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Artificial Intelligence Based Hybrid ASFO-ESVM for Load Demand Prediction in Micro Grid Energy Management

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Abstract

Predicting load demand is relevant when used in microgrid energy management systems to address issues such as nonlinear and dynamic consumption data. In this research, the author presents a fusion of Adaptive Sunflower Optimization (ASFO) and Enhanced Support Vector Machine (ESVM) methods to predict the load demand in micro grid environment. The ASFO algorithm enhances the efficiency of the ESVM through a fine-tuning meta-heuristic algorithm based on the sunflower natural organisms. This integration of ASFO and ESVM eliminates many of the drawbacks associated with the basic performance of the task, namely low speed of convergence, overtraining, and the presence of local minima in choosing the parameters. Some of the general parameters used in training and validating the model include load and meteorological data features involving, weather, temporal, load histories are the main contributors in the analysis. Comparisons with other ML algorithm 'shave been made in respect of relative performance against established methods, such as Random Forest (RF) and Particle Swarm Optimization based with ESVM (PSO-ESVM). The findings infer that lower values of Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (SMAPE) and higher consistency index (d) are yielded by the proposed hybrid ASFO-ESVM model. For instance, even on working days of the week, the precision of the load forecasts was higher with the hybrid model than with the other options. The outcomes do prove that the proposed ASFO-ESVM model is very reliable and precise in its concerning aspect of load demand forecasting as it can be seen in the results obtained for different situations. Relatively, this work estimates a cost effective and feasible method for micro grid energy predictions which can enhance decisions in matters concerning power production, distribution, and control of energy. The study shows how these techniques are relevant towards the complexity and dynamism of the contemporary energy systems.

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Keywords: Enhanced Support Vector Machine (ESVM); Adaptive Sunflower Optimization (ASFO); Combined optimization model; Non-linear data forecasting; Energy supply; Optimization of parameters; Artificial intelligence; Meta-hybrid algorithms; Feature extraction and Smart grid systems

1. Introduction

Load demand prediction efficiency relies heavily on artificial intelligence (AI) based ML technologies used for micro grid, which may be used for demand forecasting, maximizing efficiency, management, and surveillance, among micro grid working procedures. These innovations process the massive amounts of information produced by sensors, DERs, and other micro grid equipment using artificial intelligence (AI) methods such as deep learning (DL) and machine learning (ML)[1].

The branch of statistics and statistical analysis, makes use of machine learning and other forms of artificial intelligence to sift through historical information in search of connections that could indicate what's to come. Micro grids data processing may take uses of statistical analysis to plan for the future generation of clean energy from sources like wind and solar energy, taking into account aspects like location, season, weather predictions, and more. Optimizing microgrid functioning and minimizing the usage of fossil fuel based energy sources that are not renewable may be achieved using this knowledge.

To optimize is to seek out, within the context of defined restrictions and goals, the most effective answer to a problem. Minimizing energy expenditures, reducing carbon emissions, and improving the dependability and endurance of DERs are all possible via efficiency of micro grids [2]. In addition to detecting and responding to crises like interruptions in power, breakdowns in equipment, and natural catastrophes, control systems based on Artificial Intelligence can forecast the micro grid's energy supply and demand and modify the generated electricity of DERs appropriately.

AI has many applications in today’s world as shown in figure 1, including proper monitoring means keeping tabs on the smart grid and all of its components to see how they're functioning and what problems they're having with the help of AI techniques. In the event of sudden increase in load demands or energy source malfunctions, an AI-based forecasting system can identify the issues and initiate the necessary actions. Since energy management is inherently intended to reduce sudden burden or maximize the efficiency of the supply system in micro grids and the specifics of its asset management strategy—optimization algorithms provide the foundation for any investigation into energy management issues.

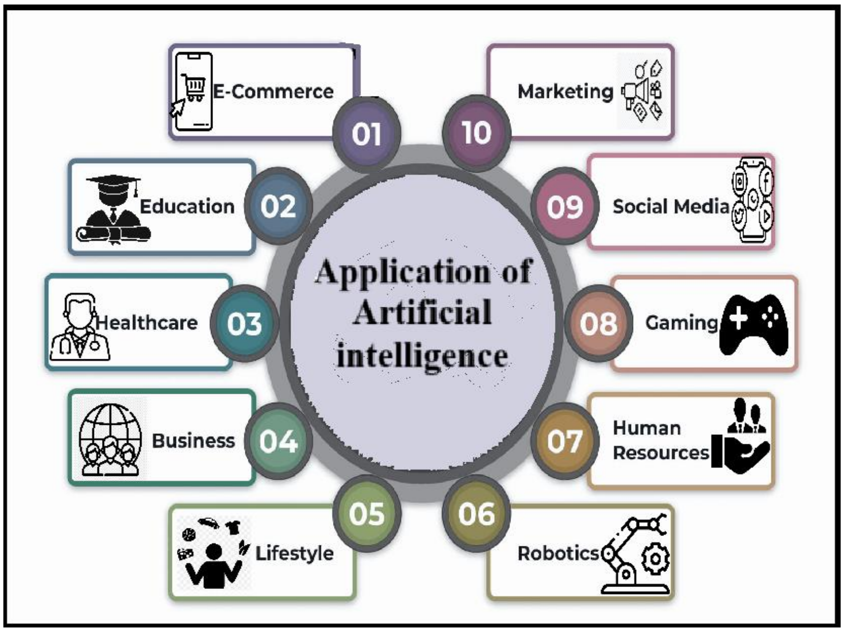

Figure 1. Uses of Artificial Intelligence

Fig. 1 shows the uses of AI in day to day life. Electricity sector is one of the most critical infrastructure to apply latest AI techniques for energy optimization. Many optimization strategies have been created by ML techniques, and their proper uses depends on the types of issues. Convex and non-convex optimization methods are the two broad classes into which they fall. Since convex issues provide greater convergence than non-convex problems, micro grid energy management mostly deals with them.

While dealing with large amount of micro grid data, there are three different optimization approaches that have been suggested for analysing the effects of data uncertainty: deterministic, stochastic, and resilient optimization [3]. The energy management problem is posed by stochastic optimization, which uses a statistical objective function, in contrast to deterministic problems, where every input has a single outcome. When dealing with energy management issues that include a little quantity of data and several uncertainties, round-robust optimization is used. Regarding the optimization procedure's unclear conditions, this strategy just considers one scenario—the worst case—and ignores all others. Consequently, for better preparation for future load demands, compared to stochastic approaches, get better optimization outcomes.

With projected significant spikes in consumption of electricity over the next several years, India's power infrastructure is vital to the country's economic development [4]. The growing demand for energy is outpacing the capacity of conventional power sources such as natural gas, coal, hydropower, and nuclear power. Wind, solar energy, and biomass power are some of the alternative options. Renewable energy sources (RES) including wind, biomass, and solar energy will need to increase their power production to match these needs. More renewable energy may be produced due to the rapid exhaustion of petroleum and coal and the development of eco-friendly technologies. To generate and consume electricity on a smaller scale, smart micro grids that include one or more renewable may be set up; however, these systems need to be tested for grid disruptions before they can be operational. With the use of grid emulators, it is possible to create simulations or models that are very realistic representations of the structure and operation of a real-life electrical power grid.

To efficiently and inexpensively satisfy load demand, micro grids are centres for regional energy distribution. In the event of a utility system failure, however, the increased demand for electricity may over whelm the system's capacity, necessitating the expansion of micro grids. The number of micro grids powered by renewable energy is growing as smaller renewable power plants replace older, bigger conventional power plants.

The world's energy crisis and pollution crisis can only be solved with the help of renewable energy sources (RES). When compared to traditional energy sources, renewable energy (RE) is much easier on the environment since it drastically reduces carbon emissions and creates almost no chemical pollutants [5]. Renewable energy systems (RES) integrated with micro grids provide scalable, eco-friendly, and uninterrupted electricity. To make the existing grid "future-proof," it is possible to balance power transfer using hybrid micro grid designs that include both conventional and renewable smart grids.

Wind energy sources can provide a substantial quantity of electricity when installed in places with enough wind all year, it is an important renewable energy source that may be used in smart grids [20]. In the future, wind power will provide around 25.7% of the world's energy, according to projections. The price of renewable energy has been reducing over the last eight years, with a 25% drop in onshore wind pricing and a beginning of a downward trend in offshore wind prices. By interconnecting the wind energy micro grid in an outlying remote area, power may be sent to homes and businesses at a reduced cost, which in turn increases the local economy, creates jobs, and encourages investors to invest in the development and widespread use of micro grid technology [6]. Numerous nations going towards integration of renewable energy sources including Europe, the United States, Japan, and China among others.

Proper mathematical modelling for analysing smart micro grid demand forecasting and ways to improve its stability with the varying load demand are the primary topics of concern. Important areas of study for grid stability research include transient stability simulation evaluations during dynamic load conditions [7].

The characteristics of distributed generation sources under different control systems, and the dynamic behaviour of different distributed generation sources to large disturbances are the main factors in smart inter connected grid stability. Just as synchronous generators do in the traditional grid, inverter-interfaced distributed generation carry out crucial tasks in the smart grid. Smart grid stability is initially defined in terms of conventional grid stability as the balance of energy supply and demand, any change in these two factors causes condition of instability in the system. The unstable system may cause major interruptions and black outs in the supply system. Hence proper load forecasting is very essential task to maintain a balanced supply system in smart grid era.

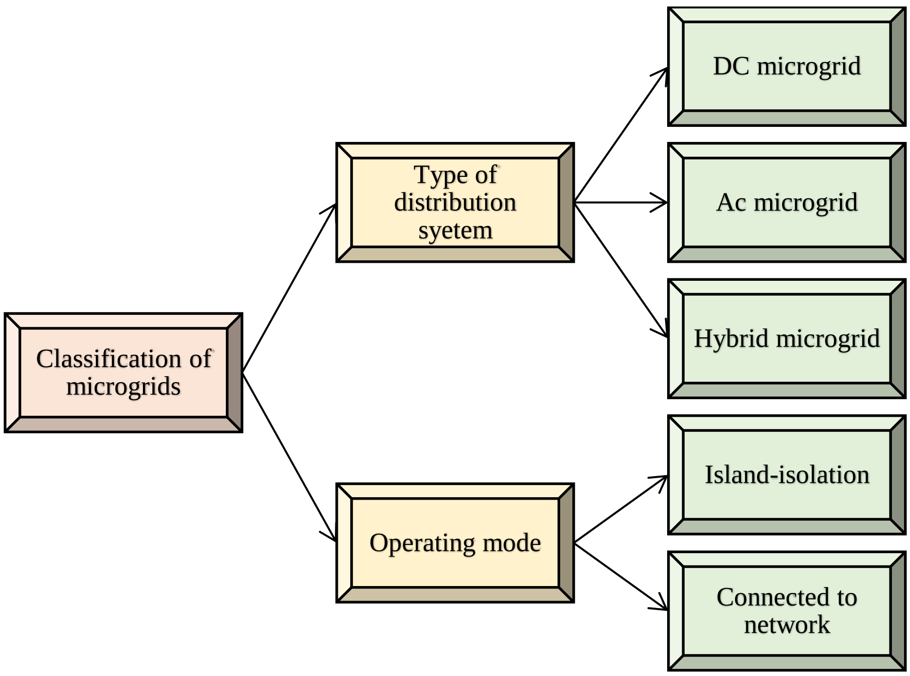

Figure 2. Various subcategories of micro grids

Fig 2 shows the various subcategories of micro grids which are the contributors in power generation and can be interconnected to fulfil the ever growing load demand. The most popular renewable energy source and an important component of smart micro grid is the solar PV source, which uses power electronics circuits based inverters to convert dc power to ac power at 50 Hz frequency and interconnects with the smart grid at the point of common coupling to supply power to the smart grid networks [8]. These DERs also include wind turbine, micro-turbines, and fuel cells etc. However, problems with reactive power scarcity, power quality, DER synchronization, and system stability arise as a result of these interconnections which may reduce power flow and can increase distribution line power losses.

The interconnection of DERs is a direct result of improvement in inverter technologies, which have made it possible to use several converters for electricity generation in a wide range of applications. Approximate 30% of the AC power is being generated by inverter based power sources in the world which plays a vital role in maintaining demand supply balance in smart grid.

Increased dependability, efficiency, and cost-effective operations are the benefits of hybrid micro grids, which mix various sources of energy. Accurate load forecasting makes it easier for DERs, and other micro grid components to run in stable condition and maintain a balanced integrated distribution system. Nevertheless, because of the intricate network architecture of hybrid micro grids, further research into coordinated management of micro grids, reactive power compensation, the intermittent nature of DERs, and iterative control techniques are required [9].

Machine learnings based data analytics methodologies have gained tremendous popularity with the availability of large amount of continuous data of micro grid for various analysis including demand forecasting for grid stability. There is an increasing need for grid stability, due to the number of consumers connected with the grid are continuously increasing. One consequence of all such increments is the dramatic uptick in the use of control techniques based on artificial intelligence for tasks like load demand forecast and grid stability characterization. Even if the learning approaches work, we still need a better way to extract qualitative features so that grid control execution is easier. Characterization and assessment of grid stability often use hybrid control systems. The hybrid technique incorporates the improvements of ML for stability of the grid forecasting and classification.

With the variety of loads and DERs interconnected with the smart grid the prime focus of electrical engineers is on reliability of the grid because it dictates how well a system can go back to a stable state after disruptions have passed. This has been a major problem with reliable system functioning, which has led to several blackouts [10]. An important yet difficult problem in energy networks is ensuring its smooth functioning and stable operation of electrically powered networks. When supplying to dynamic and uncertain loads, the accuracy of the power demand forecasts made using different methods of machine learning becomes quite useful. Smart grid load is becoming more unpredictable due to the proliferation of renewable energy sources (RES), calling for more intricate solutions. A popular classification and prediction technique, the ESVM methodology's accuracy has been found very accurate with the functions and parameters used.

2. Related Work

To satisfy increasing energy needs, the concept of a micro grid is gaining popularity. Since converters are usually used to connect micro grid distributed energy sources (DERs) to the utility grid, micro grid power attributes are different from those of a regular grid. However, micro grid load forecasting categorizations suggestions, and research methodologies are much behind the times.

This chapter provides a high-level overview of works done till now in micro grid load demand prediction, their limitations associated with load forecasting methods, the need of intelligent control devices, and the methods currently in use [19]. In depth discussion on how ML could be applied to different hierarchical control layers of the smart grid environment has been included.

Researchers presented the emergence of vital consumer/prosumers focused integrated energy systems and the proliferation of distributed energy resources (DERs) are two factors contributing to micro grids' rising popularity. Integrating, coordinating, and governing various DERs is a formidable obstacle to managing the energy transformation in supply network. In dynamic smart grid scenarios, traditional control approaches do not work. One approach that might be considered for future micro grid networks to enhance load management is the application of ML technologies on huge amount of data available and obtain the desired results to get better efficiency.

Authors suggested that the management of energy is an important issue in today's era of grid connected or isolated micro grid system. Uses of Machine Learning techniques have created opportunities to optimize the energy cost with the help of proper optimizer and correct algorithm. Use of Particle Swarm Optimization has been done in connected and isolated mode of micro grid to check the effectiveness of the proposed algorithm in this work [20].

Investigators proposed a short term load forecasting hybrid method for a micro grid using combination of feed forward neural network based on Harris Hawks Optimization and Stationary Wavelet Packet Transform. The work shows that a properly designed, intelligent grid maximizes the use of energy resources and services. Energy management, new resource setup, and load forecasting for better grid stability are all handled by intelligent algorithms using data obtained through modern communication channels. Residential consumers, data communication channels and the system control centres make up the three levels of intelligent distribution systems. Smart meters, Head End System, inverters etc are all part of the micro grid energy management systems [21]. Communication channels and relays and switches are examples of smart equipment that may increase grid efficiency, share information, and control group loads to make the system stable.

Authors presented a long-term load forecasting model based on MMoE-RNN-Informer which considers seasonal effects on power generation and load demand. The authors used a MMoE multi task learning model to relate the characteristics all loads and then they used RNN to efficiently utilize the historical data of consumption. Inter connected DER power sources make micro grid systems, in which prosumers take power to maximize economic advantages. These are gradually replacing the idea of centralised, fossil fuel based generation. Micro grid networks provide facilities for smart consumers that includes both individual customers and a shared energy resource [22], the local energy pool, so that people may exchange power with one another without having to buy individual renewable energy generators.

Researchers proposed a metaheuristic algorithm based on population. The algorithm is inspired by process of flowers pollination known as adoptive flower pollination algorithm (APFPA).A flexible and adoptive structure is used as control variable. To improve the performance of the algorithm control parameters were dynamically adjusted. This has created balance and diversity in exploitation and exploration.

All these modern features of micro grid make it more vulnerable and unstable. Hence the energy sector has quickly adopted AI solutions to improve real-time and speedy demand response, and distributed energy resource efficiency. In order to manage both systematic and random disruptions, grid operators strive to make all power grid choices with resilience, self-learning, and foresight. With the help of real-time energy pricing and AI-developed, computationally efficient algorithms, smart prosumers will be able to make lucrative power trading choices based on their production and consumption data.

Authors developed a MATLAB model for energy management system of a micro grid to fulfil the consumer load demand and solar resource load forecasting. Extreme learning machine algorithm is used in the work and is validated for better results. In order to solve technical problems, anticipate prices, estimate energy use, and identify faults, the energy industry has used expert systems, ANN, and fuzzy logic. Within smart homes and for demand-side management (DSM) in general, these methods are helpful for energy management in residential settings [23]. Using deep learning-based fault libraries and error diagnostic analysis models, Qiao et al. presented an optimization for electric energy meters that takes into account both unique and shared distributed area load circumstances.

Researchers presented that the use of AI is very essential to handle large amount of data generated on real time in power system to handle demand response balance. Optimization algorithms can be useful to address instant solutions to respond to the varying demands. Proper selection of the right optimization algorithm can decrease the cost of energy generated. Improved power distribution systems with increased resilience, self-organization, and troubleshooting capabilities are the goals of Distributed Intelligence technology. Distributed generation and storage capacity, automated regulation, bidirectional information and power flow, comprises intelligent decentralized energy units. This necessitates the use of distribution grid monitoring and management systems that are more sophisticated and intelligent than DERs alone for the better grid stability.

Energy management, monitoring, and fault detection are all functions of distributed grid management, which has been the subject of research into the operation and control of distributed generation. Distributed grid synchronization has also solved the problem of online voltage regulation [24]. To address the issue of scattered individual controllers of distributed units, decentralized control approaches have been suggested, control actions are done based on local knowledge.

Authors highlighted the problems arising due to intermittent nature of solar PV based power sources and proposed a hybrid forecasting method using trained self-organizing map (SOM) network and an optimized kernel extreme learning machine (KELM) method to accurately predict the solar power generation during different time of the day and seasonal conditions. The owner system topologies that use distributed operation include features like energy management, load forecasting for power management and grid stability, are mainly depend on converter management, and power management. As a result of security and operational delays, conventional SCADA systems have failed to meet expectations. Algorithms for distributed load balancing work to improve the stability and resilience of distributed systems by optimizing the loads of individual peers. When it comes to smart grid demand management and distributed data storage, AI and ML technologies are useful. The authors show how far down the path to AI-powered distribution grid operator assistance for managing large-scale penetration of renewable energy sources based on regional energy trading markets and forecasting of demand [25].

Many power system applications use AI methods, such as envelop time series ML models, time series classification, and multivariate convolutional neural networks are popular. Additionally micro grid, distributed energy sources networks, demand response analysis and dynamic power trading analytics have all made use of AI. Along with this controlling micro grids using ML algorithms for tasks such as predicting energy consumption, loads, stability, demand-response, fault diagnostics, and power flow management. New machine learning techniques have recently been developed, such as active ML approach for tracking power system stability, ML model for evaluating power system performance based on decision trees, and non-linear SMOTE method for predicting voltage stability in the short-term time period. Micro grids responsiveness, efficiency, security, stability, and dependability may be enhanced via the use of machine learning (ML) methods, which are covered in this paper.

Researchers have developed ML techniques like multi-layer perceptron, gradient boosting machine, random forest, and linear regression to forecast the stability of power systems. Success rate of 99% was achieved by multidimensional long short-term memory (LSTM) method, surpassing that of competing algorithms such as recurrent neural networks and gated recurrent units.

To make a micro grid more responsive, efficient, and dependable, grid stability analysis is essential. Researchers have assessed grid stability using Random Forest, ELM, and artificial neural networks (ANN). Using a low error of 0.2391 RMSE. The ML model developed by researchers for forecasting voltage stability made greater use of artificial neural networks using the Gram-Schmidt orthogonalization approach.

An ensemble learning strategy based on stacking was developed to be effective in demand prediction. The researchers came up with six machine learning techniques to forecast the stability of networks; two of them, support vector machine and Naive Bayes, achieved an accuracy of 97.1%. To evaluate the long-term stability of voltage, they looked at how well an AI method based on kernel extreme learning machines performed. To forecast the load demand in real-time, many approaches have employed a meta-classifier that consisted of a gradient boosting decision tree and various basic classifiers. Findings show that ML can anticipate load prediction in the face of dynamically changing power demand and assist prevent blackout. Table 1 consists of compilation of learning models frequently used in recent time for prediction of load demand in micro grid using ML techniques.

Table 1: A Compilation of the Learning Models.

S. No	**Citations**	**Research Work**	**Findings**	**Methodologies Used**	**Advantages**	**Limitations**
1	Mashael M et al. 2024 [11]	Hybrid Deep Learning and Beluga Whale Optimization (LFS-HDLBWO).	Average Error Rate of 3.43% is obtained.	Z – Score normalization	Discussions and findings of the prediction algorithms.	Hybrid methodology used for data analysis.
2	ChaoranZhenget al. 2022[12].	GA ReinforcedDeep Neural Network for Net Electric Load Forecasting in Microgrids	Predictions accuracy using the GA–BP neural network with a 96% overall success rate.	GA–BP neural network	Excellent forecasting precision	Restricted to a subset of algorithms; generalizability to other systems in the actual world has not been tested.

3	Sivakavi Naga VenkataBr amareswar a Rao et al. 2022 [13].	Applicationof linear regression (quadratic), support vector machines, long short-term memory, and artificial neural networks (ANN) to forecast the load demand in the short term.	Artificial Neural Networks are the best forecasting technique for day-ahead load demand forecasting with 95% accuracy.	ANN methods are providing best accuracy results.	Picking out features enhanced model efficiency	Minimal investigation on other methods of feature selection
4	Ubaidet al. [14] 2024	A Hybrid Model for Short-Term Load Forecasting using Spike Neural Network	Assessment of grid stability A 93% success rate was attained with multi-directional LSTM.	Multi-directional Long Short-Term Memory (LSTM)	Incredibly accurate analysis of time series and predictions	Difficulty with computation and difficulties with live application
5	Arash Moradzadeh [15] et al. 2020	Short-Term Load Forecasting of Microgrid via Hybrid Support Vector Regression and Long Short-Term Memory Algorithms	The most accurate model was the stacking ensemble model, which reached 97%.	Techniques for ensemble learning (e.g., Support Vector Regression and LSTM)	Enhancement of generalizability by cross-validation	Restrictions on use; only short term load forecasting is feasible.
6	Waqas Ahmad et al. [16] 2021	Towards Short Term Electricity Load Forecasting Using Improved Support Vector Machine and Extreme Learning Machine	Improved Support Vector Machine with Genetic Algo SVM-GS got accuracy of 96.3%.	An assortment of classifiers, such as XGB, SVM, and Genetic Algo.	Excellent forecast precision	Reliability beyond the datasets that were evaluated has not been investigated.
7	Jihoon Moon et.al [17] 2018	Hybrid Short-Term Load Forecasting Scheme Using Random Forest and Multilayer Perceptron	With a Random Forest and Multi LayerPerceptronmethod, the accuracy rate was 75%.	RF, KNN, Multi-Layer Perceptron	Less precise than competing models	It's possible that pre-processing constraints (such min-max normalization) don't apply to everything.

8	Han Ma et.al [17] 2020	Short-Term Load Forecasting of Microgrid Based on Chaotic Particle Swarm Optimization	Particle Swarm Optimization along with Least Square Support Vector Machine (LSSVM) with error of 4.09%	Particle Swarm Optimization along with Least Square Support Vector Machine (LSSVM	Predicting voltage stability with high accuracy	Focused on limited aspects of stability; other factors not considered

To make a micro grid more responsive, efficient, and dependable, many algorithms based on ML have been proposed. Its analysis is essential. Researchers have assessed micro grid demand forecasting using Random Forest, ELM, and artificial neural networks (ANN). The ML model developed by researchers for made greater use of artificial neural networks.

3. The Objectives of The Research Work

The major contribution of this paper will be:

- To introduce a machine learning based Adaptive Sunflower Optimization (ASFO) approach for quick optimization.
- To introduce Enhanced Support Vector Machine (ESVM) which is superior to the regular Support Vector Machine (SVM) in context of prediction accuracy.
- To evaluate the effectiveness of the hybrid ASFO-ESVM technique for demand forecasting for solar PV based microgrid systems for real time load scheduling.
- Performance of the proposed ASFO-ESVM hybrid technique is compared with other AI based forecasting approaches to check its effectiveness.

4. The Data Set Used

This dataset aims at Load Demand forecasting by using a novel hybrid Adaptive Sunflower Optimization (ASFO) with an Enhanced Support Vector Machine (SVM). It consists of load and weather data of Solar PV Park of 10MW solar power generation ofKarur region in Tamil Nadu for a period of three years from January 2019 to December 2021. The meteorological data is based on the measurements of the weather station in Karur.

For training and validation, data from 2019.01 to 2020.12 is used, and the seasonal data of 2021 is applied for testing. It is important for classifying the set period as working weeks, from Monday to Friday and the rest of the days include Saturdays, Sundays and public holidays.

The model employs six categories of data inputs to predict load demand:

- Hourly load demand of a certain day in a week.
- Load demand that is required for the same hour on the same day from the previous week.
- Hourly load demand same day one hour before.
- Demand of load of the same hour of the previous day.
- Working day or weekend.
- Day of the week.

This data also involves relative humidity, air temperature records, amount of solar radiation received, and wind speed.

The assessment of the dataset was done and computed by MATLAB R2018. Temporal effects are reflected in historical load and control data, while behavioural and environmental inputs include day types and weather respectively. When integrating ASFO and ESVM, the model increases the correct rate of forecasting the electricity demand which is crucial when scheduling the power generation and utilization of the available micro grid resources.

5. Proposed Model

Modern society could not function without electricity, which has many positive effects on both public well-being and the economy. And yet, there is still a lot of complexity and expense involved in power generation, transmission, and distribution. In order to anticipate and prepare for potential active loads at different load buses, load forecasting is an essential activity. A load prediction may be either short-term (STLF), medium-term (MTLF), or long-term (LTLF). STLF may be finished in a matter of minutes, days, or weeks, which opens up additional possibilities for demand side management and preparing power supplies for the day ahead. Income estimations, unit service planning, and trade in energy are all helped by MTLF's and long-term predictions, which may span weeks or even years. LTLF is designed to help with electrical system expansion strategies and handling assets with a time horizon of five or more decades, giving policymakers a clearer picture of the situation.

Power acquisition, generation, load shifting, voltage management, network setup, infrastructure development, and load forecasting are all crucial business considerations. All parties involved in the generation, transmission, distribution, and selling of energy rely on them. This includes ISOs, financial institutions, and energy providers.

When it comes to forecast power demand there are four main types of models: physical techniques, statistical approaches, classic mathematical models, and AI based hybrid models. Non-linear features of time series may go unaddressed by statistical methods, even if they work well for linear models. Physical prediction algorithms are susceptible to external factors and encounter challenges with massive amount of computer and physical data collections. For load prediction, hybrid approaches incorporate many kinds of methodologies into one model. For example, proposed Adaptive Sunflower Optimization Techniques and Enhanced Support Vector Machine algorithms are examples of hybrid AI methods.

Predicting electricity load has been done using the RF, ANN, SVM, and PSO algorithms. When working with data that is very ambiguous, the reliability of these models becomes questionable. The ANN approach has some drawbacks, such as a poor convergence rate, over-adaptation, and a quick migration to local optimization. Hence more complex solutions are required since micro grid load demand is becoming more unpredictable due to the proliferation of RES. When it comes to algorithms for prediction and classification, the SVM algorithm is well-known. Picking the right functions and parameters also have a major influence on how accurate the predictions end up. High computational cost and potential for over-fitting during the training procedure are also the influencing factors while selecting the exact AI model.

5.1 Adaptive Sunflower Optimization Method

The Sunflower Optimization technique (SFO) is a bio-inspired optimization approach that attempts to replicate the heliotropic development of sunflowers. One variation of this algorithm is the Adaptive Sunflower Optimization (ASFO) Approach. It is well-known that sunflowers face the direction of the sun so that they may carry out respiration as efficiently as possible. The ASFO technique is an improved version of SFO that uses adaptive processes to solve optimization issues more quickly, with more accurate solutions, and with more resilience. Fig 3 shows the stages of the ASFO algorithm that are implemented in the proposed model.

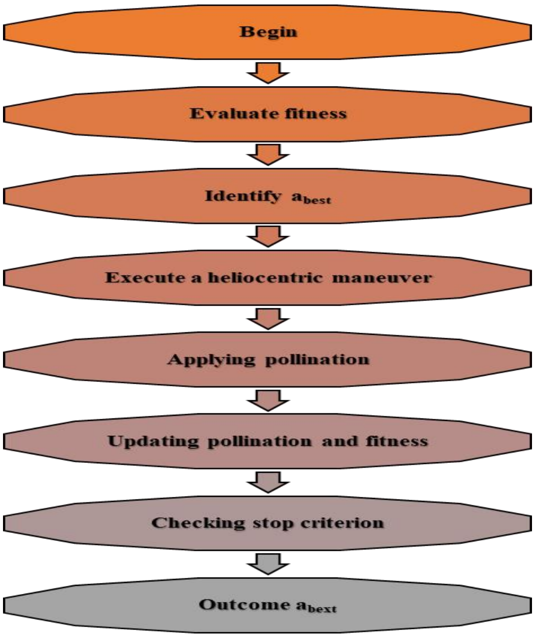

Figure 3. Flowchart of ASFO

A comprehensive explanation is provided here:

One metaphor used by the SFO methodology is a sunflower area, where sunflowers stand for various options and the sun for the best one. Sunshine intensity is proportional to the numerical value of the goal function; as a general rule, superior solutions are given more sunshine brightness. Heliotropism—the tendency of SFO to face the sun—and pollinating and reproduction—the processes that keep variety alive and make search for planets possible—rule SFO's behavior.

To address issues including delayed data mining, over-fitting during the training procedure, the ASFO approach expands and changes SFO. Here are the main changes:

a. Adaptive Step Size: In order to achieve heliotropic motions, the ASFO algorithm uses an adaptive step dimension that becomes larger in the beginning repetitions to cover more ground and gets smaller as it refines and converges on the best resolution.

b. Dynamic Pollination Mechanism: In contrast to SFO's rigid or oversimplified approach, ASFO maintains variety while adjusting pollination frequency and type according to its requirements for performance.

c. Adaptive Objective Weighting: ASFO is great at addressing complicated issues with multiple factors because it continually alters the significance of goals according to how they affect the overall excellence of the response.

d. Local Search Enhancement: Finding solutions close to the global optimum is the goal of ASFO's local search operations. Convergence is accelerated and the likelihood of being stranded in local optima is decreased with this hybrid strategy.

Objective function: One of the objectives of optimizing is to reduce (or maximise) an objective function f(x), while x represents a potential solution such as:

$$f(a): \mathbb{R}^d \to \mathbb{R} \quad (1)$$

Adaptive step size: To strike an equilibrium between the two processes, the step size (t) lowers in an unpredictable way during repetitions.

$$\alpha(t) = \alpha_0 \cdot \exp(-\lambda \cdot t) \quad (2)$$

Another option is to utilize a normalization format that considers the variety of the population:

$$\alpha(t) = \alpha_0 \cdot \left(1 - \frac{t}{x_{max}}\right)^2 \quad (3)$$

Diversity measure: Adjusting parameters automatically is done using diversity of populations DM.

$$DM = \frac{1}{m}\sum_{i=1}^{m}\|a_i - \bar{a}\| \quad (4)$$

$$\bar{a} = \frac{1}{m}\sum_{i=1}^{m} a_i \quad (5)$$

Changes are made to parameters such as the size of steps or search global frequency if diversity falls beneath a minimum threshold DM min.

Convergence Criterion: When one of these conditions is met, the algorithm terminates:

When T max iterations have been completed, the process is complete. There is a minor threshold ϵ below which the increase in fitness Δf is not significant.

$$\Delta f = \left|f_{best}^{(t)} - f_{best}^{(t-1)}\right| < \epsilon \quad (6)$$

Multi-Objective Optimization: When optimizing for many objectives at once, the objective vector f(a) is considered:

$$f(a) = [f_1(a), f_2(a), \cdots f_k(a)] \quad (7)$$

To contrast the the two options a_i and a_j we apply Pareto supremacy is applied:

$$a_i < a_j \ if\ and\ only\ if\ f_m(a_i) \le f_m(a_j), \forall m \exists m\ such\ that\ fm(a_i) < f_m(a_j) \quad (8)$$

Adaptive Parameter Control: Through feedback systems that are determined by fitness or diversity, characteristics such as α(t), G_P, and β may be changed in real-time.

$$\beta(t) = \beta_0 \cdot \left(1 + \frac{t}{T\max}\right)^{-1} \quad (9)$$

$\alpha(t) = \alpha_0 \cdot \frac{f_b - f_w}{f_b + \epsilon}$ (10)

Where d = dimensionality of search space, α_0= initial step, λ = A decay constant regulates the rate of decline, t = current time, x_{max} = max repetitions, $\bar{a}$ = centroid of population, k = number of objectives, f_b&f_w = best nd worst fitness value.

Algorithm 1: Adaptive Sunflower Optimization Method

Step 1: Initialization

Set the initial population of "m" sunflowers to $\{a_i\}_{i=1}^{m}$ here the $a_i$option alternative is to be considered.

Determine whether you want to maximize or reduce the objective function f(x).

Precisely configure the algorithm:

Maximize repetition X_{max},

Step size parameter that adapts α(t),

Prospect of Global search G_p,

Settings for pollination management β and γ,

End

Step 2: Fitness Evaluation

Assess the health of every sunflower:

$f_i = f(a_i), \forall_i \in \{1,2,\dots m\}$ (11)

Figure out what will work best (the "sun" remedy):

$a_{best} = \underset{a_i}{arg\ min}\ f(a_i)$ (in the case of reduction issues) (12)

Step 3: Heliotropic Movement (Exploitation)

Every sunflower adjusts its movement to a_{best}

$a_i^{(t+1)} = a_i^{(t)} + \alpha(t).s.\left(a_{best} - a_i^{(t)}\right) + \beta.rand(-1,1)$ (13)

Here $\alpha(t)$ = adaptive step size reducing with iteration t, s ∈ [0,1] = random factor for diversity, β = randomness of local search, rand(-1,1) = random number between -1 and 1.

Step 4: Pollination

Do either worldwide or regional pollination depending on G_P

Global pollination: For enhancing discovery, global pollination makes use of Levy flights.

$a_i^{(t+1)} = a_i^{(t)} + \gamma \cdot L(a_i, a_{best})$ (14)

Levy flight $L \sim \frac{u}{|v|^{1/\beta}}, u \sim m(0, \sigma_u^2), v \sim m(0, \sigma_v^2)$ (14)

Local pollination: During the process of local pollination, random motions around the present site are performed

$a_i^{(t+1)} = a_i^{(t)} + \delta \cdot rand(-1,1)$ (15)

Step 5: Updating the fitness

Estimate of the new spots $\left\{a_i^{(t+1)}\right\}_{i=1}^{m}$ and updating of fitness ideals $\left\{f_i^{(t+1)}\right\}_{i=1}^{m}$

Step 6: Adaptivity Check

An iteration t and diversity of populations should be used for dynamically changing characteristics $\alpha(t)$, $G_P$and others.

Step 7: Stop criterion

Just keep going till you reach the stopping requirement.

Adaptive Sunflower Optimization (ASFO) method combines movements inspired from nature with control adaptability to offer a resistant and generally applicable optimization approach. This lends it better to complex real world optimization problems since it is well capable of updating parameter settings.

5.2. Enhanced Support Vector Machine (ESVM)

In the context of prediction and predicting applications, the Enhanced Support Vector Machine (ESVM) is an enhancement over the regular Support Vector Machine (SVM). The upgrades include of methods that increase accuracy, generalizations, or efficiency. This is often accomplished by tackling issues related to parametric efficiency, feature selection, or preparing the data.

- Objective for Linearly Separable Data: In order to divide the information into two distinct groups, the SVM aims to locate a hyper plane that has the biggest margin, where $B_k \in \{-1,1\}$. This is the optimization issue:

$$min\frac{1}{2}\|x\|^2, subject\ to\ B_k(x^T a_k + b) \geq 1, \forall i \quad (16)$$

The restrictions guarantee a minimum accuracy of 1 in classifying any information points.

- Soft Margin for Non-Separable Data: In order to deal with information that is not separable by linearity, slack variables $\xi_k \geq 0$ is used to permit certain infractions:

$$min\frac{1}{2}\|x\|^2 + c\sum_{k=1}^{m}\xi_k\ , subject\ to\ B_k\ ((x^T a_k + b) \geq 1 - \xi_k, \forall_k \quad (17)$$

- Dual Formulation: To make computing more efficient, the primary issue may be split into two:

$$\max_{\alpha}\sum_{k=1}^{m}\alpha_k - \frac{1}{2}\sum_{k=1}^{m}\sum_{l=1}^{m}\alpha_k\alpha_l B_k B_l I(a_k, a_l), \text{ subject to } 0<= \alpha_k <= C, \sum_{l=1}^{m}\alpha_k B_k = 0 \quad (18)$$

- Kernel Trick: To deal with information that isn't linear, the kernel function I calculates dots that occur in environments with more dimensions than two, regardless of changing a:

$$I(a_k, a_l) = \phi(a_k)^T\phi(a_l) \quad (19)$$

Common kernels are as Linear, Polynomial and Radial Basis function (RBF).

Linear: $I(a_k, a_l) = a_k^T a_l$ (20)

Polynomial: $I(a_k, a_l) = (a_k^T a_l + c)^d$ (21)

$$I(a_k, a_l) = \exp\left(-\frac{\|a_k - a_l\|^2}{2\sigma^2}\right) \quad (22)$$

Where x = weight of the vector defining the hyperplane, b = bias shifting hyperplane, $\|x\|^2$ = margin maximization, c> 0 = Optimal optimization of margins and slack penalties are balanced by the periodicity variable, ξi = Extent to which point i is misclassified, α_i = Lagrange multipliers, $I(a_k, a_l)$ = kernel function, $\phi(x)$ = maps into higher dimensional space.

Fig 4 shows the stages of the ESVM algorithm that are implemented in the proposed model.

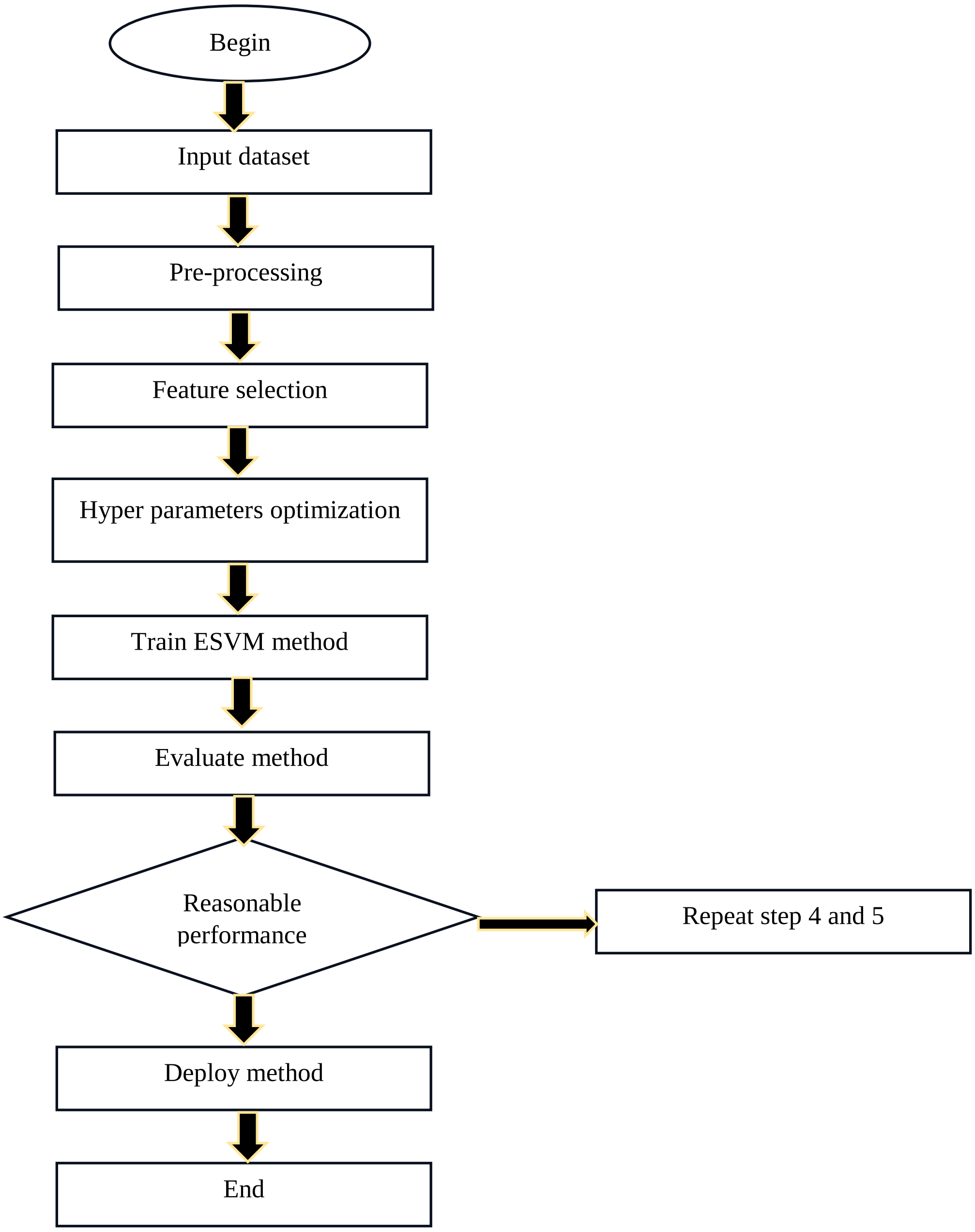

Figure 4. Flowchart of ESVM

5.3. Enhancements in SVM

ESVM is further improvement of standard SVM based on several improvements included in it. To optimize these two values, it employs other hyper parameters optimization methods such as parameter search, random search, meta-heuristic driven algorithms that include PSO and GA. Data pre-processing techniques like Recursive Feature Elimination (RFE), Principal Component Analysis (PCA) make feature selection where they remove unwanted features making the process faster. To deal with class imbalance, ESVM employs cost-sensitive learning or resampling while it considers hybrid kernels for combining and analysing the complex interrelationships of data. Fig 4 shows the stages of the ESVM algorithm that were implemented. It also includes data pre-processing diverse techniques such as normalization, outliers' detection, and noisy data management, thus making it suitable especially for high dimensions and imbalanced data sets.

- Hyper parameter Optimization: ESVM makes a process of selecting C and γ for the SVM model more automatized. These are optimized using: Grid search, Random search and Evolutionary algorithm.

$$I(a_k, a_l) = \exp(-\gamma \|a_k - a_l\|^2) \quad (23)$$

- Feature Selection: The feature selection in ESVM aims at choosing the most significant features out of features into tiny subset for effective modelling. While Recursive Feature Elimination (RFE) emphasizes the features, and Principal Component Analysis (PCA) will project the data into lower dimensions. This reduces noise, increases measures of interpretability, and counteracts overfitting in high dimensionality datasets.

RFE: Continuously removes the less significant features according to SVM weights:

$$x_l = \sum_{k=1}^{m} \alpha_k B_k \phi_l(a_k) \qquad (24)$$

PCA: Extracts the most variable elements and uses them to project the information into a lower-dimensional storage:

$$a' = w^T a \qquad (25)$$

- Cost-Sensitive Learning: The cost-sensitive learning requires different penalties for misclassifications for different classes to help introduce balance with regard to the classes. In ESVM, the objective function is changed by adding class-specific penalties (c1, c2), to provide a greater emphasis to the minority class mistake. This is important particularly when dealing with imbalanced data sets because it makes possible to enhance results such as recall and F1 score of a less popular class.

$$min \frac{1}{2}\left(\|x\|^2 + c1 \sum_{k\epsilon class1} \xi_k + c_2 \sum_{k\epsilon class2} \xi_k\right) \qquad (26)$$

Class sizes have an opposite relationship to the punishment C1 or C2, which means that minority classes are given greater weight.

- Hybrid Kernels: The use of multiple kernel functions is then incorporated into ESVM and referred to as hybrid kernels. For example, a hybrid kernel might mix linear and RBF kernels:

11. $I(a_k, a_l) = \alpha I_1 + (1 - \alpha) I_2$ (27)

This facilitates a compromise between global linearity and local nonlinearity RBF giving ESVM flexibility and accuracy.

- Outlier Detection and Pre-processing: In ESVM, two steps, outlier detection, and pre-processing are used to deal with anomalous or extreme data which may mislead the model. There are features, to enumerate, such as Z-score normalization where outliers are identified or Isolation Forests and normalization for features scaling. A series of pre-processing techniques including missing data handling, and class balancing enhance the performance of the chosen model.

Z-score = $\frac{a - \mu}{\sigma}$ (28)

Isolation forests: $score = \frac{path\ length(a)}{No\ of\ trees}$ (29)

route durations that are smaller than average suggest outliers.

- Levy Flight for Optimization: Levy Flight which is employed in ESVM for optimization is as a walk with step size in the correlated random manner and allows the searching range being large and small. The update rule:

$$a_{t+1} = a_t + \beta \frac{\sin(\pi u)}{|v|^{1/\lambda}} \qquad (30)$$

uses random variables u,v to come out of local optima and do efficient tuning of all the hyper parameters.

- Decision Boundary: Accordingly on the optimal plane, the selection of boundary in ESVM is responsible for separating the various information classes. To be characterized as:

$$f(a) = sign(\sum_{k=1}^{m} \alpha_k B_k I(a_k, a) + b) \qquad (31)$$

It incorporates bias b, kernel modifications, and support vector additions respectively. The border improves the margin to its maximum potential, which guarantees reliable classification accuracy.

Where γ = manages the impact of only one training case, x_l = weight of feature l, w = matrix of principal components, μ = mean, σ = standard deviation.

Algorithm 2: Enhanced Support Vector Machine (ESVM)

Input: Dataset D = $\{(a_k,B_k)\}_{k=1}^{m}$, kernel function I, regularization range C, and parameter range γ

Outcome: Method that has been optimised with certain functionalities and hyper parameters

Step 1: Pre-processing

Normalization of data utilizing below equation were μ and σ are mean and standard deviation

$$a' = \frac{a-\mu}{\sigma} \tag{32}$$

Take care of data that is absent by either deleting it or reconstructing it.

Use Isolation Forests or Z-score to identify and eliminate any outliers that may be present.

Under sampling or the SMOTE may be used for successfully distributing classes.

Step 2: Feature Selection

Employ RFE to prioritize characteristics and eliminate those that are not relevant.

Use PCA to reduce the dimensions of the data while keeping the elements that have the biggest variability.

Step 3: Hyperparameter Optimization

Specify the ranges of values for both C and γ.

Utilize either of the following methods to get optimal performance:

Perform a grid search by analysing each potential pairing of C and γ.

Searching at random involves selecting combos at random from within predetermined limits.

Metaheuristic Optimization

Put the population of possible remedies into its initial state.

Determine the level of fitness determined by the performance of a cross-valid

Identify the best values for C and γ by repeatedly updating the answers.

Step 4: Train the Method

Find a solution to the issue of double improvement using eq 19.

The computation of the decision function using eq 32.

Step 5: Estimate Performance

Cross-validation and measures like as accuracy, precision, recall, and F1-score should be used in the evaluation process.

In the event that the performance is not adequate, revisit Step 2 or Step 3 in order to make adjustments.

Step 6: Final Method Deployment

ESVM models that have been trained should be deployed for use in real-world scenarios.

The Enhanced Support Vector Machine (ESVM) extends the classical SVM through formula (25) by adding feature selection, hyper parameter selection, and reliable pre-processing. Its mathematical basis is based on the imposition of margins and kernel methods and contains additional improvements relevant to modern calls to machine learning.

5.4. Proposed Hybrid ASFO-ESVM Method

To improve the performance of the ESVM approach, the ASFO method is used. For enhancing the precision of forecasting for meteorological days, this paper presents a theoretical hybrid technique that is based on ASFO-ESVM. As can be seen in Fig 5, the solution framework that has been developed is made up of three different subsystems: a pre-processing unit, a support vector machine unit, and a sunflower optimization unit. In the phase of pre-processing, the data for the chosen time period is obtained from the historical dataset; this occurs throughout the stage. The ASFO-ESVM approach is able to accurately predict data and evaluate the statistical error performances of information on the weather. During training, factors like as temperature, irradiance, surface temperature, and duration are taken into consideration.

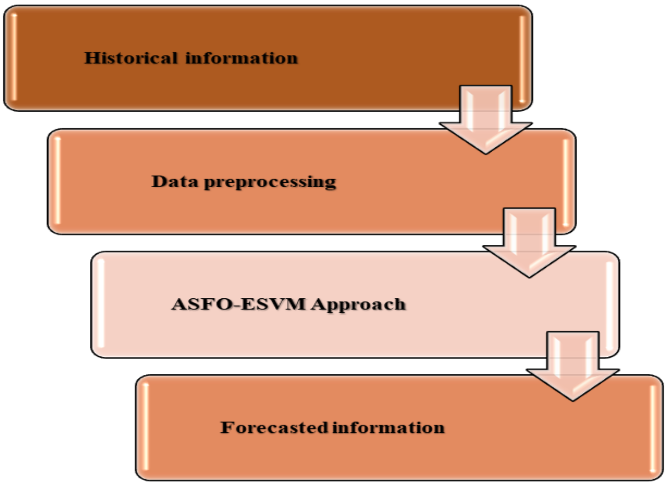

Figure 5. The Solution Mode of ASFO-ESVM

The ASFO meta-heuristic approach mimics the actions of sunflowers to find the optimal solution of the ESVM method. Because of its numerous advantages over competing modelling approaches, the ASFO approach has been selected. The ASFO procedure being carried out in stages to evaluate potential possibilities, including searching for and exploiting them. ESVM techniques are very efficient at effectively handling big datasets. See Fig 6 represents the proposed hybrid ASFO-ESVM approach's process.

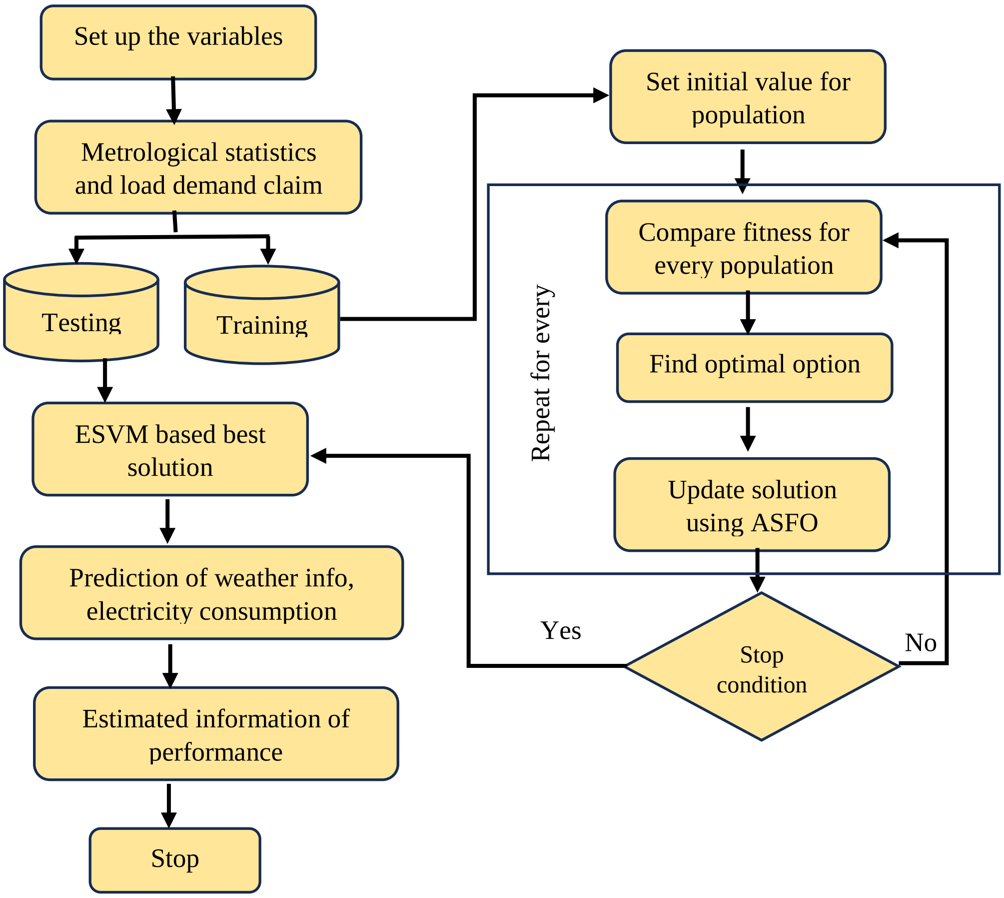

Figure 6. Approach Suggested by ASFO-ESVM

The experimental data stream was used for investigating and predicting the weather characteristics required for the PV systems, the results were used to optimize the energy distribution. The subjected model has considered important inputs such as light, temperature, day-night conditions and surface temperature. These variables were therefore chosen to provide important aspects relating to energy generation and user consumption.

A study uses Adaptive Sunflower Optimization (ASFO) algorithm to improve the classification ability of the Enhanced Support Vector Machine (ESVM). The ASFO makes enhancement to the ESVM's parameter settings by employing meta-heuristic sunflower-based algorithm. The sequential process of the ASFO-ESVM model is as follows:

- Initialize ASFO Parameters: Assuming the initial population, a_k and setting constraint on the maximum number of iterations to 500 for efficiency.
- Analyse Initial Population: Computation of the objective functions of all population members will be done and then evaluate the ASFO parameters for the initial population.
- Update ASFO Position: Find out whether moving through to other areas for the other iterations of the example problem will yield more of an optimum value as compared to the local optimum. If so, modify the positions to increase or do more at improving the worth of the individuals in the populace.
- Identify Ideal Solution: By comparing the fitness value of the candidate solutions, the sunflower denoting the value a_b is the best solution.
- Stopping Criteria: That is when certain stopping criteria have been fulfilled such as the maximum iterations have been exceeded or the level of accuracy has been achieved.
- Transfer Best Solution to ESVM: Based on these -optimized" parameters, the ESVM then pro- duces the prediction model.
- Evaluate ESVM Performance: Meanwhile, the effectiveness of sought solution during training is evaluated in terms of the ESVM model. During the testing phase, four statistical measures of errors are used in determining prediction effectiveness.

6. Result and Discussion

Experimental evaluation of the proposed ASFO-ESVM model for weather data and load demand of grid connected photovoltaic (PV) systems was conducted using an experimental dataset. The evaluation used Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (SMAPE), Numerical Agreement Factor (d), Accuracy, Precision as well as classification of the F1-score with a view of providing a vivid picture of the model's accuracy to predict the demand. These metrics were compared with the standard techniques like Random Forest (RF), standalone ESVM and Particle Swarm Optimization based ESVM (PSO-ESVM).

The outcome established across the summer, winter, autumn and spring, weekdays and weekends also exhibited that the proposed ASFO-ESVM model outperformed all other models. It performed better in terms of accuracy, precision, and F1-scores compared to other approaches all the time, guaranteeing reasonable and accurate forecasts in nonlinear and chaotic milieu. Significantly, the model has better MAPE and SMAPE coupled with a higher agreement index (d) to underscore high accuracy of the model in the modelling of slight shifts in energy demand trends.

This section expands on the detailed performance of the ASFO-ESVM model, and then demonstrates its flexibility and reliability in energy forecasting as a viable option in structuring microgrids.

6.1. Accuracy: Accuracy determines correctly predicted instances of load demands in relation to the overall instances that have been predicted. For classification-based evaluation:

$$Acc = \frac{Correctly\ Predicted\ positive\ case + Correctly\ Predicted\ negative\ case}{Total\ prediction} \tag{33}$$

6.2. F1-score: The F1 score highlights a balanced relationship amongst recall and precision by providing the harmonic average of the two:

$$Fs = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{34}$$

Precision: Precision measures how many beneficial findings were successfully anticipated relative to the overall number of positive discoveries anticipated:

$$Pre = \frac{Correctly\ predicted\ positive\ cases}{Correctly\ predicted\ positive\ cases + Incorrectly\ predicted\ positive\ cases} \tag{35}$$

6.3. MAPE: The mean absolute percentage error (MAPE) between expected (E_t) and observed (O_t) values is computed as:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{O_t - E_t}{O_t}\right| * 100 \quad (36)$$

6.4. Symmetric Mean Absolute Percentage Error (SMAPE): Through the process of standardizing the error regarding both current and expected values, SMAPE provides a more symmetrical error metric:

$$SMAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{E_t - O_t}{(|O_t| + |E_t|)/2}\right| * 100 \quad (37)$$

6.5. Higher agreement index (d): Scaling from 0 to 1, with 1 indicating complete agreement, the conformity index quantifies the level of precision among the actual and anticipated values:

$$d = 1 - \frac{\sum_{t=1}^{N}(O_t - E_t)^2}{\sum_{t=1}^{N}(|E_t - \bar{O}_t| + |O_t - \bar{O}_t|)^2} \quad (38)$$

6.6. RMSE: The root-mean-squared error (RMSE) is a metric that quantifies the average squared variance among the actual and anticipated values:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(E_t - O_t)^2} \quad (39)$$

6.7. MAE: The mean absolute error (MAE) among actual and anticipated values is calculated:

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|E_t - O_t| \quad (40)$$

Here N = sample count, E_t = forecasted load demand, O_t = actual load demand, t = duration.

All the above metrics have a specific importance in measuring the performance, like accuracy of ASFO-ESVM model to predict the load demand and weather data for solar PV systems. In combination, these metrics demonstrate how the hybrid model is suitable when working on non-linear, dynamic data. Table 2 contains the performance of existing and proposed models in terms of accuracy, f1-score, and precision.

Table 2: Performance evaluation of the Proposed ASFO-ESVM method

Model	Accuracy (%)	F1-Score (%)	Precision (%)
ESVM	86.42	84.67	83.21
RF	87.32	85.12	86.34
PSO-ESVM	90.56	90.12	90.01
Proposed ASFO-ESVM	97.72	97.85	97.13

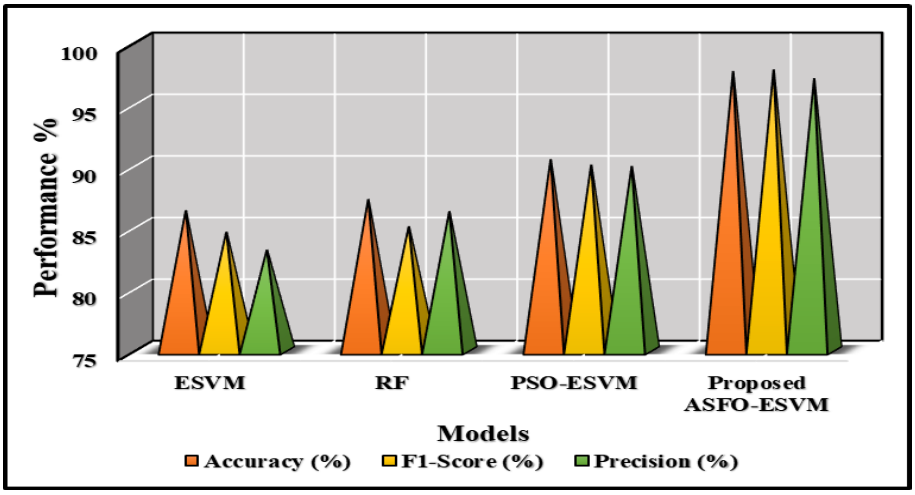

Figure 7. Visual illustration of comparing the proposed method to the existing one for accuracy, f1-score, and precision

In the Table2 and Fig 7, it can be seen that how different methods fared. These methods include RF, PSO-ESVM, Random Forest, and the proposed ASFO-ESVM. The three most important criteria for assessment are precision, accuracy, and F1-score.With an accuracy of only 86.42 percent, ESVM is clearly not up to the mark of dealing with complicated non-linear patterns. Although it still has problems with dynamic datasets, Random Forest improves by 87.32% with the help of ensemble learning. With PSO-ESVM, prediction accuracy is improved to 90.56% by decreasing overfitting and optimizing ESVM parameters. With an impressive 97.72% accuracy, the suggested ASFO-ESVM approach proves to be the best option for optimizing ESVM parameters and adapting to different types of data.

An excellent statistic for unbalanced datasets, the F1-score strikes a compromise between recall (to reduce false negatives) and accuracy (to avoid false positives). With an F1-score of 97.85%, the suggested ASFO-ESVM outperforms all other models in terms of reducing over- and under-prediction mistakes.The accuracy of the predictions is measured by precision; a greater value indicates a lower number of false alarms. The moderate dependability in positive case prediction is shown by ESVM's 83.21% performance. As a result of more effective false positive filtering, RF improves somewhat to 86.34%. PSO-ESVM significantly improves the accuracy of recognizing genuine positive instances, increasing precision to 90.01%. In high-demand settings in particular, the suggested ASFO-ESVM shines with an accuracy of 97.13%, demonstrating its resilience in avoiding false positives.

Table 3: Reviewing MAPE, RMAPE, and the Agreement Index Every Day

Model	MAPE (%)	RMAPE (%)	Agreement Index (d)
ESVM	3.65	3.3	0.81
RF	2.57	2.5	0.85
PSO-ESVM	1.88	1.69	0.90
Proposed ASFO-ESVM	1.25	1.27	0.92

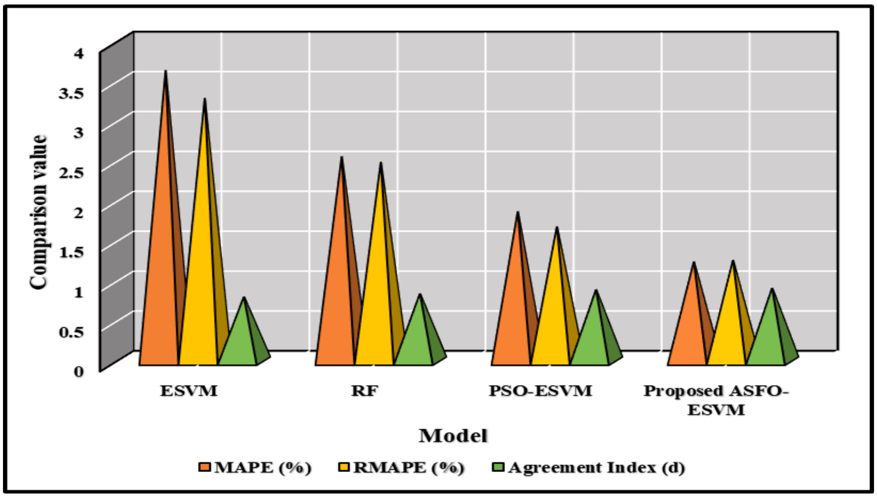

Figure 8. Visualization of Daily Comparisons of the MAPE, RMAPE, and Agreement Index

Here Table 3 and Fig 8shows how four different approaches fared in terms of MAPE, RMAPE and Agreement Index (d) on per day basis for : Enhanced Support Vector Machine (ESVM), Random Forest (RF), PSO-based ESVM (PSO-ESVM), and the proposed ASFO-ESVM. Regardless of the season, the findings reveal that the ASFO-ESVM model attains the lowest MAPE, proving its greater accuracy, particularly in settings as unpredictable weather. By comparing the expected and actual values, the RMAPE measure normalizes mistakes, providing a clearer picture of their magnitude. With its continually decreased RMAPE, the ASFO-ESVM model guarantees great accuracy and flexibility to data fluctuations.

By comparing the expected and actual values, the Agreement Index (d) determines the precision of forecasts. An agreement index indicates near-perfect predicted alignment with actual values, further demonstrating the constant outperformance of the ASFO-ESVM model compared to others. Its high index is consistent throughout the year. Finally, when comparing the three measures MAPE, RMAPE, and Agreement Index, the ASFO-ESVM technique clearly shows that it is the best forecasting method, surpassing ESVM, RF, and PSO-ESVM. In very dynamic situations, such as summer, when weather and temperature change the greatest, the suggested ASFO-ESVM approach proved best. Ultimately, when it comes to microgrid energy management, the ASFO-ESVM technique is the way to go for accurate seasonal load demand and consumption predictions.

Table 4: Reviewing MAPE, RMAPE, and the Agreement Index Weekly

Model	MAPE (%)	RMAPE (%)	Agreement Index (d)
ESVM	4.05	4.12	0.82
RF	3.45	3.51	0.86
PSO-ESVM	2.45	2.48	0.90
Proposed ASFO-ESVM	1.8	1.88	0.93

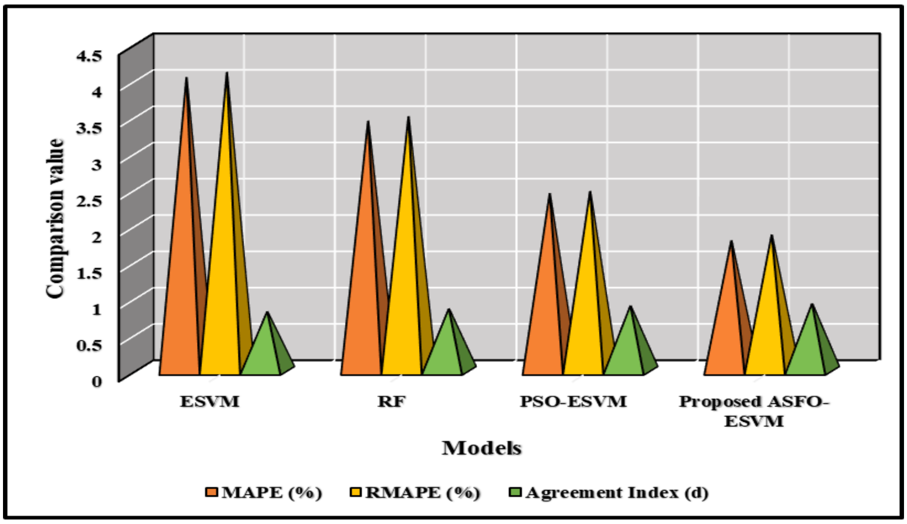

Figure 9. Visualization of Weekly Comparisons of the MAPE, RMAPE, and Agreement Index

Performance analysis based on the established evaluation metrics namely, Mean Absolute Percentage Error (MAPE), Relative Mean Absolute Percentage Error (RMAPE), and Agreement Index (d) of the four models namely enhanced support vector machine (ESVM), random forest (RF), Particle Swarm Optimization based ESVM (PSO-ESVM), and the proposed ASFO-ESVM is illustrated in the present Table 4 and Fig 9. ESVM possesses the largest MAPE and RMAPE of 4.05% and 4.12%, individually. This shows that its predictive bias is greater than those of the other models at an estimated 12.6%. The Agreement Index (d) is 0.82 which can be consider moderate in link with actual data yet there is scope for enhancement.

In terms of prediction accuracy, RF gives marginally better results than ESVM with MAPE of 3.45 % and RMAPE of 3.51%. The Agreement Index (d) raises up to 0.86, which demonstrates the improvement of the forecasted and actual values. PSO-ESVM get better still, with MAPE of 2.45% and RMAPE 2.48%, more accurate than any of the classifier models. The Agreement Index (d) in turn also rises to 0.90, indicating improved consistency in prediction. The Proposed ASFO-ESVM has the lowest MAPE of 1.8% and RMAPE of 1.88% thus confirming the improved accuracy of the model. It can be concluded that the value of the Agreement Index (d) is equal to 0.93 as it characterizes the high level of agreement with the actual values. Altogether, it can be noted that all three analysed metrics point out that the proposed ASFO-ESVM model offers the most accurate, reliable, and consistent predictions even to a greater extent in comparison with the examined methods.

Table 5: Results compared to earlier work using the ASFO-ESVM prediction approach

Model	RMSE	MAE
ESVM	2.25	1.78
RF	1.55	1.77
PSO-ESVM	1.33	1.35
Proposed ASFO-ESVM	0.89	0.78

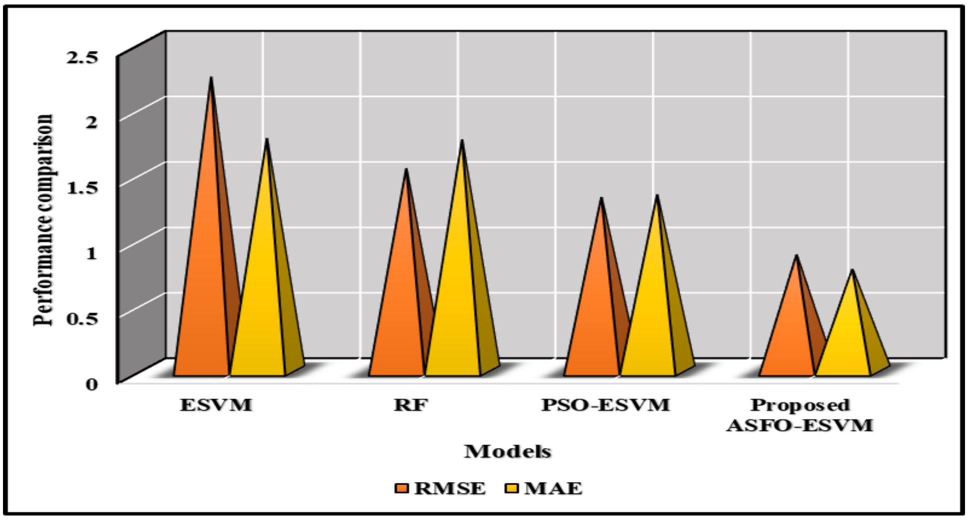

Figure 10. Graphical depiction of the ASFO-ESVM prediction approach effectiveness in relation to prior research

The Table 5 and Fig 10 shows the results of models including the ESVM, the RF, the PSO-ESVM, and the Proposed ASFO-ESVM, based on the RMSE and MAE. These metrics allow the assessment of the predictive capability of the models, at different levels, from large errors to small ones. Because RMSE involved squaring of differences, it provides larger errors with higher weight as compared to MAD. The lowest RMSE reaches 0.89 at the Proposed ASFO-ESVM, which stipulates that it provides a least number of large errors. PSO-ESVM follows this with 1.33, therefore suggesting better results on error minimisation, as compared to conventional models. RF also has a larger RMSE of 1.55 which means that, it is more influenced with large errors.

In general, ESVM is less effective for handling large prediction errors with the largest RMSE of 2.25. MAE, on the other hand, performs every error on the same level due to the mean averages between the difference of estimated and actual values. The Proposed ASFO-ESVM has a lowest MAE of 0.78 outcompeting other models; hence, it underlines fewer errors. Following is PSO-ESVM with 1.35 which is less consistent but better than the pure PSO system. The MAE of RF is 1.77 and for ESVM the MAE is 1.78 which shows that ESVM is making a greater number and larger prediction errors than the other three methods. Thus, the proposed ASFO-ESVM demonstrates a highest RMSE, as well as, MAE in contrast to all other models, and it minimizes both a large error and an average error. This makes it the most accurate and reliable model in cases where predictions are required.

7. Conclusion

The work on the load demand forecasting is extremely important for the improvement of the microgrid energy management systems, which are related to the conditions of the present dynamic increase in the energy requirements and connections to renewable resources. In this study, the conventional or standalone predictive models' drawbacks were brought to light. These difficulties have been mitigated by developing a novel bi-level ASFO algorithm combined with ESVM. The ASFO algorithm proved useful in improving ESVM parameters through meta-heuristic computations based on natures, which helped in increasing the model's ability to work on intricate non-linear datasets and overcoming problems relating to local minima. The model was calibrated against historical load demand and meteorology data sets for relevant parameters such as temperature, humidity, irradiance, time details. Comparisons with the other techniques that are available in literature, the Random Forest (RF) and Particle Swarm Optimization based Extreme SVM (PSO-ESVM) were conducted in the study and the recognition of the proposed ASFO-ESVM model's effectiveness. This led to a higher accuracy of the model as characterized by reduced Mean Absolute Percentage Error (MAPE) and the Symmetric Mean Absolute Percentage Error (SMAPE), while maintaining high consistency indices 'd'. The proposed model is also significantly superior to the other models under the various seasons and time periods of analysis.

This paper emphasizes the way in which the current study enables the utilization of hybrid methods and extra linear techniques for enhancing the predictability of non-stationary data systems, especially those that have high variability and complex relationships. Consequently, the ASFO-ESVM model adoptability from different perspectives indicates that it could offer a valuable, namely scalable, reliable, and efficient, tool for load demand forecasting supporting more proficient decisions in energy production, distribution, and management. The findings confirm that the combination of state-of-the-art machine learning algorithms and meta-heuristic optimization methods can address the requirements of contemporary energy systems. The future work implications can be on the inclusion of extra variables, expansion of the model to other areas and, the integration of the model to real time microgrid management for the improvement of performance.

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