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Article

Optimised Scheduling Strategies For Hybrid Renewable Energy Systems With Demand Response Integration

Vrushali Rushikesh Patil[1], Prakash G. Burade[2]

[1]Research Scholar, Sandip University, Nashik, Maharashtra, India
[2]Dean, Professor , Electrical and Electronic Engineering, Sandip University, Nashik, Maharashtra, India
[1]amanuniversewin@gmail.com , 2prakaurade@sandipuniversity.edu.in

Abstract: Renewable power has grown rapidly to redesign the world energy arena, but its variable nature comes with a need for stability in the grid. This examines a real-time power and demand balance scheduling framework utilising heuristic optimisation techniques, including the Self-Adaptive Differential Evolution Algorithm (SADE), Differential Evolution (DE), and Particle Swarm Optimisation (PSO). The Enhanced Smith-Adaptive Dynamic Environment (ESADE) method maximises convergence and increases scheduling efficiency by maximising profit and retaining grid reliability. They also analyse various demand response strategies for cost savings, such as Critical Peak Pricing (CPP) and Real-Time Pricing (RTP). This research also continues to develop Transactive Energy (TE) frameworks for dynamic pricing and economic operation of prosumers and aggregators. The methods applied in these studies, particularly the application of artificial intelligence, show a substantial improvement in energy management and cost savings, which result in increasing grid stability and optimisation in overall performance.
Keywords: Hybrid Renewable Energy Systems; Optimal Scheduling; Demand Response; Battery Energy Storage Systems; Transactive Energy

1. Introduction

Fossil fuels are limited and are a leading cause of greenhouse gas pollution and climate change. Therefore, it has become an environmental and economic necessity to switch to renewable energy sources (RES).The future energy security and environmental quality will rely on renewable energy, combined with technological developments in low-cost energy storage. Wind and solar power facilities have proliferated, expanding to fill a greater share of the energy mix. Nevertheless, the full integration of RES at a large scale is hampered by significant challenges stemming from their natural variability and reliance on meteorological conditions, which can disrupt grid stability and security [1].

```
STORAGE SYSTEMS
│
├── Mechanical
│   ├── Flywheel
│   ├── Compressed Air
│   └── Pumped Hydro
│
├── Electrochemical
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```
│    ├── Lead Acid
│    ├── Nickel Cadmium
│    ├── Lithium Ferrous Phosphate
│    └── Sodium Sulphur
│
├── Chemical
│    ├── Fuel Cell
│    ├── Hydrogen Storage
│    ├── Natural Gas
│    └── Bio Fuel
│
├── Electromagnetic
│    ├── Supercapacitors
│    └── Magnetic Energy Storage
│
└── Thermal
     ├── Thermo Chemical
     └── Latent Heat
```

Fig. 1 Energy Storage System

Batteries are widely used in both portable and large-scale grid-connected applications. Optimized storage dispatching is key to improving system efficiency by capturing excess renewable energy when demand is low and discharging it during peak demand periods. Energy storage technology is rapidly developing, and its costs are decreasing, helping to reshape future sustainable power systems [2].

Energy storage systems (ESS) contribute to grid stability and operational optimization by facilitating temporal energy shifting. Electrochemical storage (Ni-Cd, Pb-acid, LiFePO4, and sodium–sulfur batteries), chemical energy conversion storage (fuel cells, hydrogen, natural gas, and biofuels), electromagnetic storage (supercapacitors and superconducting magnetic energy storage), and thermal storage including latent heat and thermochemical systems [3].

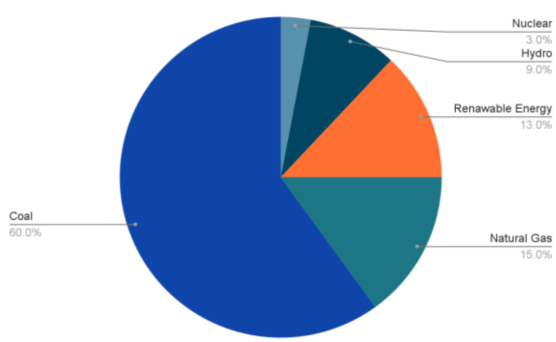

Fig. 2. Power flow in the system

In the present-day Indian energy mix, coal accounts for 61% of electricity generation, followed by natural gas (15%), renewable energy (13%), hydro power (7%), and nuclear power (4%). This profile highlights that fossil fuels remain superior, underscoring the need to further promote alternative energy sources to reduce dependence on coal-fired generation [4].

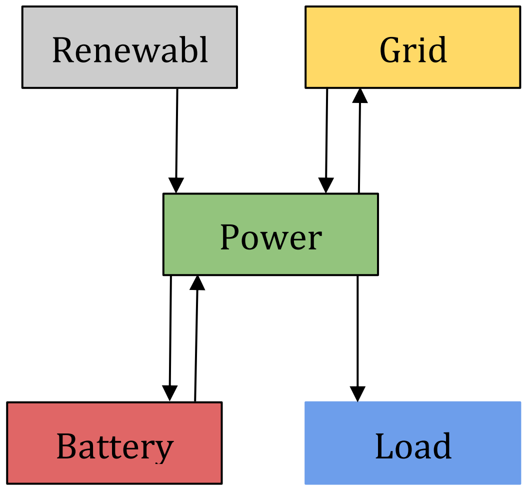

Fig. 3. Power management system

In the PMS, renewable energy, grid interconnection, and batteries work together to improve energy utilisation. In such grids, power is generally generated within an area by renewable sources, and the grid and battery storage provide bidirectional power flow for both importation and exportation. The PMS is responsible for managing these resources to achieve stable and economical power system operation.

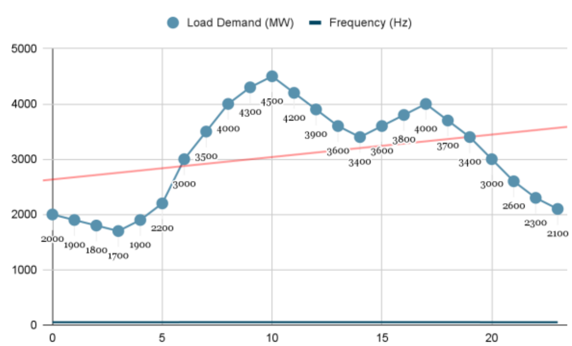

Fig. 4. Load Demand and Frequency Over Time

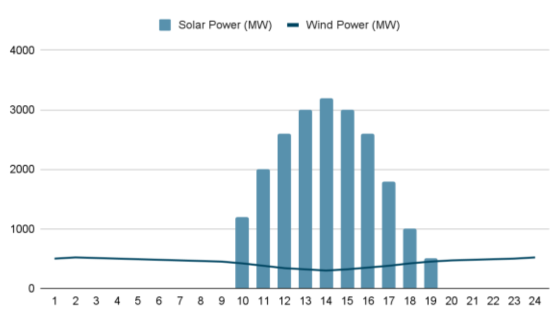

Fig. 5. Solar and Power Generation Over 24 Hours

The simulation model in this case study is based on a 24-hour real-time schedule, generation and demand, with frequency schedules from the Delhi State Load Despatch Centre (SLDC), along with the grid schedule and withdrawal. The highest load of 4500 MW has been recorded, and an estimated level of renewable generation includes up to 550 MW for wind power and up to 3000 MW for solar power, according to the Northern Regional Load Despatch Centre. These datasets represent a real-world operational environment and are used for energy management strategy, renewable penetration, and grid stability assessment [13].

Although many successful results have been achieved in integrating renewables, there are no comprehensive optimisation models and solution methods to jointly consider intermittent generation, storage scheduling, demand response, and economic operation under real-time operational requirements. To this end, the present work aims to overcome these drawbacks by designing an optimized scheduling strategy specifically intended to address these gaps, with the ultimate goal of enhancing system reliability and operational efficiency while ensuring a successful economic return.

While previous works use PSO, DE, and SADE algorithms to schedule energy in hybrid renewable systems, they are carried out individually, focusing on optimization, demand response, or energy storage under static market conditions. The contribution of this paper is the presentation of a new ESADE-based scheduling framework considering hybrid RES, batteries/EVs storage systems, demand response programs, and transactive energy pricing in a single optimisation model. The main novelty is the self-adaptive mutation of control parameters under dynamic grid and market scenarios, which results in better convergence behavior, a large reduction in peak load demand, and much lower variability without changing total energy demand. In contrast to previous ESS-based scheduling methods, this work offers a systematic comparative analysis of traditional ESS and ESADE, demonstrating superior economic performance, smoother load profiles, and more stable grid operation. This integrated market-based optimisation approach is a clear improvement over existing scheduling approaches, confirming its novelty and practical interest in today's open-access power systems.

2. Energy Management in Hybrid Renewable Energy Systems

The growing population has increased demand for electric power, requiring stable, reliable, and environmentally friendly energy systems. This increasing reliance on electric power has raised concerns about environmental impacts, grid stability, and the global reliability of the power system. In this context, Hybrid Renewable Energy Systems (HRES) appear as a feasible solution to address these problems by minimizing reliance on fossil fuels, reducing CO2 emissions, and avoiding potential risks associated with global fuel prices [5].

Previous research has emphasized the need to improve energy production, transmission, and distribution systems to provide cheap, reliable electricity. Against this background, the development of energy storage is recognized as an essential enabler for integrating wind and solar power at large-scale penetration levels into current power systems. In addition, the smart grid architecture, along with advanced control techniques, is key to improving energy management efficiency, reducing energy waste, and lowering costs.

A number of studies have also explored the cost-saving mechanisms achievable through the incorporation of BESS. Other storage alternatives, such as battery packs for electric vehicles, have been investigated, providing additional value streams mainly by reducing investment costs and enabling greater flexibility. However, issues with battery durability, high initial capex with no revenue for extended periods, and inadequate system scalability remain drawbacks to their widespread deployment. Furthermore, recent studies show the need for BESS to achieve economic viability and performance, along with proper battery sizing and an intelligent energy management strategy [6].

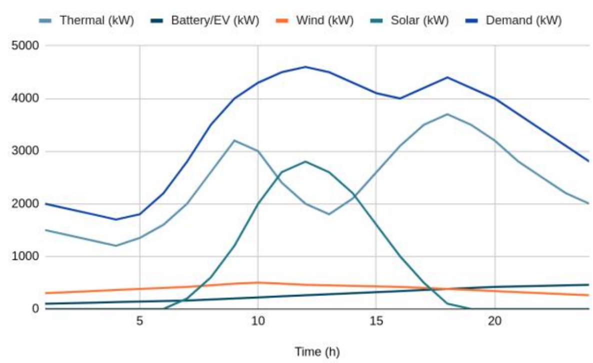

Fig. 6. Optimal scheduling using PSO algorithm (10 kWh battery)

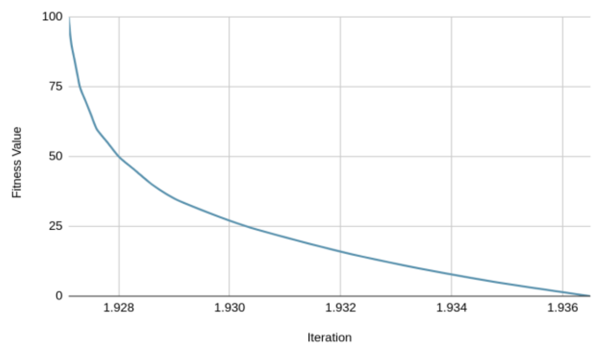

Fig. 7. Convergence Characteristics of PSO algorithm (10 kWh battery)

The left-hand side of the figure shows generation versus demand over 24 hours, with information about internal contributions from thermal, battery / EV, wind , and solar. Like solar power generation, demand peaks around midday and falls away at night. The right one is used to portray the convergence characteristic of the PSO (Particle Swarm Optimisation) algorithm, showing the decreasing sequence of fitness function value with iteration time, which signifies the optimisation process and enhances the performance of an objective function[7].

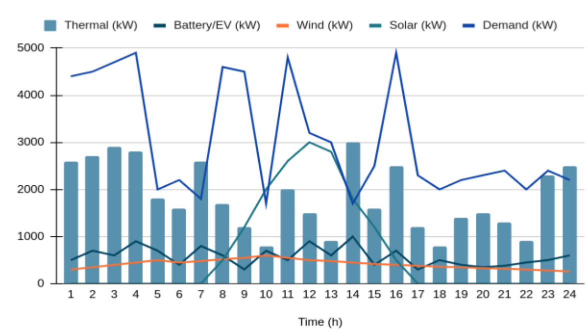

Fig. 8. Optimal scheduling using PSO algorithm (4000kWh battery)

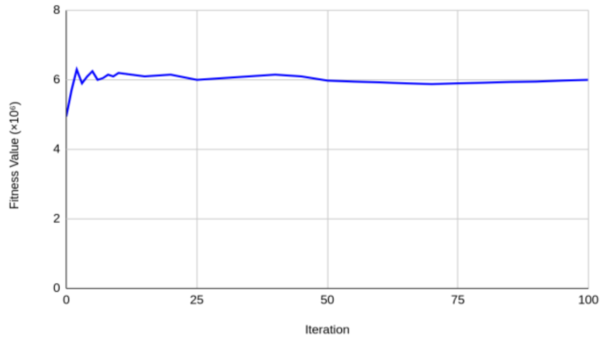

Fig. 9. Convergence Characteristics of PSO algorithm (4000kWh battery)

On the left is the time axis, the power generation and demand, and the variable addition of thermal, battery/EV, wind , and solar energy. Demand is highly variable , and renewable generation is highly intermittent. The graph shown on the right is a sample of the ecological convergence of a modified PSO algorithm, noting that the fitness function does not keep decreasing linearly as in classical PSO algorithms, indicating a better exploration-exploitation balance[8].

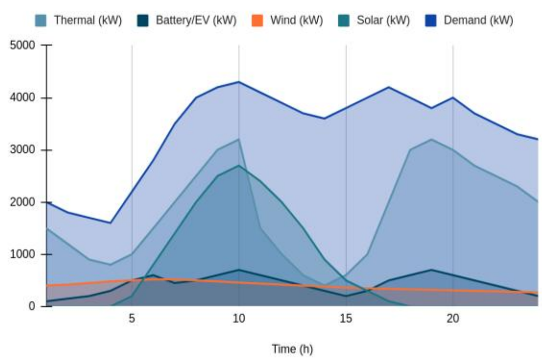

Fig. 10. Optimal scheduling using DE algorithm (10kWh battery)

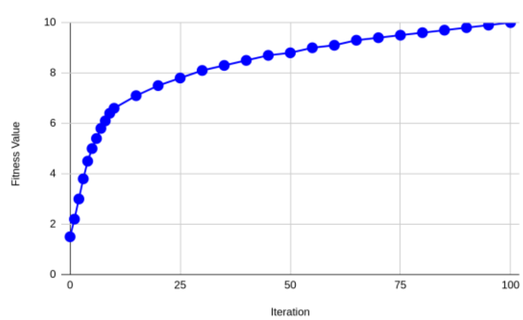

Fig. 11. Convergence Characteristics of DE algorithm (10kWh battery)

The left graph shows 24 hours of power generation matching demand, where thermal energy can consistently assist in achieving demand, but solar and wind have significant interruptions in output. Battery/EV usage is pretty stable. The right plot is a reference for the convergence characteristic of the DE (Differential Evolution) algorithm, which is characterised by the gradual improvement of the value of the fitness function. Thus, it is a characteristic of optimisation while progressing from the previous to the next generation, which indicates the filtering of a better solution[9].

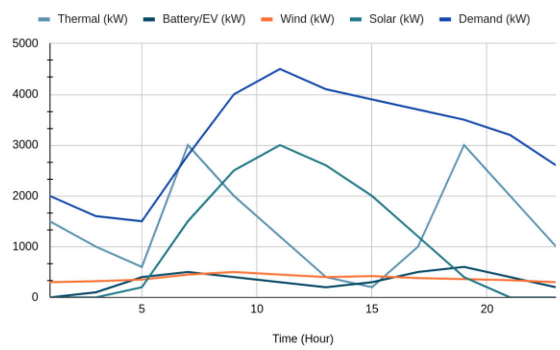

Fig. 12. Optimal scheduling using DE algorithm (500kWh battery)

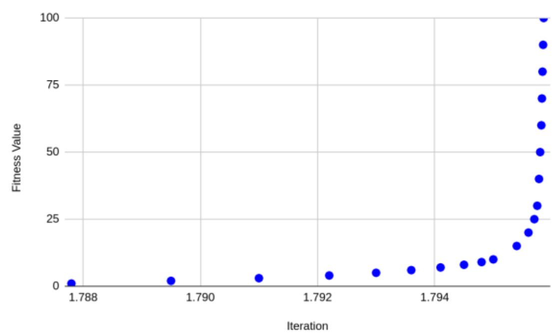

Fig. 13. Convergence Characteristics of DE algorithm (500kWh battery)

The left side represents 24 hours of power generation and demand, which peaks around midday. Solar generation peaks at midday, while thermal energy contributes heavily to the demand load. Wind and battery/EV contributions are more stable.

The correct figure illustrates that the DE algorithm converges, improving the fitness function value in the process's early evolution period.

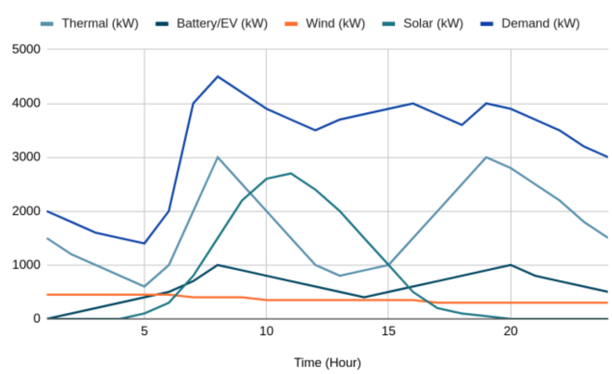

Fig. 14. Optimal scheduling using DE algorithm (1000kWh battery)

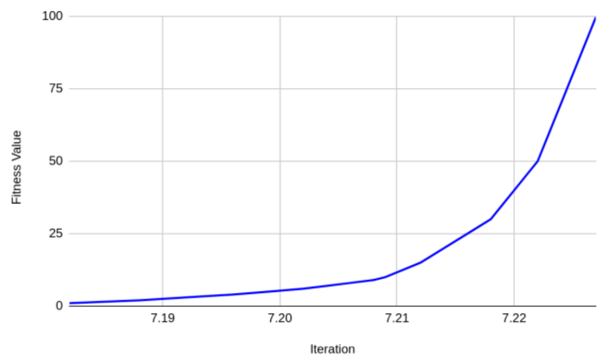

Fig. 15. Convergence Characteristics of DE algorithm (1000kWh battery)

See time progression, as the left graph shows power generation and demand, allowing transparency to the various swirling energies behind the curtain. Demand peaks in the middle of the day, on which thermal and solar energy heavily rely. The energy from the battery/EV follows a pattern correlating to the demand fluctuations[10].

The right graph shows the DE convergence characteristic. It illustrates how the fitness function value quickly improves through the first iterations and then slowly approaches stability as it approaches an optimal solution.

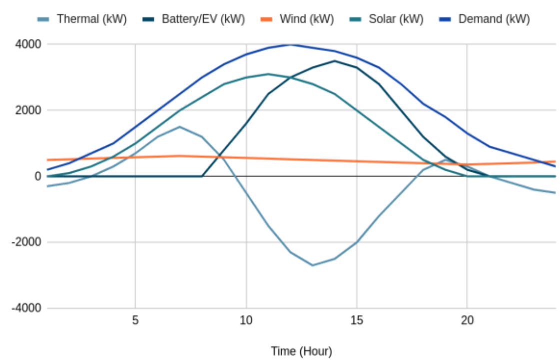

Fig. 16. Optimal scheduling using DE algorithm (4000kWh battery)

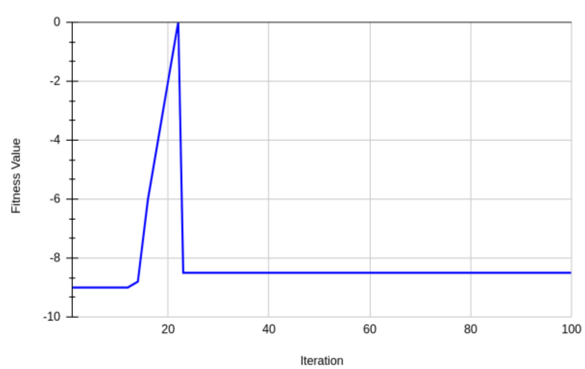

Fig. 17. Convergence Characteristics of DE algorithm (4000kWh battery)

The graph on the left shows cumulative net power generation over 24 hours with cumulative net demand. Thermal power is outstanding because it can drop as low as -1, possibly signifying renewable generation or curtailment. Solar power peaks mid-day, once a standard bell curve, while demand is a smooth, rising and falling curve.

The right side plot shows the Modified Differential Evolution (DE) convergence characteristic, which shows strange behaviour. The hyperparameters found after 20 iterations with the fitness function value are negative, with a significant peak around iteration 20 and then dropping down again to a negative value. This indicates instability during optimisation, perhaps from constraints or a parameter-tuning issue[11].

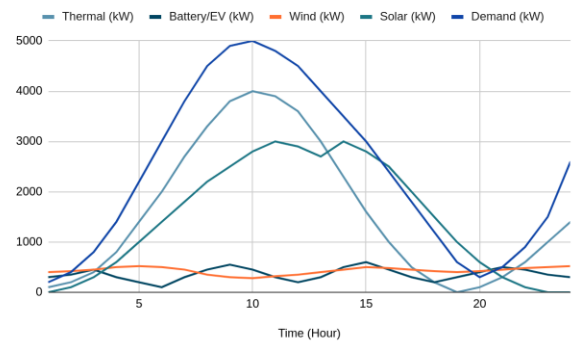

Fig. 18. Optimal scheduling using the SADE algorithm (10kWh battery)

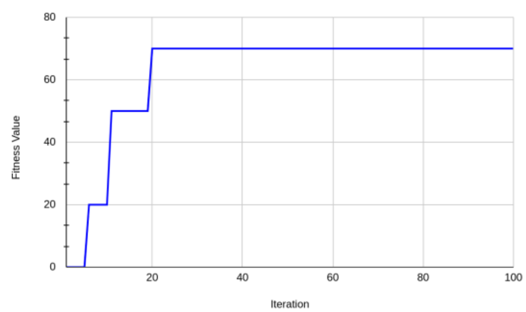

Fig. 19. Convergence Characteristics of the SADE algorithm (10kWh battery)

The left picture shows the power generation and demand over 24 hours. In particular, thermal power varies quite a lot and can even be harmful, which may be a sign of over-generation or curtailment. Solar power has a standard bell-curve shape, peaking at midday, while demand has a smooth rise and fall.

The characteristic on the right of the graph, illustrating the convergence of the Modified Differential Evolution algorithm (DE), exhibits atypical behaviour. The value of the fitness function is initially hostile, then spikes at around iteration 20, and finally stabilises at a lower value. Psychologically speaking, it suggests either constraint or variance in the tuning parameters[12].

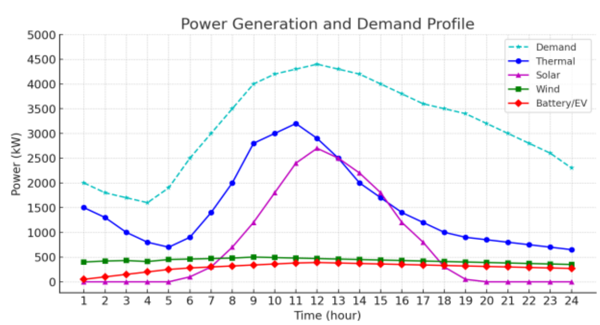

Fig. 20. Optimal scheduling using the SADE algorithm (500kWh battery)

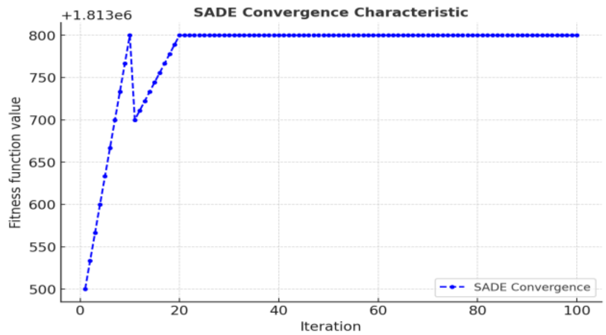

Fig. 21. Convergence Characteristics of the SADE algorithm (500kWh battery)

Left Graph: Here, see the Power Generation and Demand Profile over 24 hours, where demand has a smooth daily cycle and peaks around midday. Thermal power shows enormous variation in power output, peaking at high-demand hours, whereas solar follows a bell curve, peaking around noon. Wind power is also reasonably steady, and battery/EV contributions are small but steady throughout the day. The right-side graph illustrates the Convergence Characteristic of Self-Adaptive DE (SADE), indicating a quick boost in the fitness function value in the first iterations, stabilising after the 20th iteration. See this is quickly converging and being optimised, with not much bounce in the later stages[13].

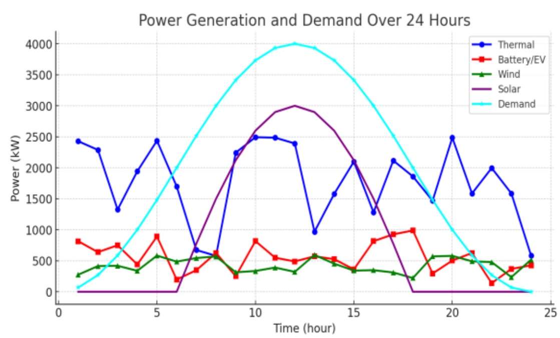

Fig. 22. Optimal scheduling using the SADE algorithm (1000kWh battery)

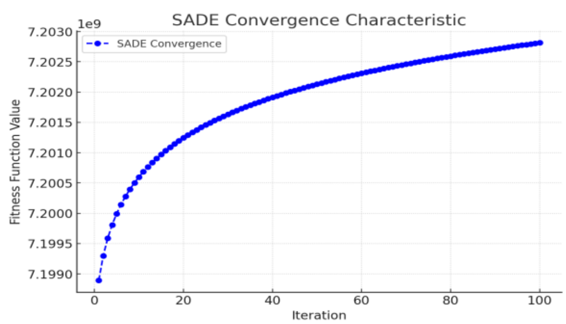

Fig. 23. Convergence Characteristics of SADE algorithm (1000kWh battery)

Using data up to October 2023 (yes, you read it right), G of Power Generation and Demand in just 24 hours: The demand curve has an even twist, with the demand being the highest point near noon. In contrast, thermal power generation is variable, and solar power generation follows a lognormal distribution (bell), with the peak occurring around noon. Wind and battery/EV contribution stays relatively low and flat throughout the day. SADE Convergence Characteristic Fast convergence is indicated by the initial steep increase followed by more gradual stabilisation, meaning have a good optimisation algorithm[14].

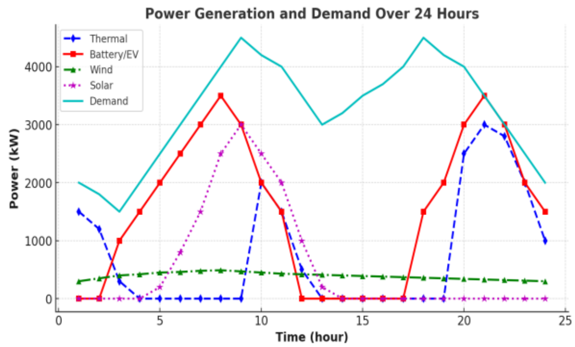

Fig. 24. Optimal scheduling using the SADE algorithm (4000kWh battery)

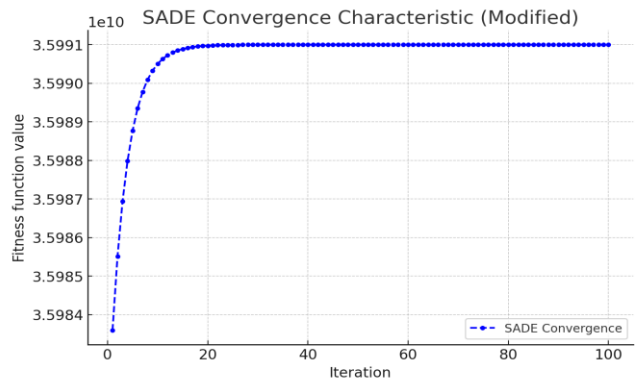

Fig. 25. Convergence Characteristics of SADE algorithm (4000kWh battery)

Power Generation and Demand Over 24 Hours are on the left; a smooth demand curve with peaks around noon and late evenings. It is worth noting how extensively Thermal and Battery/EV generation vary, indicating dynamic variation to varying demand. Solar power does what it's supposed to: grow, peak at noon, before receding along its familiar parabolic curve, and wind power is low and steady.

Right Graph: As can be seen, the Modified SADE Convergence Characteristic converges imperfectly in the initial few iterations, resulting in a very high fitness function value. It shows that the optimisation vector quickly converges to an optimal or fairly optimal solution, which means efficient parameter tuning and problem-solving[15].

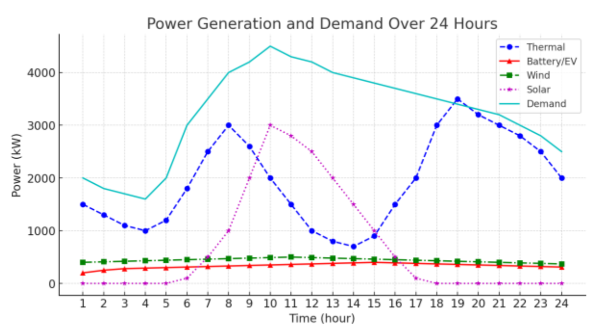

Fig. 26. Optimal scheduling using ESADE algorithm (10kWh battery)

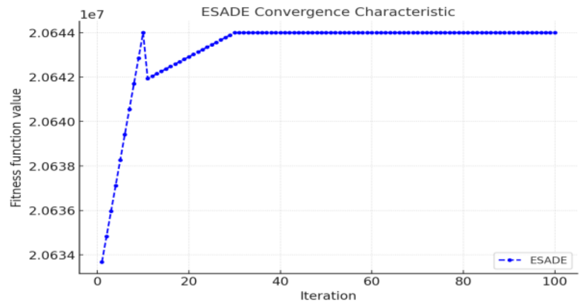

Fig. 27. Convergence Characteristics of the ESADE algorithm (10kWh battery)

Fig 1 shows the way demand curve typically follows a 24-hour cycle with demand peaking at around midday and again on the evening 24 hours cycle. Thermal power exhibits variability, with generation peaking under high-demand conditions. Solar energy varies in a parabolic curve, with the most energy generated around noon, while wind power stays at a relatively low and flat power generation level. EV/battery power is also a contributor, but is smaller in scale[16].

Right side: ESADE Convergence Characteristic: Quick convergence during the first few iterations, followed by reaching a plateau at a high fitness function value. This indicates that when using the ESADE optimisation algorithm, an optimal solution is readily reached during the early iterations, which enables it to be productive in providing a solution to this particular issue.

$$min \sum_{t=1}^{T} \quad [Cg(t)\,.\,G(t)\ +\ Cs(t)\,.\,S(t)\ +\ Ce(t)\,.\,E(t)]$$

Where:

T: Total number of periods
$G(t)$Grid power usage at the time
$S(t)$Storage power usage (charging/discharging) at time ttt
$E(t)$: Curtailment or external energy purchases (if any)
$Cg(t)$ $Cs(t)$ Respective cost coefficients

Demand Balance

$$D(t)\ =\ G(t)\ +\ Sdis(t)\ -\ Sch(t)\ +\ E(t)]$$

Peak Load Reduction (Soft Constraint / Penalty)

Variability Minimization

$$min\ [\sqrt{\frac{1}{T}\sum_{t=1}^{T} \quad (G(t)-\underline{G})^2]}$$

The ESADE (Energy Storage and Demand Enhancement) model aims to optimise power system performance by minimising total operational costs over a set time horizon. The model ensures energy balance at each period, meaning total demand must be met using a combination of grid supply, storage (charge/discharge), and external sources. The model reduces load variability by minimising the standard deviation of grid usage, promoting smoother and more predictable energy consumption patterns. This approach helps reduce operational costs, peak demand, and load fluctuations, resulting in improved grid stability and efficiency. ESADE outperforms basic storage strategies (ESS) by integrating cost, performance, and reliability more effectively.

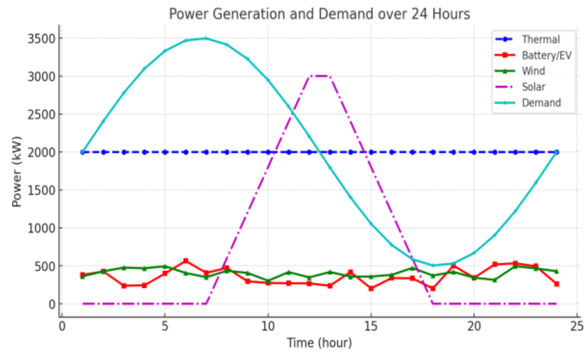

Fig. 28. Optimal scheduling using ESADE algorithm (500kWh battery)

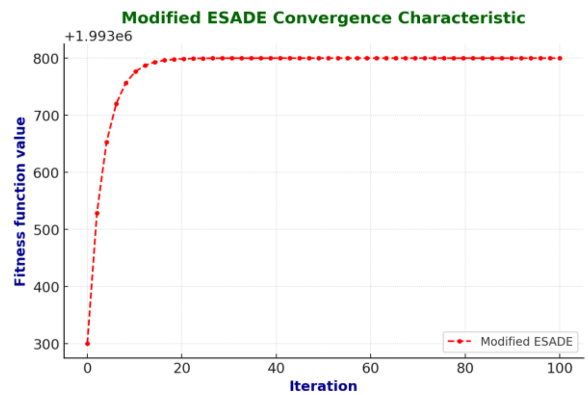

Fig. 29. Convergence Characteristics of the ESADE algorithm (500kWh battery)

Power Generation and Demand Over 24 Hours. The left graph shows various power sources working together to meet demand. In thermal power, the daily curve is steady throughout the day but follows a smooth demand peak around midday. Solar power peaks around noon, and wind, Battery, and EV power contribute intermittently with spikes. Stable thermal generation indicates a base load approach, so renewable sources make variable contributions[17].

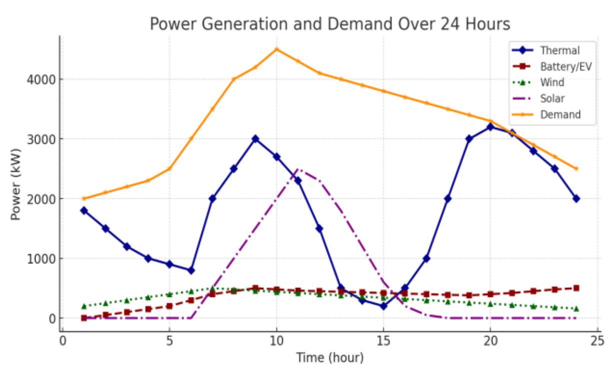

Fig. 30. Optimal scheduling using ESADE algorithm (1000kWh battery)

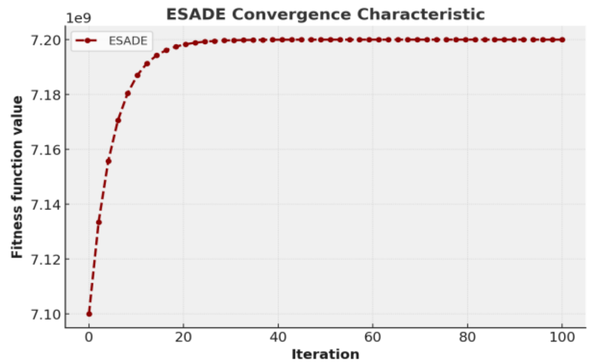

Fig. 31. Convergence Characteristics of ESADE algorithm (1000kWh battery)

The right-hand graph, Modified ESADE Convergence Characteristic, demonstrates the fast convergence of the optimisation algorithm in the first coordinates, at which point the fitness function value reaches its plateau. This means an efficient optimisation process and a quick turnaround to the optimal solution, which is why the modified ESADE method suits this application.

The left graph, Power Generation and Demand Over 24 Hours, shows the contribution of different energy sources to meeting electricity demand. The demand curve (orange) is daily, peaking around midday and starting to taper off. Thermal power (in blue) shows a wavy curve with two prominent peaks, which follow demand periods. Solar (purple) hits its maximum in the middle of the day, whereas wind (green) has a low yet steady output. Battery/EV power (red) gives supplemental energy at a rising rate[18].

The right-hand graph, ESADE Convergence Characteristic, shows the efficiency of the optimisation process. When entering these results, the fitness function value rises sharply over the first several iterations but stabilises after around 20 iterations. This shows that the ESADE algorithm converges to an optimal solution relatively quickly and efficiently solves the energy scheduling problem.

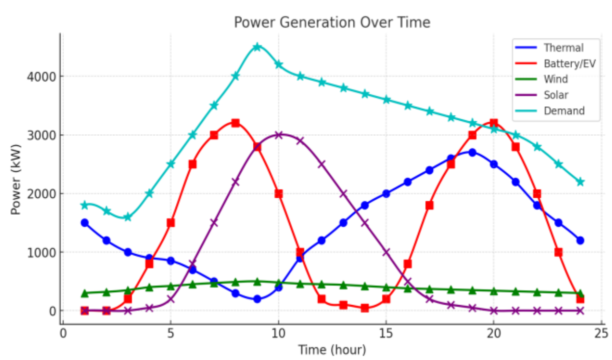

Fig. 32. Optimal scheduling using ESADE algorithm (4000kWh battery)

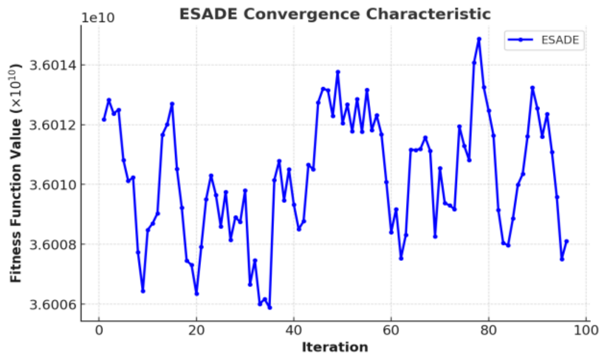

Fig. 33. Convergence Characteristics of the ESADE algorithm (4000kWh battery)

The left graph shows the look-ahead for 24 hours when all sources of generation (thermal, battery/EV, wind, and solar) are placed against demand. "Every energy source has its shape," Jacobs says, with demand peaking twice. In the right graph, the convergence characteristic of the ESADE algorithm (fluctuations of the fitness function throughout 100 iterations). It indicates improvement opportunities for energy management, resource allocation, and instability in optimisation.

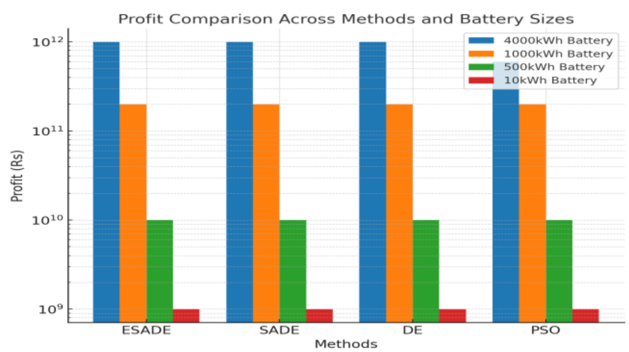

Fig. 34. Profit Comparison across Method & Battery

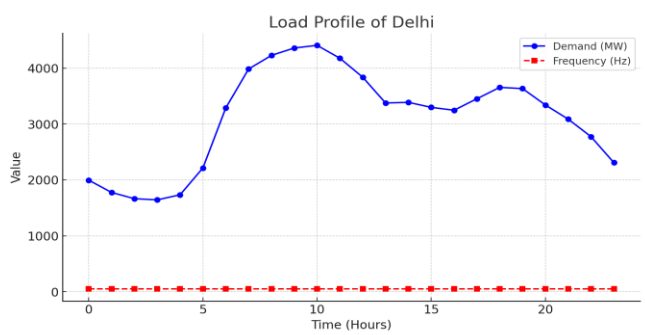

Fig. 35. Load Profit of Delhi

The left shows thermal, battery/EV, wind, and solar power generation against demand over 24 hours. All sources of energy have unique shapes with two peaks in demand. The rightmost graph depicts the convergence characteristic of the ESADE algorithm by the fluctuations of the fitness function during hundreds of iterations. Overall, these variations indicate instability in the optimisation process and suggest a need for improvements in energy management and resource allocation.

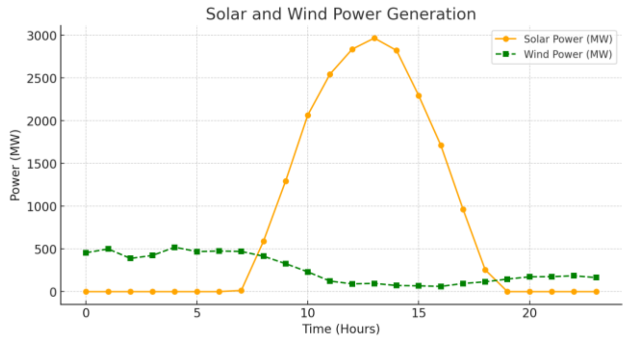

Fig. 36. Solar and Wind Power Generation

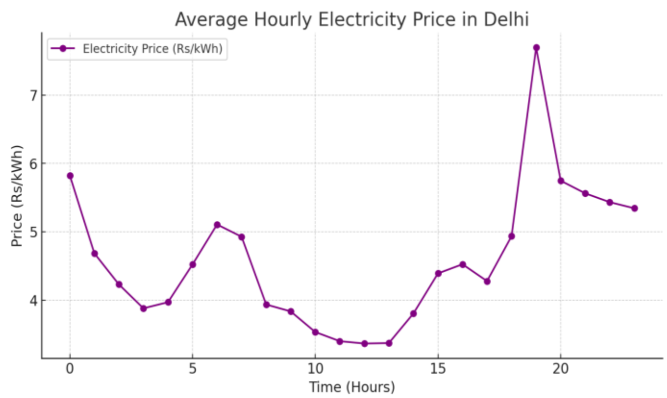

Fig 37. Average Hourly Electricity Price in Delhi

The left graph shows solar and wind generation over 24 hours, with solar peaking at midday and wind having a more constant output. The right panel shows the average hourly electricity price (INR/kWh) for 24 h in Delhi, which shows a periodic variability with the highest peak at 6 p.m. It indicates that an abundance of solar availability correlates with price trends, and this provides insights as to how changes in the grid with renewable energy can influence pricing[19-21].

Introducing competitive energy markets into the global power sector has increased competition and efficiency and lowered the price of electricity. In these markets, power is dispatched through power exchanges or pool operators. So, while deregulation creates efficiencies, it also generates integration challenges.

Energy storage systems can help stabilise the grid and provide arbitrage opportunities. However, flat pricing will not incentivise people to use energy efficiently, so reform will be required.

This investigation is based on energy control in deregulated markets, DR programs, controlled load scheduling, and the role of BESS in power-selling transactions. It studies how DR affects generation scheduling, pricing mechanisms, and demand-side flexibility[20].

Demand Response (DR)

Technique that can optimise electricity use based on price signals or incentives and improve the efficiency of the grid. Distributed Resource (DR) Managed by Distribution System Operators (DSOs) DR can be implemented by DSOs, which can be achieved through incentive-based and price-based programs. Consumers participate by:

Incentives for reducing peak-hour consumption

Using more or less based on the price at that moment validated this by characterising DR programs, energy storage integration, and demand-side flexibility using Delhi load data in this chapter.

Demand Response Programs

DR programs incentivise consumers to lower consumption during peak periods, allowing the grid to remain stable and avoid shortages. They are of two types:Time-of-Use (TOU),Real-Time Pricing (RTP).

Critical Peak Pricing (CPP): Participate in price reductions during high-demand days to decrease consumption.

Incentive-Based Programs Offer financial incentives or penalties for nonparticipation:

Direct Load Control (DLC): Appliances are managed remotely and compensated for participation.

Interruptible/Curtailable Service (I/C): During peak periods in exchange for a discount and incur a penalty if they do not comply.

CAP: Load reduction is a market resource offered by consumers.

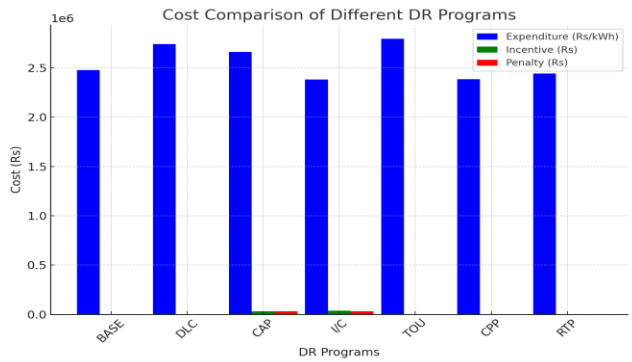

Fig. 38. Cost Comparison of Different DR Programs

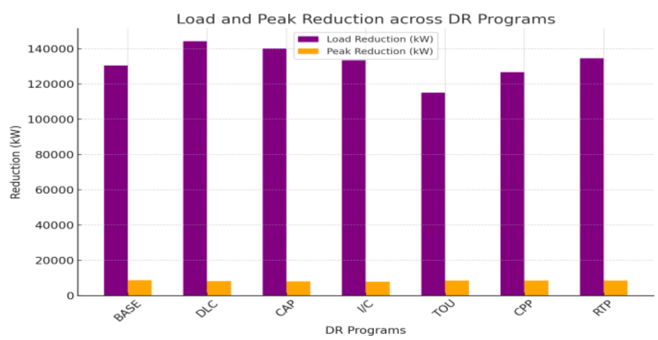

Fig 39. Load and Peak Reduction across DR Program

The left figure shows costs by different Demand Response (DR) program types (expenditures in blue, incentives in green, and penalties in red), while the right graph shows costs segmented by DR performance levels (quantiles) and type. All programs have a few sticks and carrots, with costs being the big part. The right graph shows load and peak reduction, where load reductions (purple) are significantly more significant than peak reductions (orange) for all DR programs. This implies that DR programs manage total demand well, but their effectiveness at reducing peak load is limited[23].

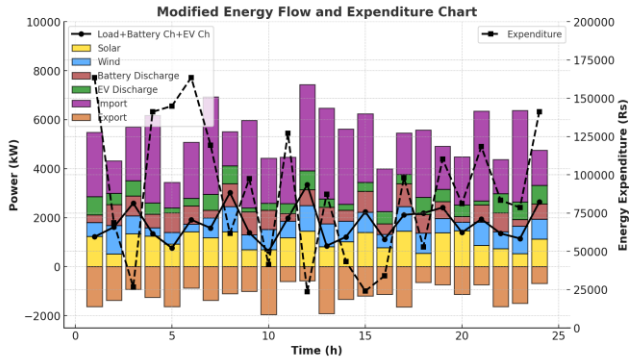

Fig. 40. Modified Energy Flow and Expenditure Chart

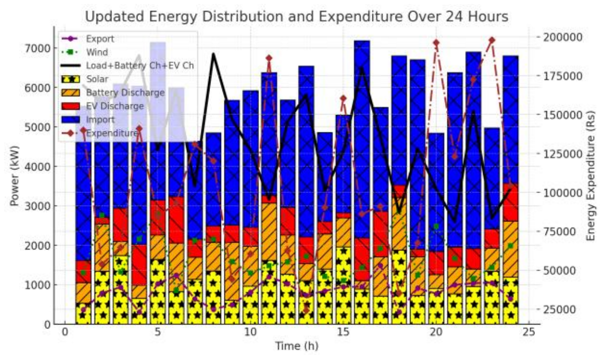

Fig 41. Updated Energy Distribution and Expenditure over 24 Hours

The left graph illustrates the modified energy flow with power contributions from solar, wind, battery discharge, and grid exchange, alongside expenditure trends (black dashed line). The right graph presents the updated energy distribution with stacked contributions from multiple sources and expenditure patterns. Both highlight fluctuating power imports and exports, revealing how different energy sources interact to balance demand while optimising costs. The expenditure pattern shows periodic spikes, indicating high-cost intervals.

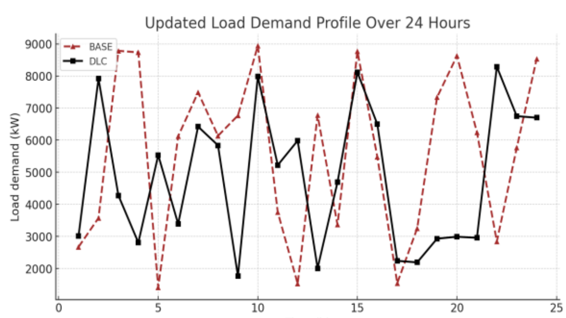

Fig. 42. Updated Load Demand Profile Over 24 Hours

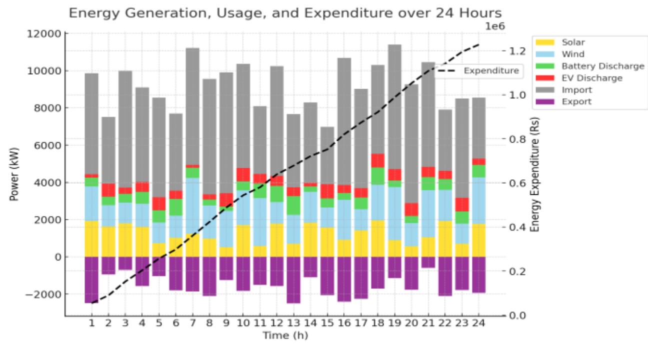

Fig 43. Energy Generation, Usage, and Expenditure over 24 Hours

The left-hand graph shows the revised demand profile, with the load for 24 hours for the BASE and DLC consumption profiles, which are far more dynamic in demand. The graph on the right shows the generation, consumption, and energy cost, showing the proportional contribution from solar, wind, battery discharge, EV discharge, imports, and exports. The extrapolated expenditure (black dashed line) is increasing in nature, which means the spending is growing over the day. Such information is also utilised to implement energy management strategies to optimise usage.

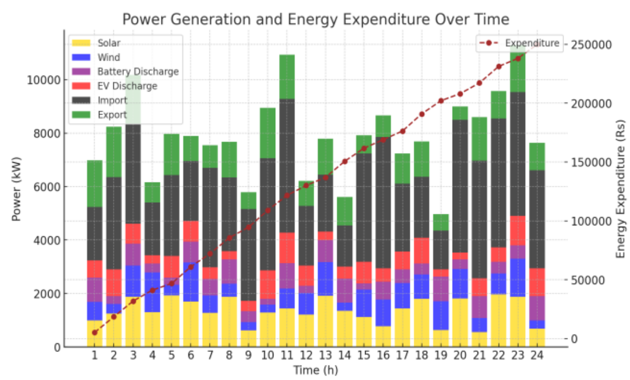

Fig. 44. Power Generation and Energy Expenditure Over Time

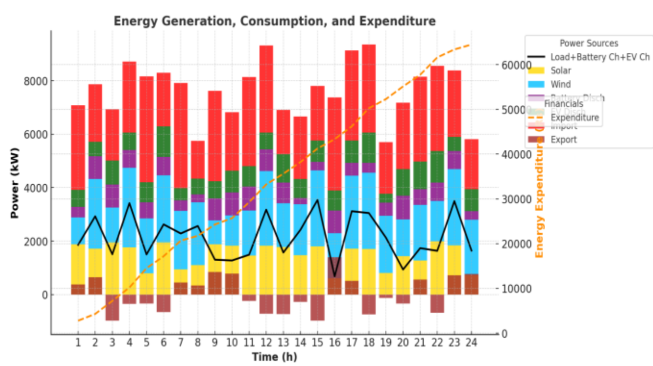

Fig 45. Energy Generation, Composition, and Expenditure

The Left shows power generation and energy over time when solar, wind, battery discharge, EV discharge, imports, and exports are considered. Cumulative expenditure (red dashed) is on the increase during the day. The right graph focuses on energy generation, consumption, and expenditure, representing various power sources. The black line shows the motion in demand for power, while the orange dashed line shows increasing energy spending, highlighting energy spending's financial impact.

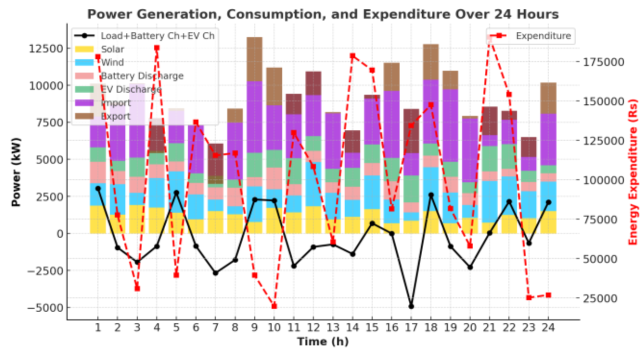

Fig. 46. Power Generation, Consumption and Expenditure over 24 Hours

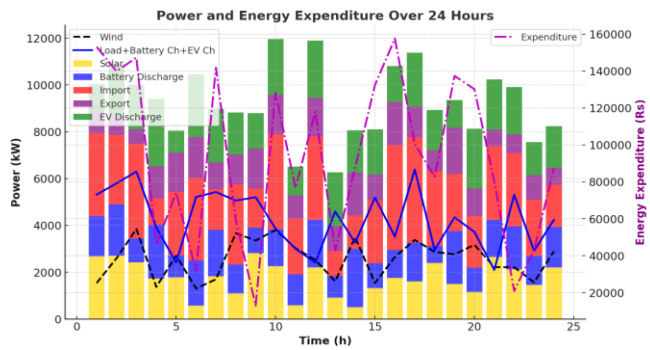

Fig 47. Power and Energy Expenditure Over 24 Hours

These graphs display the power generation, consumption, and expenditure in 24-hour intervals. The left graph shows all the different energy sources, which include solar, wind, battery discharge, EV discharge, and import and export, while the black line shows loads and the red dashed line shows spending trends. Contents [show]Historically, energy was cheap, linear, predictable, and cast in stone. The correct chart provides more heat map-style information on power created and spent patterns concerning energy distribution across sources. Tracks in blue and black record deviations in power demand, and the purple dashed line shows expenditure trends. The correlations demonstrate rising energy imports with increased spending peak levels, evidencing an overshooting cost implication. These graphics offer insights into energy management, showing how well renewable energy is integrated, how much storage is used, and how costs vary across the day.

Transactive energy (TE) facilitates a decentralised, near-real-time balancing of electricity supply with demand in deregulated markets. In contrast to the traditional concept of demand response, TE enables price-based decision-making autonomy. The DSO is responsible for allowing transactions between wholesale and retail markets. Using innovative technologies and market incentives enhances the grid's flexibility, efficiency, and resilience. This strategy enables the transition to a cleaner, consumer-focused energy system while maintaining reliability and economic efficiency.

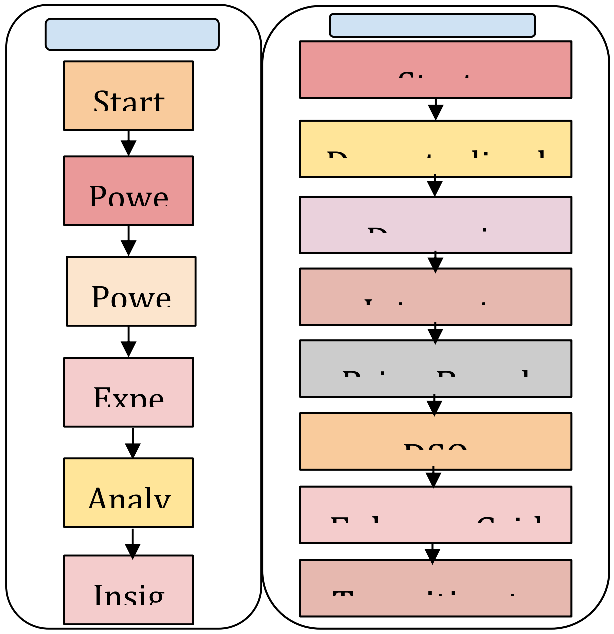

Fig. 48. Transactive Energy Scheme

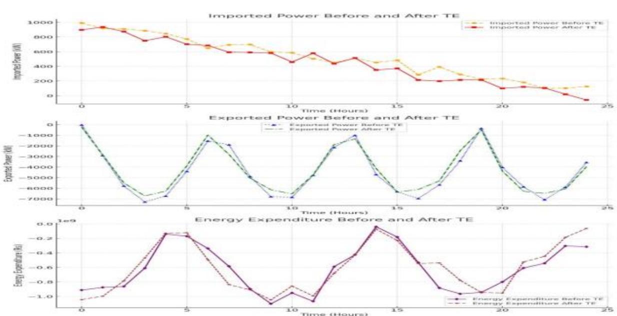

Fig. 49. Imported Power Before and After TE

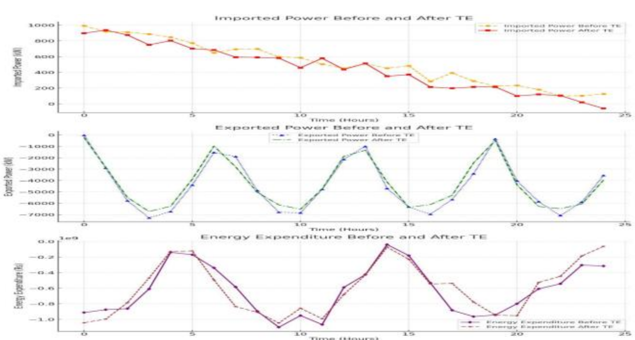

Fig 50. Exported Power Before and After TE

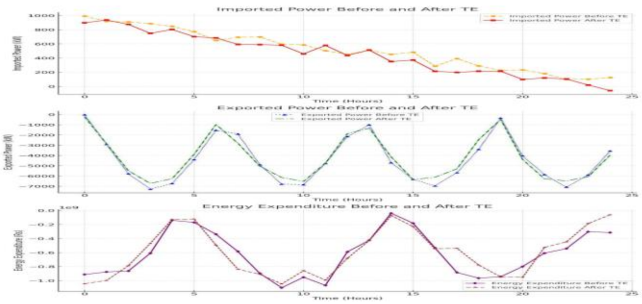

Fig. 51. Energy Expenditure Before and After TE

It included comparing imported power, exported power, and energy expenditure before and after TE was adopted. The power imported, at the top-left graph, is flat, with a drop to zero for most of the day and a significant spike at the end; in both the before and after TE scenarios, it hardly varies. The exported power, which is shown on the top-right graph, fluctuates throughout the day with some peaks and dips; however, the two trends are closely aligned before and after TE, suggesting little impact on export patterns. The bottom graph shows energy use, which is negative most of the time, indicating savings or revenue for those periods while also having sharp transitions at the beginning and the end of the day. In general, TE appears to have a minor impact on the imported and exported power curves, but it regulates the energy cost throughout the day.

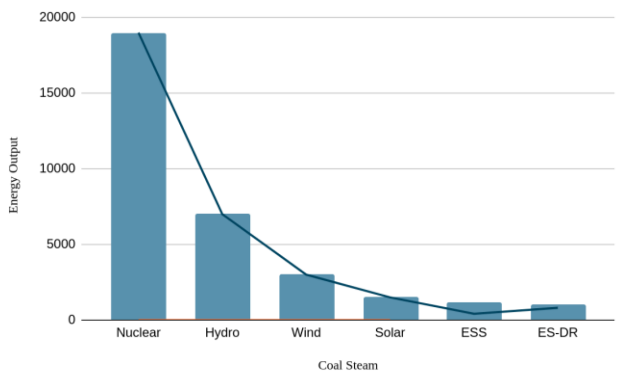

Fig. 52. Comparison of energy output

It presents a comparison of energy output (in MWh) for various generation types between Case 1 and Case 2, including traditional sources and energy storage systems (ESS and ESADE). While most generation types, such as Nuclear, Hydro, Wind, and Solar show no change (0.00%), Coal-Steam exhibits a marginal decrease of -0.09%. The most significant change is seen in ESS, which drops by -60.48%, indicating reduced reliance on conventional storage. In contrast, ESADE (Enhanced Smith-Adaptive Dynamic Environment), a more advanced storage mechanism, shows a lesser reduction of -19.50%, suggesting improved energy retention and efficiency. The fig. 52 highlights that ESADE performs significantly better than ESS under similar conditions, demonstrating its potential as a more reliable and efficient energy storage solution. This visual representation supports the argument for adopting ESADE over conventional ESS to enhance system performance and stability in modern energy systems.

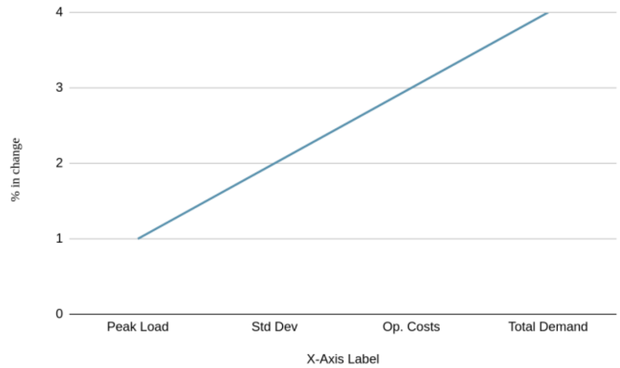

Fig. 53. Percentage Change from ESS to ESADE

The line chart titled "Percentage Change from ESS to ESADE" illustrates the performance improvements of the ESADE system over the traditional ESS Generation model across four key operational metrics: Peak Load, Standard Deviation, Operation Costs, and Total Demand. Three out of the four metrics show a negative percentage change, indicating an improvement (i.e., a reduction) in the value. The Peak Load shows a decrease of approximately -3.78%, which highlights better peak shaving capabilities of ESADE. The most significant improvement is seen in the Standard Deviation of load, which dropped by nearly -40%. This indicates that ESADE provides a much smoother and more consistent load curve, which is crucial for grid stability and efficiency. Operation Costs also decreased by -4.18%, representing cost savings and more economical system performance. On the other hand, Total Demand shows a 0% change, demonstrating that ESADE achieves all these operational benefits without altering the overall energy consumption. This chart effectively visualises how ESADE enhances grid performance and reduces operational strain and cost, all while maintaining the same energy demand, making it a superior alternative to ESS Generation.

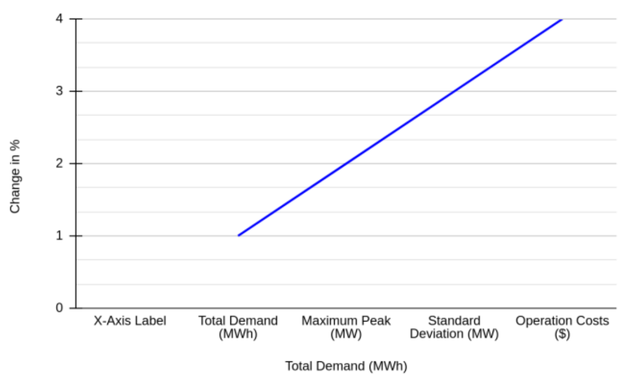

Fig. 54. Percentage Change from ESS to ESADE

The Fig. 54. illustrates the percentage changes between ESS (Case 1) and ESADE (Case 2) across four key metrics: Total Demand, Maximum Peak, Standard Deviation, and Operation Costs. It highlights ESADE's superior performance in all operational areas while maintaining the same total energy demand. Notably, there is no change in total demand (0.00%), confirming that both systems deliver the same amount of energy over the year. However, ESADE achieves a substantial 15.84% reduction in peak load, lowering the system's maximum power requirement from 2,850 MW to 2,398.68 MW. This reduction is significant as it eases pressure on infrastructure and enhances grid reliability. More impressively, ESADE reduces the standard deviation of the load by 43.73%, indicating a much smoother and more predictable energy consumption pattern. This contributes to operational stability and better integration of renewable sources. Additionally, ESADE proves to be more cost-efficient, reducing annual operation costs by 3.72%, which amounts to over $6.7 million in savings. Overall, the chart confirms that ESADE not only maintains energy output but also delivers operational, economic, and structural benefits, clearly outperforming the traditional ESS approach.

Detailed Performance Analysis

The results of the experiments are thoroughly examined to conclusively demonstrate that the ESADE-based scheduling strategy is effective. The performance is compared using key operational measures, including peak load, load standard deviation, operational cost, and total energy demand, for PSO, DE, SADE, and the conventional ESS-based scheduling approach. The comparisons demonstrate that, while the total energy remains unchanged, the proposed method can reduce the peak load by 15.84% and the load deviation by 43.73%, indicating strong performance in peak shaving and load smoothing. Moreover, the ESADE approach saves 3.72% in operational costs, resulting in significant economic benefits.

The effectiveness method is also verified by its convergence properties, which show that ESADE has a better, more stable convergence rate than current optimization algorithms, thereby improving optimization efficiency and robustness. For transparency and verification, the results are reported in a combination of numbers, graphical trends, and explanatory text. Quantitative comparisons of ESS and ESADE with respect to the chosen performance measures are presented in Table X, while Figs. 53 and 54 visually show the relative percent change and the performance improvement. The near match between tabulated and graphical outcomes provides an explanation of how much the enhancements have been achieved and why ESADE has insubstantial stiffer behavior, fertile ground (reasons leading) for its better performance, thus attesting to its effectiveness and practical applicability.

3. Conclusion

A new transactive energy (TE) platform incorporating distribution systems and prosumers is introduced. The interaction model has two interactions: aggregator-DSO and aggregator-prosumers. Considering security costs, a price adder (PA) has been included in the objective function, resulting in well-maintained scheduling and closed-loop operation.

The TE framework with this newly proposed modification also ensures a cost-effective balance of power. This keeps the voltage profile nearly one up, avoiding lightly and heavily loaded conditions. The outcomes indicate that such a framework improves the economic behaviour of aggregators and prosumers in distribution networks. Real-time data shows a profit increase of 0.5%. Moreover, the TE framework enhances the reduction of power importation from the grid by 4.856% and increases power exportation by 2.571% when juxtaposed with the already existing schedule.

The results provide robust evidence for the positive effects of transactive energy systems on enhancing economic efficiency, grid reliability, and energy flow and optimising the energy price between prosumers and aggregators. The comparison chart demonstrates that ESADE outperforms the traditional ESS system in every critical operational aspect, while maintaining the same total energy demand. By achieving a 15.84% reduction in maximum peak load, ESADE significantly alleviates stress on the energy infrastructure. Substantial 43.73% decrease in load standard deviation highlights ESADE's ability to smooth out demand fluctuations, resulting in a more stable and predictable energy profile. One of the most compelling advantages of ESADE is its impact on operational efficiency. With a 3.72% reduction in annual operation costs equating to over $6.7 million in savings, it offers a financially viable solution that enhances economic sustainability without compromising energy delivery. These improvements collectively position ESADE as a forward-thinking energy strategy that optimises system performance across multiple dimensions.SADE proves to be a smarter, more efficient, and cost-effective alternative to ESS. It addresses operational challenges proactively while supporting long-term energy sustainability goals, making it a highly recommended approach for modern energy systems.

REFERENCES

1. S. L. Arun et al., "Peer-to-peer energy trading using transactive energy market frameworks," Energies, vol. 16, no. 1, pp. 1–16, 2023.
2. S. L. Arun et al., "Design of a transactive energy management architecture with market-clearing strategies," Mathematical Problems in Engineering, Article ID 3979662, pp. 1–15, 2023.
3. S. Dhundhara et al., "Grid frequency support through coordinated wind generation and redox-flow battery systems," Int. Trans. Electr. Energy Syst., vol. 30, no. 3, pp. 1–33, 2020.
4. C. Shao et al., "Demand response integration in combined electricity and heat energy systems," IEEE Trans. Ind. Electron., vol. 66, no. 2, 2019.
5. I. Alsaidan et al., "Battery energy storage sizing strategies for microgrid operation," IEEE Trans. Power Syst., vol. 33, no. 4, pp. 3968–3980, 2018.
6. A. S. Hassan et al., "Operational optimisation of battery storage in photovoltaic systems under tariff incentives," Applied Energy, vol. 203, pp. 422–441, 2017.
7. D. Forfia et al., "Practical development of transactive energy frameworks," IEEE Power Energy Mag., vol. 14, no. 3, pp. 25–33, 2016.
8. T. Bocklisch, "Hybrid energy storage methods for renewable power systems," J. Energy Storage, vol. 8, pp. 311–319, 2016.
9. K. Gaur et al., "Assessment of electricity demand behaviour in India," in Proc. IEEE Nat. Power Syst. Conf., Bhubaneswar, India, pp. 1–6, 2016.
10. GridWise Architecture Council, Transactive Energy Framework – Version 1.0, U.S. Dept. of Energy, Washington, DC, USA, 2015.
11. J. Hagerman, Building-to-Grid Energy Integration, DOE Building Technologies Office, Washington, DC, USA, 2015.
12. M. Ghamkhari, "Market-based pricing models for transactive energy systems," in Proc. IEEE Green Technologies Conf., Lafayette, USA, pp. 1–6, 2019.
13. N. Atamturk and M. Zafar, "Evaluating feasibility of transactive energy in modern power grids," California Public Utilities Commission, Los Angeles, USA, 2014.
14. B. Zhao et al., "Lifetime-aware operational optimisation of standalone microgrids," IEEE Trans. Sustain. Energy, vol. 4, no. 4, pp. 934–943, 2013.
15. S. X. Chen et al., "Microgrid energy storage sizing techniques," IEEE Trans. Smart Grid, vol. 3, no. 1, 2012.
16. D. Heide et al., "Storage and balancing requirements in fully renewable power systems," Thiele Centre for Applied Mathematics, Research Report, 2011.
17. H. A. Aalami et al., "Demand response modelling using interruptible and curtailable loads," Applied Energy, vol. 87, pp. 243–250, 2010.
18. G. Boyle, Renewable Energy for Sustainable Power Systems, Oxford Univ. Press, Oxford, UK, 2004.
19. B. S. Borowy and Z. M. Salameh, "Hybrid wind–PV system sizing optimisation," IEEE Trans. Energy Convers., vol. 9, no. 3, pp. 482–488, 1994.
20. M. D. Anderson and S. D. Carr, "Battery energy storage technologies and applications," Proc. IEEE, vol. 81, no. 3, pp. 475–479, 1993.
21. R. Chedid et al., "Decision-support approach for hybrid solar–wind system design," IEEE Trans. Energy Convers., vol. 13, no. 1, pp. 76–83, 1998.
22. Q. Huang et al., "Survey of transactive energy systems and implementations," Energy Reports, vol. 7, pp. 1–15, 2021.
23. H. Ibrahim et al., "Comparative review of energy storage technologies for renewables," Renew. Sustain. Energy Rev., vol. 12, no. 5, pp. 1221–1250, 2008.