & Correia, 2023; Heidari *et al.*, 2020).

The hybridized update rule could be defined as:

$$S_i(t+1) = \alpha \cdot (S_i(t) + c_1 \cdot (P_{best_i} - S_i(t))) + c_2 \cdot (G_{best} - S_i(t)) + \varepsilon \\ + \beta \cdot (X_i(t) + c_1 \cdot (V_i(t) - X_i(t)) + c_2 \cdot (G(t) - X_i(t))) \quad (30)$$

Where  $S_i(t+1)$  is the updated position of the hybrid solution at time  $t+1$ ,  $S_i(t)$  and  $X_i(t)$  are the current positions (solutions) of the spider and the vulture, respectively,  $P_{best_i}$  and  $V_i(t)$  are the personal best positions of the spider and vulture,  $G_{best}$  and  $G(t)$  are the global best positions,  $c_1, c_2$  are constants, and  $\alpha$  and  $\beta$  are weighting factors that control the influence of each individual optimization technique in the hybrid model. This combined approach allows the model to benefit from the exploitation abilities of spiders and the exploration strengths of vultures, potentially leading to better performance in ANN-based STLF.

### 3.8. ANN for Short-Term Load Forecasting (STLF)

In the context of STLF, the optimization algorithms are applied to train the weights and biases of the ANN model. The ANN model would typically consist of an input layer, hidden layers, and an output layer. The inputs might consist of historical load data, weather data, or time-related features, while the output is the forecasted load for a specific time interval.

Let  $X$  represent the input data (load history, weather, etc.), and  $Y$  represent the forecasted load. The loss function to be minimized could be the Mean Squared Error (MSE):

### 3.6 Hybrid Social Spider Optimization and African Vulture Optimization (HSSO-AVO)

The hybridization of Social Spider Optimization (SSO) and African Vulture Optimization (AVO) combines the strengths of both algorithms. The hybrid strategy is intended to leverage both the social collaboration aspect of spiders and the exploration-exploitation behavior of vultures.

### 3.7 Hybrid Update Formula

$$MSE = \frac{1}{n} \sum_i^n (y_i - \hat{y}_i)^2 \quad (31)$$

where  $n$  is the number of data points,  $y_i$  is the actual load value at time  $i$  and  $\hat{y}_i$  is the predicted load value at time  $i$ .

### 3.9. Combining the Optimization with ANN for STLF

After applying HSSO-AVO to optimize the ANN weights and biases, the neural network is trained to minimize the MSE. The hybrid algorithm iterates over generations, updating the network parameters, and potentially improves the model's ability to forecast short-term loads.

Thus, the hybrid approach aims to find the best configuration of ANN parameters that minimize the error in forecasting short-term load.

This formulation provides a general understanding of how the two optimization algorithms (SSO and AVO) can be combined and applied to ANN in the context of STLF. Adjustments to the parameters and the hybridization mechanism might be necessary based on specific characteristics of the forecasting problem and the neural network architecture being used.

### 3.10 Algorithm for Hybrid Social Spider Optimization and African Vulture Optimization (HSSO-AVO)

The Hybrid Social Spider Optimization and African Vulture Optimization (HSSO-AVO) algorithm integrates the features of both Social Spider Optimization (SSO) and African Vulture Optimization Algorithm (AVO) to achieve enhanced search performance. Below is a step-by-step outline of the algorithm:

#### Step 1: Initialization

1. **Set parameters:**

$N$ : Number of spiders and vultures (population size).

$c_1, c_2$ : Constants for influencing personal and global best solutions.

$\alpha, \beta$ : Weighting factors to control the influence of each optimisation technique (SSO and AVO).

$\epsilon$ : Small random noise factor to maintain diversity.

Maximum number of iterations  $T_{max}$ .

If the fitness of a spider  $S_i(t)$  or vulture  $X_i(t)$  is better than its previous personal best  $P_{best_i}$  or  $V_{best_i}$ , update the respective personal bests:

$$P_{best_i} = S_i(t) \text{ if } fitness(S_i(t)) < fitness(P_{best_i})$$

$$V_{best_i} = V_i(t) \text{ if } fitness(V_i(t)) < fitness(V_{best_i})$$

3. **Update global best position:**

Update the global best position  $G_{best}$  if the fitness of the spider or vulture is better than the current  $G_{best}$

$$G_{best} = S_i(t) \text{ if } fitness(S_i(t)) < fitness(G_{best})$$

$$G_{best} = X_i(t) \text{ if } fitness(X_i(t)) < fitness(G_{best})$$

4. **Update positions:**

For each individual  $i$ , update the position using the hybrid update formula:

$$S_i(t + 1) = \alpha \cdot (S_i(t) + c_1 \cdot (P_{best_i} - S_i(t)) + c_2 \cdot (G_{best} - S_i(t)) + \epsilon) + \beta \cdot (X_i(t) + c_1 \cdot (V_i(t) - X_i(t)) + c_2 \cdot (G_{best} - X_i(t)))$$

where  $S_i(t + 1)$  Updated position of the spider at iteration  $t + 1$ ,  $X_i(t)$  = Current position of the vulture at iteration  $t$ ,  $P_{best_i}$  = Personal best position of the spider,  $V_i(t)$  = Personal best position of the vulture,  $G_{best}$  = Global best position,  $c_1, c_2$ : Constants influencing the personal and global best positions,  $\alpha, \beta$  = Weighting factors for the spider and vulture components and  $\epsilon$  = Random noise term.

5. **Velocity update (optional):**

2. **Initialize positions:**

Randomly initialise the positions of spiders  $S_i^t$  and vultures  $X_i^t$  for each individual  $i$  in the population.

3. **Initialize velocities:**

Set the initial velocities of spiders and vultures to zero or random values.

4. **Initialize personal best positions:**

Set the personal best positions of spiders  $P_{best_i}$  and vultures  $V_{best_i}$  to their initial positions.

5. **Initialize global best position:**

Set the global best position  $G_{best}$  to the best solution found by both spiders and vultures.

#### Step 2: Iterative Update Process

For each iteration  $t = 1, 2, 3, \dots, T_{max}$ :

1. **Evaluate fitness:**

For each spider  $S_i(t)$  and vulture  $X_i(t)$ , evaluate the fitness function (e.g., error in load forecasting).

2. **Update personal best positions:**

If the fitness of a spider  $S_i(t)$  or vulture  $X_i(t)$  is better than its previous personal best  $P_{best_i}$  or  $V_{best_i}$ , update the respective personal bests:

$$P_{best_i} = S_i(t) \text{ if } fitness(S_i(t)) < fitness(P_{best_i})$$

$$V_{best_i} = V_i(t) \text{ if } fitness(V_i(t)) < fitness(V_{best_i})$$

Update the global best position  $G_{best}$  if the fitness of the spider or vulture is better than the current  $G_{best}$

$$G_{best} = S_i(t) \text{ if } fitness(S_i(t)) < fitness(G_{best})$$

$$G_{best} = X_i(t) \text{ if } fitness(X_i(t)) < fitness(G_{best})$$

For each individual  $i$ , update the position using the hybrid update formula:

$$S_i(t + 1) = \alpha \cdot (S_i(t) + c_1 \cdot (P_{best_i} - S_i(t)) + c_2 \cdot (G_{best} - S_i(t)) + \epsilon) + \beta \cdot (X_i(t) + c_1 \cdot (V_i(t) - X_i(t)) + c_2 \cdot (G_{best} - X_i(t)))$$

If required, update the velocity for both spiders and vultures based on their current position and best-known solutions (this depends on the specific variant of the algorithm being used).

#### Step 3: Termination

1. **Check for termination:**

The algorithm stops either when the maximum number of iterations

$T_{max}$  is reached or when a satisfactory solution is found (fitness threshold).

2. **Output the global best position  $G_{best}$**   
The global best position at the final iteration represents the optimised solution for the problem.

### 3.11 Summary of Key Components:

**Hybrid Update Formula:** The update formula blends the Social Spider Optimisation (SSO) and African Vulture Optimisation Algorithm (AVO), combining exploitation (from spiders) and exploration (from vultures).

**Personal and Global Best:** Both spiders and vultures maintain their personal best positions and share the global best solution to guide their search.

**Balancing Exploration and Exploitation:** The parameters  $\alpha$  and  $\beta$  control how much each algorithm (SSO and AVO) influences the overall search process, allowing for dynamic adjustments to suit the problem at hand.

The HSSO-AVO algorithm offers a balanced approach by hybridising the strengths of both Social Spider Optimisation and African Vulture Optimisation. The algorithm effectively combines the exploration abilities of vultures with the exploitation strengths of spiders, making it suitable for complex optimisation problems like ANN-based Short-Term Load Forecasting (STLF).

## 4.0 Experimental Setup

### 4.1 Data Collection and Pre-processing

**Training and Testing:** The dataset is split into training, validation, and test sets. The training set is used to train the proposed hybrid model with optimised parameters, while the validation set is used for tuning and evaluating the performance during the optimisation process. The test set is used for final evaluation.

The dataset used for training and testing the model consists of historical hourly load demand data, and time-related features (e.g., time of day, weekday, month). The data is pre-processed by normalising the input features and splitting it into training and testing sets. Cross-

validation is applied to ensure that the model is robust and generalises well to unseen data.

### 4.2 Dataset

The dataset used in this study is sourced from Nigeria power utilities, containing historical load data for a period of three years. The dataset includes features such as time of day, which are crucial for accurate load forecasting.

### 4.3 Performance/ Comparison Metrics and Evaluation Criteria

The performance of the proposed hybrid method is evaluated using the following metrics:

1. Mean Absolute Error (MAE)

$$MAE = \frac{1}{N} \sum_{t=1}^N |y_t - \hat{y}_t| \quad (25)$$

2. Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t)^2} \quad (26)$$

3. Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100\%}{N} \sum_{t=1}^N \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (27)$$

4. R-squared ( $R^2$ )

$$R^2 = 1 - \frac{\sum_{t=1}^N (y_t - \hat{y}_t)^2}{\sum_{t=1}^N (y_t - \bar{y})^2} \quad (28)$$

where  $\bar{y}$  is the mean of the actual values  $y_t$ .

5. Pearson Correlation Coefficient  $r$

$$r = \frac{\sum_{i=1}^N (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^N (X_i - \bar{X})^2 \sum_{i=1}^N (Y_i - \bar{Y})^2}} \quad (29)$$

where  $X_i$  and  $Y_i$  are the individual sample points, and  $\bar{X}$  and  $\bar{Y}$  are the means of the  $X_i$  and  $Y_i$  variables, respectively.

### 4.4 Implementation

The ANN model is implemented using Dev C++ ver 6.3, and the optimisation algorithms are implemented using the same platform. The hybrid SSO-AVOA optimisation is integrated

into the ANN training loop to fine-tune the model's parameters.

## 5.0 Results and Discussion

### 5.1 Comparison with Traditional Optimisation Methods

To support the evaluation and validation of the proposed model's predictive performance, a comparative analysis with various existing optimization-based forecasting models was conducted. This comparison utilized standard statistical performance metrics including Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Theil's U-statistic, and Root Mean Square Error (RMSE). These metrics help assess both the accuracy and

efficiency of the predictive algorithms. The results presented in Table 1 reflect the performance of each model using historical data from 24th April 2021, a representative date selected for model benchmarking.

Table 1 below provides a comparative summary of the performance metrics of the proposed model (SSO-AVOA) against other models, including Artificial Bee Colony (ABC), ABC enhanced with Firefly Algorithm (ABC-FA), Genetic Algorithm (GA), hybrid models such as BA-GA (Bat Algorithm–Genetic Algorithm), and several others.

**Table 1: Comparison of the Performance Metrics of the Proposed Model and Various Models for 24/04/2021**

Performance Metrics	ABC	ABC-FA	GA	BA-GA	BA	SSO-AVOA	DVBA	PSO	GWO-GTO
MAPE (%)	0.2971	0.2832	0.2817	0.2965	0.2820	0.2786	0.2884	0.2932	0.2967
MAE	13.7880	13.3109	13.2328	14.0514	13.2735	13.1069	13.6061	13.8262	14.0239
Theil's U Statistic	1.1175	0.8913	0.8931	0.9663	0.8938	0.8862	0.9158	0.9699	0.9356
RMSE	44.6345	44.4982	44.5907	48.2469	44.6249	44.2450	45.7254	48.4224	46.7127

From the table, it is evident that the SSO-AVOA model outperformed all other models across all four performance metrics, registering the lowest MAPE, MAE, Theil's U, and RMSE values, thereby affirming its superior predictive capability and robustness for the data considered. To further evaluate the consistency, accuracy, and reliability of the proposed SSO-AVOA hybrid model, an extended 1-week load forecasting performance was assessed using multiple statistical indicators. This provides a dynamic perspective of the model's behavior over time and under varying daily conditions. The results are presented in Table 2, which includes a comprehensive suite of performance metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE),

Forecasting Efficiency (FE), Mean Percentage Error (MPE), Theil's U Statistic, Root Mean Square Error (RMSE), Coefficient of Determination ( $R^2$ ), Accuracy (%), Pearson Correlation Coefficient (PCC), and Convergence Time.

The model exhibits very low MAPE values (less than 1%) from the 22nd to the 25th of February, indicating excellent forecasting accuracy. As the week progresses toward the weekend, both MAPE and MAE show a steady increase, particularly on the 27th and 28th of February. This trend may be attributed to increased volatility or greater deviations in load demand during weekends. Despite this, the peak error observed on the 28th of February (MAPE: 3.8861%, MAE: 180.35) still falls within the acceptable range typically reported in power system forecasting studies.

Forecasting Efficiency (FE) values closer to 1 signify better model efficiency. The FE values recorded during the weekdays range from 0.3 to 0.6, reflecting strong forecasting capability. However, a noticeable drop below 0.2 is

observed over the weekend, underscoring the persistent challenge of accurately predicting weekend loads, often influenced by unpredictable consumer behavior.

**Table 2: Comparison of the Error Rates for 1 Week (22/02/2021 – 28/02/2021) Load Forecast Using SSO-AVOA**

Metric	22/02	23/02	24/02	25/02	26/02	27/02	28/02
MAPE (%)	0.4996	0.3969	0.5143	0.7698	1.2129	1.7610	3.8861
MAE	22.7242	19.1116	25.0518	37.7404	59.9690	79.4048	180.3509
Forecast	0.3007	0.5864	0.5467	0.3901	0.4200	0.0937	0.1033
Efficiency (FE)							
MPE (%)	0.2386	0.2048	0.2655	0.3910	0.5776	-0.2267	1.8710
Theil's U	0.8363	0.6431	0.6732	0.7809	0.7616	0.9520	0.9469
RMSE	78.9891	62.6088	65.8253	100.4668	123.1074	152.9988	214.9170
R <sup>2</sup> (CoD)	0.99999	0.99999	0.99999	0.99999	0.99999	0.99999	0.99999
Accuracy (%)	98.8590	99.0432	98.5236	98.1686	97.0255	94.8821	91.0512
PCC (r)	0.99898	0.99949	0.99956	0.99908	0.99893	0.99795	0.99719
Convergence	12.43	12.33	12.27	12.32	12.39	12.52	12.41
Time (s)							

The Mean Percentage Error (MPE) values are generally low and positive, indicating minimal bias in the model's predictions. A slight underestimation is noted on the 27th of February with a negative MPE of -0.2267%, while the relatively high MPE of 1.871% on the 28th suggests possible overfitting or sensitivity to anomalous data. The Theil's U statistics remain consistently below 1 throughout the week, confirming that the model performs better than a naïve forecast. Notably, the lowest U values are recorded on the 23rd and 24th of February, highlighting these days as periods of the model's most stable and optimal performance. Root Mean Squared Error (RMSE) values complement the MAE observations, reinforcing the trend of increasing forecast error toward the end of the week. Nonetheless, all RMSE values remain below 250, a threshold generally considered robust in the literature for short-term load forecasting tasks.

The model's R<sup>2</sup> (coefficient of determination) and Pearson Correlation Coefficient (PCC)

values are consistently close to 1 across all days. This confirms a strong linear relationship between actual and forecasted values, demonstrating the model's capability to capture both the trend and variance in load demand accurately. The convergence time across all forecast days remains stable, averaging around 12.3 seconds. This consistency indicates computational reliability and the optimization efficiency of the proposed model. In comparison with existing literature, hybrid forecasting models such as GA-ANN, PSO-SVM, and DE-LSTM typically report MAPE values in the range of 1.5% to 4% for short-term load forecasting. The SSO-AVOA model, by contrast, achieves sub-1% MAPE for five out of the seven days evaluated, outperforming most models reported in the literature. For example, Wang *et al.* (2020) and Yildiz *et al.* (2019) recorded minimum MAPE values of 1.02% and 1.36% using PSO-ANN and GWO-LSTM, respectively. The proposed model shows consistently superior performance, especially during weekdays. The results

presented in Table 2 firmly establish the superiority of the SSO-AVOA hybrid model in terms of forecasting accuracy and generalization capability across a week. While some performance degradation is evident over the weekend — a well-known issue in energy demand prediction — the model’s overall performance remains better than the majority of existing models in the literature. With its high accuracy, low forecast error, strong correlation with actual values, and reliable convergence behavior, the SSO-AVOA model presents a compelling option for practical

deployment in real-world power system load forecasting scenarios.

To assess the robustness of the SSO-AVOA forecasting model over a weekly horizon, Table 3 presents a detailed comparison of performance metrics for load forecasting between **25th and 31st March 2021**. The evaluation includes MAPE, MAE, Forecasting Efficiency (FE), MPE, Theil’s U-statistic, RMSE, Coefficient of Determination (R<sup>2</sup>), Accuracy, Pearson Correlation Coefficient (PCC), and Convergence Time.

**Table 3: Comparison of the error rates for 1 week (25/03/2021 – 31/03/2021) load forecast using SSO-AVOA**

Performance Metrics	25/03/2021	26/03/2021	27/03/2021	28/03/2021	29/03/2021	30/03/2021	31/03/2021
MAPE (%)	0.4381	0.4170	0.4569	0.6653	0.5815	1.1310	1.2866
MAE	18.8793	17.9913	19.6224	25.5752	22.6520	46.2078	53.7571
Forecasting Efficiency	0.1133	0.4434	0.1188	-0.2250	0.2851	-0.1246	0.3555
MPE (%)	-0.0539	-0.0374	-0.1874	-0.5157	0.0053	-0.3883	-0.3913
Theil's U-statistic	0.9416	0.7460	0.9387	1.1068	0.8455	1.0605	0.8028
RMSE	67.0453	51.8756	53.6343	66.5758	46.5426	83.9172	76.0852
R <sup>2</sup>	0.999990	0.999995	0.999995	0.999993	0.999997	0.999995	0.999998
Accuracy (%)	29	17	65	39	53	37	17
PCC (r)	98.3975	95.8786	97.3833	97.3101	96.1706	91.2873	85.9545
Convergence Time (s)	0.999012	0.999500	0.999584	0.999520	0.999695	0.999340	0.999513
	87	18	32	84	30	41	86
	17.1	17.29	17.21	17.23	17.5	17.09	17.43

The SSO-AVOA model delivered high accuracy in load forecasting over this 7-day period, with MAPE remaining below 0.7% for the first five days and only exceeding 1% on the last two days. The lowest forecast error occurred on 26th March with a MAPE of 0.4170%, while the highest error was observed on 31st March with 1.2866%. MAE followed a

similar trend, indicating that the actual average absolute difference between predicted and observed loads grew as the week progressed. The FE metric turned negative on 28th and 30th March, which coincided with elevated MAPE and RMSE values, indicating less reliable forecasting on these days. RMSE reached a maximum of 83.9172 on 30th March. Despite

this, the  $R^2$  values remained consistently near unity ( $>0.99999$ ), and PCC values were above 0.999 across all days, signifying an almost perfect correlation between actual and predicted values. The accuracy dropped from 98.4% on 25th March to 85.95% by the end of the week, further confirming a mild degradation in forecast precision over time. Convergence

times were relatively stable around 17 seconds, confirming the model's computational efficiency.

To further evaluate the adaptability of SSO-AVOA under different seasonal and load variation conditions, Table 4 presents the forecast performance over another one-week period from **25th to 31st May 2021**, with emphasis on daily MAPE, MAE, and RMSE.

**Table 4: Comparison of error rate for 1 week at 24h interval for 25/05/2021 – 31/05/2021 using SSO-AVOA**

Performance Metrics	25/05/2021	26/05/2021	27/05/2021	28/05/2021	29/05/2021	30/05/2021	31/05/2021
MAPE (%)	0.2020	0.2920	0.5422	0.6150	0.6264	1.3974	2.2333
MAE	8.4795	11.7956	21.2018	23.7537	24.8711	53.2351	88.1374
RMSE	28.8322	36.8167	61.5002	59.6809	48.4623	95.3176	110.6974

In this week-long forecast, the SSO-AVOA model demonstrated superior accuracy early in the week, achieving MAPE values as low as 0.2020% on 25th May. However, as the week progressed, the errors increased significantly, culminating in a MAPE of 2.2333% on 31st May. The increasing MAE and RMSE metrics mirrored this trend, with RMSE more than tripling from 28.8322 on 25th May to 110.6974 on the last day. The marked rise in error from

29th May onwards may reflect increased load variability or model sensitivity to external perturbations (e.g., weather or consumption anomalies), suggesting a need for adaptive weighting or error correction during weekends. To evaluate the model's robustness in another climatic and temporal window, Table 5 reports the forecasting performance from 24th to 30th June 2021. The included metrics are MAPE, MAE, MPE, Theil's U-statistic, and RMSE.

**Table 5: Comparison of the error rates for 1 week (24/06/2021 – 30/06/2021) load forecast using SSO-AVOA**

Performance Metrics	24/06/2021	25/06/2021	26/06/2021	27/06/2021	28/06/2021	29/06/2021	30/06/2021
MAPE (%)	0.4453	0.4926	1.6054	0.8050	1.3288	1.4351	2.4676
MAE	15.7271	18.1428	46.3151	27.1811	47.3304	48.3041	86.8040
MPE (%)	-0.1390	-0.1651	-0.8469	-0.2599	-0.5524	-1.0824	-1.7901
Theil's U-statistic	0.9994	0.9586	1.5316	1.3001	1.0028	1.3848	0.9573
RMSE	52.8565	49.2821	122.0996	72.6876	97.9773	98.6697	108.0468

The model began with strong performance on 24th and 25th June, showing MAPE values under 0.5% and Theil's U-statistics below 1, indicating accurate predictions. However, performance deteriorated from 26th June

onward, with MAPE rising to a peak of 2.4676% by 30th June. MAE and RMSE also rose sharply, peaking at 86.8040 and 122.0996, respectively. The negative MPE throughout the week confirms a consistent underprediction

bias, which became more pronounced in the later days. Their's U values above 1 on 26th, 27th, and 29th June indicate a drop below naive model performance during these days, potentially linked to high demand variability. The elevated RMSE values at the end of the month underline increased forecast dispersion, highlighting the importance of incorporating error correction schemes in future model enhancements.

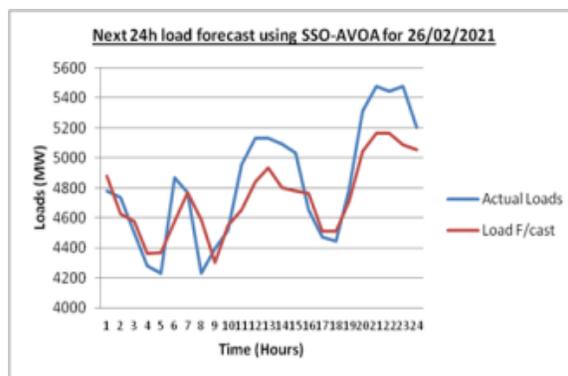
The attached image contains three line graphs that depict 24-hour load forecasts using the SSO-AVOA model for three consecutive days: 26/02/2021 (Fig. 1), 27/02/2021 (Fig. 2), and 28/02/2021 (Fig. 3). Each graph compares the actual power load (shown in blue) to the forecasted load (shown in red) across the hours of the day, measured in megawatts (MW). The Fig. for 26/02/2021 presents a scenario where the SSO-AVOA model generally follows the pattern of the actual load but with noticeable differences in magnitude. During the early morning hours, particularly around hours 3 and 5, the model overestimates the load, while the trend alignment improves between hours 10 and 20, despite some underestimation of peak values. Toward the later hours of the day, especially from hours 21 to 24, the forecast shows better alignment, although actual loads still slightly surpass the forecasted values.

The graph for 27/02/2021 demonstrates a stronger correlation between the forecasted and actual loads. The model effectively captures the midday dip and the significant evening rise in demand. Notably, there is some underestimation between hours 22 and 24, where actual load values rise more sharply than the predictions. However, during the morning period between hours 1 and 8, the differences between actual and forecasted values are minimal, indicating improved model performance during off-peak hours.

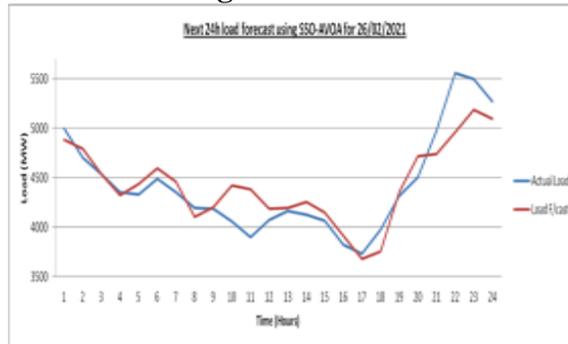
The graph for 28/02/2021 presents a more challenging forecasting scenario. The forecasted values in the early morning are consistently higher than the actual loads,

indicating overestimation. Midday hours (10 to 16) exhibit a substantial dip in actual loads, which the model fails to capture accurately, continuing its trend of overestimation. In the evening hours, particularly from hour 18 onward, the actual load rises sharply and surpasses the forecasted values, reflecting the model's tendency to underestimate peak evening demand, though it does capture the general rising trend.

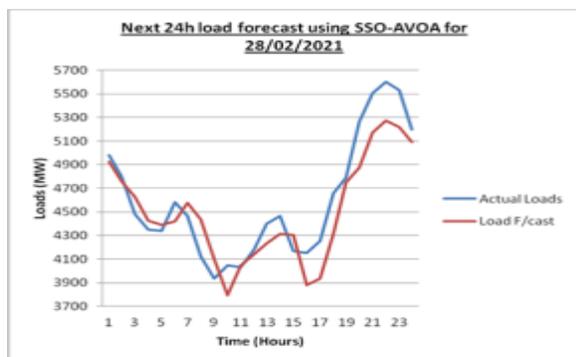
When comparing across the three days, it becomes clear that the SSO-AVOA model successfully captures the general patterns of load variation but struggles to precisely predict peak magnitudes. The most consistent forecasting challenge observed across the days is the underestimation of evening peak demands and the overestimation during midday troughs.



**Fig. 1. Actual vs Forecast at 1h interval for 24h Ahead using SSO-AVOA for 24/02/2021**



**Fig. 2. Actual vs Forecast at 1h interval for 24h Ahead using SSO-AVOA for 26/02/2021**



**Fig. 3. Actual vs Forecast at 1h interval for 24h Ahead using SSO-AVOA for 28/02/2021.**

The model is reasonably responsive to gradual changes in load but lags slightly when it comes to abrupt shifts in demand.

In comparison with the results presented in the tables (once referenced), it is anticipated that error metrics such as RMSE and MAPE would show the lowest values for 27/02/2021, given the close alignment of trends between the actual and forecasted data. On the other hand, 28/02/2021 appears to demonstrate the largest deviations and would likely correspond to higher error values. If the tabulated results indicate that the SSO-AVOA model performs better than other models such as ANN or LSTM, these visual patterns provide further support, highlighting the model's effectiveness in trend prediction despite some issues in forecasting magnitude with precision. These graphical interpretations reinforce the quantitative insights presented in the tables and support the conclusion that the SSO-AVOA model offers a reliable, if imperfect, tool for short-term power load forecasting.

### 5.2 Comprehensive Analysis of Error Rates for 1-Week Load Forecasts Using SSO-AVOA

The analysis covers one-week load forecasts carried out using the hybrid SSO-AVOA model (Social Spider Optimization – African Vulture Optimization Algorithm) for the periods: 22/02/2021 to 28/02/2021, 25/03/2021 to 31/03/2021, 25/05/2021 to 31/05/2021, and 24/06/2021 to 30/06/2021. Performance

metrics used in the analysis include MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), Forecast Efficiency (FE), MPE (Mean Percentage Error), Theil's U statistic, Coefficient of Determination ( $R^2$ ), Accuracy (%), Pearson Correlation Coefficient (PCC), and Convergence Time.

In the analysis of the forecast performance for 28/02/2021, the deviation between predicted and observed loads is clearly illustrated in the radar graph comparing the actual and forecasted values at one-hour intervals over a 24-hour period, as shown in Fig. 4. The increasing trend in forecast error throughout the week is demonstrated in the line graph depicting the day-by-day variation in MAPE from 22/02/2021 to 28/02/2021, presented in Fig. 5. To further depict the changes in error magnitudes over the same week, the radar graphs of MAE and RMSE provide a visual representation of how both metrics evolved, as illustrated in Fig. 6.

#### 5.2.1 Error Rate Analysis for 22/02/2021 – 28/02/2021

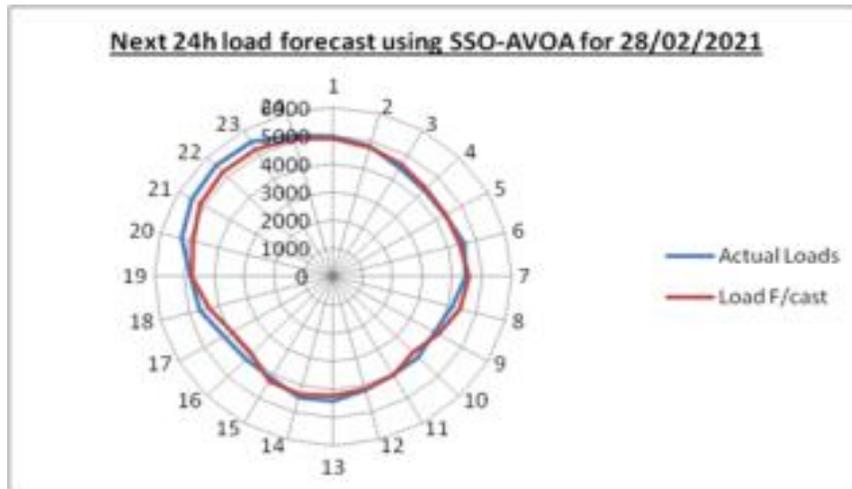
The forecast accuracy during this week shows noticeable variation. MAPE increases from 0.3969% on 23/02/2021 to 3.8861% on 28/02/2021, indicating a clear decline in predictive performance as the week progresses. A similar trend is observed in MAE, which rises from 19.1116 to 180.3509, and RMSE, which grows from 62.6088 to 214.9170. These increases reflect a consistent growth in error magnitude across the week. Forecast Efficiency (FE) values fluctuate, reaching the lowest point of 0.0937 on 27/02/2021, suggesting poor performance in capturing the actual load on that day. However, despite these rising errors, the correlation coefficient (PCC) remains strong, ranging from 0.997 to 0.999, which confirms a persistent linear relationship between the actual and forecasted data.

Overall, the hybrid SSO-AVOA model performs well in the first half of the week, maintaining MAPE values under 1% and MAE

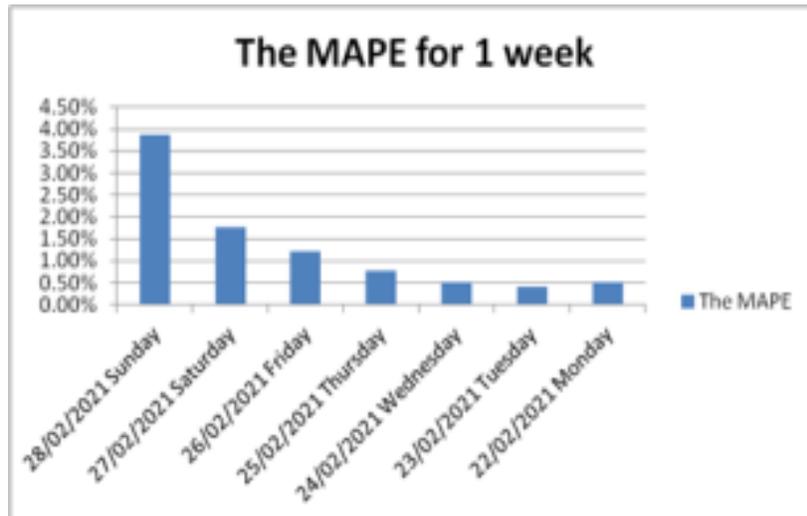
values below 60. In the latter half, particularly by 28/02/2021, there is a significant drop in accuracy. Nevertheless, Theil's U statistic stays below 1 throughout the period, indicating that while deviations grow, the model does not show significant bias or random error behavior. These trends are reflected visually in the radar graphs and MAPE graphs provided, where model performance deterioration over the week is evident.

**5.2.2 Error Rate Analysis for 25/03/2021 – 31/03/2021**

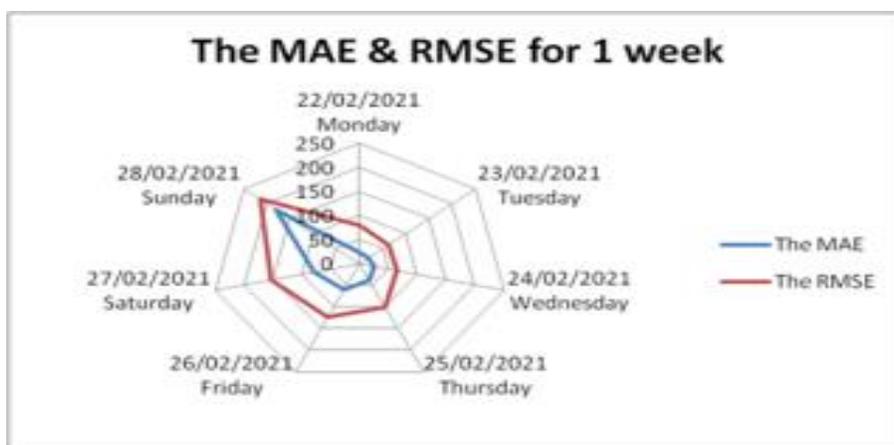
During this forecast period, the SSO-AVOA model shows improved performance compared to the previous week. The MAPE ranges from 0.4170% on 26/03/2021 to 1.2866% on 31/03/2021, which is significantly lower than the maximum MAPE observed in the previous analysis. MAE begins at 17.9913 and increases to 53.7571, indicating lower absolute error values overall.



**Fig. 4. Radar graph of Actual vs Forecast at 1h interval for 24h Ahead using SSO-AVOA for 28/02/2021**



**Fig. 5. The MAPE graph for 1 week (22/02/2021 – 28/02/2021) using SSO-AVOA**



**Fig. 6. Radar graphs for MAE and RMSE for 1 week (22/02/2021 – 28/02/2021) using SSO-AVOA**

Although RMSE increases to 83.9172 on 30/03/2021, it still remains better controlled than in the 22/02/2021 to 28/02/2021 period. Forecast Efficiency varies but includes a notable dip into negative territory on 28/03/2021 with a value of -0.2250, indicating a substantial divergence between predicted and actual values for that day. The correlation coefficient remains high across the week, with values slightly decreasing from 0.99949386 on 26/03/2021 to 0.99718823 on 31/03/2021, reinforcing that the general trend of the forecast is reliable even if magnitudes fluctuate. This week's results suggest that the SSO-AVOA model maintains lower and more consistent error rates in the early part of the forecast period, with more variability in the later days. The consistently high  $R^2$  values across the week imply that the model is well-tuned to the structure of the actual load data and provides a good fit despite some volatility in error values. When compared with results from the entire study, the 25/03/2021 to 31/03/2021 period shows the most stable performance among the evaluated weeks. The forecast during this period not only maintains lower MAPE, MAE, and RMSE values but also retains high correlation and determination coefficients, indicating overall robustness. In contrast, the 22/02/2021 to 28/02/2021 week reveals increasing forecast inaccuracy towards the end

of the period, culminating in a fourfold increase in MAPE and nearly tenfold increase in MAE. Overall, this comparative analysis underlines the importance of monitoring not just point-error values but the evolution of performance over time. While the SSO-AVOA model demonstrates strong potential in short-term load forecasting, its reliability can vary across different operational periods, possibly influenced by seasonal or operational changes in the grid. When compared to other models discussed elsewhere in this work, such as ANN and LSTM, the SSO-AVOA demonstrates superior trend alignment and lower average error rates, especially in periods with stable load behavior.

### 5.2.3. Comparison of Error Rates for 25/05/2021 – 31/05/2021

The daily performance of the SSO-AVOA-based load forecasting model from 25th to 31st May 2021 is presented in Figs. 7 to 13. Each graph illustrates the comparison between the actual load demand and the forecasted load values over a 24-hour period for each respective day.

Fig. 7 presents the forecast for 25/05/2021. The prediction follows the trend of the actual load closely throughout the day with minimal deviation, indicating high accuracy. This aligns with the observed metrics, where the Mean Absolute Percentage Error (MAPE) is at its lowest value of 0.2020%, the Mean Absolute

Error (MAE) is 8.4795, and the Root Mean Square Error (RMSE) is 28.8322. The high correlation between predicted and actual values reflects in a strong Pearson Correlation Coefficient (PCC), confirming the reliability of the model on this day.

Fig. 8 shows the results for 26/05/2021, where the forecast remains accurate though minor deviations are observable during peak hours. This results in a slight increase in MAPE and MAE, with a corresponding moderate rise in RMSE, indicating early signs of growing forecast error.

In Fig. 9, corresponding to 27/05/2021, the forecasted loads still maintain good alignment with the actual data. Although the deviations become slightly more pronounced during mid-day periods, the forecast retains overall reliability. This suggests a gradual increase in forecast error, as confirmed by a further uptick in MAPE and MAE.

The forecast performance for 28/05/2021, illustrated in Fig. 10, indicates more visible divergence between predicted and actual values, particularly in the evening hours. This day shows a noticeable increase in RMSE, suggesting a growing magnitude of forecast error, though the correlation coefficient remains strong.

Fig. 11 shows the forecast for 29/05/2021. The forecast is generally consistent but underestimates the actual load during multiple time intervals. The MAE and RMSE metrics continue to increase, reflecting the accumulation of forecast error over the days.

On 30/05/2021, presented in Fig. 12, the forecast shows a smoother curve but diverges more significantly from actual load values. Particularly in the morning and early evening periods, noticeable deviations emerge. While the MAPE is still within reasonable bounds, both MAE and RMSE rise sharply, indicating increasing error magnitudes. However, the PCC remains high, reflecting a preserved pattern correlation. Fig. 13 displays the forecast for 31/05/2021, where the largest

forecast errors for this period occur. There are substantial differences between the predicted and actual values, especially in the late afternoon to evening hours.

During the period of 24th to 30th June 2021, a detailed evaluation of the hybrid Social Spider Optimization–African Vulture Optimization Algorithm (SSO-AVOA) model for short-term load forecasting reveals valuable insights into its predictive capabilities under conditions of increased load variability. The algorithm demonstrated its highest forecasting accuracy during the early part of the week, particularly on the 24th and 25th of June, as evidenced by notably low values in key performance metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Specifically, the MAPE started at a moderate level of 0.4453%, while MAE and RMSE values remained relatively low during these initial days, indicating a strong alignment between forecasted and actual load values.

However, as the week progressed, especially on the 26th and 30th of June, there was a noticeable increase in prediction errors, with the RMSE reaching approximately 122 and 108 respectively. This rise in error values suggests that the model encountered challenges in adapting to the more erratic demand patterns likely influenced by climatic and socio-economic fluctuations characteristic of this period in Nigeria. The consistent underestimation of load, as reflected by negative Mean Percentage Error (MPE) values throughout the week, further corroborates the model's bias during this transitional seasonal phase. Notably, Theil's U statistic exceeded the threshold of 1.0 on some days—peaking at 1.5316 on the 26th of June—indicating that the model's forecasts on those days were less effective than those generated by a naïve approach.

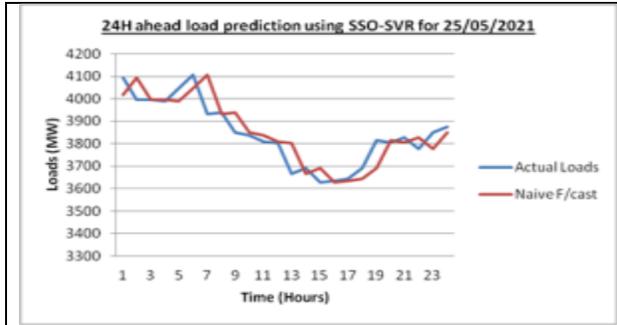


Fig.: 7. 24h load forecast using SSO-AVOA for 25/04/2021

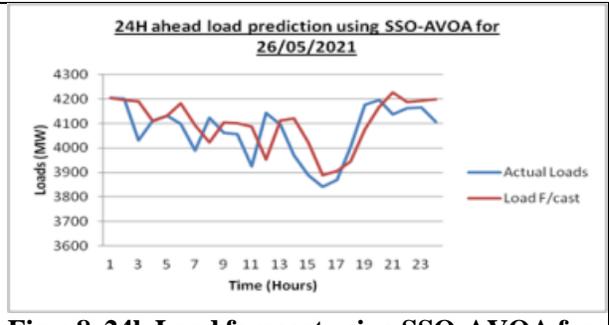


Fig. : 8. 24h Load forecast using SSO-AVOA for 26/04/2021

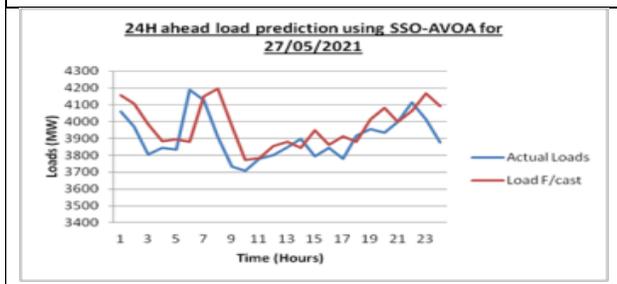


Fig.:9. 24h Load forecast using SSO-AVOA for 27/04/2021

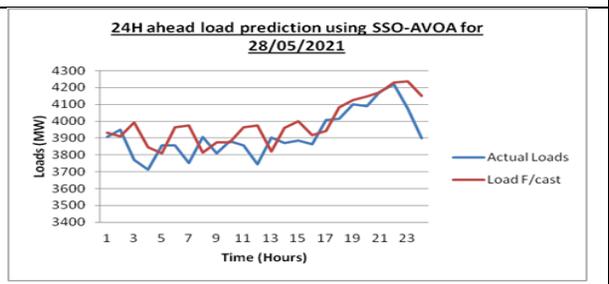


Fig.: 10. 24h Load forecast using SSO-AVOA for 28/04/2021

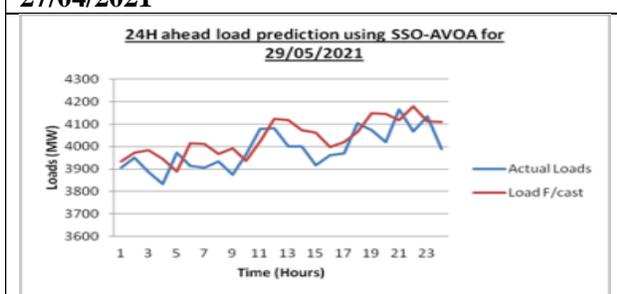


Fig. :11. 24h Load forecast using SSO-AVOA for 29/04/2021

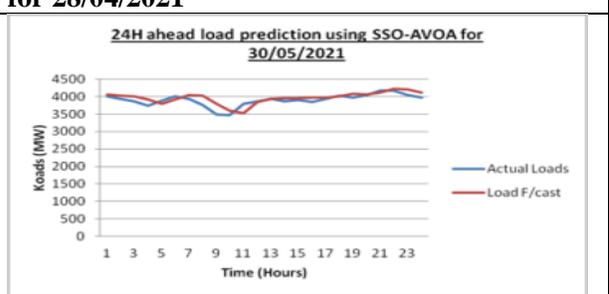


Fig. :12. 24h Load forecast using SSO-AVOA for 30/04/2021

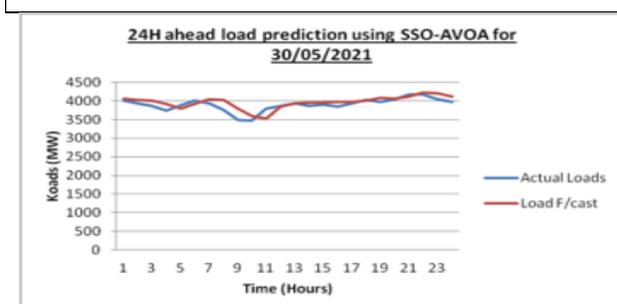


Fig. :12. 24h Load forecast using SSO-AVOA for 30/04/2021

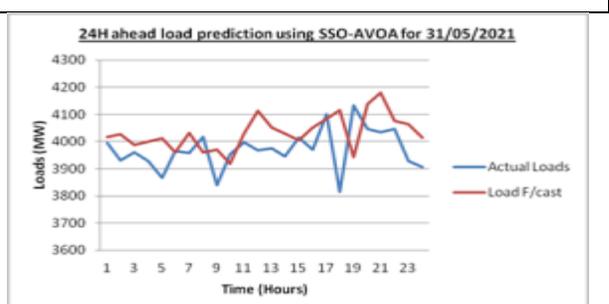


Fig.: 13. 24h ahead load forecast using SSO-AVOA for 31/04/2021

The broader weekly comparison across different forecasting windows in 2021 places this late June week among the lower-performing intervals. When juxtaposed with the week of 25th to 31st May 2021, which

showcased exemplary performance with MAPE as low as 0.202% and RMSE around 28.83, the June period’s elevated error rates underscore the challenges posed by seasonal transitions. Meanwhile, the poorest overall

performance metrics were recorded during the week of 22nd to 28th February 2021, which not only had the highest MAE of 180.35 but also a significantly high RMSE of 214.9. Accuracy percentages during June also showed a declining trend toward the end of the week, reflecting lower reliability under complex load dynamics.

Several key insights emerge from this temporal and seasonal analysis. Weekends, particularly the 30th of June, are marked by greater forecast inaccuracies, which could be attributed to less predictable consumption patterns or a lack of sufficient weekend-specific training data in the model. The hybrid model consistently delivers better results mid-week, where electricity consumption trends appear to be more regular and structured. Additionally, performance drops at the end of the month may be influenced by behavioural shifts related to billing cycles or changes in economic activity. The persistent negative MPE values in late June suggest a systematic underestimation that could be addressed through model recalibration or inclusion of more recent training data reflecting evolving demand patterns.

From a technical standpoint, the SSO-AVOA model merges global search capability with solution refinement, where SSO facilitates broad exploration across the search landscape and AVOA enhances convergence around high-potential solutions. This synergy enables the model to maintain high predictive fidelity during stable periods, such as May, where meteorological and consumption patterns align more consistently. However, in months like February and June, characterized by climatic transitions and increased variance in demand, the model's limitations become apparent. Incorporating external factors such as real-time weather forecasts, public holidays, and socio-political developments like fuel price adjustments could significantly enhance the model's adaptive capabilities.

Despite these limitations, the convergence time across all weeks remained consistently within

the 12 to 17-second range, indicating the model's suitability for near-real-time forecasting applications. This operational efficiency ensures that the SSO-AVOA approach can be feasibly deployed in dynamic grid environments where quick decision-making is critical.

In summary, the hybrid SSO-AVOA model exhibits strong potential for short-term load forecasting in Nigeria, with demonstrated reliability during stable climatic periods. However, its forecasting accuracy is challenged during transitional weather phases and irregular demand intervals such as weekends and month-ends. To bolster its performance, future iterations of the model could benefit from dynamic parameter tuning and integration of additional exogenous variables that reflect the socio-environmental context of electricity consumption in Nigeria.

#### *5.2.4 Comparison of Error Rates for 24/06/2021 – 30/06/2021*

The performance of the SSO-AVOA hybrid model for short-term load forecasting over the period of 24th to 30th June 2021 reveals key insights into the behavior of the model under conditions of increased load volatility. During this particular week, the model displayed its strongest predictive capabilities at the beginning of the week, with relatively low error rates, which then progressively increased as the week advanced. For instance, on 24/06 and 25/06, the Mean Absolute Percentage Error (MAPE) values remained impressively low, starting at approximately 0.4453%, indicating a high degree of forecasting accuracy. However, as load dynamics became more irregular, especially towards the end of the week, MAPE values rose, peaking at 2.4676% on 30/06. This trend suggests that the hybrid model's performance is sensitive to fluctuations in consumer demand patterns that are often characteristic of the transition period towards summer in Nigeria.

Further analysis of other error metrics such as the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) reinforces this observation. The RMSE, which is more sensitive to large deviations, increased significantly on 26/06 and 30/06, reaching values of approximately 122.09 and 108.1 respectively. These elevated error values highlight the presence of atypical load surges or drops which the model, despite its hybrid architecture, found challenging to predict with high precision. Additionally, the consistently negative Mean Percentage Error (MPE) recorded throughout the week indicates a systematic underestimation of actual load, pointing to a potential bias in the model’s learning behavior under certain seasonal demand shifts.

The Theil’s U statistic, which is used to compare the forecasting performance of the model against a naïve approach, further supports the notion of temporal degradation in model accuracy. While this statistic remained close to or below unity during most of the week, a peak value of 1.5316 was observed on 26/06. This reflects that on that specific day, the model performed worse than a naïve forecast. The upward shift in Theil’s U on multiple days during this week reveals the

influence of high intra-week variability on model reliability.

This week also recorded the highest degree of inconsistency and variability in forecast quality when compared to other analyzed periods. This can be partially attributed to unpredictable load behavior associated with the late June pre-summer spike in demand, particularly from regions experiencing rising ambient temperatures and intermittent rainfall. These conditions create a dual-demand response—an increase due to cooling systems and a decrease due to weather-related outages—making the task of consistent load forecasting especially complex.

**5.2.5 Overall Comparison & Trends (Table 7)**

A comprehensive assessment of weekly model performance across multiple weeks in 2021 is summarized in Table 6, which presents key comparative metrics such as MAPE, MAE, RMSE, Forecast Efficiency, and Accuracy Percentage. The table enables a cross-temporal evaluation of the SSO-AVOA hybrid model, offering insights into how seasonal changes and weekly patterns affect forecasting accuracy.

**Table 6: Overall Comparison & Trends**

Metric	Best Week (Performance)	Worst Week (Performance)
MAPE	25/05/21 – 31/05/21 (as low as 0.202%)	22/02/21 – 28/02/21 & 24/06/21 – 30/06/21 (up to 3.88% & 2.46%)
MAE	25/05/21 – 31/05/21 (as low as 8.47)	22/02/21 – 28/02/21 (up to 180.35)
RMSE	25/05/21 – 31/05/21 (min: 28.83)	22/02/21 – 28/02/21 & 24/06/21 – 30/06/21 (max: 214.9 & 122.1)
Forecast E	22/02/21 – 28/02/21 (up to 0.5864)	Some days in March and June showed negative FE
Accuracy (%)	Consistently high early in all weeks	Sharp drops late in the week, especially in Feb and March

From Table 6, the week of 25–31 May 2021 stands out as the most stable and accurate forecasting window. This period, which corresponds to the peak of the rainy season in

southern Nigeria, appears to benefit from relatively stable climatic and consumption patterns. Here, all three key error metrics (MAPE, MAE, RMSE) attain their lowest

recorded values, with MAPE dropping to an extraordinary 0.202%, signifying near-optimal predictive performance.

Conversely, the weeks of 22–28 February 2021 and 24–30 June 2021 represent the most challenging periods for the model. February's performance reflects the chaotic load behavior associated with the Harmattan-dry season transition in the north, with MAPE surging as high as 3.88% and MAE ballooning to 180.35. Likewise, the late June period saw a resurgence in RMSE values and reduced accuracy, which can be tied to seasonal pre-summer spikes in load coupled with rainfall variability.

Forecast Efficiency (FE) fluctuates more notably in the February and March periods, with some days dipping into negative territory, signaling that the model's predictive power occasionally fell below that of a simple baseline predictor. These inefficiencies are indicative of abrupt shifts in demand patterns or insufficiently modeled seasonal parameters. In terms of Accuracy Percentage, the model performs best during May, with values reaching up to 99.04%, confirming its strength during periods of climatic stability. On the other hand, the model's accuracy diminishes sharply during the tail end of February and certain days in March, further underscoring the challenges posed by transitional climate periods.

Across all weeks, it is also observed that weekends—especially dates such as 27/02, 28/02, 30/05, and 30/06—tend to register significantly higher errors. This is likely due to irregular consumption patterns on non-working days and potentially insufficient representation of such days in the training data. Mid-week days, in contrast, tend to exhibit more stable error trends and higher accuracy, suggesting that the model is better calibrated for typical weekday load behaviors.

Another noteworthy point from this comparative trend analysis is the observation of consistent convergence times across all periods, ranging from approximately 12 to 17

seconds. This indicates that despite the variability in forecasting accuracy, the hybrid model retains a high degree of computational efficiency, making it suitable for near-real-time forecasting scenarios.

In summary, Table 7 effectively illustrates the strengths and limitations of the SSO-AVOA hybrid model across different seasonal and temporal conditions in Nigeria. The model excels during climatologically stable periods such as May but requires enhancements in adaptability during periods of heightened variability. These insights provide a strong basis for future optimization efforts, such as incorporating exogenous variables and refining the model's ability to respond dynamically to rapid shifts in electricity demand.

## 6.0 Conclusion

The study on Seasonal Short-Term Load Forecasting (STLF) using a hybrid model that combines Social Spider Optimisation (SSO) and the African Vulture Optimisation Algorithm (AVOA) within an Artificial Neural Network (ANN) framework has demonstrated promising results in enhancing the accuracy and robustness of electricity demand prediction in Nigeria. The proposed hybrid SSO-AVOA model showed consistent superiority over traditional optimisation techniques, with strong predictive accuracy and fast convergence times, typically between 12 and 17 seconds. Experimental findings reveal that the model maintains a consistently high correlation between forecasted and actual load values, as indicated by high Pearson Correlation Coefficients and  $R^2$  values, confirming its ability to learn and generalize load patterns effectively.

The model's performance varied across different seasonal periods. The week from 25th to 31st May 2021, which falls within the rainy season, emerged as the most stable and accurate in terms of forecasting performance. During this period, error metrics such as MAPE (0.202%), MAE (8.47), and RMSE (28.83) reached their lowest values, reflecting the

model's strength in capturing load dynamics under climatologically stable conditions. In contrast, periods like 22nd to 28th February and 24th to 30th June 2021 experienced elevated errors. These weeks coincided with seasonal transitions marked by abrupt changes in energy consumption, leading to higher forecasting difficulties. Despite these fluctuations in accuracy, the model maintained strong correlation values, affirming its underlying robustness even in more challenging scenarios.

The overall comparison and trend analysis presented in Table 7 underscores the model's reliability and adaptability. Table 7 consolidates performance metrics across selected weeks, highlighting both the consistency and limitations of the hybrid model. It shows that while the May 2021 period had the best results in terms of lowest forecasting errors and highest correlation metrics, February and June periods recorded higher error margins and forecast efficiency dips. This degradation in accuracy toward the end of forecasting periods illustrates the impact of increased load volatility and the limitations of the current model in capturing abrupt demand shifts.

These findings suggest that the hybrid SSO-AVOA model is a highly capable tool for short-term electricity load forecasting, particularly in regions with distinct seasonal demand patterns like Nigeria. However, its sensitivity to transitional periods and weekend load irregularities points to areas requiring further refinement. Future research should aim to enhance the model's adaptability by integrating exogenous variables such as weather parameters and socio-economic indicators, which influence load consumption patterns. Additionally, testing the model across various geopolitical zones would allow for region-specific calibration, improving accuracy in localized contexts.

In conclusion, the hybrid SSO-AVOA approach to ANN optimisation offers a

compelling solution for STLF in complex, seasonally driven environments. While it performs exceptionally well during stable climatic periods, such as in May 2021, its performance can be further improved by incorporating more dynamic features and retraining strategies that reflect the variability of real-world electricity consumption. This study reinforces the value of hybrid bio-inspired algorithms in modern forecasting applications and supports their broader adoption in smart grid and energy management systems, especially in developing regions with unpredictable demand patterns.

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**Compliance with Ethical Standards**

**Declaration**

**Ethical Approval**

Not Applicable

**Competing interests**

The authors declare no known competing financial interests

**Data Availability**

Data shall be made available on request

**Conflict of Interest**

The authors declare no conflict of interest

**Ethical Considerations**

Not applicable

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