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# A TOT: tri-optimized-tariff based strategic residential load management with greedy optimization in IEEE33-bus system: a case study with renewable energy penetration

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**ABSTRACT**

The efficiency of a load management system in terms of its energy performance index (EPI) depends on its capacity to enhance the reliability, resilience, and cost effectiveness of the existing system. Artificial intelligence (AI) is crucial in this shift from classical to AI-based power system planning, optimizing renewable energy (RE) and reducing grid-stress. On the other hand, proper placement of resources is essential to achieve benefits and reduce transmission losses. Utility sectors of different states has revealed that in certain areas amongst different type of loads, domestic loads accounts for a substantial proportion of energy consumption. Therefore, the present work deals with optimum load scheduling, integration of RE, energy storage (ES) and proposed tri-optimized-tariff (TOT) for prosumers. We have found that the weighted-K-nearest-neighbor (KNN) method excels in selecting features for household appliances and ES scheduling. The composite greedy optimization (CGO) technique outperforms existing methods in optimization. These results demonstrate the efficiency and real-world potential of our model. We have conducted a case study and developed an AI-based strategic-residential-load-management-system (SRLMS), which we have tested on the IEEE33 bus system, showing cost effectiveness and improved EPI for prosumers. This work encourages the development of a harmonious relationship between utility-sectors and prosumers.



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## 1. INTRODUCTION

Meeting the ever-growing load demand and managing grid stress has become a significant challenge in today's world. This load demand fluctuates due to various factors, including human habits, economic growth, the acceptance of new technology advancements, geographical location, and demographic cycles. The energy profile of a nation is shaped by these parameters and is often characterized by the per capita energy consumption. Utility sectors have provided data indicating that in some countries, more than 25% of the total energy is consumed by the domestic sector. This shift has transformed domestic consumers into domestic prosumers, playing a pivotal role in addressing the current power scenario. Extensive research has been conducted on load profiles and the scheduling of home appliances. These efforts have led to the development of smart home energy management systems. In some research articles, several practical constraints have been identified in existing energy management systems, many of which are related to human interaction, unavailable power supply and consumers' preferences [1], [2]. To partially address this concern, recent developments have focused on integrating renewable energy sources, with efficient communication and optimization schemes proving to be quite effective in improving energy management systems [3], [4]. However, it is worth noting that some research efforts have aimed to minimize prosumer interaction [5]–[7]. To enhance the effectiveness of existing energy management systems, researchers have incorporated various factors, including consumer satisfaction levels and energy costs, along with the integration of renewable energy sources [8]–[10]. The utilization of energy storage systems (ESS) and the development of scheduling strategies for ESS play a vital role in designing an efficient energy management system which have been tackled in some research studies [11]–[13]. As a result, in-depth modelling of energy storage systems has become a more relevant research topic [14], [15]. Additionally, a body of research has demonstrated that achieving the most effective optimal charging and discharging schedules for ESS is achievable through time-of-use tariff schemes [16]–[20]. Conversely, only a limited number of research efforts have delved into the design of new tariff structure based on the availability of RES, incorporating the scheduling of ESS and household appliances. Recognizing this gap, our research focuses on various techniques for feature selection to establish judicious model for optimizing charging and discharging of ESS and its sizing, as well as the scheduling of household appliances. These efforts culminate in the introduction of an innovative tri optimized tariff (TOT) structure proposal. To confirm this, we have employed composite greedy optimization (CGO) technique in a comprehensive case study.

Numerous countries worldwide have implemented a range of energy conservation codes and star-leveling programs [21] aimed at advancing energy efficiency within the domestic sector. In this article, we delve into the concept of the energy performance index. While some research has assessed the model's effectiveness in IEEE Bus systems, only a selected few have delved into crucial dimensions, including cost reduction, voltage stability improvement, and power loss mitigation [14], [22]–[28] which has been summarized in Table 1. Recognizing these research gaps, our study conducts a rigorous assessment of our designed model in the IEEE 33 Bus system. Our results have primarily focused on reducing grid stress, quantified through peak to average ration (PAR) reduction, lowering monthly electricity bills for consumers, minimizing operational cost, reducing transmission power losses, enhancing consumer preferences, and improving stability indices, which in turn has motivated the design and development of a strategic residential load management system (SRLMS) achieved by judicious load scheduling and ESS scheduling optimizing the size and location of photovoltaic (PV) generation.

Table 1. Summarized relevant work

| Research papers as in ref. sec. | Tested on IEEE Bus | Parameters addressed | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | RE penetration | PAR reduction | ESS scheduling | Consumers' preference | operating cost | Reduction in monthly bill | Transmission loss | Stability index |
| [29] | × | ✓ | ✓ | × | ✓ | × | ✓ | × | ✓ |
| [30] | × | ✓ | ✓ | × | × | × | ✓ | × | ✓ |
| [31] | × | ✓ | ✓ | × | ✓ | × | ✓ | × | ✓ |
| [32] | × | ✓ | × | × | × | × | ✓ | × | × |
| [33] | × | ✓ | × | × | ✓ | × | ✓ | × | × |
| [34] | × | ✓ | ✓ | × | × | × | ✓ | × | ✓ |
| [35] | × | ✓ | ✓ | × | ✓ | × | ✓ | × | ✓ |
| [36] | × | ✓ | ✓ | × | × | × | ✓ | × | ✓ |
| [37] | × | ✓ | ✓ | × | ✓ | × | ✓ | × | ✓ |
| [38] | × | ✓ | ✓ | × | × | × | ✓ | × | ✓ |
| [11] | × | ✓ | × | ✓ | ✓ | × | ✓ | × | × |
| [39] | × | ✓ | × | ✓ | × | × | × | × | × |
| [40] | × | ✓ | ✓ | ✓ | ✓ | × | × | × | ✓ |
| [41] | × | ✓ | ✓ | ✓ | ✓ | × | × | × | ✓ |
| [42] | × | ✓ | × | ✓ | ✓ | × | × | × | × |
| [43] | × | ✓ | ✓ | × | ✓ | × | × | × | ✓ |
| [44] | × | ✓ | ✓ | × | ✓ | × | × | × | ✓ |
| [22] | ✓ | ✓ | ✓ | × | × | × | ✓ | ✓ | × |
| [23] | ✓ | ✓ | × | ✓ | × | ✓ | × | ✓ | × |
| [24] | ✓ | ✓ | × | ✓ | × | ✓ | × | ✓ | ✓ |
| [14] | × | ✓ | ✓ | × | × | × | ✓ | ✓ | × |
| [25] | ✓ | ✓ | × | × | × | × | × | ✓ | ✓ |
| [26] | ✓ | ✓ | × | × | × | × | × | ✓ | ✓ |
| [27] | ✓ | ✓ | × | ✓ | × | × | ✓ | × | × |
| [28] | ✓ | ✓ | × | × | × | ✓ | × | ✓ | ✓ |
| [45] | ✓ | ✓ | × | ✓ | × | ✓ | × | ✓ | × |
| [46] | ✓ | ✓ | × | ✓ | × | × | × | ✓ | × |
| [47] | ✓ | ✓ | × | ✓ | × | ✓ | ✓ | × | × |
| [48] | × | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | × |
| SRLMS | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Contribution and paper organization: recognizing the limitations in the previous research works, we have formulated a SRLMS for domestic sectors situated in tropical countries. The novelty of the proposed SRLMS is tabulated below.

- We have explored different feature selection techniques to select appropriate parameters for scheduling of home appliances and ESS and conducted a comparative study.
- We have formulated a deterministic rule-based strategy for judicious scheduling of ESS.
- We have proposed a TOT structure to enhance the effectiveness of SRLMS.
- To improve the efficiency of SRLMS, we have proposed CGO technique.
- Finally, the model has been tested on IEEE 33 Bus System to assess its viability.

In the following sections, different methods, mathematical models, a rule-based strategy used in designing the system, has been presented. And finally results obtained after testing of the system on IEEE33 bus has been discussed.

## 2. SYSTEM DESIGN

Efficient energy management within the existing grid infrastructure holds paramount importance, making EMS a critical component. From the utility's standpoint, our proposed SRLMS is tasked with intricately managing energy consumption, thus mitigating PAR, and line losses. Simultaneously, from the consumers' perspective, its primary role is to curtail electricity expenses and improve EPI.

To achieve our outlined goals, we have designed a versatile model followed by different methods, mathematical modeling, and a deterministic rule-based strategy. The system adeptly handles load scheduling, ESS scheduling and TOT incorporation. To validate our model's effectiveness, we have showcased its capabilities through a testing on the IEEE33 bus system.

### 2.1. Methods

#### 2.1.1 Forecasting: auto-regressive-integrated-moving-average-with-exogenous-variables

Demand forecasting constitutes the foundational and critical element of an electrical power system, particularly the load management system. In this study, various forecasting tools were evaluated, with the auto-regressive-integrated-moving-average-with-exogenous-variables (ARIMAX), a multivariate approach, emerging as the most effective method for load forecasting and RE availability forecasting, outperforming other techniques. Leveraging this classical method has enabled us to achieve an almost error-free forecasted demand profile.

#### 2.1.2. Feature selection

In this research paper, we have evaluated seven features for scheduling household appliances and nine features for scheduling ESS using four distinct methods: complex tree, gaussian support vector machine (SVM), weighted K-nearest neighbor (KNN), and bagged trees which have been shown in Tables 2 and 3. Tables 2 and 3 have presented a comparative assessment of these four methods, considering model accuracy and prediction speed. Our findings have indicated that WKNN is outperforming the other methods based on the accuracy. Based on these results, we have selected most crucial features for designing the load scheduling model ESS scheduling model.

Table 2. Feature selection for household appliances scheduling

| Method used | Analysis based on the parameters | Predictors | Remarks |
|---|---|---|---|
| – Complex tree<br>– Gaussian SVM<br>– Weighted KNN<br>– Bagged trees | – Model accuracy<br>– Prediction speed | – Appliance rating<br>– No. of appliances<br>– Energy consumption<br>– Operation time<br>– No. of START time<br>– Operation frequency<br>– Peak hour operation | – Weighted KNN is outperforming the other methods<br>– 3 features have been selected.<br>– More than 85% accuracy has been achieved using WKNN with the selected features. |

#### 2.1.3. Optimization

Residential prosumer demand profiles are shaped by geographic conditions and demographics. In this context, we explored various optimization approaches, culminating in the development of a hybrid technique merging genetic algorithm (GA) and particle swarm optimization (PSO). This innovative approach, termed as composite greedy optimization (CGO), leverages greedy selection methods to identify both personal best and global best solutions. To balance demand and supply effectively, we employed the multiple knapsack problem (MKP) as a foundation, followed by the application of CGO to reach the optimal solution.

Particle swarm optimization with iterative pbest and gbest update in Algorithm 1. Here particles have been randomly initialized with position and velocity. Each particle settles at its own best position: pbest and best among all particles are considered as global best position: gbest. Based on its inertia, personal and global states positions and velocities are updated for each particle in every iteration. The objective function is evaluated, and both pbest and gbest are updated whenever better solutions are found. This loop continues for T iterations and finally, gbest represents the best solution identified by the particle at the end.

Algorithm 1. Particle swarm optimization with iterative pbest and gbest update

```
– Input F, lb, ub, N,T;
– Evaluate pbest, gbest and assign values;
– start Loop for x from 1 to T;
– start Loop for y from 1 to N;
– Evaluate velocity and position of xth and yth particle;
– Evaluate F ;
– modify Np, Pbest and gbest;
– all loops end;
– P in next iteration=present P+Pbest;
– iterate T times;
– printf (result);
```

Table 3. Feature selection for ESS scheduling

| Method used | Analysis based on the parameters | Predictors | Remarks |
|---|---|---|---|
| – Complex tree<br>– Gaussian SVM<br>– Weighted KNN<br>– Bagged trees | – Model accuracy<br>– Prediction speed | – ESS cycle<br>– Energy consumption<br>– Availability of RES<br>– Charging and discharging rate<br>– ESS efficiency<br>– No. of members in the considered area<br>– Holidays<br>– Electricity expenses | – Weighted KNN is outperforming the other methods<br>– 4 features have been selected.<br>– More than 85% accuracy has been achieved using WKNN with the selected features. |

## 2.2. Mathematical modeling
### 2.2.1. Energy consumption

Here we have considered that prosumers are using H household appliances and total number of appliances used by each prosumer is N like H1, H2, …, HN. The starting time of appliances is 'SH1' and finishing time 'FH1'. Operation time vector of H1 appliance,

$$\phi_{H1} = [\alpha_{1GH1}, \alpha_{1PVH1}, \alpha_{2GH1}, \alpha_{2PVH1}, \ldots, \alpha_{24GH1}, \alpha_{24PVH1}] \tag{1}$$

$\alpha_{tGH1}$ is time slot of using energy from conventional sources to meet the demand of H1 at time t which is either known or predicted.
$\alpha_{tPVH1}$ is time slot of using RES to meet the demand of H1 at time t which is either known or predicted.

Consumers need to inform the appliances rating $\beta_H$ and switching ON time of the appliances $f_H$. Total consumption by a1 appliance,

$$\sigma_{H1} = \sum_{t=1}^{T} \sum_{H_1 \epsilon \mathrm{A}} \beta_{H1}(\alpha_{GH1} + \alpha_{PVH1}) \tag{2}$$

Similarly, the electricity expense for a1 over 24 hours,

$$\delta_{H1} = \sum_{t=1}^{T} \sum_{H_1 \epsilon \mathrm{A}} \beta_{H1}(\gamma_G^t \alpha_{GH1}^t + \gamma_{PV}^t \alpha_{PVH1}^t) \tag{3}$$

where the unit energy price is $\gamma$.

#### 2.2.2. Scheduling of household appliances

Here, we have considered $\tau_{rH1}$ is the request time and $\tau_{wH1}$ is waiting time of H1 respectively. Therefore,

$$\tau_{wH1} = | S_{H1} - \tau_{rH1} | \quad (4)$$

Total waiting time for each of H appliance can be calculated as,

$$\tau_w = \sum_{i=1}^{N} \tau_{wHi} \quad (5)$$

Here, we have considered,

$$\theta_{H1}^{t} = \frac{\text{run-time}}{\text{number of switch ON}} \quad (6)$$

Utilization factor for each appliance,

$$U^{e}_{Hi} = \frac{1}{24} \sum \theta_{Hi}^{t} \quad (7)$$

Therefore, priority ranking can be done for all of the appliances,

$$\lambda_{Hi} = [U^{e}_{Hi}] * [\theta_{Hi}^{*}] \quad \forall \text{ Hi } \epsilon \text{ H} \quad (8)$$

Based on this ranking, we have effectively categorized the load into three distinct categories: Rank 1 load (which cannot be interrupted), Rank 2 load (which may be interrupted with minimal delay time), and Rank 3 load (which can be interrupted). In alignment with these categories, we have systematically organized the appliances based on their computed priority levels.

#### 2.2.3. Scheduling of ESS

Here we have outlined the charging-discharging processes of a battery, considering factors such as its round-trip efficiency, state of charge (SOC), and rate of charging-discharging. Within this section, we specifically focus on a battery with a 10 kW capacity. Round efficiency,

$$\eta_r = \eta_{ch} * \eta_{dch} \quad (9)$$

$\eta_{ch}$ = 0.98 and $\eta_{dch}$ = 0.95.
Here, we have set, SOCmin = 15% and SOCmax = 90%.
Time to get full charge = 5 hours

$$Energy\ used = Change\ in\ SOC * \frac{Battery\ capacity}{\eta_{\text{charging}}} \quad (10)$$

Throughout the charging process,

$$Energy\ discharged = Change\ in\ SOC * \text{Battery capacity} * \eta_{\text{discharging}} \quad (11)$$

Battery scheduling introduces three conditions for each of two distinct cases. Consequently, in a subsequent section of this paper, we have presented a deterministic rule-based strategy aimed at optimizing the scheduling of ESS.

#### 2.2.4. Proposed tri optimized tariff

An approach based on pricing proves to be an effective method for mitigating demand in peak hours and implementing judicious energy usage. In this process, two critical steps involve adjusting energy prices and ensuring that users have up-to-date information. As energy prices rise during periods of scarcity, prosumers are incentivized to curtail their peak hour consumption and opt for RES. We have considered the pricing for RES is invariable with time.

In this paper, we have introduced a novel tariff scheme considering three important parameters (efficient use of RES, judicious energy consumption in peak hours, reduction in monthly electricity expense), which is known as TOT. We have illustrated the design process of this new TOT structure through a flowchart depicted in Figure 1.

Here, we have defined γPP as the unit energy price during peak hours, γOPP as the unit energy price during off-peak hours, and γIP as the unit energy price during intermediate hours.

$$\text{Here, x} = \frac{Consumption\ during\ peak\ pricing\ hours}{consumption\ over\ 24\ hours} * 100\% \tag{12}$$

$$\gamma PP.new\ =\ Tariff\ 2\ +\ (x\%\ of\ Tariff\ 2) \tag{13}$$

$$Rebate\ =\ (20 + (20 - x))\ \%\ of\ (\lambda PP\ *\ \gamma PP.new) \tag{14}$$

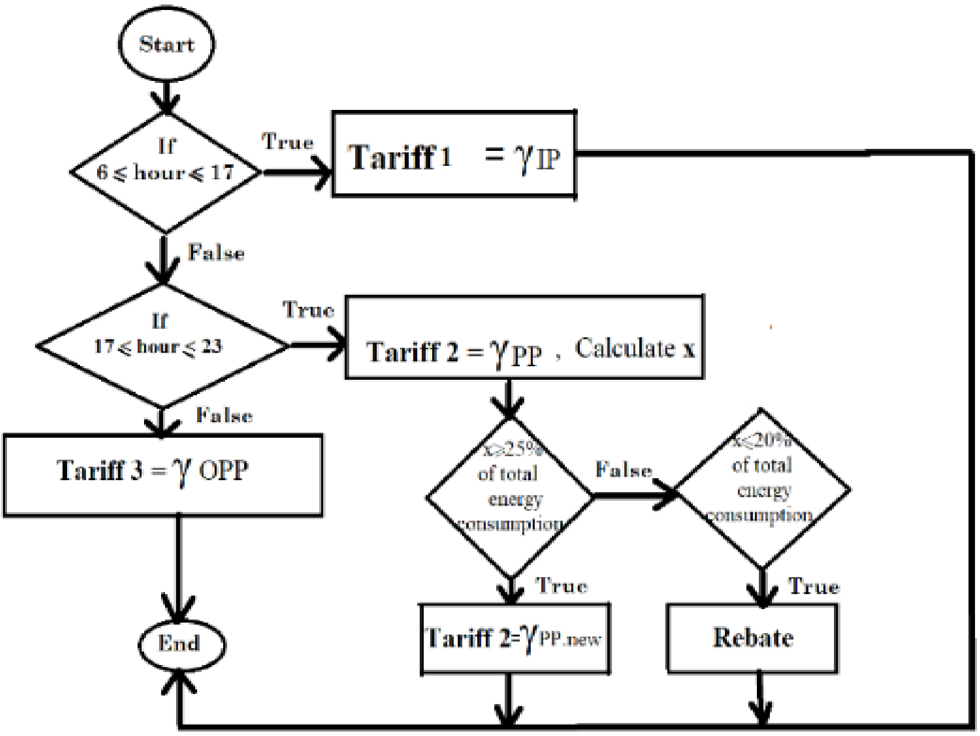


Figure 1. Flow-chart of the proposed tariff

### 2.3. ESS scheduling strategy

In this section, we have introduced a strategy designed to optimize the scheduling of ESS efficiently. We have assumed λP, λOP, and λI to represent energy consumption during specific time intervals as peak hours, off-peak hours, and intermediate hours respectively. Here 5:00 pm to 11:00 pm has been considered as peak hours, 11:00 pm to 6:00 am as off-peak hours and 6:00 am to 5:00 pm as intermediate hours respectively.

Additionally, we have designated **γ**PP, **γ**OPP, and **γ**IP as the energy pricing per unit corresponding to peak hours, off-peak hours, and intermediate hours. The ESS scheduling depends on the following parameters (shown in Table 4).

CASE 1: when $\lambda_P < \lambda_{OP}$ and $\lambda_P < \lambda_I$,

Condition 1,

$$\frac{\boldsymbol{\gamma}PP}{\boldsymbol{\gamma}OPP} * \frac{\lambda_P}{\lambda_{OP}} > \eta_r * \frac{\boldsymbol{\gamma}OPP}{\boldsymbol{\gamma}IP} * \frac{\lambda_{OP}}{\lambda_I} \tag{15}$$

Condition 2,

$$\frac{\boldsymbol{\gamma}OPP}{\boldsymbol{\gamma}IP} * \frac{\lambda_{OP}}{\lambda_I} > \eta_r * \frac{\boldsymbol{\gamma}IP}{\boldsymbol{\gamma}PP} * \frac{\lambda_I}{\lambda_P} \tag{16}$$

Condition 3,

$$\frac{\gamma IP}{\gamma PP} * \frac{\lambda_I}{\lambda_P} > \eta_r * \frac{\lambda PP}{\lambda OPP} * \frac{\lambda_P}{\lambda_{OP}} \tag{17}$$

CASE 2: When λP > λOP and λP
Condition 1,

$$\frac{\gamma PP}{\gamma OPP} * \frac{\lambda_P}{\lambda_{OP}} < \eta_r * \frac{\gamma OPP}{\gamma IP} * \frac{\lambda_{OP}}{\lambda_I} \tag{18}$$

Condition 2,

$$\frac{\gamma OPP}{\gamma IP} * \frac{\lambda_{OP}}{\lambda_I} < \eta_r * \frac{\gamma IP}{\gamma PP} * \frac{\lambda_I}{\lambda_P} \tag{19}$$

Condition 3,

$$\frac{\gamma IP}{\gamma PP} * \frac{\lambda_I}{\lambda_P} < \eta_r * \frac{\gamma PP}{\gamma OPP} * \frac{\lambda_P}{\lambda_{OP}} \tag{20}$$

Table 4. Deterministic strategy for ESS scheduling

| | Condition (CASE 1&2) | 11pm – 6am | 6am – 5pm | 5pm – 11pm |
|---|---|---|---|---|
| Clear sky (sufficient solar energy) | 1 | N/A | C | D |
| | 2 | D | C | D |
| | 3 | N/A | C/D | D |
| Cloudy sky (insufficient solar energy) | 1 | C | D | N/A |
| | 2 | C | D | D |
| | 3 | C | D | C / C |

Here C represents the charging state and D represents the discharging state of ESS.

## 3. TESTING ON IEEE 33 BUS SYSTEM

### 3.1. Simulink model description

IEEE 33 bus system is the network of IEEE standards and consists one generator, several load points. Due to its easy data availability, IEEE33 bus has find wide application in various research works. Specification: radial distribution system, no. of buses = 33, no. of lines = 32, voltage level = 12.66 kV, load size = 3.715 MW and 2.3M Var, DG unit voltage = 12.66 kV, and fixed penetration level (30%)

### 3.2. Load flow analysis

The load flow analysis has been carried out using Tustin/backward Euler solver in MATLAB. Algorithm 2 shows the step-by-step procedure for Newton–Raphson power flow analysis.

Algorithm 2. Step-by-Step Procedure for Newton–Raphson Power Flow Analysis:

```
Step 1: Initialization of bus data, line data, load data and generated data for some information like bus voltage limit, line parameters, load demand, generator characteristics and initial voltage value etc. and initial bus voltage magnitude, phase angle and maximum number of iterations etc.
Step 2: Formulation of power flow equations for each bus individually.
Step 3: Application of the Newton-Raphson method as its convergence properties and accuracy is better than others. It iteratively updates the voltage magnitudes and angles until the power flow equations are satisfied.
Step 4: Calculation of Jacobian Matrix which in turn helps in updating the voltage for next iteration.
Step 5: Checking for convergence.
Step 6: Repetition for next iterations if not converged.
Step 7: With the convergence of the algorithm, the steady-state operating conditions of the power system, including voltage magnitudes and angles at each bus, line currents, and power flows are obtained.
```

The Newton–Raphson power flow method begins by initializing all required electrical system data. This includes the line parameters, bus voltage limits, generator outputs, and initial guesses for voltage magnitudes and angles. Power flow equations are then formulated for each bus based on system topology and load characteristics. The Newton–Raphson power flow method initializes system data and voltage estimates, then repeatedly computes power mismatches and updates voltages using the Jacobian matrix. This continues until the mismatches are very small. The final result gives the system's steady-state voltages, angles, and power flows.

### 3.3. Optimization to suitably locate PV sources

Here we have used CGO as optimization tool to determine optimum size, and location for PV based generation on IEEE33 bus.

## 4. RESULTS AND DISCUSSION

Utilizing data gathered from both physical surveys and online surveys we have developed an effective model in MATLAB Simulink. The outcomes of this research are grouped into three perspectives: prosumers' standpoint, utility sector's viewpoint, and environmental considerations.

### 4.1. Prosumers' preference

#### 4.1.1. Monthly electricity bill

In this research article, the flexible and efficient use of RES and ESS with a TOT scheme can reduce the monthly electricity expense. Consumers need to specify the details of their home-appliances and their load requirement a day ahead or they can follow the demand profile suggested by the controller of the utility company. Consumers have the option to select and announce the most suitable tariff plan one day in advance. By adopting this approach, consumers can maximize their benefits as shown in Figure 2 and Table 5.

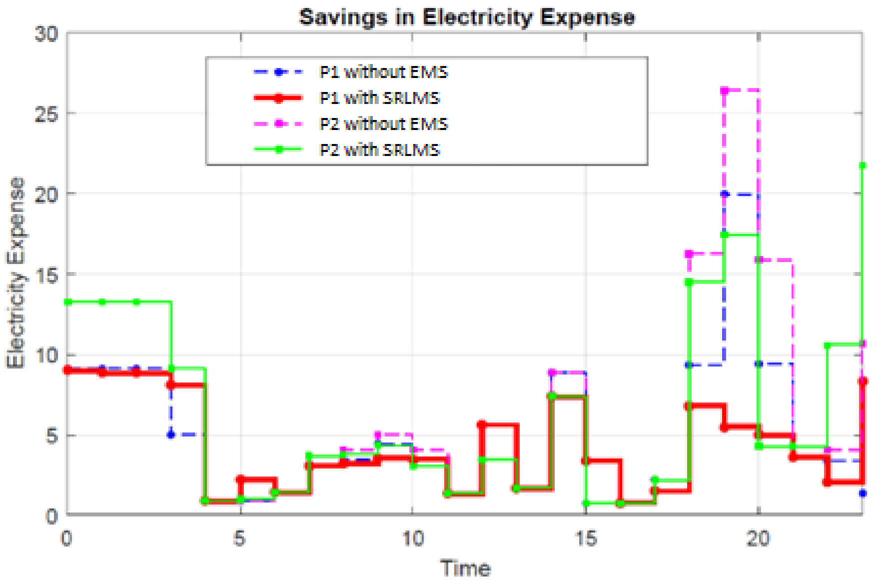


Figure 2. Cost curve

Table 5. The performance of proposed SRLMS based on electricity expense

| Prosumers | Electricity bill (30 days) | | Savings (in %) |
|---|---|---|---|
| | Without EMS | With SRLMS | |
| Prosumer 1 | 4,375 | 3,165 | 28% |
| Prosumer 2 | 6,600 | 4,720 | 29% |

#### 4.1.2. EPI

The star rating of any residential building can be calculated based on its energy performance index (EPI).

$$EPI\ calculation\ = annual\ energy\ consumption\ (kWh)/built\ up\ area\ (sq.meter)\ (under\ certain\ conditions)$$

For a period (14.12.2018 – 31.12.2024), in a tropical country EPI varying in the range of 29-39 represents 4-star rating and EPI less than 29 represents 5 star rating. Due to the significant reduction in energy consumption as shown in Figure 3, an improvement in EPI and further improvement in star rating by at least 1 unit can be achieved, which in turn assures more subsidies from the federal agencies.

### 4.2. Utility sectors' preference
#### 4.2.1. Peak to average ratio
Reduction in PAR reduces grid stress and electricity cost for the prosumers.

$$\text{PAR} = \left(\sum_{i=1}^{N} \sigma_{Hi}^{t}\right) max \ / \frac{1}{T} \left(\sum_{i=1}^{N} \sigma_{Hi}^{t}\right) \tag{21}$$

The result is shown in Figure 4.

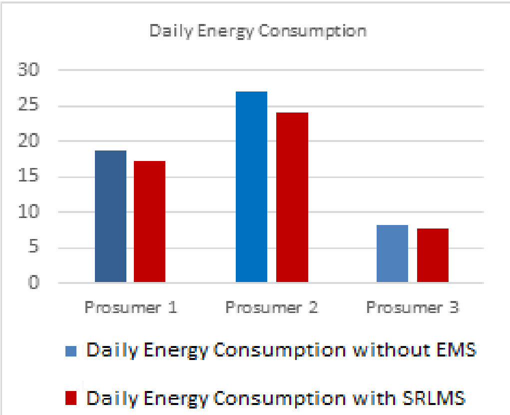


Figure 3. Reduction in energy consumption

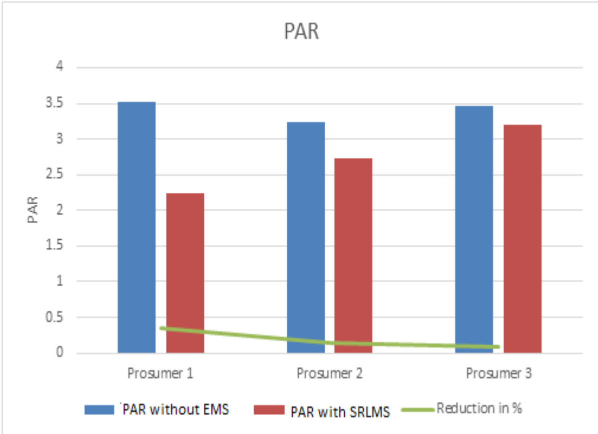


Figure 4. PAR reduction

#### 4.2.2. Voltage profile at each bus
The load flow analysis has been carried out using Newton Raphson method. It is converged in 6 iterations. From Figure 5 it can be concluded that by using the proposed SRLMS voltage profile has been significantly improved at bus number 18, 26, and 33.

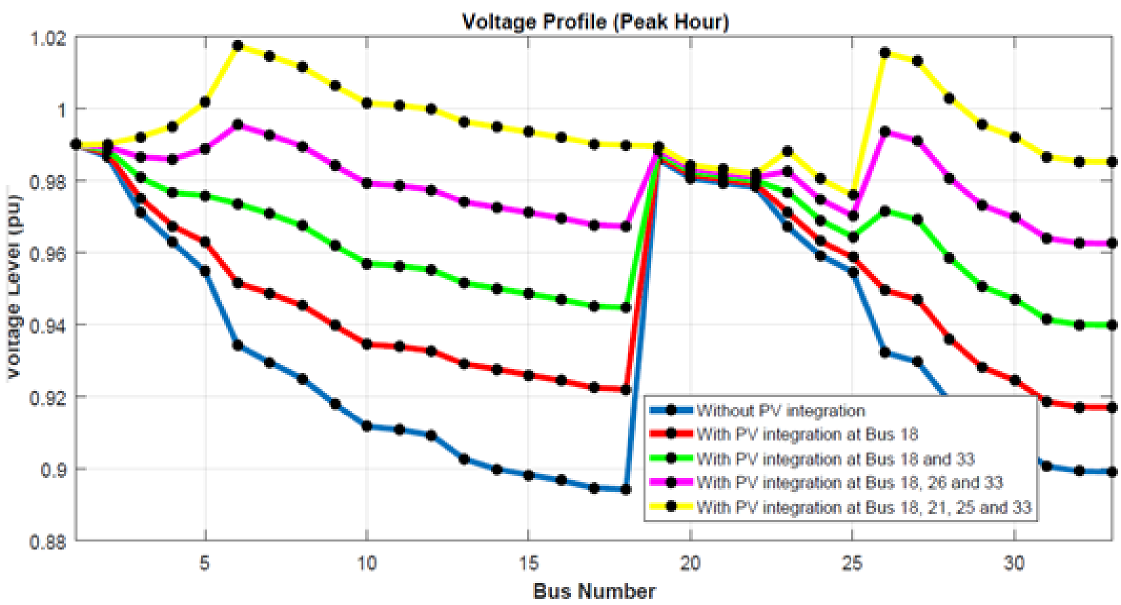


Figure 5. Voltage profile

#### 4.2.3. Reduction in transmission losses with optimized PV integration

The amount of reduction in transmission losses due to optimal placement of PV sources has been tabulated in Table 6.

Table 6. Reduction in transmission losses

| Condition | Load condition | Power loss | |
|---|---|---|---|
| | | P | Q |
| Without PV integration | Fixed load | 206.63 kW | 137.8 KVAR |
| | Peak hours | 243.5 kW | 163.1 KVAR |
| With 1.31 MW PV integration at BUS 18 | Fixed load | 121.46 KW | 79.6 KVAR |
| With (2)1.31 MW PV integration at BUS 18 and 26 | | 68.2 kW | 48.7 KVAR |
| With (3)1.31 MW PV integration at BUS 33, 26, and 18 | | 66.1 kW | 50.6 KVAR |
| With (4)1.31 MW PV integration at BUS 33, 25, 21, and 18) | | 114.7 kW | 85.2 KVAR |
| With 1.31 MW PV integration at BUS 33 | Peak hours | 153.45 KW | 99.6 KVAR |
| With (2)1.31 MW PV integration at BUS 33 and 26 | | 87.9 kW | 61.1 KVAR |
| With (3)1.31 MW PV integration at BUS 33, 26, and 18 | | 74 kW | 55.9 KVAR |
| With (4)1.31 MW PV integration at BUS 33, 25, 21, and 18) | | 111.39 kW | 83.61 VAR |

### 4.3. Environmental aspect

It has been estimated that 0.93 kg of $CO_2$ is produced by 1 kWh generation. In this case study, we have found that daily approximately 2 tonnes of $CO_2$ emission can be reduced by using SRLMS which a tree can absorb in 100 years.

## 5. CONCLUSION

This paper comprehensively addresses various aspects of a strategic load management system employing artificial intelligence. The intelligent SRLMS has shown significant improvement through the implementation of several key steps, such as, including load scheduling, RE penetration and energy storage system scheduling. Our research has focused on understanding diverse demand patterns among domestic prosumers. Moreover, the efficiency of this system is further amplified by the incorporation of a newly proposed TOT. Our system outperforms in the application of a rule-based strategy for charging and discharging the ESS. To validate the effectiveness of the designed model, we have conducted a case study considering different demand patterns of domestic consumers with dual objectives. Firstly, it empowers prosumers to indirectly participate in the utility market, resulting in significant reductions in their monthly electricity expenses without compromising their preferences. Simultaneously, it contributes in enhancing EPI, fostering eco-friendly practices, and promoting initiatives by utilities and federal agencies to conserve energy. Additionally, we have assessed the model's performance on an IEEE 33 bus system, revealing substantial reductions in transmission losses due to optimal placement of distributed solar energy generation. This testing phase also enables the design of a judicious model that efficiently reduce grid stress while ensuring uninterrupted, high-quality power supply to prosumers. In summary, the SRLMS serves the interests of prosumers and utility sectors, showcasing its potential in optimizing energy usage and fostering a healthy relationship between stakeholders.

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## AUTHOR CONTRIBUTIONS STATEMENT

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

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

## CONFLICT OF INTEREST STATEMENT

We have no conflicts of interest to disclose.

## DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [K.G]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

## REFERENCES


[1] R. Sharifi, S. H. Fathi, and V. Vahidinasab, "A review on demand-side tools in electricity market," *Renewable and Sustainable Energy Reviews*, vol. 72, pp. 565–572, May 2017, doi: 10.1016/j.rser.2017.01.020.

[2] C. W. Gellings, "Evolving practice of demand-side management," *Journal of Modern Power Systems and Clean Energy*, vol. 5, no. 1, pp. 1–9, Dec. 2017, doi: 10.1007/s40565-016-0252-1.

[3] B. P. Esther and K. S. Kumar, "A survey on residential demand side management architecture, approaches, optimization models and methods," *Renewable and Sustainable Energy Reviews*, vol. 59, pp. 342–351, Jun. 2016, doi: 10.1016/j.rser.2015.12.282.

[4] T. Logenthiran, D. Srinivasan, and T. Z. Shun, "Demand side management in smart grid using heuristic optimization," *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1244–1252, Sep. 2012, doi: 10.1109/TSG.2012.2195686.

[5] Z. Xu, Y. Gao, M. Hussain, and P. Cheng, "Demand side management for smart grid based on smart home appliances with renewable energy sources and an energy storage system," *Mathematical Problems in Engineering*, vol. 2020, pp. 1–20, Apr. 2020, doi: 10.1155/2020/9545439.

[6] H. Ahmad, A. Ahmad, and S. Ahmad, "Efficient energy management in a microgrid," in *2018 International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET)*, Sep. 2018, pp. 1–5, doi: 10.1109/PGSRET.2018.8685946.

[7] Y. Wang, L. Liu, R. Wennersten, and Q. Sun, "Peak shaving and valley filling potential of energy management system in high-rise residential building," *Energy Procedia*, vol. 158, pp. 6201–6207, Feb. 2019, doi: 10.1016/j.egypro.2019.01.487.

[8] M. N. Naz, M. Naeem, M. Iqbal, and M. Imran, "Economically efficient and environment friendly energy management in rural area," *Journal of Renewable and Sustainable Energy*, vol. 9, no. 1, Jan. 2017, doi: 10.1063/1.4973713.

[9] F. Issi and O. Kaplan, "The determination of load profiles and power consumptions of home appliances," *Energies*, vol. 11, no. 3, p. 607, Mar. 2018, doi: 10.3390/en11030607.

[10] S. Ahmad, M. Naeem, and A. Ahmad, "Low complexity approach for energy management in residential buildings," *International Transactions on Electrical Energy Systems*, vol. 29, no. 1, p. e2680, Aug. 2019, doi: 10.1002/etep.2680.

[11] S. A. Malik, T. M. Gondal, S. Ahmad, M. Adil, and R. Qureshi, "Towards optimization approaches in smart grid a review," in *2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*, Jan. 2019, pp. 1–5, doi: 10.1109/ICOMET.2019.8673392.

[12] T. T. Nguyen, T. T. Ngoc, T. T. Nguyen, T. P. Nguyen, and N. A. Nguyen, "Optimization of location and size of distributed generations for maximizing their capacity and minimizing power loss of distribution system based on cuckoo search algorithm," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 4, pp. 1769–1776, Aug. 2021, doi: 10.11591/EEI.V10I4.2278.

[13] S. Ahmad, A. Ahmad, and R. Yaqub, "Optimized energy consumption and demand side management in smart grid," in *Smart Technologies: Breakthroughs in Research and Practice*, IGI Global, 2017, pp. 550–574.

[14] H. M. Hussain, N. Javaid, S. Iqbal, Q. Ul Hasan, K. Aurangzeb, and M. Alhussein, "An efficient demand side management system with a new optimized home energy management controller in smart grid," *Energies*, vol. 11, no. 1, p. 190, Jan. 2018, doi: 10.3390/en11010190.

[15] R. Yaqub, S. Ahmad, A. Ahmad, and M. Amin, "Smart energy-consumption management system considering consumers' spending goals (SEMS-CCSG)," *International Transactions on Electrical Energy Systems*, vol. 26, no. 7, pp. 1570–1584, Jul. 2016, doi: 10.1002/etep.2167.

[16] S. Ahmad, M. M. Alhaisoni, M. Naeem, A. Ahmad, and M. Altaf, "Joint energy management and energy trading in residential microgrid system," *IEEE Access*, vol. 8, pp. 123334–123346, 2020, doi: 10.1109/ACCESS.2020.3007154.

[17] K. Zhang *et al.*, "Incentive-driven energy trading in the smart grid," *IEEE Access*, vol. 4, pp. 1243–1257, 2016, doi: 10.1109/ACCESS.2016.2543841.

[18] A. Conchado and P. Linares, "The economic impact of demand-response programs on power systems. a survey of the state of the art," in *Handbook of Networks in Power Systems I*, Springer Berlin Heidelberg, 2012, pp. 281–301.

[19] J. M. Lujano-Rojas, C. Monteiro, R. Dufo-López, and J. L. Bernal-Agustín, “Optimum residential load management strategy for real time pricing (RTP) demand response programs,” *Energy Policy*, vol. 45, pp. 671–679, Jun. 2012, doi: 10.1016/j.enpol.2012.03.019.
[20] S. Joseph and E. A. Jasmin, “Demand response program for smart grid through real time pricing and home energy management system,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 5, pp. 4558–4567, Oct. 2021, doi: 10.11591/ijece.v11i5.pp4558-4567.
[21] H. Khalid, F. R. Amin, and C. Chen, “Comparing the status and challenges of demand-side management (DSM) implementation in Asia-Pacific region: a case study of China’s power sector,” *Energy Procedia*, vol. 152, pp. 101–108, Oct. 2018, doi: 10.1016/j.egypro.2018.09.066.
[22] K. Goswami, A. Ganguly, and A. Kumar Sil, “Comparing univariate and multivariate methods for short term load forecasting,” in *2018 International Conference on Computing, Power and Communication Technologies (GUCON)*, Sep. 2018, pp. 972–976, doi: 10.1109/GUCON.2018.8675059.
[23] J. Wang, K. J. Li, Z. Javid, and Y. Sun, “Distributed optimal coordinated operation for distribution system with the integration of residential microgrids,” *Applied Sciences (Switzerland)*, vol. 9, no. 10, p. 2136, May 2019, doi: 10.3390/app9102136.
[24] A. Azizivahed, S. Ghavidel, M. J. Ghadi, L. Li, and J. Zhang, “Multi-objective energy management approach considering energy storages in distribution networks with respect to voltage security,” in *Proceedings of the IEEE International Conference on Industrial Technology*, Feb. 2019, vol. 2019-February, pp. 661–666, doi: 10.1109/ICIT.2019.8755035.
[25] S. Katyara *et al.*, “Leveraging a genetic algorithm for the optimal placement of distributed generation and the need for energy management strategies using a fuzzy inference system,” *Electronics (Switzerland)*, vol. 10, no. 2, pp. 1–18, Jan. 2021, doi: 10.3390/electronics10020172.
[26] A. Singh, A. Shrestha, S. Phuyal, B. Adhikary, and A. Papadaki, “Particle swarm optimization approach for distributed generation allocation planning for voltage profile improvement,” 2018.
[27] P. Karimyan, B. Vahidi, M. Abedi, and S. M. Ahadi, “Optimal dispatchable DG allocation in a distribution network considering load growth with a mixed-PSO algorithm,” *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 24, no. 4, pp. 3049–3065, 2016, doi: 10.3906/elk-1404-207.
[28] R. Lin and F. Fang, “Energy management method on integrated energy system based on multi-agent game,” in *2019 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC)*, Aug. 2019, pp. 564–570, doi: 10.1109/SDPC.2019.00107.
[29] V. S. K. V. Harish and A. Kumar, “Demand side management in India: action plan, policies and regulations,” *Renewable and Sustainable Energy Reviews*, vol. 33, pp. 613–624, May 2014, doi: 10.1016/j.rser.2014.02.021.
[30] Z. Zhao, W. C. Lee, Y. Shin, and K. Bin Song, “An optimal power scheduling method for demand response in home energy management system,” *IEEE Transactions on Smart Grid*, vol. 4, no. 3, pp. 1391–1400, Sep. 2013, doi: 10.1109/TSG.2013.2251018.
[31] H. K. Nguyen, J. Bin Song, and Z. Han, “Distributed demand side management with energy storage in smart grid,” *IEEE Transactions on Parallel and Distributed Systems*, vol. 26, no. 12, pp. 3346–3357, Dec. 2015, doi: 10.1109/TPDS.2014.2372781.
[32] M. A. Khan, N. Javaid, A. Mahmood, Z. A. Khan, and N. Alrajeh, “A generic demand-side management model for smart grid,” *International Journal of Energy Research*, vol. 39, no. 7, pp. 954–964, Mar. 2015, doi: 10.1002/er.3304.
[33] D. Mahmood *et al.*, “Realistic scheduling mechanism for smart homes,” *Energies*, vol. 9, no. 3, p. 202, Mar. 2016, doi: 10.3390/en9030202.
[34] J. Ma, H. H. Chen, L. Song, and Y. Li, “Residential load scheduling in smart grid: a cost efficiency perspective,” *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 771–784, 2016, doi: 10.1109/TSG.2015.2419818.
[35] S. Rahim *et al.*, “Exploiting heuristic algorithms to efficiently utilize energy management controllers with renewable energy sources,” *Energy and Buildings*, vol. 129, pp. 452–470, Oct. 2016, doi: 10.1016/j.enbuild.2016.08.008.
[36] J. T. Flores, W. C. Celeste, D. J. C. Coura, S. D. D. Rissino, H. R. O. Rocha, and R. E. N. Moraes, “Demand planning in smart homes,” *IEEE Latin America Transactions*, vol. 14, no. 7, pp. 3247–3255, Jul. 2016, doi: 10.1109/TLA.2016.7587627.
[37] M. B. Rasheed *et al.*, “Real time information based energy management using customer preferences and dynamic pricing in smart homes,” *Energies*, vol. 9, no. 7, p. 542, Jul. 2016, doi: 10.3390/en9070542.
[38] P. Samadi, V. W. S. Wong, and R. Schober, “Load scheduling and power trading in systems with high penetration of renewable energy resources,” *IEEE Transactions on Smart Grid*, vol. 7, no. 4, pp. 1802–1812, Jul. 2016, doi: 10.1109/TSG.2015.2435708.
[39] K. Ma, T. Yao, J. Yang, and X. Guan, “Residential power scheduling for demand response in smart grid,” *International Journal of Electrical Power and Energy Systems*, vol. 78, pp. 320–325, Jun. 2016, doi: 10.1016/j.ijepes.2015.11.099.
[40] A. Ahmad *et al.*, “An optimized home energy management system with integrated renewable energy and storage resources,” *Energies*, vol. 10, no. 4, p. 549, Apr. 2017, doi: 10.3390/en10040549.
[41] H. T. Dinh, J. Yun, D. M. Kim, K. H. Lee, and D. Kim, “A home energy management system with renewable energy and energy storage utilizing main grid and electricity selling,” *IEEE Access*, vol. 8, pp. 49436–49450, 2020, doi: 10.1109/ACCESS.2020.2979189.
[42] S. M. Hameed, H. K. AL-Qaysi, A. S. Kaittan, and M. H. Ali, “Evaluation of electrical load estimation in Diyala governorate (Baaquba city) based on fuzzy inference system,” *International Journal of Electrical and Computer Engineering*, vol. 11, no. 5, pp. 3757–3762, Oct. 2021, doi: 10.11591/ijece.v11i5.pp3757-3762.
[43] M. Suresh, P. Maniraj, S. Sundar, T. Logeswaran, and P. Tamilarasu, “Peak time load management in domestic sector,” *International Journal of Innovative Technology and Exploring Engineering*, vol. 9, no. 1, pp. 2761–2763, Nov. 2019, doi: 10.35940/ijitee.A5221.119119.
[44] A. Ganguly, K. Goswami, A. Mukherjee, and A. K. Sil, “Short-term load forecasting for peak load reduction using artificial neural network technique,” in *Advances in Computer, Communication and Control: Proceedings of ETES 2018 Lecture Notes in Networks and Systems*, vol. 41, Springer Singapore, 2019, pp. 551–559.
[45] D. Salman, M. Kusaf, Y. K. Elmi, and A. Almasri, “Optimal power systems planning for IEEE-14 bus test system application,” in *2022 10th International Conference on Smart Grid (icSmartGrid)*, Jun. 2022, pp. 290–295, doi: 10.1109/icSmartGrid55722.2022.9848574.
[46] O. Lukacevic, M. Calasan, and S. Mujovic, “Impact of optimal ESS allocation in IEEE 24-test bus system on total production cost,” in *2019 20th International Symposium on Power Electronics (Ee)*, Oct. 2019, pp. 1–5, doi: 10.1109/PEE.2019.8923464.
[47] B. N. Alhasnawi, B. H. Jasim, Z.-A. S. A. Rahman, J. M. Guerrero, and M. D. Esteban, “A novel internet of energy based optimal multi-agent control scheme for microgrid including renewable energy resources,” *International Journal of Environmental Research and Public Health*, vol. 18, no. 15, p. 8146, Jul. 2021, doi: 10.3390/ijerph18158146.

[48] E. Giglio, G. Luzzani, V. Terranova, G. Trivigno, A. Niccolai, and F. Grimaccia, "An efficient artificial intelligence energy management system for urban building integrating photovoltaic and storage," *IEEE Access*, vol. 11, pp. 18673–18688, 2023, doi: 10.1109/ACCESS.2023.3247636.

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