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ABC OPTIMIZATION ALGORITHM BASED ENERGY EFFICIENT ROUTING SCHEME FOR WSNs.

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Abstract

In a smart grid, the best energy scheduling is essential to the overall system's energy usage. In reality, effective scheduling can save a significant amount of energy for larger systems. Regarding the smart grid's integration of renewable energy sources, this study explores real-time task scheduling to maximize energy consumption. Analyzing how variations in renewable energy affect grid synchronization, assessing the effectiveness of various optimization techniques, and identifying key challenges and their solutions are the main objectives. We further enhance the algorithm's search performance by merging chaotic local search with memory-based chaotic map selection, and by replacing the initial selection strategy with a novel fitness-distance balance-based selection method.To address the issue of premature convergence in the MHS process, a

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novel fitness-distance-balance (FDB)-based selection technique is created in this study. The important results demonstrate how power system stability is impacted by variations in renewable energy. Energy storage and sophisticated prediction techniques are crucial for mitigating these effects.

Keywords: scheduling in real time, optimization of energy, Grid integration, smart grid, renewable energy, scheduling algorithms, Resources for Distributed Energy, Optimization of the Power System.

INTRODUCTION

Most big cities have a high rate of air pollution exposure, which is extremely concerning because it can have fatal consequences for people's health and well-being. Furthermore, it is extremely difficult to accurately estimate and continuously forecast pollution levels. This study introduced and improved a vector autoregressive (VAR) with neural network, one of the space-temporal models [1]. It is possible to meet the energy demand with proper planning. Both cheap costs for the final customer and efficient utilization of resources depend on careful planning. On the other hand, inappropriate demand estimation can lead to resource waste and an energy crisis. The factors influencing power usage can be effectively modelled to enable precise estimation [2].In general, time-series forecasting techniques fall within the category of statistical machine learning (ML) techniques and their combinations. Time-series data's linear features are predicted by statistical methods, which are unable to identify complicated and nonlinear patterns [3]. The first area is bio-inspired procedures, where a variety of methods are suggested. Particle Swarm Optimisation (PSO) draws inspiration from the intelligence and mobility of swarms. The survival tactics of rabbits, such as random concealment and detour foraging, served as the model for the optimisation of artificial rabbits [4]. Because of the conflicting interests, this creates a difficult position for politicians. Agricultural policy planning, investment decisions, and marketing strategies all depend on accurate agricultural commodity price forecasts [5].The environmental problems brought on by the use of fossil fuels and the ongoing rise in energy demand have steadily drawn attention from all around the world to wind power generation. Wind power generation and installation worldwide are on the rise, with a strong development trend [6]. As a result, a reliable one-day forecast of solar radiation and wind speed is essential to a secure and stable hybrid energy system.This forecast guarantees the safe integration of renewable energy sources (RES), which supply high-quality electricity at a reasonable cost, as well as the reliable and safe operation of electrical systems.Here, we suggest a unique hybrid approach to estimating solar irradiance and wind speed [7].MEC research is currently focused on this service because it has experienced several unresolved difficulties at the server level, also known as the edge layer, and the user level, also known as the device layer.The first and most important problem is deciding if offloading is good for the user and whether to split jobs according to their

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dependencies or unload the entire set of activities [8]. The stock market trading optimal portfolio problemis addressed by the novel method proposed in this study. Our innovative portfolio trading approach outperforms previous benchmark techniques in a real-market setting by using three features [9].Although demand for items is influenced by brand loyalty, a precise pricing strategy is necessary to determine a fair price. For perishable food, this study offers a pricing model that takes into account the product's brand value as well as the expenses of rival manufacturers [10].In order to handle environmental changes in DMO, The vector autoregressive (VAR) proposed in this paper is a combination of environment-aware hyper mutation and vector auto regression (VAR).VAR creates a VAR model that takes into account the connections between decision components in order to accurately forecast moving solutions in dynamic circumstances [11].In order to estimate demand for businesses, Abbasimehr et al.) used an LSTM model, which automatically chooses the optimum forecasting model for a given time series by taking into account various combinations of LSTM hyperparameters using a grid search technique. Ma et al. used an LSTM model to anticipate the lifespan of industrial supplies (Ma & Mao, 2020). Although these techniques enhance the LSTM model to differing degrees, they ignore a number of influential elements. When predicting and analyzing stocks over time, many methods consider information from multiple states.By utilizing a DPA to optimize the aircraft maintenance inspection process, Deng, Santos, and Curran (2020) minimized time and economic costs by shortening the interval between two aircraft maintenance procedures. In contrast, Wang, Kang, and Liu (2020) put up a model that consists of three elements. Initially, they suggested a dynamic programming model to tackle the scheduling issue of electric bus fleets.Second, they put forth an inverse order matching technique that takes workload variations and the process of battery capacity degradation into consideration.

PROPOSED SYSTEM

2.1smart grid application cases for DL

Through initiatives and use case trials, the scientific community and industry have shown a great deal of interest in the application of DL for DR and SGs. Figure 1 shows how DL models are used in smart grids for demand response. Optimised energy use, intelligent data filtering, improved energy trade projections, efficient coordination between the decentralised plants, automated energy distribution, precise detection, and self-responsiveness to different grid issues are all benefits of DL. When DL is used effectively, it gives customers direct control over how much power they use and how it is distributed, which promotes consumer transparency on energy management. Forecasting the EV's loading, unloading, and future maintenance can be done with DL.The most common use cases for DL adoption for DR and SGs are highlighted in this section.

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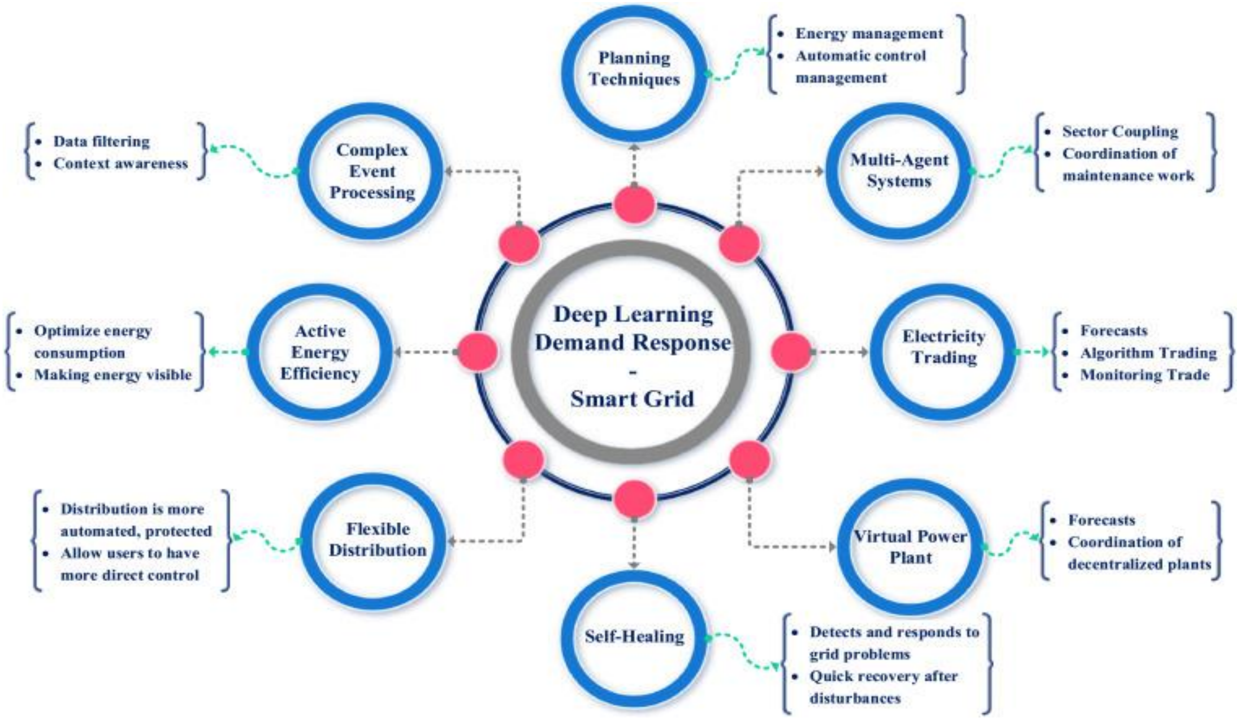

Fig. 1. Deep learning's function in smart grid demand response.

2.2 Real-time incentive-based smart grids

In order to calm the power systems, it is vital to balance the production and consumption of electricity. Both the producer and the consumer will be required to pay more if supply and demand are not aligned. To balance energy variation and enhance grid authenticity, several models have been developed thus far. The entire computation part of the reinforcement method relies on a mapping table, which may be implemented in several real-world applications with relative ease.

2.3 Modelling energy storage devices for smart grids

A model for the smart grid's energy storage system must be constructed before dynamic programming can be used to start solving the energy consumption dispatching problem. The smart grid's fundamental energy storage system layout is depicted in Figure 2. The three primary components of the smart grid energy storage system—the battery system, super capacitor system, and DC/DC DC converter—are the subject of this article. One of these, the DC converter, connects the battery system in parallel to the DC bus. Both devices have constant internal resistance; the Rint model is used to simulate the battery, and the internal resistance model is used to model the super capacitor.Because the states of batteries & super capacitors are equally

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important in smart power grids, single state variables are insufficient to describe how they change. In traditional states, state features can be represented by a single state variable.

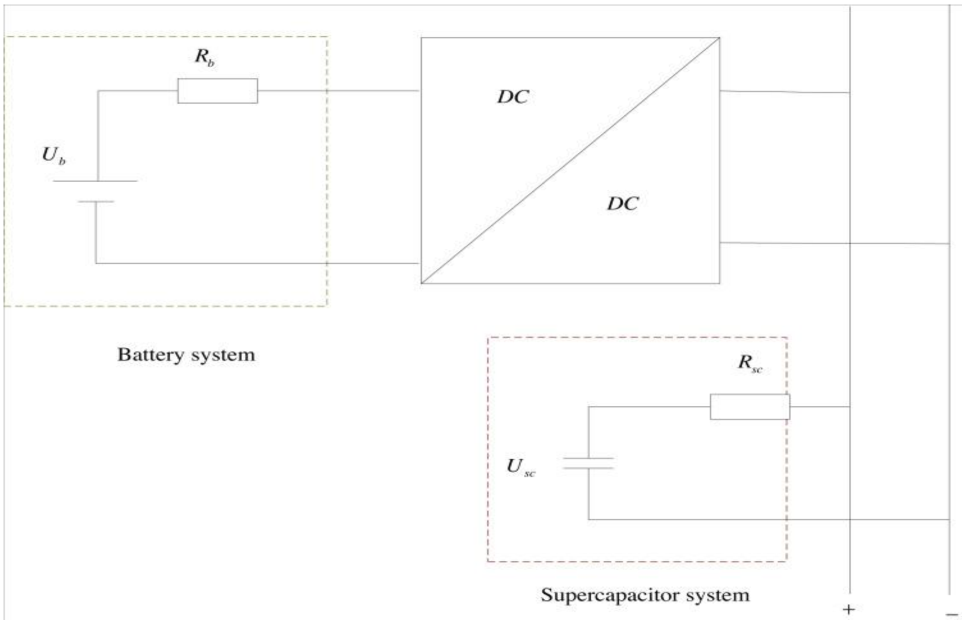

Figure 2. Schematic diagram of smart grid energy storage system.

The energy storage system's fundamental smart grid setup is displayed. The DC/DC DC converter, supercapacitor system, and battery system are the three main parts of a smart grid energy storage system that are examined in this article. Of them, the DC converter is used to link the battery system in parallel to the DC bus. With the internal resistance held constant, the battery and supercapacitorare subjected to the Rint model and the internal resistance model, respectively.

The power demand of a smart grid node at the k discrete event interval is assumed tois $P_{req}(k)$, Eq. (1) illustrates the energy flow relationship of the on-board hybrid energy storage system.

$$= \begin{cases} (I_b(k)U_b(k) - I_b^2(k)\eta + I_{SC}(k)U_{sc}(k) - I_{sc}^2(k)R_{sc}P_{req}(k) < 0 \; P_{req}(k) \\ \frac{I_b(k)U_b(k)+I_b^2(k)R_b}{\eta} + I_{sc}(k)U_{sc}(k) + I_{sc}^2(k)R_{sc}P_{req}(k) < 0 \end{cases} \quad (1)$$

$U_b(k)$ represents the super capacitor no-load voltage,$I_b(k)$ represents the super capacitor current, $U_{sc}(k)$ represents the battery no-load voltage, and $I_{sc}(k)$ represents the battery current. η represents the DC converter efficiency. When$P_{req}(k) > 0$ is greater than zero, the smart grid is operating; when$P_{req}(k) < 0$ is less than zero, the smart grid reduces its energy consumption.

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$$U_b(k) = aSOC_b^4(k) + bSOC_b^3(k) + \cdots + e \quad (2)$$

In relation to its charge state, which is determined by dividing the square root of its voltage measurement in one state by the square of its voltage value in a fully charged state, a super capacitor's empty voltage acts as follows:

$$U_{sc}(k) = \sqrt{U_{sc,N} \, .SOC_{sc}(k)} \quad (3)$$

where, $U_{sc}(k)$ is the voltage of the super capacitor under full charge; $SOC_{sc}(k)$ is the charged state of the ultra capacitor at the k discrete time interval.

Consequently, if the battery's $P_b(k)$, output power is chosen as the decision variable $j(k)$ and the super capacitor's and battery's SOC are considered as the system's state variables $z_1(k)$ and $z_2(k)$,the super capacitor's output power may be calculated as follows:

$$P_{sc}(k) = P_{req}(k) - u(k) \quad (4)$$

As the state variables & choice factors in the k-th phase impact the state values in the k + 1-th phase, Eq. (5) illustrates a discrete scenario of the equation for state of a smart grid battery system.

$$\begin{cases} z_1(k) = f_1(z_1(k, u(k)) \\ z_2(k) = f_2(z_2(k), u(k)) \end{cases} \quad (5)$$

where f_1 and f_2 are the state variables' transfer functions$z_1(k)$ and $z_2(k)$, respectively.

$$\begin{cases} I_b(k) = \frac{U_b(k) - \sqrt{U_b^2(k) - 4R_b u(k)}}{2R_b} \\ z_1(k+1) = z_1(k) - \frac{I_b(k)\Delta t(k)}{Q_{b,N}} \end{cases} \quad (6)$$

$$\begin{cases} I_{sc}(k) = \frac{U_{sc}(k) - \sqrt{U_{sc}^2(k) - 4R_{sc}P_{sc}(k)}}{2R_{sc}} \\ z_2(k+1) = z_2(k) - \frac{P_{sc}(k)I_{sc}^2(k)R_{sc}}{\frac{1}{2}C_{sc,N}U_{sc,N}^2} \end{cases} \quad (7)$$

where $\Delta t(k)$ is the length of the k phase, $Q_{b,N}$ is the battery's rated capacity, $C_{sc,N}$ is the super capacitor's rated capacitance,$U_{sc,N}$ and is the super capacitor's rated voltage. For a given state variable at the n-th stage, the optimal objective function can be expressed as follows:

$$J\big(z_1(n), z_2(n)\big) = \min_{u(n)} \Big(L\big(z_1(n), z_2(n), u(n)\big)\Big) \quad (8)$$

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The cost function, represented by the letter L, represents the loss value of the smart grid energy storage system. In the k-th phase, the state variables are determined using Eq. (9), which displays the optimal objective function used to identify the best course of action. When the grid energy storage system moves from the kth state to the final state process, this is the overall loss value.

$$J\big(z_1(k), z_2(k)\big) = \min_{u(n)} \Big(L\big(z_1(k), z_2(k), u(k)\big) + J(z_1(k+1), z_2(k+1))\Big) \quad (9)$$

where $z_1(k)$ and $z_2(k)$ are the smart grid's state variables, while $u(k)$ serves as the decision variable.

Edge Computing attempts to overcome this issue by manipulating data on integrated devices that analyse data at the infrastructure's edge. An enhanced architecture that processes data from the smart grid using the smart home is shown in Figure 3. Among the many issues facing the current electrical grid are unforeseen interruptions and power outages, undetectable customer theft, set electricity pricing, etc. These difficulties raise the price of electricity and fuel the expanding need for fossil fuels. The following ideas are offered by the smart grid to address the performance and efficiency issues with traditional networks.

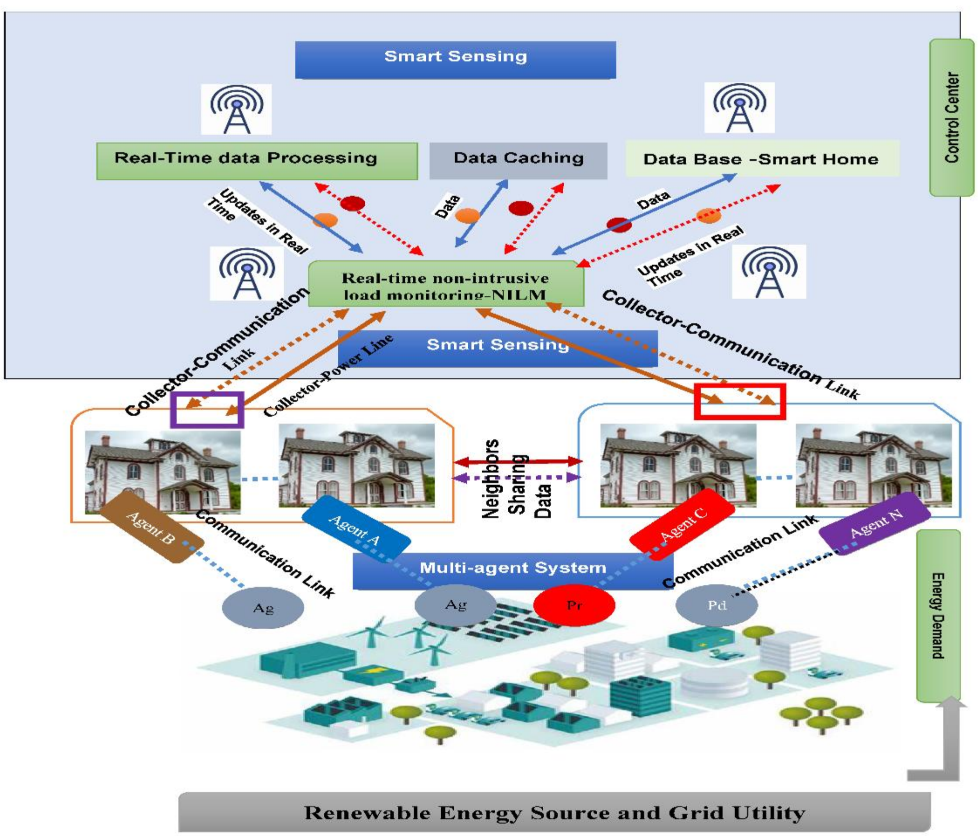

Figure 3. The Model of the Smart Grid.

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In order to reduce costs, save energy, and improve security, interoperability, and dependability, smart grids (SGs) employ cutting-edge information, networking, and real-time monitoring and control technologies. Real-time information on network protection, monitoring, and control can be obtained using smart sensors (SSs). A sustainable energy infrastructure is anticipated to be provided by the smart grid through bi-directional data, energy flows through sophisticated knowledge, interaction, and communication infrastructure. The idea of consumers is seen as appealing and will play a crucial role in this smart grid. Customers in this situation can be identified as both energy producers and energy dealers at the same time. Together with using energy, consumers also contribute to the network and/or excess energy generated locally by renewable energy sources (e.g., wind turbines, solar power).

By using fossil fuels, there are environmental, societal, and economic problems that need to be addressed. To influence customers in the energy exchange system, the smart grid enables stakeholders to build communities based on a variety of characteristics, including energy usage. When using renewable electricity, consumers have a large selection of electricity markets to choose from, and they can establish an average megawatt-hour for a particular calculation. As an alternative, power outages can be managed on a regular basis to boost the battery's storage system and capacity. Numerous power connectors are present in the SG network.

Hybrid Vector Autoregression Fitness Distance Balance Algorithm

A VAR model and an FDB technique are combined in a hybrid vector autoregression (VAR) fitness distance balance (FDB) approach, which may be used for time series forecasting or optimisation tasks. A population of solutions is searched for optimal solutions using the FDB algorithm, while the VAR model records the interactions between variables across time. The FDB algorithm improves its capacity to find good solutions by selecting and diversifying the population using fitness and distance information. The goal of FDB as a selection technique is to find one or more candidate solutions that are better suited for the population search. The reference sites that direct the search process are identified using Fitness Distance Balance (FDB), a potent selection technique.

The most promising choices for solutions to enhance the population's search process are identified using the FDB. Multiple variables are predicted by VAR models, which are multivariate time series models, using both their own historical values and those of other variables in the system. They make the assumption that the lagged values of other variables in the system as well as their own lagged values have an impact on the current values of variables. In economics, VAR models are frequently used to forecast macroeconomic variables. Evolutionary algorithms employ FDB as a selection technique to strike a balance between exploration and exploitation. It chooses people for reproduction by weighing their distance from other members of the population as well as their fitness, or how well they perform.FDB

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contributes to the preservation of population variety by choosing individuals who are fit and sufficiently apart from one another to avoid an early convergence to less-than-ideal solutions.Vector autoregression (VAR) is a multivariate time series model that uses a system of n equations to describe n distinct, stable response variables that are linear functions of lagged responses along with additional components. The degree p of a VAR model also distinguishes it; in a VAR(p) model, each equation has p delays for each system variable.

```
%%%% Hybrid Vector Autoregression Fitness Distance Balance Algorithm%%%%
% Sources with variable maximum generation
% You can define the profiles by using vectors.
% TWind:Time vector for wind profile
% TSol:Timevector for solar profile
CmaxWind=6*[0.9 0.9 0.8 0.8 0.8 0.7 0.6 0.5 0.4 0.4 0.4 0.3 0.3 0.3 0.3 0.3 0.4 0.4 0.5
0.5 0.5 0.6 0.7 0.8];
TWind=[0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23];
CmaxSol=4*[0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.1 0.3 0.5 0.6 0.8 0.9 0.9 0.9 0.8 0.7 0.6 0.4
0.2 0.0 0.0 0.0 0.0];
TSol=[0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23];
% Payoff matrix
payoff={[0,4],[4,0],[5,3];
   [4,0],[0,4],[5,3];
   [3,5],[3,5],[6,6]};
celldisp(payoff)

%%
% Nash equilibrium for mixed strategy
[v,NE] = NashEquilibriumMixedStr(payoff);
celldisp(v)
celldisp(NE)
%%%%Reinforcement Learning
%%Initialization
r2d = 180/pi;
lenHouse = 30;
widHouse = 10;
htHouse = 4;
pitRoof = 40/r2d;
numWindows = 6;
htWindows = 1;
```

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```
widWindows = 1;
windowArea = numWindows*htWindows*widWindows;
wallArea = 2*lenHouse*htHouse + 2*widHouse*htHouse + ...
    2*(1/cos(pitRoof/2))*widHouse*lenHouse + ...
    tan(pitRoof)*widHouse - windowArea;
% -------------------------------
kWall = 0.038*3600;   % hour is the time unit
LWall = .2;
RWall = LWall/(kWall*wallArea);
kWindow = 0.78*3600;  % hour is the time unit
LWindow = .01;
RWindow = LWindow/(kWindow*windowArea);
Req = RWall*RWindow/(RWall + RWindow);
c = 1005.4;
THeater = 60;
Mdot = 3600;  % hour is the time unit
densAir = 1.2250;
M = (lenHouse*widHouse*htHouse+tan(pitRoof)*widHouse*lenHouse)*densAir;
disp('Reinforcement learning using Q-LEARNING')
cost = 0.09/3.6e6;
TinIC = 10;

% Runs the simulation in background without open simulink model.
fprintf('Price control simulation is running in background mode. Please wait until the
end of simulation ...\n');
sim('ClosedLoopGenerationControlGeneric');
fprintf('Price control simulation is completed. The results are drawn in figures\n');
```

RESULTS

Figure 4 illustrates the relationship between total load and grid capacity over a 24-hour period. The blue bars represent the grid's capacity (load it can handle), while the orange segments indicate the excess load beyond that capacity. This visualization highlights a persistent and escalating mismatch between energy demand and the grid's supply capability, emphasizing the urgent need for demand-side managementor infrastructure upgrades to prevent overload and ensure stable power delivery.

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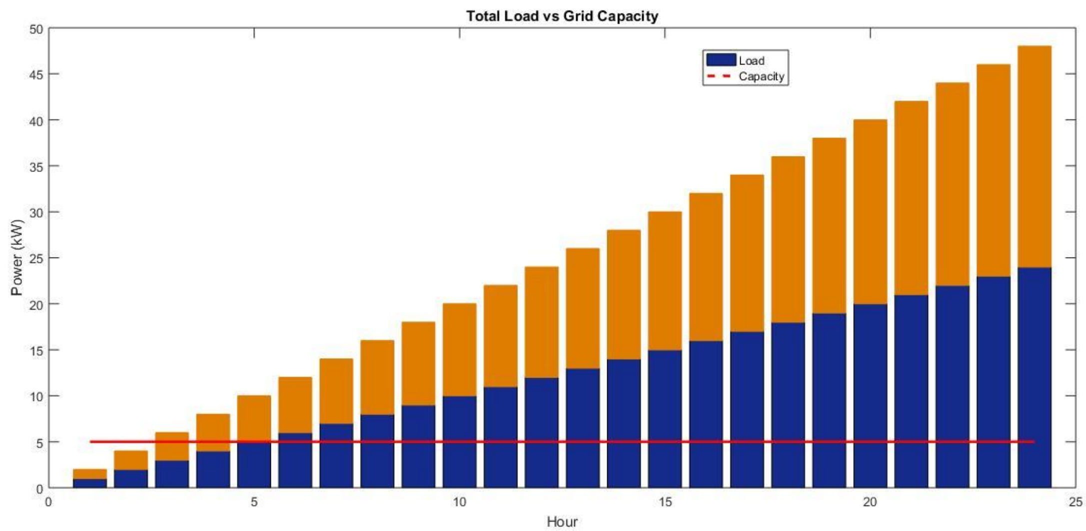

FIGURE:4 Total Load vs Grid Capacity

Figure 5 shows the variation in time-of-use electricity pricing across a 24-hour period. The green bars represent the price per kilowatt-hour ($/kWh) for each hour of the day. This pricing structure incentivizes Customers should switch to off-peak hours when energy prices are lower, promoting demand-side energy efficiency and helping to balance the load on the grid.

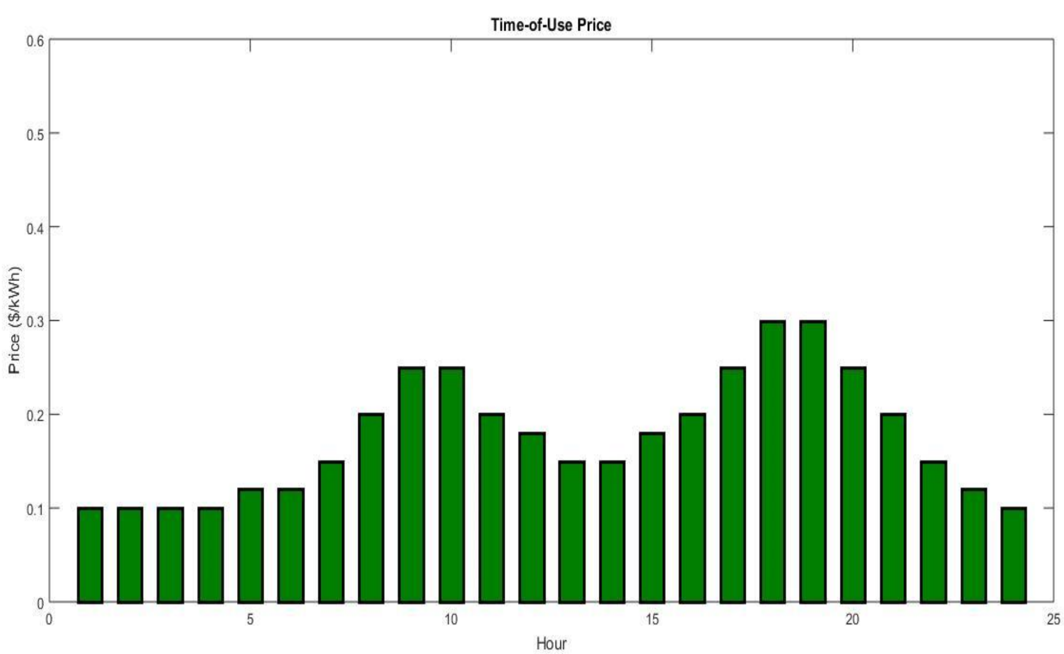

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FIGURE:5 Time-of-Use Price vs Hours

Figure 6 depicts the hourly power consumption before any scheduling adjustments were implemented. The data shows a relatively high and uneven energy demand throughout the day, with noticeable fluctuations. Such unscheduled and unoptimized consumption patterns can lead to inefficiencies, increased energy costs, and higher stress on the grid during peak hours. This underscores the need for demand-side management strategies, such as load scheduling or time-of-use pricing, to distribute energy usage more evenly.

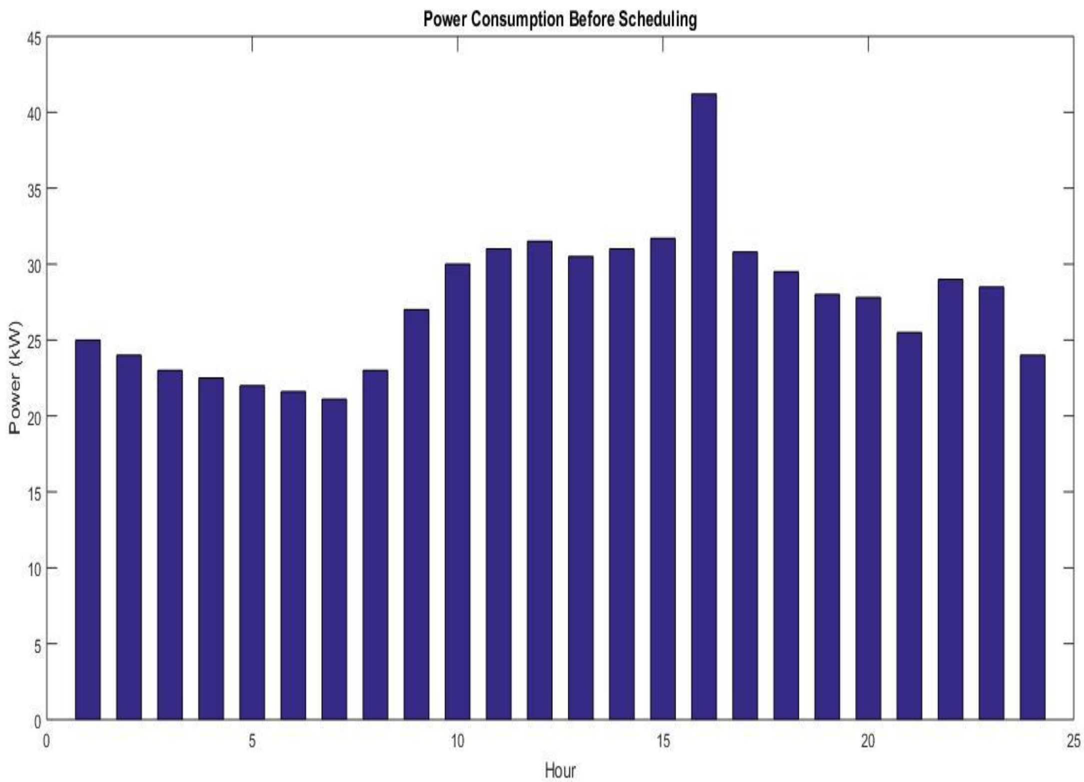

FIGURE:6 Power Consumption Before Scheduling

Figure 7 presents the power consumption profile after scheduling has been applied, showing a significant improvement in load distribution compared to the unscheduled scenario. The red bars indicate a smooth and gradual increase in power usage throughout the 24-hour period, eliminating sharp peaks and dips. This even distribution suggests that demand-side management strategies, such as load shifting or smart scheduling, have effectively balanced energy use, reducing strain on the grid and enhancing efficiency. Such an optimized pattern not only supports grid stability but also aligns better with time-of-use pricing models, potentially lowering overall energy costs.

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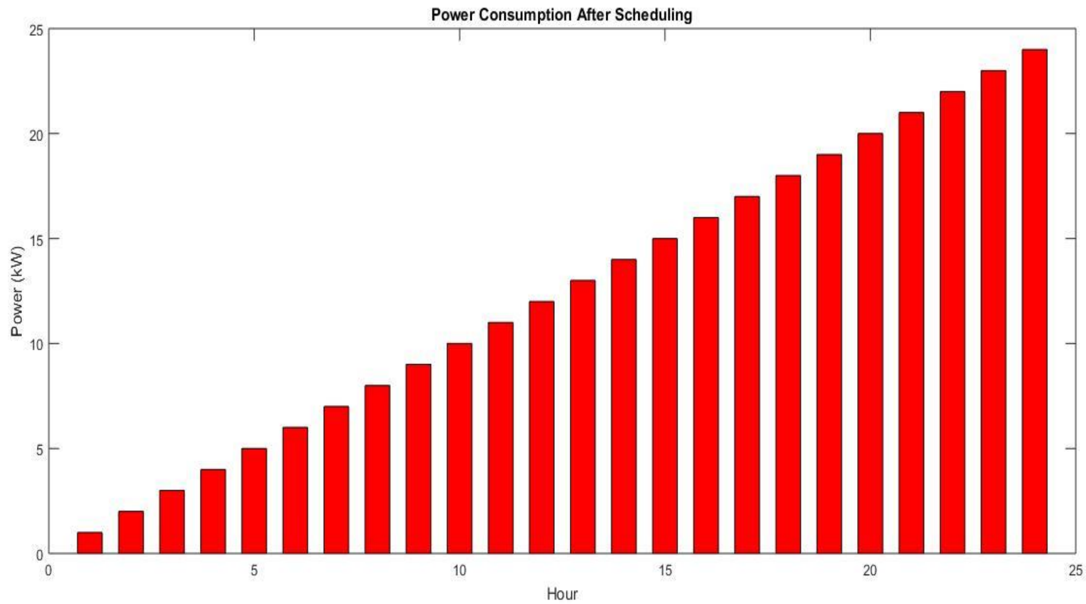

FIGURE:7 Power Consumption After Scheduling

Figure 8 displays the base load forecast using a Vector AutoRegression (VAR) model across a 24-hour period. The chart shows a consistent and stable power consumption prediction of approximately 1 kW for each hour, indicated by evenly spaced colored circles. This suggests that the base load—representing the minimum constant level of demand—remains uniform throughout the day without significant fluctuations. Such a stable forecast is crucial for energy planning, as it provides a reliable foundation upon which dynamic or peak loads can be scheduled, enhancing overall grid efficiency and reducing the risk of overloading.

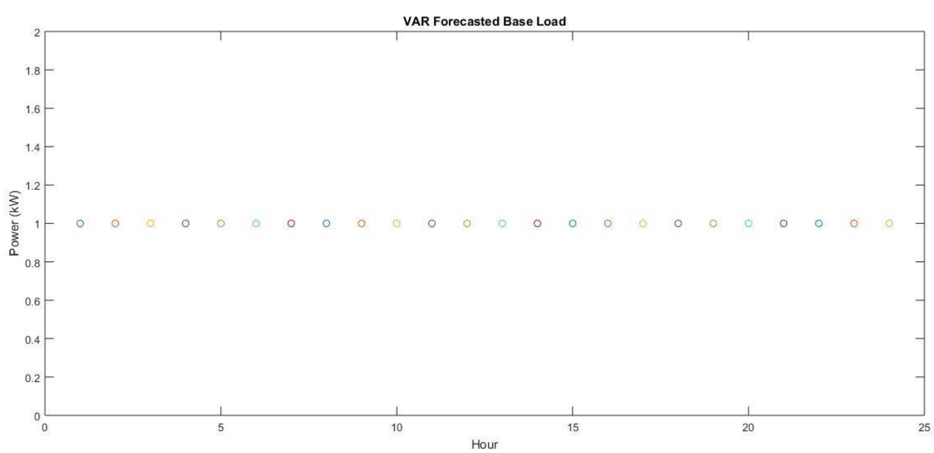

FIGURE: 8VAR Forecasted Base Load

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Conclusions

Because of the rise of smart residential communities, residential smart grid scheduling in the power market is facing an unprecedented challenge. The smart grid scheduling model for smart residential communities is proposed in this article based on the residential load. Reducing the user's electricity costs is the model's objective. Without sacrificing customer comfort, it effectively arranges all community resources under different programs, reducing residential peak load, energy consumption, and power costs for users. It is also confirmed by the results that a hybrid application of various deep learning algorithms tends to perform better than individual prediction models.To ensure grid stability and dependability, resilient grid architecture, support, and advanced forecasting are necessary. How well different algorithms handle these issues shows how much further study and improvement is needed. These tactics are essential for getting beyond the challenges posed by integrating renewable energy sources and enhancing smart grids' overall effectiveness. A thorough approach involving advanced forecasting techniques, effective optimisation techniques, and strategic policy support is needed to integrate renewable energy into intelligent networks. These conditions need to be met in order to ensure a stable, efficient, and sustainable energy future.

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