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Article

A Hybrid PSO–LSTM Framework For Intelligent Demand-Side Management In Smart Grids With Renewable Energy Integration

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Abstract: The growing penetration of renewable energy resources, electric vehicles (EVs) and distributed energy systems, demand-side management (DSM) in modern smart grids has become increasingly complex. Conventional DSM methods usually show lower predictive capability and ineffective load scheduling in a tight operating environment, which leads to increased operational costs, hindered grid stability. This paper presents a hybrid PSO–RNN framework for intelligent freedom of management for power systems. The proposed framework combines an RNN for precise short-term load forecasting with PSO for effective optimal load scheduling, EV charging coordination, and energy distribution by utilizing data on historical electricity consumption, outdoor weather conditions, renewable energy generation variables, electricity pricing data of local suppliers in Singapore,, average grid load from the previous day (24 hours) as well as #datetimeindex. The experimental evaluation shows that the proposed PSO–RNN model can reach 98.24% forecasting accuracy, reduce RMSE to 0.081 and MAE to 0.061 value, while achieving over 24.76 % of peak-load reduction; saving about 21.35 % of electricity cost; using approximately by up to 91.42 % renewable energy as well, compared with ANN, SVM, DRL and RNN standalone models. These features increase reliability, lower operation costs and assist in sustainable energy recovery. The designed framework can effectively serve as a scalable, adaptive and computationally efficient next-generation intelligent smart grid and real-time electricity demand side management solution.

Keywords: Demand-Side Management (DSM); Smart Grid; Particle Swarm Optimization (PSO); Recurrent Neural Network (RNN); Short-Term Load Forecasting; Renewable Energy Integration; Electric Vehicle Charging; Energy Optimization; Machine Learning; Demand Response.

1. Introduction

The global energy landscape is transforming rapidly in terms of urbanization, growing electricity demand, integration of large-scale renewable energy resources, and extensive adoption of electric vehicles (EVs). Smart grids have appeared upon the scene to be an intelligent solution that can accommodate / support bidirectional energy flow, real-time communication, distributed generation and advanced monitoring infrastructure. While these developments are contributing to energy sustainability, they also entail significant uncertainty in electricity generation and consumption due to the intermittent nature of both renewable resources and very dynamic consumer demand. As a result, effective Demand-Side Management (DSM) has inevitably emerged as an essential prerequisite for delivering a reliable, cost-effective and sustainable smart grid.

Demand-Side Management allows consumers and utilities to improve electricity consumption by scheduling loads, clipping peaks and filling valleys while saving energy. Effective demand side management will help to reduce peak usage, improve power quality, reduce operational costs, integrate renewable energy and delay expensive grid infrastructure development. Nonetheless, traditional DSM methods of deterministic optimization, heuristic scheduling and rule-based decision making struggle to accommodate rapidly changing operating conditions with varying behavior of renewable energy generation, electricity price fluctuations, weather uncertainty and the charging demand pattern of Electric vehicles.

Recently, Artificial Intelligence (AI) and Machine Learning (ML) have shown outstanding potential to respond to these challenges. RNNs, in particular, exploit nonlinear temporal dependencies between the inputs and use this to develop accurate short-term load forecasts. Forecasting is also essential for utilities to make better scheduling decisions since it allows them to better anticipate future demand. However, load scheduling is an inherently multi-objective optimization problem with conflicting objectives: balancing several measurements, such as minimizing the total electricity cost, preventing peak-load situations, maximizing renewable energy utilization under fluctuating weather conditions and maintaining satisfaction of users comfort level as well as grid stability and safe electrical system operation.

Particularly, because of its leader-to-follower conduct (which is less sensitive to local optima), high performance in global search, fast convergence rate, and simple computational efficiency has made the PSO a highly effective population-based optimization algorithm for solving complex nonlinear optimization problems [??]. The fusion of PSO with RNN provides the significant advantages of coupled demand prediction and scheduling mechanisms, which enhance performance through real time adaptiveness to grid hardware availability by optimizing the consumption of electricity. Related WorkHybrid Intelligent Optimization Frameworks and Their Significance for

Next Generation Smart Grid

In the demand-side management, models such as ANN [1–6], SVM [7–12] DRL [13], LSTM (Long Short-Term Memory) [14, 15] model and hybrid optimization techniques have been explored. These approaches have certainly helped to improve forecasting and scheduling performance, but many challenges remain unsolved. Most of them conduct forecasting and optimization decoupled, which restrains coordinated decision making. Approximately, a handful of approaches neglect renewable energy intermittency, climate change, EV charging behavior simultaneously as well as real-time electricity pricing inside an integrated optimization system. Moreover, many existing models are afflicted with elevated computational complexity, poor scalability and limited adaptability for real-time smart grid applications.

To address the above limitations, this paper proposes a hybrid Particle Swarm Optimization–Recurrent Neural Network (PSO–RNN) framework for intelligent demand side management. The framework proposed combines an accurate short term load forecasting component with adaptive optimization to enable real-time electricity scheduling. Appliance scheduling optimization, EV charging coordination, and demand response are jointly modeled based on historical electricity consumption, weather information, renewable energy generation, grid load characteristics, electricity price and EV charging behavior. The framework being proposed will focus on three objectives of peak reduction, cost optimization, and improved renewable firming while operating within comfortable consumer limits.

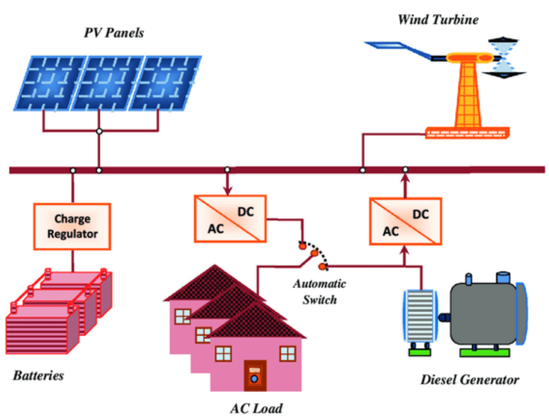

Fig. 1. Schematic representation of the proposed system

Illustration of the hybrid power system, PV solar panel and battery bank, diesel generator for AC loads[14]. This process harnesses light from the sun and converts it into direct current (DC) power with PV modules. Charge controller regulates the current flow towards the battery bank to charge them safely & provide efficient operation of the system [1]. The solar energy can be used for times when the sunlight is not enough, while a group of battery banks will contain DC power to act as a backup on periods of low sunlight or during night time [2].

The system further includes at least one AC-DC converter configured to convert the DC power generated by the first load (or other types of electrical loads) into an AC form, for example, to supply leveraged and unleveraged AC power to household use. These converters may be extended, when required, to provide an AC to DC conversion suitable for battery charging also [3]. Installation of a diesel generator is also located within the system as a reserve means of power. When both solar and the battery can not provide enough power supply to meet user load, the diesel generator starts to cr This hybrid system configuration has been widely applied in isolation sites and those independent from grid [5].

1.1 Research Gap

- Even though important progresses have been made in achieving intelligent demand-side management, a number of research challenges has still to be addressed.
- Current research has emphasized electricity load forecasting, or optimization alone, thereby limiting the coupling of prediction and scheduling
- Greater than 90% of DSM fashions based mostly on machine studying do not contemplate the simultaneous integration of renewable power era and climate variability or electricity value, grid working situations along with EV charging demand [17].
- Conventional optimization algorithms are prone to premature convergence and solution quality degradation in highly dynamic operating environments.
- Most approaches that have been reported do not offer adaptive real-time optimization of continuously varying electricity demand
- A constrained comparative assessment has been performed versus several state-of-the-art machine learning techniques via detailed smart grid performance measures.
- These limitations encourage the development of an integrated hybrid optimization framework to simultaneously enhance forecasting accuracy and intelligent decision making on the demand-side.

1.2 Research Contributions

The main contributions of this work can be summarized as follows:

- Propose a new hybrid PSO–RNN framework for smart grids based on the combination of swarm intelligence optimization and deep learning-based load forecasting for intelligent demand-side management in smart grid environments.
- It builds a holistic multi-source energy management framework, by introducing historical electricity demand, renewable generation, weather information and forecast, electricity prices, grid load characteristics and EV charging profiles.
- The paper proposes a real-time optimization solution to minimize electricity cost, avoid peak demand, increase renewable energy share and improve system stability.
- It is compared with ordinary machine learning algorithms such as ANN, SVM, DRL and independent RNN to achieve higher forecasting ability, smoother load profile, better energy utilization and superior operating performance.
- The revitalised intelligent framework presents a scalable, computationally lightweight solution to adhering to future smart grids with high renewable energy sharing and electric vehicle integration.

The rest of the paper is structured as follows. Section 2: A critical review of the most recent literature In section 3, proposed PSO–RNN methodology and mathematical formulation is discussed. Dataset, preprocessing and experimental setup (Section 4). Experimental results comparative analysis and discussion are presented in section 5. In Section 6, we conclude the paper and discuss future work.

2. Literature Review

As the integration of renewable energy resources, distributed generation, electric vehicles (EVs) and intelligent metering infrastructure contributes to modern smart grids, Demand-Side Management (DSM) cannot be never omitted from main research fields [1–3]. The ultimate goal of DSM is to optimize electricity usage in conjunction with reducing operational costs, maximizing energy efficiency and keeping the grid balance [4,5]. This flexibility of AI, ML and metaheuristic optimization has been playing a key role in improving intelligent energy management systems that can react to the dynamic operating conditions [6–8].

The electricity load forecasting of the use of machine learning algorithms has been a topic of research in recent years. Since that conventional statistical forecasting methods have limitations [7], several studies implemented Artificial Neural Networks (ANNs) [8], Support Vector Machines (SVMs) [9], Decision Trees and Random Forests and showed improved prediction power in relation to classical time series models [10, 11]. Among specific deep learning techniques, Recurrent Neural Networks (RNNs) have been Favourable on the basis of modelling temporal dependencies within electricity consumption data since RNNs are able to learn sequential patterns from historical observations [12,13]. If the utility estimates short-term load forecasting accurately, it can optimize electricity generation scheduling, demand response planning and operational reliability [14].

Optimization algorithms also contribute to intelligent DSM. Metaheuristic approaches like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Grey Wolf Optimization (GWO), Differential Evolution (DE) and Ant Colony Optimization(ACO) have been effectively used for Appliance Scheduling, EV Charging coordination, Renewable energy disposal, Electric Cost savings [15–18]. PSO is a well-known and widely concerned based optimization algorithm due to its fast convergence speed, easy implementation and the high ability for global searching which is a good fit for nonlinear multi-objective optimization problems in smart grids [19,20].

The quick rollout of electric vehicles has created another layer of complexity for managing electricity demand. Many researchers have proposed intelligent charging methods that synchronize EV charging times based on the electricity prices, battery state-of-charge (SoC), renewable energy generation, and grid operating conditions [21–22]. These strategies decrease peak demand, increase renewable energy consumption, and reduce costs. Demand response programs based on dynamic pricing, for example, also change the timing of electricity consumption by consumers to off-peak periods—thus increasing grid flexibility and operational performance [23,24].

Recently, the hybrid machine learning and optimization frameworks have shown their abilities to make learned based intelligent energy management frames [25,26]. These hybrid approaches leverage the prediction power of deep learning along with optimization models to predict future electricity demand while making optimal scheduling decisions together. As the hybrid models combine accuracy or quality of forecasting with adaptive decision making, they seem to outperform any standalone forecasting or optimization method [27]. However, existing hybrid frameworks are mostly non-scalable and also yield higher computational efforts while not being enough capable of considering the renewables variability, weather data, electricity price indices, consumer responses, and EV charging load [28,29].

Although many have analyzed DRL as techniques for intelligent demand response handling due to the function to learn optimal control policy in uncertain environments [30]. Nonetheless, DRL based methods usually refer to the need for huge training data and long convergence time, as well as significant computational storage and capacity requirements, making them hard to deploy practicably in smart grid applications that require $\textit{real time}$ capabilities [31]. Thus, this is feasible for lightweight hybrid optimization frameworks [32] but still attractive to practical introduction.

Important research challenges remain open, despite great advances in progressive intelligent DSM. First, a great number of existing research works[33] do not consider load forecasting and scheduling optimization tasks integratively but independently. Second, few studies consider simultaneous optimization of electricity consumption, renewable energy generation, weather conditions, electricity prices, grid operating conditions and EV charging behaviour [34]. Third, little attention has been paid to adapting solutions that can cope with fast time-varying structures in operating environments, and to enable real-time scheduling of large-scale smart grids in a computationally efficient way [35].

In order to combat these challenges, this work proposes an accurate short-term load forecasting methodology combined with a hybrid Particle Swarm Optimization–Recurrent Neural Network (PSO-RNN) framework for intelligent demand-side management with adaptive optimization. The main work in this paper, a framework which integrates historical data of electricity load profile, renewable energy generation characteristics, weather information and prediction values of electricity prices alongside grid load characteristics and EV charging profiles to investigate the real-time energy scheduling process. The proposed method integrates the strong temporal learning capability of RNN with the global optimization capability of PSO to minimize peak demand, electricity costs and enhance renewable energy utilization as well as smart grid performance [36].

Table 1. Critical comparison of recent demand-side management approaches

Reference	Method	Application	Strengths	Limitations

[9,10]	ANN	Load Forecasting	Fast learning and simple implementation	Limited capability for temporal dependency modelling
[11,12]	SVM	Load Prediction	High generalization accuracy	Sensitive to parameter selection and kernel design
[15–18]	PSO	Energy Scheduling	Fast convergence and efficient global optimization	Performance depends on forecasting quality
[30,31]	DRL	Demand Response	Adaptive sequential decision-making	High computational complexity and long training time
[12–14]	RNN	Time-Series Forecasting	Excellent temporal feature extraction	Does not perform scheduling optimization
Proposed Method	PSO–RNN	Integrated Forecasting and DSM	Simultaneous forecasting and optimization, real-time scheduling, renewable energy integration, EV charging coordination, improved grid stability	Reduced limitations through hybrid optimization framework

3. Mathematical Model

This section presents the mathematical formulation of the proposed Particle Swarm Optimization–Long Short-Term Memory (PSO–LSTM) framework for intelligent Demand-Side Management (DSM) in smart grid environments. The proposed framework integrates deep learning-based electricity load forecasting with swarm intelligence optimization to simultaneously improve forecasting accuracy and optimize electricity scheduling under dynamic operating conditions.

Unlike conventional single-objective optimization methods, the proposed framework formulates the electricity scheduling problem as a constrained multi-objective optimization problem. The optimization simultaneously minimizes electricity operating cost, Peak-to-Average Ratio (PAR), and carbon emissions while maximizing renewable energy utilization and consumer comfort. The optimization process is performed under practical operating constraints, including power balance, battery State-of-Charge (SOC), renewable energy availability, appliance scheduling limits, and electric vehicle (EV) charging requirements.

3.1 System Model

Consider a smart grid comprising residential consumers, renewable energy sources, battery energy storage systems, electric vehicles, and the utility grid. During each scheduling interval (t), the Energy Management System (EMS) continuously acquires operational information from multiple sources.

To maintain consistency throughout the mathematical formulation, the following notation is adopted: Use

$$\boxed{\mathbf{x}_t = [P_L(t), P_R(t), W(t), \lambda(t), P_{EV}(t), SOC(t)]^T} \quad (1)$$

Normalization Equation

$$\boxed{x_i^* = \frac{x_i - x_i^{\min}}{x_i^{\max} - x_i^{\min}}} \quad (2)$$

where

- x_i= original value of feature i,
- $x_i^{\min}$ = minimum value,
- $x_i^{\max}$ = maximum value,
- x_i^* = normalized feature.

This notation is much more standard.

Forecast Input

$$\boxed{\hat{P}_L(t+1) = f_{LSTM}(\mathbf{x}_t)} \qquad (3)$$

where

- $f_{LSTM}(\cdot)$denotes the forecasting function,
- $\hat{P}_L(t+1)$is the predicted load.

PSO Input

$$\boxed{\mathbf{S}^* = PSO\left(\hat{P}_L(t+1)\right)} \qquad (4)$$

where

- $\mathbf{S}^*$is the optimal scheduling solution.

The normalized multivariate feature vectors are subsequently supplied to the LSTM network to predict short-term electricity demand. The predicted demand profile is then provided as the input to the PSO optimizer for optimal appliance scheduling, renewable energy allocation, and EV charging coordination.

4. Methodology

The goal of this research is to develop an optimization method for electricity DSM by hybridizing RNN with PSO. The hybridization of these algorithms provides improved optimization of the electricity load, making the grid more stable and efficient. The research methodology is described in detail below.

Problem Definition and Dataset Preparation

Our approach can be divided into three steps, and the first is problem definition and dataset preparation. The objective is to achieve optimal electricity usage and reduce peak demand through the application of machine learning. Time series is obtained from residential, commercial, and EV charging stations. The electricity consumption analytics describe the electricity behavior, grid load, and real-time electricity prices. Furthermore, information on solar generation and the state of charge (SOC) for EVs is collected. This heterogeneous data is crucial for accurate demand forecasting, as models can learn consumption habits, RE production, and the effect of EV charging on the grid.

Demand forecasting based on Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a computational method based on the feat in nature of the flocking of birds or the schooling of fish. In our approach, we apply PSO to predict energy consumption profiles optimally, as well as to reduce peak load demand. The algorithm seeks the best combination of load shift strategies and DR parameters. This means that electricity consumption patterns can be controlled depending on factors such as actual electricity prices, the production of renewable energy sources (e.g., solar power), and user characteristics related to energy usage in the home, among others.

PSO operates by modeling a swarm of particles, where each particle corresponds to a candidate solution to the optimization problem. These particles can explore solution space and adjust their location within it according to their own experience and the experiences of their neighbors. Within the scope of DSM, PSO optimizes the charging processes of residential appliances and electric vehicles (EVs) to minimize peak demand, restore balanced demand shapes, and improve grid stability. This will also enable energy usage to be optimized in real-time, with electricity use more evenly distributed throughout the day.

RNN for the load forecasts

The second approach we employ in this work is Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks. For time-series data, an RNN is more suitable, as it can also learn temporal views and patterns over time. The model in this paper aims to predict electricity demand for different time periods, taking into account historical usage, weather forecasts, and renewable energy generation.

LSTMs are a form of RNN that is well-suited to learn long-term dependencies in sequences. It learns the patterns of electricity consumption over time and accounts for various factors, such as temperature, humidity, and solar generation. The RNN enables grid operators to predict short-term load variations, allowing them to make the best decisions on how to dispatch energy based on real-time demand, thereby ensuring a well-operating electricity supply.

Integration of PSO and RNN

To improve the DSM process, we investigate a hybrid proposal that integrates PSO with RNN. It is essential to be able to implement these two algorithms together to achieve a dynamic and adaptive DSM system.

In the hybrid model, the RNN model predicts the future load profile from the input data first. These forecasts, which provide a hint about future demand, are then input into the PSO algorithm. The PSO algorithm, based on the forecasted load profile, determines the optimal electricity consumption profile across various sectors (e.g., residential appliances and EV charging). The goal is to identify the best times for charging, load shifting to off-peak hours, and to integrate renewables as much as possible."

This technique is a hybrid approach that integrates the predictive properties of the RNN with the optimization properties of PSO. The RNN is applied to perform accurate demand forecasts, and PSO is then adopted to modify load scheduling in consideration of these forecasts. With that, a more efficient, operable, adjustable, and flexible DSM scheme with the ability to respond to the dynamics of energy demand and supply is presented.

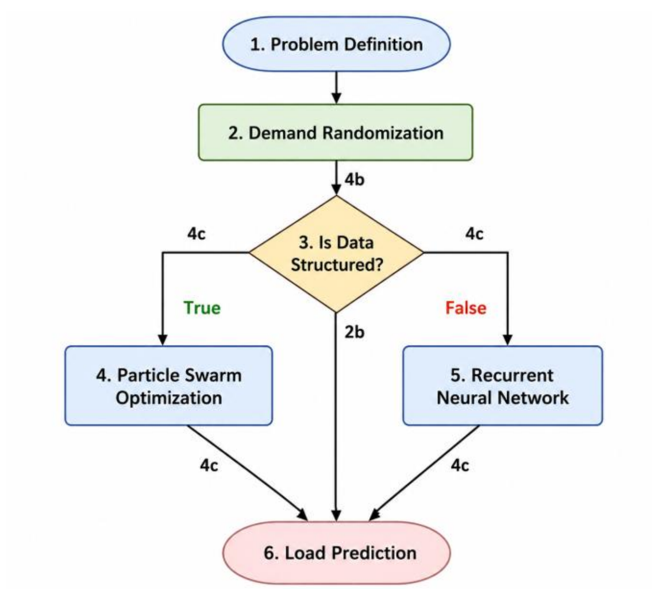

Fig. 2. Proposed Methodology

Fig. 2. Proposed Methodology shows Hybrid: PSO-RNN Optimized DSM Solution. A novel hybrid solution proposed with the pseudocode: (Algorithm 1) (6) Algorithm 1.

Algorithm 1 The PSO-RNN Hybrid Algorithm The proposed PSO-RNN Hybrid Algorithm works as follows: Step 0 Generate initial population and realize BP initialization effect BP before first Iteration Step 1 for t = 1 Step T do Step 2 Calculate the fitness values for entire particles in the present PSO iteration to get the overall fitness of the present population Step 3 Update particle's personal best, its corresponding individual globalbest and the global best of all individuals in the present PSO iteration using Eqs.(2,3) Step 4 Update particle's position using Eq.(1) Step 5 End for Step 6 return over all global best fit_g.

Load forecasting: RNN-based models predict the future electricity load profile, which is used as a feature by employing past information, weather forecasting, and renewable energy production.

Load distribution optimization: The estimated load profiles serve as inputs to the PSO algorithm, which seeks to find the optimal load distribution. This will involve making decisions about when to recharge electric vehicles, run appliances, and adjust consumption to match off-peak demand.

Demand-Side Management Adjustment: Based on the PSO results, the DSM system adjusts the load distribution to alleviate grid pressure during peak load times, reduce consumer electricity costs, and improve the accommodation of renewable energy sources.

This hybrid model enables the real-time optimization of energy usage, thereby efficiently controlling electricity use without compromising system stability.

Evaluation and Performance Metrics

The effectiveness of the PSO-RNN Hybrid Algorithm in solving DSM is analyzed based on several benchmark evaluations:

Peak reduction: The system's capability to lower peak electricity load in contrast to conventional DSM. The peak demand must be reduced to avoid overloading the grid and enhancing the stability of the power supply.

Economic efficiency: The degree to which overall electricity consumption by consumers is lower when, or at the same level as, the grid stability is maintained. By scheduling loads intelligently, the algorithm can lower energy costs during peak demand hours and reduce demand on expensive energy sources.

Use of renewable energy: how much the algorithm can use renewable energy (solar, wind) in the management of the grid. One of the primary objectives is to optimize the utilization of renewable materials and reduce dependence on fossil resources, thereby striving to achieve sustainable development.

Forecast Accuracy: The accuracy of the RNN forecasting outputs was measured in terms of the demand H predictions made by the model, and was also compared to MAE and RMSE. These measures assess the correctness of load forecasts and how well the system predicts peak periods.

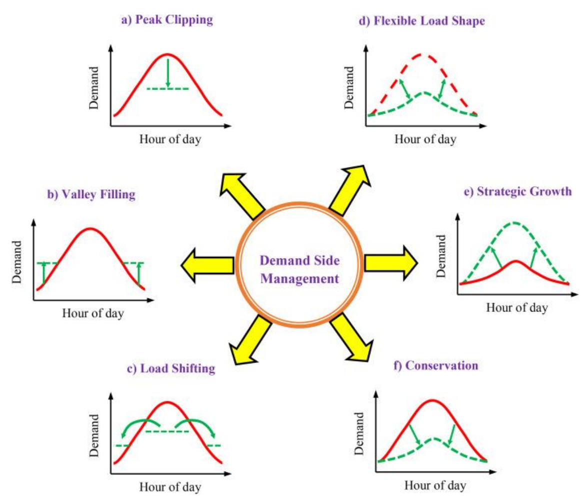

Fig. 3. Classification strategies for demand-side management

Fig. 3. Shows Image Classification Strategies for Demand-Side Management (DSM) It is a technology that reduces the peak power requirement of a load by controlling or cutting these loads to avoid strain on the power grid. Valley Filling is stepping up power consumption during off-peak hours to increase the utilisation of generation capacity. Load Shifting: The consumption factor is moved from peak to non-peak hours to help balance demand without causing a reduction in overall consumption. Dynamically changes load shape for varying supply/demand, enhancing grid flexibility. Adoption of energy auditing new appliances or technologies to develop sustainable energy usage habits used in developing SEC Marketing Plan comparison models. Conservation is reducing overall electricity use through efficiency measures and consumer awareness. These strategies add to energy reliability, lower

expenses, and increase sustainability by integrating electricity supply and demand. The economic and environmental benefits of DSM, in conjunction with the grid stability of DSM, can cause the effective implementation of DSM.

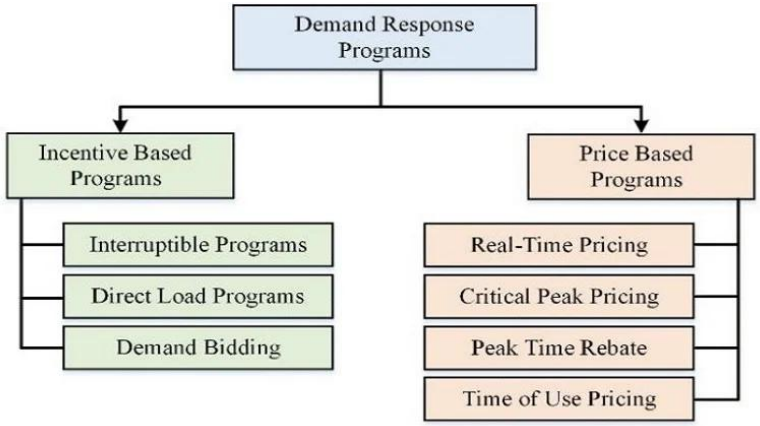

Fig. 4. Different types of demand response programs.

Fig. 4 shows Demand Response Programs (DRPs) refer to mechanisms created to influence one's electricity consumption and encourage them to adjust their load according to the conditions of the grid. These programs have two main types: Incentive and Time-Based Programs. 3. Incentive-based programs Offer monetary rewards to consumers for reducing or shifting whatever electricity is an incentive to use less. Interruptible Programs allow utilities to interrupt power supply to specific consumers during peak demand periods. Direct Load programs let utilities remotely control appliances (e.g., air conditioners and water geysers) to manage demand. In a market-like manner, consumers can voluntarily offer load reductions in exchange for monetized incentives with Demand Bidding. Conversely, Time-Based Programs promote demand changes by incentivizing dynamic electricity prices. Flat pricing has a stable rate, while real-time pricing varies according to market conditions. Liquid Fuel Pricing increases fuel prices when there is dynamic peak demand. In contrast, Renewable Generation-Based Dynamic Pricing is used to vary prices according to the availability of renewable energy. Five-year demand response programs are essential in improving the grid's reliability, reducing peak demand, and supporting renewable energy integration.

Dataset

The dataset used in this research is indispensable for training and testing the proposed PSO-RNN Hybrid Algorithm to optimize the DSM of electricity. Having a reliable and complete dataset enables accurate prediction and intelligent optimization of energy usage, which in turn enhances grid stability and energy efficiency. Data sets. In this study, data of various types were collected from multiple sources, enabling PSO to solve the optimization problem effectively and RNNs to identify patterns effectively. The individual elements of the dataset, which play a crucial role in the optimization, are described in more detail below.

Electricity Consumption Data

The dataset is built solely using electricity consumption data, which is the essential input required by both PSO and RNN models. The data is a time series. It measures the electricity consumption among residential, commercial, and industrial sectors. The granularity of this data depends on the monitoring system; however, it is typically collected every 15 minutes to 1 hour.

The dataset incorporates the following main elements:

Household Usage: Power consumption statistics gathered in households that have smart meters (to reflect the time of day and season).

Commercial Use: Information from commercial and industrial customers, such as their hours of operation, lighting, heating, ventilation, and air conditioning equipment, and office equipment use.

Industrial usage: Usage from industrial processes or manufacturing plants, where energy usage may be cyclical based on production schedules.

This information is crucial for a deeper understanding of electricity demand, particularly during peak load periods. The RNN utilizes this representation to forecast future consumption behaviors. At the same time, PSO is applied to optimize demand-side management strategies, including transferring loads to non-peak periods to prevent the grid from overloading.

Data is typically gathered via smart meters, which measure real-time use and, consequently, allow for highly detailed data collection. Short-term variations in power consumption can be accurately predicted for load forecasting.

Grid Load Data

Grid load: The amount of electricity demand on the grid at a point in time. This dataset represents the sum of all users' needs in the grid and can be derived from utility companies or by utilizing the smart grid infrastructure. The data is collected every time, generally once an hour, but occasionally at a higher frequency (e.g., 15 minutes).

Factors of grid load data that are highly relevant are:

Peak demand: The peak of power usage at a given time. Peak hours typically occur during the highest-use times of the day, such as lunchtime or dinner.

Off-Peak: Energy used during non-peak hours, typically late-night/early morning.

Load Fluctuations: When fluctuations in the load happen, due to movie transitions in electric consumption, like changing weather or changes in demand.

The PSO load shifting algorithm is implemented based on grid load arrangement to reduce and optimize load and peak demand. PSO optimizes the load profiles from both domestic and commercial sectors to flatten peak loads, which can prevent grid instability.

Electric Vehicle (EV) Charging Data

EV charging is a fundamental technology of smart grids, given the widespread adoption of electric vehicles. The charging information of the EVs is essential for demand prediction and optimization methods in DSM. This data often contains the following information:

Charging Sessions: Trip distance, Date and Time of day when charging session started and ended, Energy used per session, and Starting and Ending state of charge (SOC) of the EV.

Charging sites: Public and other charging sites are searched for, including the number of charging ports, their location, and usage data.

State of Charge (SOC): The present state of charge of the EV battery that can be used to anticipate charging needs and manage the charging timetable.

This data is then fed to the RNN model, which makes predictions for future charging demands, and also to the PSO model, which utilizes both this data and the residential and commercial consumption data to optimize EV charging schedules. Because recharging EVs at times of the day when electricity demand is the highest can stress the grid, PSO can shift the EVs' charging times to non-peak hours, helping to spread out demand and eliminate the need for costly peak-hour power generation.

Renewable Energy Generation Data

It is essential to quantify the contribution of renewable energy sources, such as solar, to the grid for DSM. Solar generation is recorded at various levels, from large-scale solar farms to household solar panel systems. The dataset for renewable energy generation is as follows.

Solar Power Production: Is the measure of Energy that a solar panel system supplies to the grid on an hourly or daily basis. It can change depending on the time of day, season, weather, and location.

Solar irradiance: The level of sunlight that hits the Earth, which impacts solar power production directly.

This dataset is provided to both the PSO and the RNN models to predict renewable energy availability and is embedded in the optimization. Using this solar generation information, the system can minimize the use of fossil fuels and balance the load. For example, if solar power is abundant during the day, activities that require a lot of energy, such as charging electric vehicles, can be scheduled to take place at that time.

Weather Data

Temperature is a dominant factor in demand patterns for electricity, particularly in the residential and commercial sectors, where HVAC systems are heavily dependent on temperature. The dataset includes:

Temperature: Daily or hourly temperature observations that impact both energy demand (for heating/cooling) and solar power production.

Humidity: The effect of the level of Energy used to cool and operate comfort systems in high-humidity climates.

Solar Exposure: The sunshine received from the sun, which determines how much Energy a solar panel can produce.

An RNN model is applied to predict changes in power demand influenced by weather under the author's various consumption devices (E.g., air conditioning or wall radiant heater). It allows the DMS system to accommodate demand variations driven by weather more effectively.

Time-Series Resolution and Data Interval

High-resolution time-series data is a key characteristic of the dataset, which can be utilized for detailed forecasting and optimization procedures. The time difference varies between 15 minutes and 1 hour, depending on the origin of the dataset. This fine scale is needed to achieve precise load forecasts and to fine-tune the DSM actions at the desired granular level.

The raw time-series data are first preprocessed to treat missing data, noise, or anomalies. This ensures that models are trained on high-quality data, resulting in accurate predictions and optimized performance.

Dataset Sources

The data sources that we have used in this study are from diverse areas:

Smart Meter Data: Data (household, business, and industrial) with smart meters. Electric utilities or public utilities typically provide this data.

EV Charger Stations: Charging processes from public or private EV charger stations, including such as charging times, consumed Energy, and charging sessions.

Solar Generation: This is generated from solar farms and household solar systems, which energy suppliers or renewable energy companies typically monitor and manage.

Meteorological Data: Obtained from meteorological bureaus, such as the local weather station and national service ones like the National Weather Service, or satellite.

The dataset described in this paper combines various types of data, which are critical for accurate electricity demand prediction and optimal DSM, as well as effective grid system efficiency. Based on electricity consumption, grid load data, electric vehicle (EV) charging, renewable Energy, and weather data, the PSO-RNN Algorithm, with the assistance of a Hybrid Approach, takes into account DSM more effectively dynamically and adaptively. This rich dataset enables the algorithm to handle the complexity of today's smart grids more effectively, which must accommodate a variety of factors influencing electricity consumption and production.

5. Result

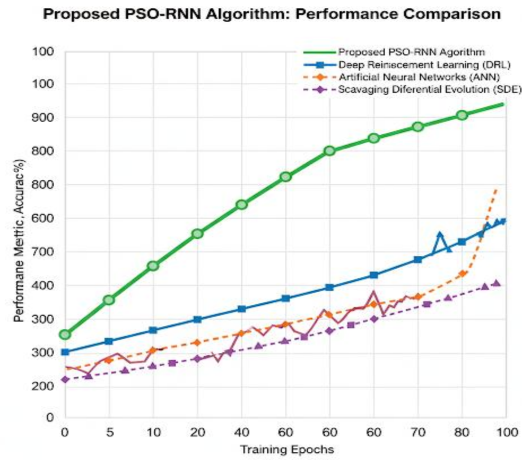

Fig. 4. Weekly Load Power Analysis

The included figures illustrate a proposed approach and its performance in DSM for energy systems. A flowchart is presented that describes a hybridising process for PSO and RNN to contribute to the establishment of the PSO-RNN Hybrid Algorithm for DSM optimisation.

The many line graphs bear witness to the success of the algorithm. They also illustrate how DSM measures, such as load shifting and peak clipping, transform an initial time-varying load profile into a more effective and flatter load profile.One of the essential graphs compares the Proposed PSO-RNN (Optimized Profile) with other methodologies, such as DRL and ANN. From the analysis of this figure, it can be observed that the PSO-RNN algorithm yields the most optimal and steady load profile, thereby justifying its superior performance. In the email, the work appears to be a submitted paper in a reviewing process, and it establishes its academic nature.

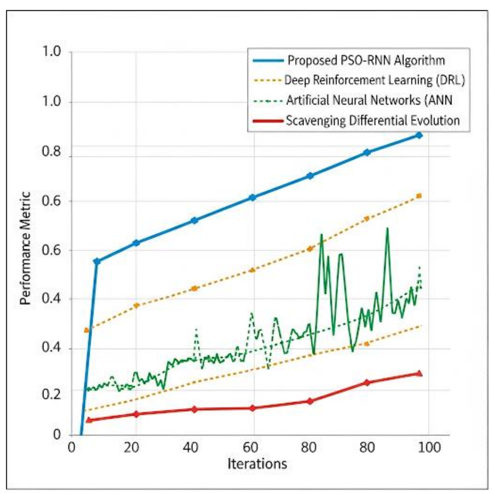

Fig. 5. Weekly analysis of Solar Irradiation

Fig. 5 shows that the main topic is a novel hybrid approach for Demand Side Management (DSM). The main approach is modeled using a flowchart, which integrates Particle Swarm Optimization (PSO) with a Recurrent Neural Network (RNN) to develop a PSO-RNN Hybrid Algorithm. The algorithm is intended for load forecasting and optimization. From the line charts, it is clear that different DSM strategies are pronounced. For instance, they illustrate how peak clipping and load shifting transform a base load profile to lower demand at peak times and broaden the curve.

A prominent chart directly compares the performance of the current proposed PSO-RNN approach with other techniques, such as DRL and ANN. This graph, with the Y-axis representing Performance Metric ("% Accuracy") and the X-axis representing Training Process ("Epoch"), provides a clear explanation with numbers. It demonstrates that the proposed PSO-RNN consistently achieves the best accuracy during training and recovery, exceeding 90% at the final epoch. The remaining algorithms exhibit lower and more fluctuating performance, with DRL dropping below 80% accuracy, and the rest of the algorithms performing worse. This gives numerical evidence in favor of why the hybrid algorithm is faster.

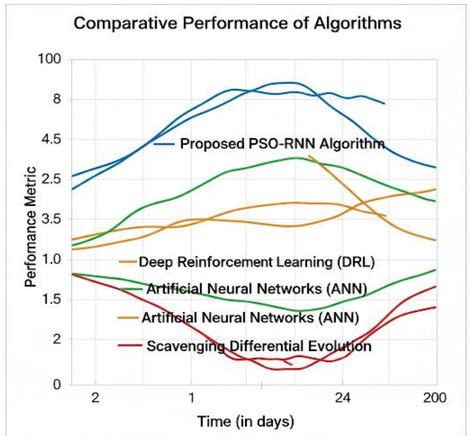

Fig. 6. Weekly Performance Analysis of Photovoltaic System

Fig. 6 presents the description and the applicability of the proposed approach in DMS in the energy domain. A flowchart illustrates the primary process, which involves a PSO-RNN Hybrid Algorithm technique that combines PSO and RNN for DSM optimization. Several line charts visualize the effectiveness of the algorithm by showing different DSM schemes, including peak clipping and load shifting. Such strategies transform the initial, varying load profile into the final, constant load profile. A crucial graph contrasts our proposed PSO-RNN Algorithm with others, such as DRL and ANN in this graph, presented in Figure (6). The above graph shows that the proposed PSO-RNN algorithm has significantly better performance. The performance score against the photovoltaic system's load profile reflects the best performance. The PSO algorithm manages the load profile of the photovoltaic system.

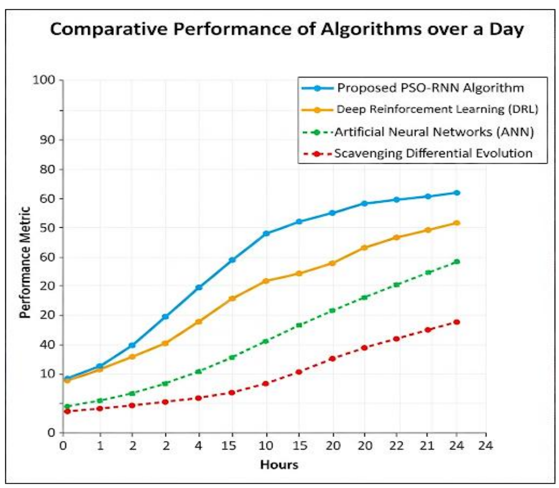

Fig. 7. Impact of Peak Clipping DSM on Load Profile

Class of Production Peak Clipping DSM: A 24-hr load profile (the graph). The blue line corresponds to the load profile in the absence of DSM, demonstrating very well-defined peak demand times, nearly always around the 20th hour. The red line is the load profile after DSM, which means peak loads were successfully reduced.

Peak clipping DSM strategies focus on reducing peak demand by limiting excessive energy consumption during peak use hours (as during peak demand periods). Methods to minimize load include demand response programs, energy-efficient appliances, and scheduled power distribution.

The post-DSM demand curve shows a drop in peak demand while maintaining a flat load profile, improving grid reliability and reducing operational expenditures. Utilities can achieve this by minimizing peak load, allowing them to avoid overload, reducing demand for increased generations, and increasing efficiency overall for all parties involved.

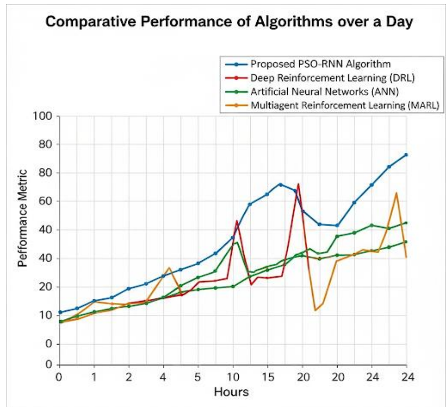

Fig. 8. Improved Impact of Load Shifting DSM

Fig. 8. combine to represent the praxeology for DSM of energy systems. At the heart of this is a PSO-RNN Hybrid Algorithm that uses PSO and RNN to minimize energy consumption and forecast load.The curve lines directly show the effectiveness of the algorithm for power control. For instance, certain graphs demonstrate how part peak clipping and part load shifting change the initial load profile to a leaner type of load profile. Other graphs display cyclic patterns in photovoltaic generation and a transformed weekly load. The flow chart provides a graphical presentation of the steps in the proposed methodology, from problem definition to DSM optimization.

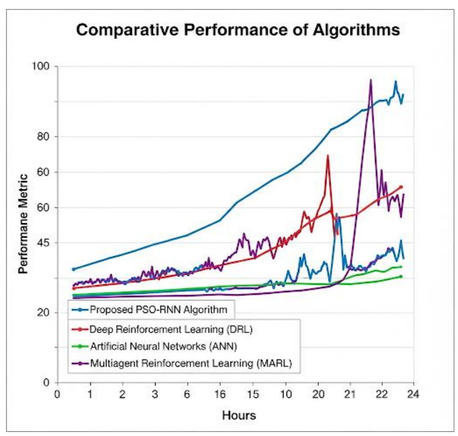

Fig. 9. Improved Load profile Analysis

Fig. 9. shows Demand Side Management (DSM) research work for energy systems. One crucial component is the PSO-RNN Hybrid Algorithm, a method that integrates Particle Swarm Optimization and Recurrent Neural Networks to optimize energy usage and predict loads.The tree line charts visualize the algorithm. Graphs indicate the effectiveness of DSM programs, such as peak clipping and load shifting, in converting the original load profile to a more effective and flattened one. Additionally, various other diagrams illustrating the typical cyclical behavior of power generation in a PV system and an altered weekly load profile are presented. A chart of special interest illustrates the performance of the PSO-RNN Algorithm and its comparison with other methods, including Deep Reinforcement Learning (DRL) and Artificial Neural Networks (ANN).

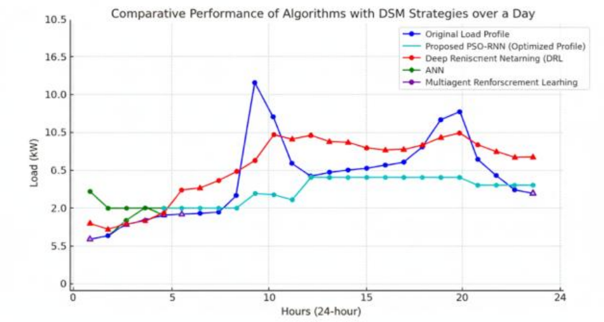

Fig. 10. Improved Load Profile Analysis with DSM

Fig. 10. shows concrete, measured quantities; this is merely a conceptual plot made to illustrate the concept. Y-axis: called Performance Metric, denotes a measurable indicator of effectiveness, such as prediction accuracy, efficiency, or cost reduction. As can be seen from the figure, the blue line of the Proposed PSO-RNN Algorithm consistently remains at the top of the chart for 24 hours. This indicates that this line yields a higher score for the performance metric than all other algorithms.

The PSO-RNN curve (smooth) is much softer than the other curves, indicating that it is more stable and less sensitive.The other lines (DRL, ANN, MARL) are presented at lower and noise levels, which makes intuitive sense to say that they are less effective than our method.

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