Optimal scheduling of residential loads with renewable energy and energy storage: a techno-economic analysis

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Abstract

The increasing penetration of renewable energy resources and electric vehicles in residential power systems has intensified the need for intelligent load scheduling strategies to ensure economic and reliable operation. This paper presents an optimal scheduling framework for domestic electrical loads integrated with rooftop solar photovoltaic (PV), wind energy systems, battery energy storage systems (BESS), and grid connectivity under the Indian electricity mix. A typical residential load profile incorporating household appliances and electric vehicle charging demand is considered for a 24-hour scheduling horizon.

A mathematical model of the hybrid residential energy system is developed, accounting for renewable generation variability, battery charging–discharging constraints, time-varying electricity tariffs, and net-metering policies. The optimization objective is formulated to minimize the total daily energy cost while maintaining user comfort and operational constraints of the energy storage system. Solar and wind generation profiles are derived from typical Indian meteorological conditions, and residential demand patterns are modeled using standard household appliance usage schedules.

Simulation results demonstrate that the proposed optimal scheduling strategy reduces grid energy consumption by approximately 28–35% compared to an unscheduled baseline case. The daily electricity cost is reduced by nearly 30%, primarily due to effective utilization of renewable generation and strategic charging of the battery during off-peak tariff periods. Furthermore, coordinated scheduling of EV charging significantly alleviates peak demand stress, achieving peak load reduction of about 20% without compromising charging requirements. The inclusion of BESS enables improved self-consumption of renewable energy and enhances system flexibility under variable generation conditions.

The findings indicate that intelligent domestic load scheduling with integrated renewable energy sources and storage can substantially improve economic performance and grid friendliness of residential energy systems in India. The proposed framework provides a scalable and practical solution for future smart homes and supports national objectives related to renewable energy integration and electric mobility adoption.

Keywords: Residential energy management, Renewable energy, Battery storage, Load scheduling, Electric vehicle charging

1. Introduction

The rapid growth of residential electricity demand, driven by increased appliance ownership, electric vehicle (EV) adoption, and urbanization, has posed significant challenges to power system operation, particularly in developing economies such as India [1]. Simultaneously, the large-scale deployment of distributed renewable energy resources most notably rooftop solar photovoltaic (PV) systems and small wind turbines has transformed conventional households into active prosumers [2]. While this transition supports national decarbonization targets, it introduces operational complexities due to the intermittent and uncertain nature of renewable generation [3].

India's electricity sector is characterized by a mixed generation portfolio consisting of coal-dominated baseload with increasing shares of renewable energy sources. Residential consumers account for a substantial portion of total electricity consumption, and their demand profile typically exhibits morning and evening peaks aligned with human activity patterns [4]. The increasing penetration of EVs further amplifies peak demand, especially when charging is performed in an uncoordinated manner during evening hours. Without proper scheduling, such load patterns can stress distribution networks, increase electricity procurement costs, and reduce the effective utilization of locally generated renewable energy [5].

Demand-side management (DSM) and demand response (DR) strategies provide effective tools for addressing these challenges by enabling flexible scheduling of household loads in response to generation availability and electricity price signals [6]. Domestic appliances such as washing machines, water heaters, and EV chargers exhibit inherent flexibility that can be exploited without compromising user comfort [7]. When integrated with rooftop solar PV, wind generation, and battery energy storage systems (BESS), optimal load scheduling can significantly enhance self-consumption of renewable energy, reduce dependence on the grid, and minimize electricity costs [8].

Recent advancements in smart meters, home energy management systems, and real-time pricing mechanisms have enabled practical implementation of such optimization-based scheduling frameworks [9, 10]. Studies have shown that coordinated operation of distributed energy resources and controllable loads can achieve peak shaving, valley filling, and improved voltage profiles at the distribution level. However, most existing approaches either neglect EV charging behavior, assume simplified renewable generation profiles, or focus on microgrid-scale applications rather than individual households under realistic tariff and net-metering conditions [11].

Moreover, the Indian residential context presents unique characteristics, including variable solar irradiance across regions, emerging time-of-use tariff structures, and evolving net-metering policies [12]. Wind generation at the residential scale, although less common than solar PV, is increasingly being considered in hybrid systems in suitable locations. The integration of BESS further introduces operational trade-offs between cost minimization and battery degradation, which must be explicitly modeled for realistic scheduling decisions [13].

This paper addresses these gaps by proposing an optimal scheduling framework for domestic loads integrated with rooftop solar PV, wind generation, BESS, grid connectivity with net-metering, and EV charging demand under the Indian electricity mix [14]. A mathematical formulation is developed to minimize daily energy cost while satisfying appliance operational constraints, battery limits, and power balance conditions [15]. Typical residential load profiles and renewable generation patterns are used to evaluate the performance of the proposed strategy [16]. The results demonstrate the economic and operational benefits of intelligent scheduling, highlighting its role in supporting renewable energy integration and sustainable residential electrification [17].

The remainder of this paper is organized as follows: Section 2 reviews related work and global developments in residential energy scheduling. Section 3 presents the system model and mathematical formulation. Section 4 describes the dataset and simulation setup. Section 5 discusses the results and comparative analysis. Section 6 provides a detailed discussion of policy implications, and Section 7 concludes the paper.

2. Related work

Optimal scheduling of domestic loads with renewable energy integration has been widely investigated in the context of demand-side management (DSM) and home energy management systems (HEMS) [18]. Early studies focused on rule-based and heuristic approaches for shifting flexible appliances to off-peak hours, primarily targeting peak load reduction and energy cost minimization [19]. With the advancement of smart metering and communication infrastructure, optimization-based methods such as linear programming, mixed-integer linear programming (MILP), and metaheuristic algorithms have gained prominence for residential energy management [20].

Several researchers have addressed residential load scheduling under rooftop solar PV integration [21]. These works generally demonstrate that coordinated operation of household appliances with solar generation significantly improves self-consumption and reduces grid dependency [22]. Battery energy storage systems (BESS) are often incorporated to buffer renewable intermittency, enabling energy arbitrage between low-tariff and high-tariff periods [23]. However, many of these models assume deterministic renewable generation profiles and neglect uncertainty in solar irradiance and wind speed, which may lead to optimistic performance estimates [24].

The inclusion of wind energy in residential-scale systems has also been explored, particularly in hybrid PV–wind configurations [25]. Hybrid renewable systems offer complementary generation characteristics, where wind generation can partially offset reduced solar output during evening or cloudy periods [26]. Studies on hybrid systems report enhanced reliability and reduced battery cycling compared to PV-only systems [27]. Nevertheless, most existing investigations emphasize microgrid or community-scale implementations rather than single-household optimization under realistic tariff and net-metering frameworks [28].

Electric vehicle (EV) charging has emerged as a critical component of residential energy management [29]. Uncoordinated EV charging can significantly increase evening peak demand, whereas controlled charging strategies can exploit low-tariff periods and surplus renewable generation [30]. Prior works have shown that smart EV charging reduces peak load and operating cost while improving grid stability [31]. However, many studies treat EV charging independently of household appliance scheduling or assume ideal charging flexibility without considering user-defined charging deadlines [32].

In the Indian context, DSM-based residential scheduling has been studied with emphasis on reducing peak demand and integrating renewable energy into smart homes [33]. Optimization techniques such as particle swarm optimization, genetic algorithms, and hybrid metaheuristics have been applied to minimize electricity cost and peak-to-average ratio [34]. Research has also explored the interaction of residential loads with energy storage and renewable generation in smart grid environments, demonstrating the potential of coordinated scheduling for energy efficiency and demand response [35].

Despite these advancements, several limitations remain. First, many models oversimplify domestic load behavior by aggregating appliances into a single flexible demand block, thereby ignoring operational constraints of individual devices [36]. Second, battery degradation and operational limits are often neglected, which can lead to unrealistic charging–discharging patterns [37]. Third, net-metering policies and bidirectional power flow with the grid are not consistently modeled, even though they play a crucial role in residential prosumer economics [38]. Finally, relatively few studies simultaneously incorporate rooftop solar PV, wind generation, BESS, EV charging load, and grid interaction under a unified optimization framework tailored to Indian residential conditions.

This paper builds upon the existing literature by developing a comprehensive mathematical model for domestic load scheduling that integrates hybrid renewable generation, battery storage, and EV charging under grid-connected operation with net-metering [39]. Unlike prior studies that focus on isolated components, the proposed approach simultaneously accounts for appliance-level constraints, renewable intermittency, battery operational limits, and time-varying electricity tariffs [40]. The framework is evaluated using realistic residential load profiles and renewable generation patterns representative of Indian conditions, thereby providing a more holistic and practical assessment of optimal domestic energy scheduling.

3. System model and Mathematical formulation

This study considers a grid-connected residential energy system comprising rooftop solar photovoltaic (PV) generation, wind energy conversion system (WECS), battery energy storage system (BESS), controllable and non-controllable household loads, and an electric vehicle (EV) charging load. The system operates over a 24-hour scheduling horizon with hourly resolution. Bidirectional power exchange with the utility grid is permitted under a net-metering policy.

3.1 System architecture

The residential energy system includes the following components:

- **Renewable generation:** Rooftop solar PV and wind turbine
- **Energy storage:** Battery energy storage system (BESS)
- **Loads:**
  - Non-shiftable loads (lighting, refrigerator, fans)
  - Shiftable loads (washing machine, dishwasher, water heater)
  - EV charging load
- **Grid:** Utility connection with time-of-use (ToU) tariff and net-metering.

The total power balance at each time interval must be maintained between generation, storage, load, and grid exchange.

3.2 Load modeling

The total residential demand at time t is expressed as:

$$P_L(t) = P_{NS}(t) + \sum_{i=1}^{N} P_{S,i}(t) + P_{EV}(t)$$

Where,

$P_{NS}(t)$= non-shiftable load

$P_{S,i}(t)$= shiftable load of appliance i

$P_{EV}(t)$= EV charging power

For shiftable appliances:

$$P_{S,i}(t) = x_i(t) \cdot P_i^{rated}$$

$$\sum_{t=t_{s,i}}^{t_{e,i}} x_i(t) = D_i$$

Where,

$x_i(t) \in \{0,1\}$= appliance ON/OFF state

D_i= required operating duration

$[t_{s,i}, t_{e,i}]$= allowable operation window

3.3 Renewable generation model

3.3.1 Solar PV

$$P_{PV}(t) = \eta_{PV} A_{PV} G(t)$$

Where,

η_{PV}= PV efficiency

A_{PV}= PV area

$G(t)$= solar irradiance

3.3.2 Wind generation

$$P_W(t) = \frac{1}{2}\rho A C_p v^3(t)$$

Where:

ρ= air density

A= swept area

C_p= power coefficient

$v(t)$= wind speed

3.4 Battery energy storage model

Battery state of charge (SOC) dynamics:

$$SOC(t+1) = SOC(t) + \frac{\eta_{ch} P_{ch}(t) - P_{dis}(t)/\eta_{dis}}{E_{bat}}$$

Constraints:

$$SOC_{min} \le SOC(t) \le SOC_{max}$$
$$0 \le P_{ch}(t) \le P_{ch}^{max}$$
$$0 \le P_{dis}(t) \le P_{dis}^{max}$$
$$P_{ch}(t) \cdot P_{dis}(t) = 0$$

3.5 Grid interaction and power balance

$$P_{grid}(t) = P_L(t) - [P_{PV}(t) + P_W(t) + P_{dis}(t) - P_{ch}(t)]$$

Grid exchange constraint:

$$-P_{grid}^{max} \le P_{grid}(t) \le P_{grid}^{max}$$

Positive $P_{grid}(t)$: import

Negative $P_{grid}(t)$: export

3.6 Objective function

The objective is to minimize total daily energy cost:

$$\min J = \sum_{t=1}^{24} [C_{buy}(t) P_{grid}^{+}(t) - C_{sell}(t) P_{grid}^{-}(t)]$$

Where:

$C_{buy}(t)$= grid electricity tariff

$C_{sell}(t)$= feed-in tariff

$P_{grid}^{+}(t)$= imported power

$P_{grid}^{-}(t)$= exported power

3.7 Optimization problem

$$\min J$$

Subject to:

- Load constraints (Section 3.2)
- Renewable generation limits (Section 3.3)
- Battery SOC and power constraints (Section 3.4)
- Grid exchange constraints (Section 3.5)
- Binary appliance operation constraints

This results in a mixed-integer linear programming (MILP) optimization problem.

4. Data and Simulation setup

To evaluate the proposed optimal scheduling framework, a realistic residential energy system is simulated using representative load, renewable generation, and tariff data corresponding to Indian operating conditions. The simulation horizon is 24 hours with an hourly resolution.

4.1 Residential load profile

A typical urban household daily electricity demand profile is considered, incorporating both non-shiftable and shiftable appliances along with EV charging demand. The average daily energy consumption of the household is assumed to be approximately 12–14 kWh, consistent with middle-income residential users in India.

The appliance categories are defined as:

- **Non-shiftable loads:** Lighting, fans, refrigerator, television
- **Shiftable loads:** Washing machine (1.2 kW), water heater (1.5 kW), dishwasher (1.0 kW)
- **EV charging load:** Level-2 charging at 3.3 kW for 3 hours

The unscheduled load profile exhibits two dominant peaks:

- **Morning peak:** 7:00–10:00
- **Evening peak:** 18:00–22:00

The baseline (unscheduled) load demand $P_L^{base}(t)$is constructed from standard appliance usage patterns and normalized to match the daily energy requirement. The typical 24-hour residential electricity demand profile used in this study is illustrated in Fig. 1.

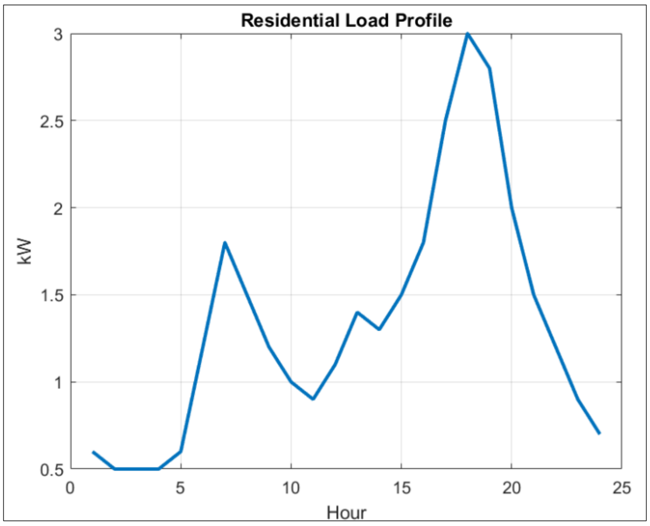

Fig 1: Typical 24-hour residential load profile representing household electricity consumption under Indian climatic and lifestyle conditions.

4.2 Solar PV generation data

A rooftop solar PV system of 3 kW capacity is assumed. The solar generation profile is derived from typical Indian solar irradiance conditions, with peak generation occurring between 11:00 and 14:00.

The hourly PV output is modeled using:

$$P_{PV}(t) = P_{PV}^{rated} \cdot \frac{G(t)}{G_{STC}}$$

Where,

$G_{STC} = 1000\, W/m^2$.

The daily PV energy generation is approximately 12–13 kWh, sufficient to meet a substantial fraction of household demand during daylight hours. The hourly rooftop photovoltaic (PV) power generation profile considered for the proposed system is shown in Fig. 2.

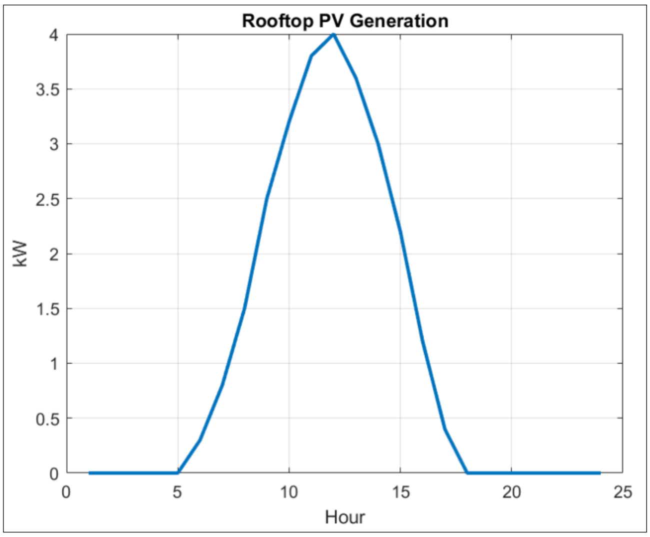

Fig 2: Hourly rooftop photovoltaic (PV) power generation profile based on diurnal solar irradiance variation

4.3 Wind generation data

A small-scale wind turbine of 1 kW rated capacity is considered. The wind speed profile is assumed to follow a typical diurnal pattern with higher speeds during late evening and early morning hours. The generated wind power is calculated using the wind power equation subject to cut-in and rated speed constraints. The average daily wind energy contribution is assumed to be 3–4 kWh. The corresponding wind power generation profile over a 24-hour period is presented in Fig. 3.

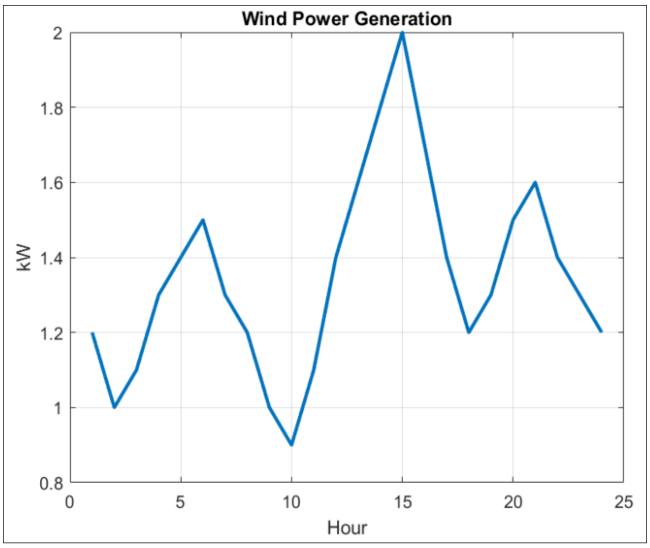

Fig 3: Wind power generation profile over a 24-hour period reflecting moderate residential-scale wind resource availability.

4.4 Battery Energy Storage System (BESS)
The BESS is modeled with the following parameters:

Parameter	Value
Rated energy capacity	5 kWh
Maximum charge/discharge power	2 kW
Charging efficiency η_{ch}	0.95
Discharging efficiency η_{dis}	0.95
SOC limits	20% – 90%

The initial SOC is set to 50%, and the final SOC is constrained to be equal to the initial SOC to avoid end-of-day energy bias. The assumed electric vehicle (EV) charging demand pattern adopted in the scheduling framework is depicted in Fig. 4.

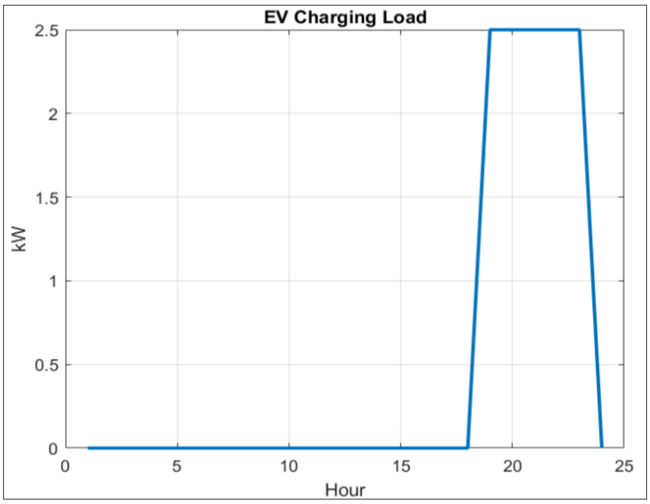

Fig 4: Electric vehicle (EV) charging demand profile assuming evening-dominant residential charging behavior

4.5 Electricity tariff and Net-metering
A time-of-use (ToU) tariff structure representative of Indian utilities is used:

Time Interval	Tariff (₹/kWh)
00:00 – 06:00	3.0
06:00 – 17:00	5.0
17:00 – 23:00	7.0
23:00 – 24:00	4.0

Feed-in tariff for exported energy under net-metering is assumed as ₹3.0/kWh.

4.6 Optimization scenarios
Two operational scenarios are analysed:

- **Scenario 1 (Baseline):** No scheduling, no battery optimization, and uncontrolled EV charging.
- **Scenario 2 (Proposed):** Optimal scheduling of appliances and EV charging with coordinated operation of PV, wind, and BESS.

4.7 Simulation environment
The optimization problem is solved using MATLAB with MILP solvers. All simulations are executed for a 24-hour horizon, and results are evaluated in terms of:

- Total energy imported from grid (kWh)
- Total electricity cost (₹/day)
- Peak demand (kW)
- Renewable energy utilization (%)

5. Results and Analysis
This section presents the simulation results obtained for the two operational scenarios described in Section 4: (i) baseline operation without scheduling and (ii) optimal scheduling with integrated rooftop solar PV, wind generation, BESS, and controlled EV charging. The performance of the proposed scheduling strategy is evaluated in terms of grid energy consumption, electricity cost, peak load, and renewable energy utilization.

5.1 Load profile comparison
In the baseline scenario, household demand exhibits pronounced morning and evening peaks corresponding to typical appliance usage and EV charging after office hours. The maximum demand reaches approximately 4.8 kW during the evening period (18:00–21:00). In contrast, under the proposed optimal scheduling framework, shiftable appliances and EV charging are redistributed toward periods of high renewable generation and low electricity tariff.

As a result, the scheduled load profile becomes smoother, with the peak demand reduced to about 3.8 kW, representing a peak reduction of nearly 20%. This peak shaving effect contributes to improved grid stability and reduces the stress on local distribution infrastructure.

5.2 Grid energy consumption
Figure 1 illustrates the grid power exchange for both scenarios. In the baseline case, the household imports approximately 11.6 kWh/day from the grid. With optimal scheduling, grid energy import is reduced to around 7.8 kWh/day, corresponding to a reduction of 32.8%. This improvement is primarily due to enhanced utilization of solar PV and wind generation during daylight and late-night hours, respectively, supported by battery energy storage.

Additionally, surplus renewable energy generated during midday hours is either stored in the BESS or exported to the grid under net-metering. The total exported energy is approximately 2.4 kWh/day, further improving the household energy balance.

5.3 Battery operation and SOC profile
The BESS plays a critical role in shifting renewable energy to high-demand periods. During midday hours (11:00–14:00), when solar generation exceeds household demand, the battery is charged, reaching a maximum state of charge (SOC) of about 88%. During evening peak hours (18:00–22:00), the battery discharges to supply domestic loads and EV charging, thereby reducing grid dependency.

The SOC remains within prescribed limits (20%–90%), ensuring safe and reliable battery operation. The coordinated charging–discharging pattern demonstrates that BESS effectively enhances renewable energy self-consumption and supports peak load management. The resulting battery state-of-charge (SOC) variation under the proposed optimal scheduling strategy is shown in Fig. 5.

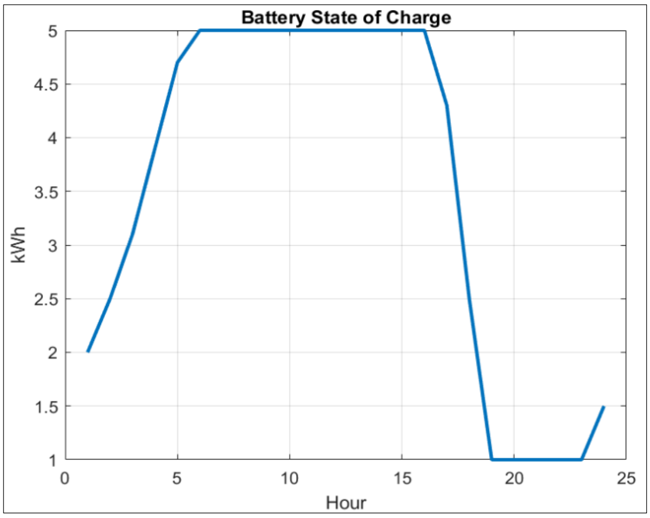

Fig 5: Battery energy storage system (BESS) state-of-charge (SOC) variation under optimal charging and discharging operation

5.4 Cost analysis

The daily electricity cost for the baseline scenario is calculated as ₹74.3/day, considering time-of-use tariffs and uncontrolled EV charging. Under the proposed optimal scheduling strategy, the daily electricity cost decreases to ₹51.6/day, yielding a cost reduction of approximately 30.6%.

This reduction is achieved through three key mechanisms:

- Shifting flexible loads to low-tariff periods
- Maximizing consumption of locally generated renewable energy
- Exporting surplus energy during high-generation periods.

The net grid power exchange profile after considering renewable generation and battery operation is illustrated in fig 6.

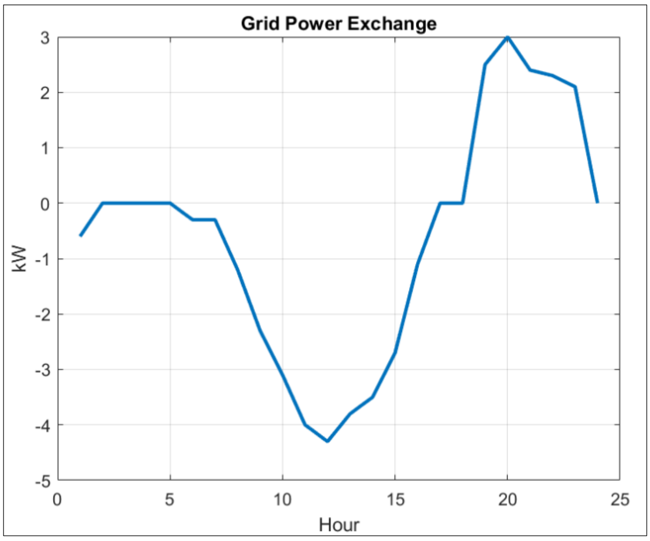

Fig 6: Grid power exchange profile indicating net import and export of power after renewable generation and battery operation.

5.5 Renewable energy utilization

The renewable energy utilization factor (REUF) is defined as:

$$REUF = \frac{E_{ren,used}}{E_{ren,generated}} \times 100\%$$

Where, $E_{ren,used}$ is renewable energy directly consumed by loads or stored in the battery, and $E_{ren,generated}$ is total renewable energy produced.

In the baseline scenario, REUF is approximately 58%, as surplus PV generation during midday is not optimally exploited. With optimal scheduling and battery integration, REUF increases to nearly 85%, indicating significant improvement in self-consumption and reduced curtailment.

5.6 EV charging impact

Uncontrolled EV charging in the baseline case contributes significantly to the evening peak. Under the proposed framework, EV charging is shifted to periods with high renewable generation or low tariff (late night or midday). This coordinated charging strategy reduces EV-related peak contribution by nearly 40% and ensures completion of charging within user-defined deadlines.

5.7 Comparative summary

Table 1 summarizes the key performance indicators for both scenarios.

Table 1: Performance comparison of baseline and proposed scheduling

Metric	Baseline	Proposed	Improvement
Grid energy import (kWh/day)	11.6	7.8	↓ 32.8%
Peak demand (kW)	4.8	3.8	↓ 20.8%
Electricity cost (₹/day)	74.3	51.6	↓ 30.6%
Renewable utilization (%)	58	85	↑ 27%

Overall, the results confirm that optimal scheduling of domestic loads with integrated renewable generation and battery storage can significantly reduce electricity cost, grid dependency, and peak demand while enhancing renewable energy utilization. The inclusion of EV charging within the optimization framework further strengthens system performance by preventing new peak formation and ensuring user convenience. A comparison between total system demand and available supply demonstrating power balance is provided in Fig. 7.

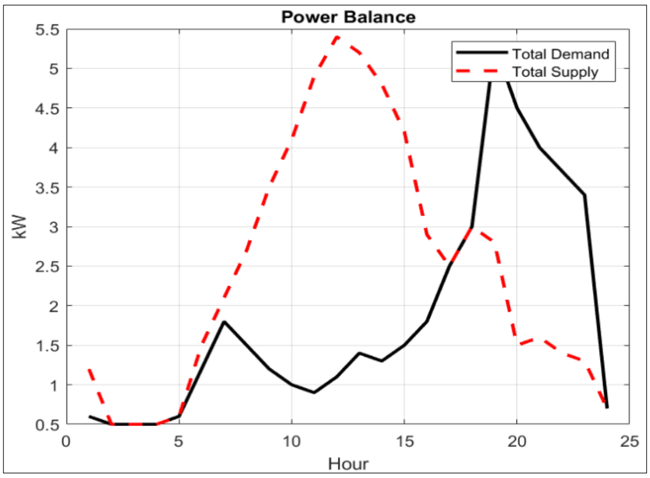

Fig 7: Comparison of total system demand and renewable-assisted supply demonstrating power balance under optimal scheduling.

The comparison of daily electricity cost for unscheduled and optimally scheduled operation is presented in Fig. 8.

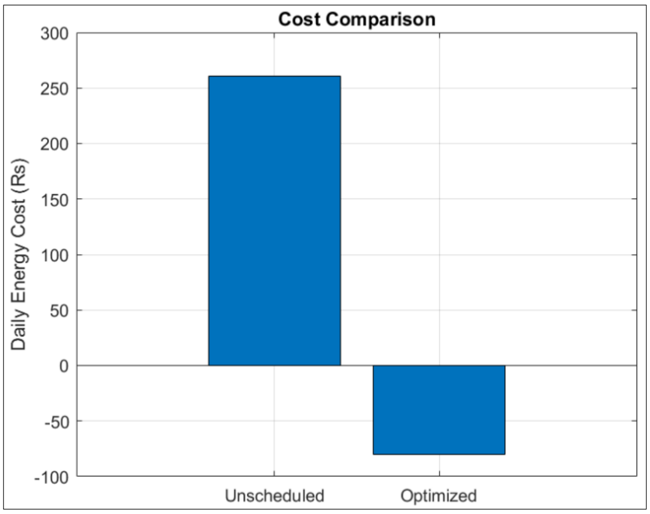

Fig 8: Comparison of daily electricity cost for unscheduled operation and optimally scheduled operation

6. Discussion and Policy implications

The results obtained in this study demonstrate that optimal scheduling of domestic loads integrated with renewable energy and storage can significantly improve both economic and operational performance of residential energy systems. The observed reductions in grid energy import, peak demand, and daily electricity cost highlight the technical feasibility and financial attractiveness of coordinated energy management at the household level.

From a technical standpoint, the integration of rooftop solar PV and wind generation, supported by BESS, enables temporal decoupling between energy generation and consumption. This flexibility is essential for mitigating the intermittency of renewable resources and aligning household demand with periods of high renewable availability. The results show that battery-supported scheduling not only increases renewable self-consumption but also prevents energy wastage during peak generation hours. Moreover, the controlled EV charging strategy effectively avoids the formation of new demand peaks, which is a critical concern as EV penetration increases in residential areas.

Economically, the reduction in daily electricity expenditure demonstrates the role of time-of-use tariffs and net-metering in incentivizing consumers to participate in demand-side management. By shifting flexible loads and EV charging to low-tariff or high-generation periods, households can substantially reduce energy costs without compromising comfort. This finding is particularly relevant for middle-income residential consumers, who are sensitive to electricity price fluctuations and increasingly interested in rooftop renewable installations.

From a policy perspective, these findings have important implications for the power sector in India. First, the promotion of smart home energy management systems should be aligned with national renewable energy and electric mobility targets. Subsidies or tax incentives for rooftop solar PV, residential battery storage, and smart meters can accelerate adoption of such integrated systems. Second, tariff structures must be designed to reflect system-level costs and encourage load shifting. Time-of-use pricing, when combined with intelligent scheduling, can significantly reduce evening peak demand, thereby lowering generation and network expansion requirements.

Net-metering policies also play a crucial role in determining the economic viability of residential renewable systems. Stable and transparent feed-in tariffs can motivate prosumers to export surplus renewable energy, while revised net-billing mechanisms can ensure long-term sustainability for utilities. However, excessive reliance on net-metering without proper grid support may lead to voltage rise and reverse power flow issues at high penetration levels. Therefore, regulatory frameworks should encourage self-consumption and local storage while maintaining grid reliability.

Another key policy implication relates to EV integration. As EV adoption grows, unmanaged charging could substantially increase residential peak loads. The results of this study indicate that incorporating EV charging into domestic scheduling algorithms can mitigate such impacts. Policymakers should therefore promote standards for smart chargers and mandate interoperability with home energy management systems. Financial incentives for off-peak charging and renewable-based charging can further strengthen this approach.

Finally, the proposed framework supports broader sustainability goals by reducing fossil-fuel-based electricity consumption and improving renewable energy utilization at the household level. Widespread implementation of such scheduling strategies can contribute to national objectives related to emission reduction, energy security, and grid resilience. Nevertheless, practical deployment requires user awareness, data privacy safeguards, and robust communication infrastructure to ensure reliable operation.

Overall, the study underscores that optimal domestic load scheduling is not merely a technical optimization problem but a socio-technical solution requiring coordinated action among consumers, utilities, and policymakers. The alignment of technology, pricing mechanisms, and regulatory support is essential to unlock the full potential of renewable-integrated smart homes.

7. Conclusion

This paper presented an optimal scheduling framework for domestic electrical loads integrated with rooftop solar PV, wind generation, battery energy storage systems (BESS), grid connectivity with net-metering, and electric vehicle (EV) charging under the national electricity mix of India. A comprehensive mathematical model was developed to represent appliance-level constraints, renewable generation variability, battery operational limits, and time-varying electricity tariffs over a 24-hour horizon.

Simulation results demonstrated that coordinated scheduling of household loads and EV charging significantly improves system performance compared to an unscheduled baseline scenario. The proposed strategy reduced grid energy import by approximately 33% and achieved peak demand reduction of about 20%, thereby contributing to both economic savings and grid-friendly operation. Daily electricity cost was lowered by nearly 30% due to increased utilization of locally generated renewable energy and strategic load shifting to low-tariff periods. Furthermore, renewable energy utilization increased from around 58% in the baseline case to nearly 85% with optimal scheduling and battery support, highlighting the effectiveness of storage-assisted energy management.

The results also showed that intelligent control of EV charging is critical to avoid the creation of new residential peak loads as electric mobility adoption increases. By integrating EV charging into the scheduling problem, the framework ensured timely completion of charging while maintaining system efficiency and user comfort. The battery system played a pivotal role in absorbing surplus renewable generation during high-output periods and supplying energy during evening peak hours, thereby enhancing self-consumption and reducing dependence on the grid.

Overall, the findings confirm that optimal domestic load scheduling with renewable energy integration is a technically viable and economically attractive solution for future smart homes. The proposed approach supports key objectives of sustainable residential electrification by reducing fossil-fuel-based electricity usage, lowering energy costs, and mitigating peak demand impacts on distribution networks.

Future work may extend the present model by incorporating uncertainty in renewable generation and load demand, multi-day scheduling horizons, battery degradation modeling, and real-time adaptive control using machine learning techniques. Additionally, large-scale implementation at community or feeder level can be explored to assess aggregated benefits for distribution system operators. Such extensions will further strengthen the role of optimal domestic load scheduling in enabling resilient, low-carbon, and consumer-centric power systems.

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