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A New Method for Improving the Performance of Domestic Utilities by Balancing Energy Generation and Peak Demand Using Ebola Optimization Technique

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Abstract

As the global energy market is growing rapidly, global warming and concern towards the energy crisis is an issue to address in the modern energy market. Addressing these issues by balancing the peak power shifting on real time in micro grids. This paper discusses about an intelligent multi-agent-based system, which allows the user to prioritize the load. Metaheuristic Ebola optimization algorithm (EOA) is discussed to address the objective of peak load shifting. electrical load appliances are considered as the load agents and smart home model using Internet of Things (IoT) meter to analyze the appliance performance and user comfort to address the power consumption uncertainty. Mathematical modelling of the proposed algorithm for energy shifting in smart home is discussed and compared with other optimization algorithm. Simulation results shows that it is efficient that energy consumption-based load allocation allows fewer energy sources taking energy consumption as objective.

Keywords: Ebola optimization algorithm, Internet of things, Load agents, Optimization.

Introduction

As energy demand rises, traditional systems become more complex, less viable, hazardous, unprofitable, and suffer from substantial power losses. This is a growing problem. Distributed energy resources, such as intermittent renewable energy, small gas or oil power plants, and energy storage, can now be used in a novel way thanks to the notion of microgrids. Microgrids can be used to lessen their reliance on the larger power grid by distributing the controllable and renewable energy that is generated locally. Individual loads are handled in the context of the energy market paradigm, with the help of local generation, storage systems, user comfort, DGs, and utilities.

Increased integration of RES into the grid has replaced or reduced traditional generators in response to rising global energy consumption and the push for sustainable development. The inherent challenge of RES is its inherent variability. In order to construct microgrids that are both autonomous and connected to the grid, many management techniques and control tactics are being employed. Numerous researchers are honing algorithms for optimising system components like energy storage system sizing and the financial advantages of doing so (1). Optimal power management, dynamic bidding strategies, and the levelized cost of each component (2).

Within the framework of the current energy market paradigm, this study proposes an efficient method of energy management using smart microgrids (SMG) to address these issues, with the ultimate goal of providing a solution that is both economical and sustainable (3). The Control Agent (CA), Energy Market Controller (EMMC), and Home Energy Management Controller (HEMC) work together to accomplish set objectives. There is a two-tiered energy management strategy provided for specific objectives (4, 5). The first step is to manage the load and plan the storage in accordance with the local generation and market prices. The second objective is to regulate the energy market using four distinct forms of priority and control agent input. By contrasting it to other optimisation techniques. Adaptive Whale Optimisation (AWO), a variant of a meta-heuristic

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methodology, can help identify a more comprehensive solution to the problem. The proposed methodology is implemented in a community test environment based on SMG. The residents of the many homes in the area have varying incomes and interests. The simulation results validate the effectiveness of the proposed effort.

To explain the uncertainty of Load, a probability density technique based on LSTM-quantile regression was developed (6). The "actual price of energy," which tries to pass on the true cost of electric power supply to customers, employs a demand response mechanism (7). Here, the system's anticipated future demand (usually within an hour) is estimated using Markov chains, and an economic dispatch of Distributed Generation plants is then carried out to determine the actual cost of energy (8). Proposed a dynamic developing power management framework in micro grid. A dynamic differential game model is modelled and analysed to solve the optimization (9). Modified particle swarm optimization (MPSO) is utilised to solve the energy management optimization problem. Genetic algorithm (GA) is also used to compare the MPSO output. In order to improve MPSO performance and achieve maximum efficiency, hierarchical control is employed in conjunction with the energy management approach (10). To keep an alternating current (AC) load going in the face of external disturbances, a hybrid DC microgrid freestanding grid system employing four sources (PVA, BESS, super capacitor, and fuel cell) is used. In order to increase the grid's power-sharing capacity, an ideal energy management approach is deduced (11). presents a control algorithm for a reliable Energy Management System (EMS) functioning in grid-linked mode, with the goal of reducing operational costs (12).

Micro grids

Since microgrids are such an important connector between dispersed renewable energy producers and the larger grid, they are the subject of intense study (13). Recent microgrid studies have concentrated on investigating load-level integration of microgrid technologies (14). Due to the complexity of safeguarding and maintaining several interconnected distributed generators, traditional power grids have become antiquated (15). A tiny microgrid platform can serve as a viable alternative to the traditional grid by integrating distributed micro resources such as distributed generators, storage devices, loads, and voltage source converters at the user end (16).

Microgrids can be set up to function as either grid-connected or stand-alone systems, depending on the available generation, the feasibility of grid connection, and the needs of the consumers (17). Microgrids powered by dispersed energy resources have transformed the conventional electricity system. Control, protection, operational stability, and reliability on the grid are all sources of concern (18). As of yet, there has been no actual implementation of microgrids in the commercial market. The proposed microgrid would be formed when solar panels are installed on one of the six dwellings as shown Figure 1 (19).

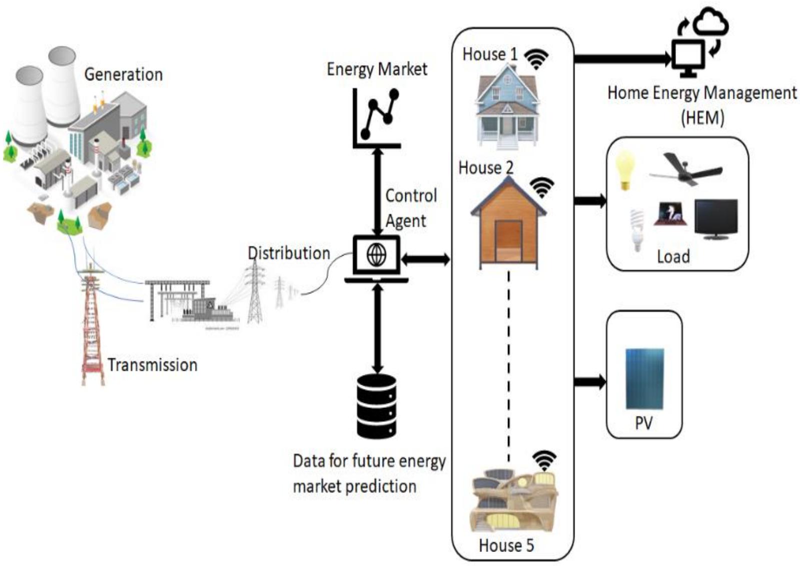

Figure 1: System model of residential energy management

Role of IOT

Electric grid efficiency and power are two of the primary goals of research into the smart grid. Information and communication technology (ICT) can be used to help improve power grid system efficiency by implementing smart energy management techniques (20). As a result of incorporating RERs, smart energy storage, and new transmission technologies into the power grid, the smart grid has gained new capabilities like real-time monitoring, fast restoration, battery displays, and automated outage management (21). Adding these new aspects complicates energy transmission and raises key issues including energy efficiency, high energy costs, and societal well-being throughout the development of smart grid energy trading systems (22).

IoT-era scenarios that involve energy trading include micro-grids, energy harvesting, and vehicle-to-grid (V2G) networks. To solve today's power issues, microgrids have been developed. Self-sustaining grids and consumers are linked by the Internet of Things (IoT). IoT brings the idea of energy sharing and load balancing in micro grids into reality by exchanging the information of Distributed generation (DG) and the load in the given area (Figure 2).

System modelling and cost function

δ – Controllable load power (Power consumed over Controllable equipment)

γ – Uncontrollable load power (Power consumed over Uncontrollable equipment)

Total power consumed by individual house without solar power generation is given in equation [1].

Power consumed = $\delta + \gamma$ [1]

Solar power generation in the selected area = α

Then the total power utilized in the individual house can be calculated using equation [2].

Power consumed = $\delta + \gamma - \alpha$ [2]

Two different case studies can be considered from the second equation. Case 1 where the generation in the micro grid stand-alone house is less than the total power consumption at specified time. Case 2 where the generation is greater than the total load consumption in the same micro grid stand-alone house at specified time.

β = electrical appliances

Let us discuss these two cases in detail with possible constrains. If the load $\delta + \gamma > \alpha$, then power is purchased from the grid. If the load $\delta + \gamma < \alpha$, then no power is utilized from the grid. In this case excess generation is sent back to the grid, assuming no outage in the line. If there is outage in the line, no power is sent back considering safety issue constrains. During such constrains, no power is sent back to the grid which leads α not being utilized, excess power generated, assuming part of the generation being utilized by the load $\delta + \gamma$. In the proposed model we concentrate on the second case where the load $\delta + \gamma < \alpha$, and during outages, where the micro grid can be isolated from the main supply controlling the generated power being utilized by the community of housed instead of send back to the grid making it self-sustainable, keeping the predicted load in consideration. This is possible by allocation the generated.

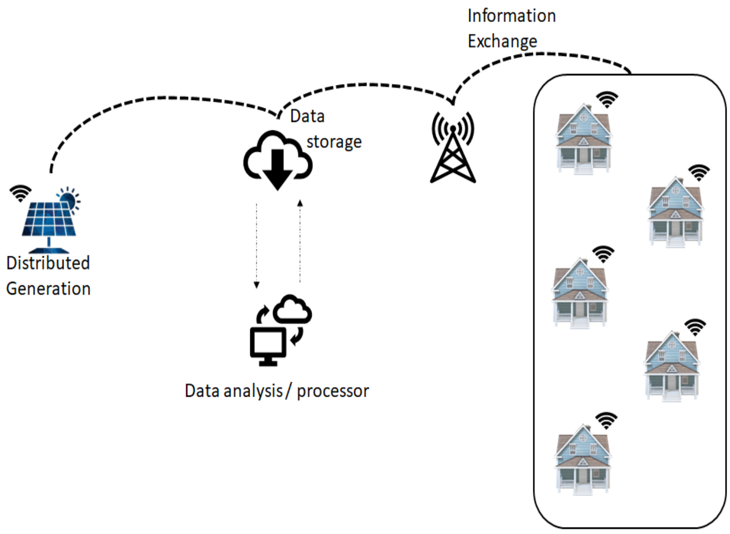

Figure 2: System diagram of the IoT-based smart buildings in the electrical power system

power being utilized by priority loads during outages. This allocation of load and bifurcation of the generated power to specified needed load is done using Ebola Optimization.

Home energy management controller

A power distribution network is considered having a number of micro grids connected to the utility grid (23). As a part of microgrid, appliances in a house home can be classified into two types based the operation pattern and electricity demand:

i) power adjustable appliances

ii) power uncontrollable appliances.

Many appliances whose operation period and power can be adaptable are power adjustable appliances such as fridge, air conditioner and so on. On the contrary, the power uncontrollable appliances are those appliances whose operation period and power consumption are fixed, such as rice cooker, oven and so on. Home energy management systems using IoT optimization have gained significant attention in recent research. These systems aim to optimize energy consumption in smart homes by utilizing IoT technologies and advanced optimization techniques. The use of deep learning-based techniques (24) and artificial intelligence (AI) optimization methods have been explored to enhance the performance of these systems (25).

Fixed loads

The loads which are adjustable by user comfort. Number of devices in this sector depends on the user need and economical factor of each house. This may reduce the complications in the network by having one way communication (26).

Power flexible loads

Loads such as AC are prioritized according to the power consumption and weather conditions, to improve the daily load curve of the system over a duration of 24hr (27).

Time controllable loads

The loads which can be shiftable to the least peak hr without compensating the comfort during 24hr. these loads are switched on during surplus power availability or least peak load during a scale of 24hr. smart plug can also be used to adjust the operating time of these loads (28).

Ebola optimization

Ebola optimization algorithm (EOA) is a metaheuristic optimization algorithm proposed by Olaide Nathaniel Oyelade *et al*. in 2022 resulted in best values on eight data sets with eight fitness and cost function (29). In this paper, with the help of study from above sited author and bifurcating the load on priority basis, we formulate the mathematical expression for household load shifting to optimize the overall cost of the operation in smart microgrid environment (30, 31). Electrical appliances are taken as load agents with s and s' are taken as shiftable and non-shiftable loads which are expressed as shown in equation [3] and [4].

$$s = s' \cdot a - a \qquad [3]$$

$$s' = 2 \cdot rand \qquad [4]$$

Δ(I) express the change in power of electrical appliances or the deviation in the load. Change in load power may be incremental or decremental depending on the maximum power compared to the solar power generated, and it can be expressed as shown in equation [5].

$$\Delta(I) = \begin{cases} dec * rand + p'(t) & P < g \\ inc * rand + p'(t) & P \geq g \end{cases} \qquad [5]$$

Peak load shifting with controllable, shiftable and non-shiftable load is expressed in equation [6]. Flowchart for the proposed EOA is shown in Figure 3.

$$p(t+1) = \begin{cases} D \cdot e^{bl} \cdot \omega \cos(2\pi l) + p'(t) & c \geq 0.5 \\ p_{rand}(t) - \omega \cdot s\left|s' \cdot p_{rand}(t) - p(t)\right| + \varepsilon\Delta(I) & c < 0.5 \end{cases}$$

[6]

Results and Discussions

Optimal load shifting of six different residential buildings is taken with priority-based load cases. Each residential buildings having control over the priority and non-priority load chosen over the duration of operation on their own. Results are shown below for different residential buildings. Figure 4 shows the power consumption over the residential building with and without Demand side management (DSM).

The optimal scheduled energy for residential building 1 is shown in Figure 5. It also gives the comparative analysis with the other optimization techniques like Whale and PSO. From the Figure 5 it can be seen that, results obtained for Ebola is better than that of other optimization techniques. The optimal scheduled energy for residential building 2 is shown in Figure 6. Here the PSO has reached the power consumption of the actual load resulting in higher price and whale optimization

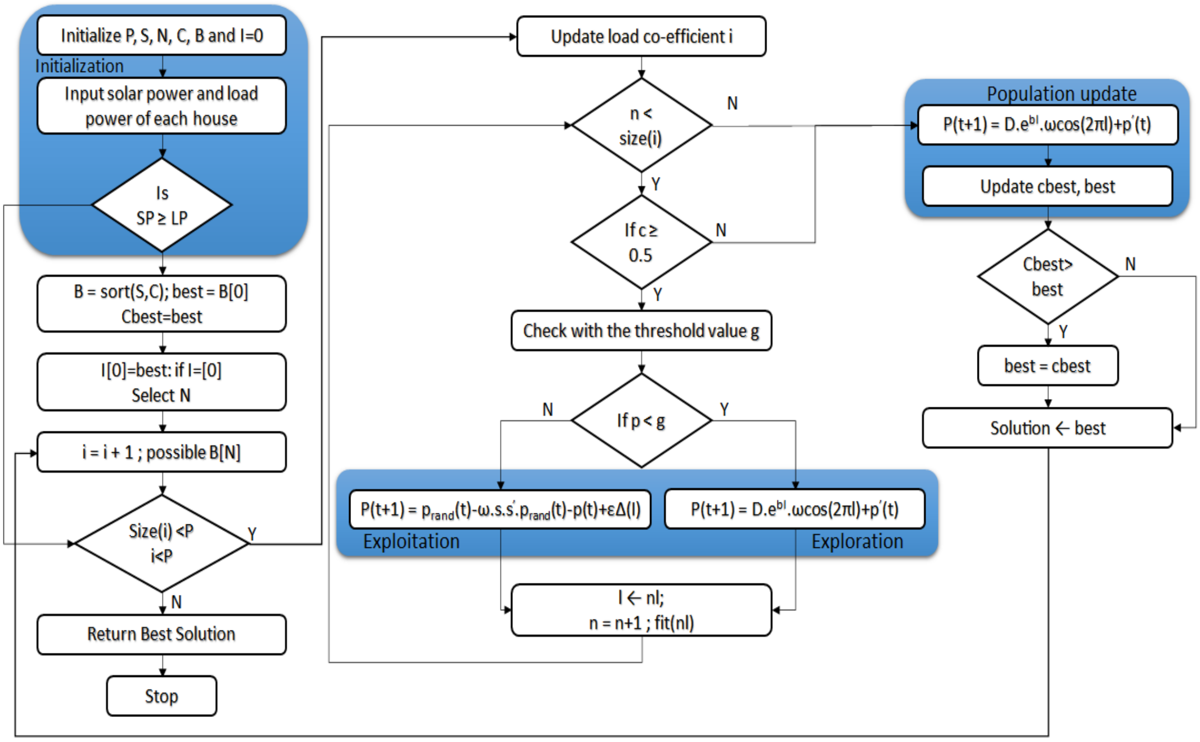

Figure 3: Flowchart of the proposed ESA metaheuristic algorithm

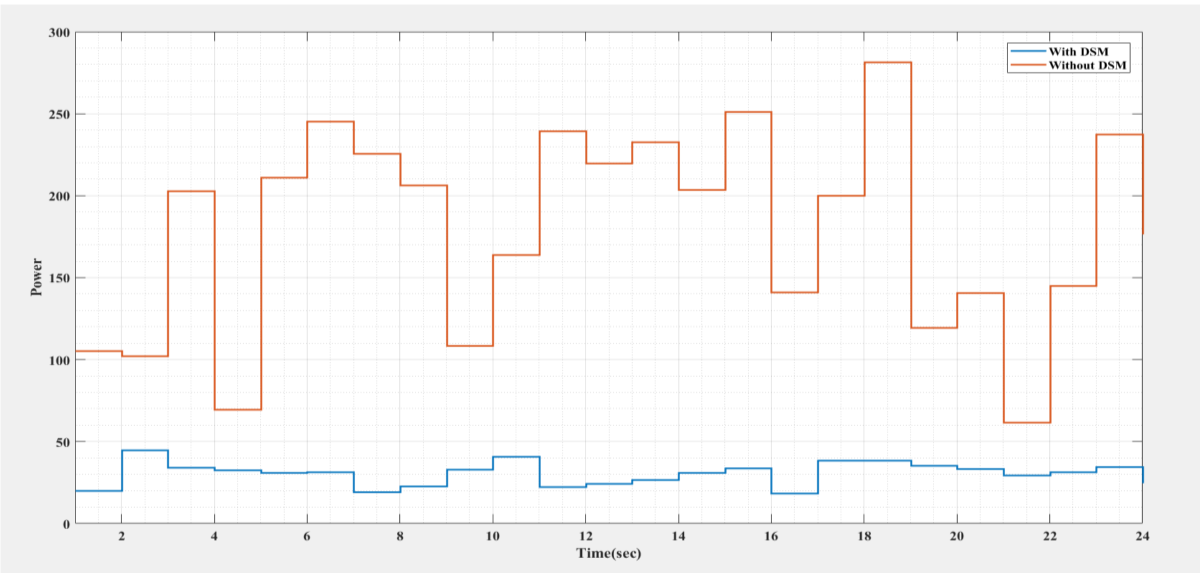

Figure 4: Management of load profiles with and without optimization

also have higher load than the proposed technique.

The optimal scheduled energy for residential building 3 is shown in Figure 7. Both the compared optimization techniques PSO and Whale having high load scheduling than that of the proposed Ebola technique resulting in low cost from proposed optimization technique.

The optimal scheduled energy for residential building 4 is shown in Figure 8. Whale and PSO optimization techniques resulted in higher energy consumption compared to the proposed technique. From the figure it is clear that proposed technique has better load optimized.

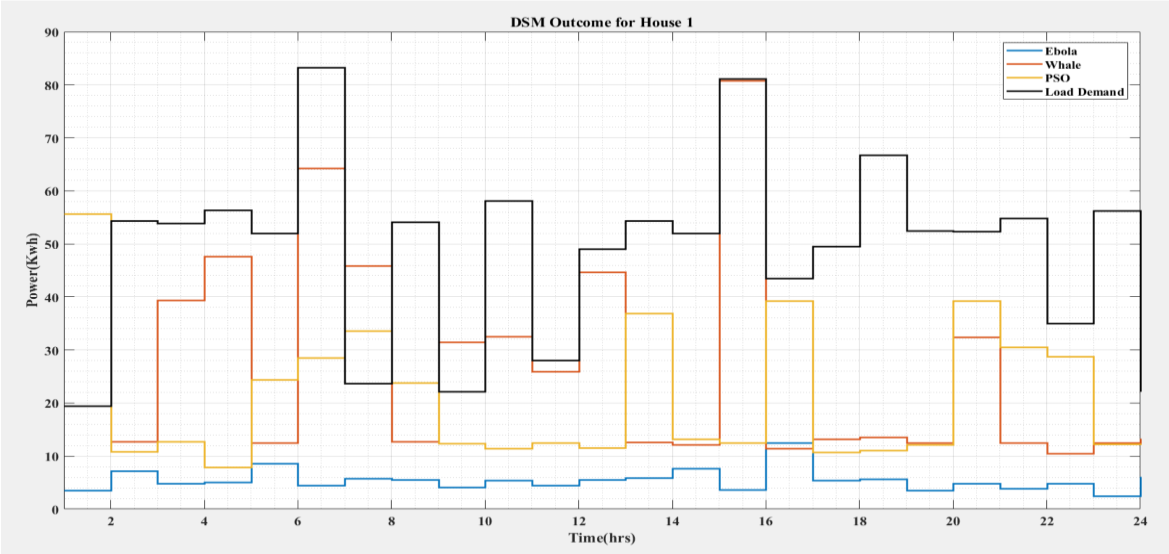

Figure 5: The optimal scheduled energy for residential building 1

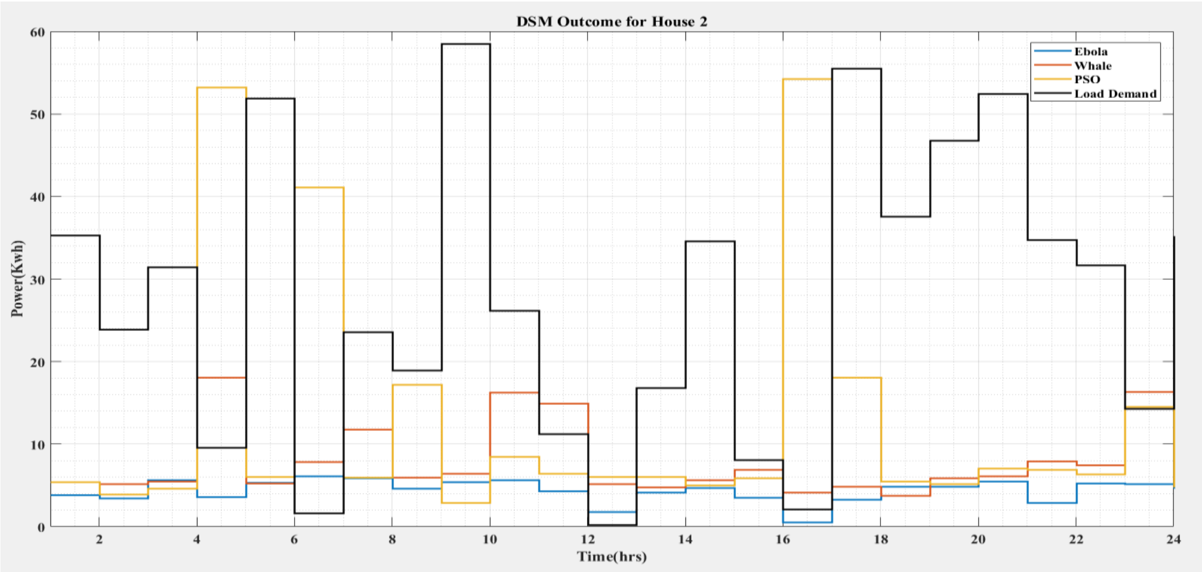

Figure 6: The optimal scheduled energy for residential building 2

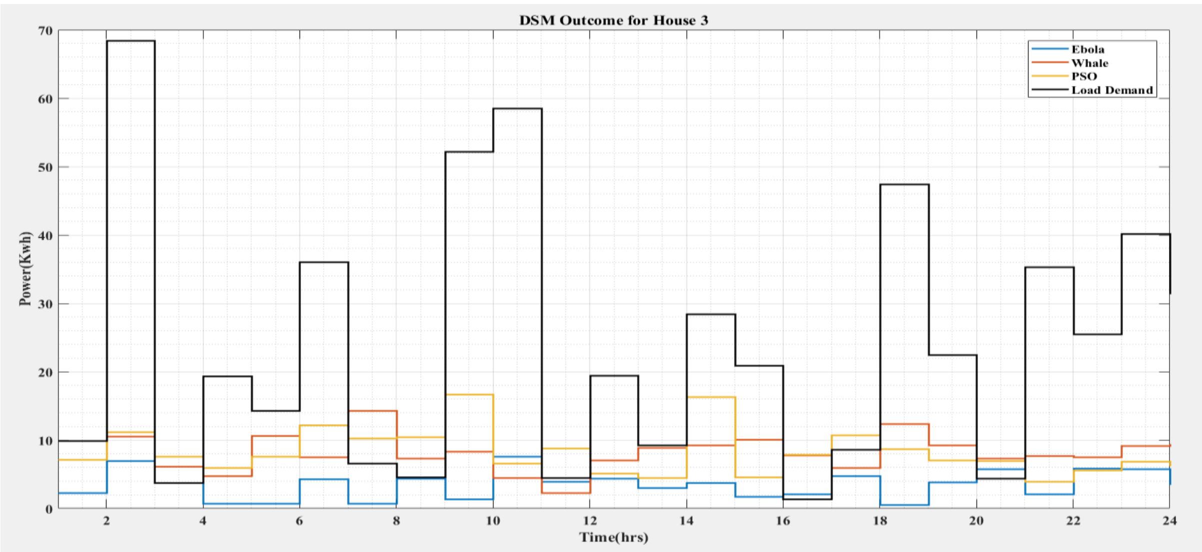

Figure 7: The optimal scheduled energy for residential building 3

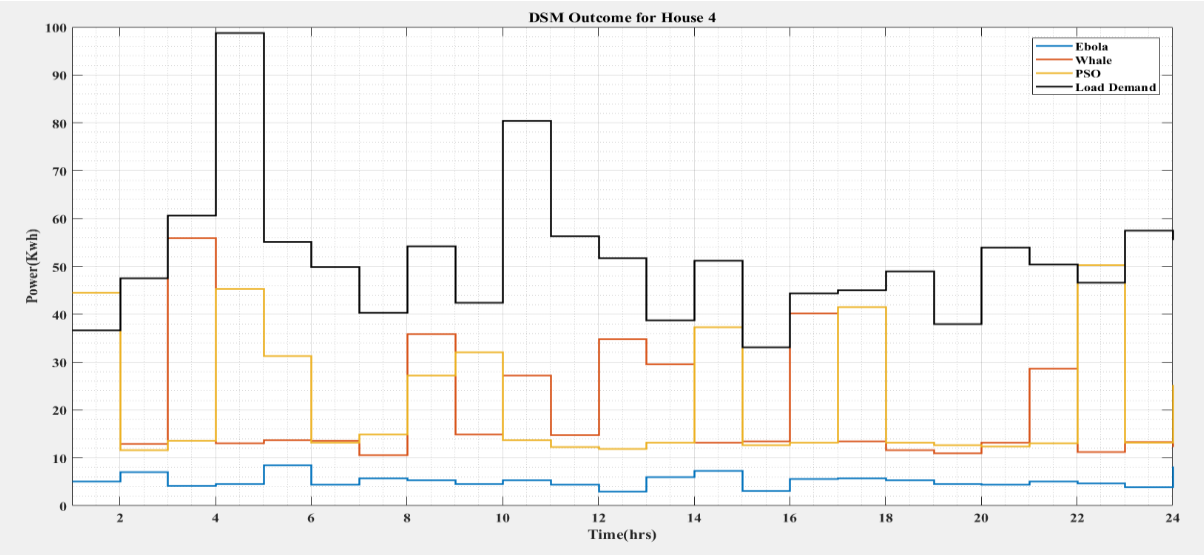

Figure 8: The optimal scheduled energy for residential building 4

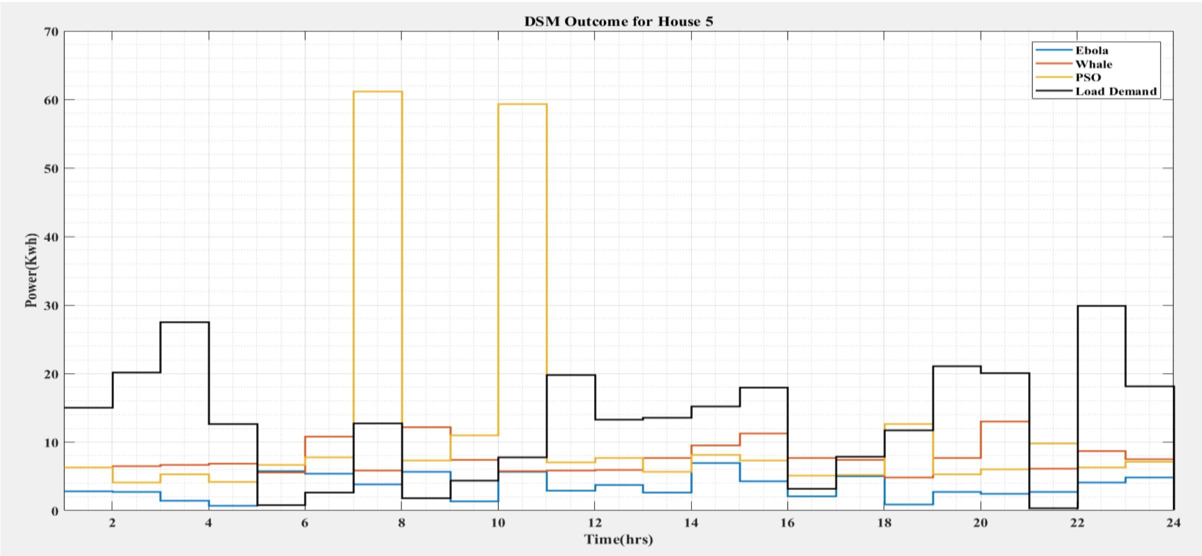

Figure 9: The optimal scheduled energy for residential building 5

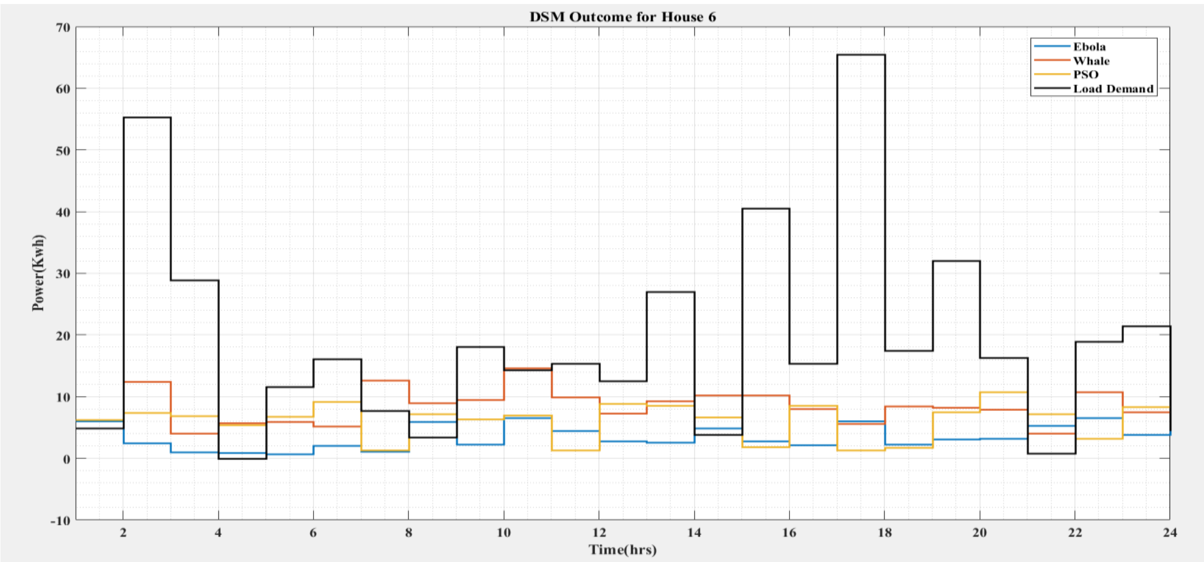

Figure 10: The optimal scheduled energy for residential building 6

The optimal scheduled energy for residential building 5 is shown in Figure 9. Load optimized with PSO is higher than the actual load at some time, it is clear that Ebola optimization has better load selection than the other two techniques.
The optimal scheduled energy for residential building 6 is shown in Figure 10. Load optimization in residential building 6 with PSO and Whale is comparatively similar in nature and Ebola optimization gives better load balance which is clearly visible in the figure.
Total energy cost in different residential buildings is shown in Figure 11. As we can see the comparative results shows that Ebola, Whale and PSO techniques used results in less cost compared to the actual energy usage without optimization. Although Whale optimization results is similar results in resident 3 and resident 5, there is a significant difference in cost at remaining residential buildings.
Average energy usage in residential buildings is shown in Figure 12. Although Whale and PSO techniques reduced the cost of energy consumption in a significant manner, Ebola optimization bought a further reduction in cost reduction, clearly showing the gap.

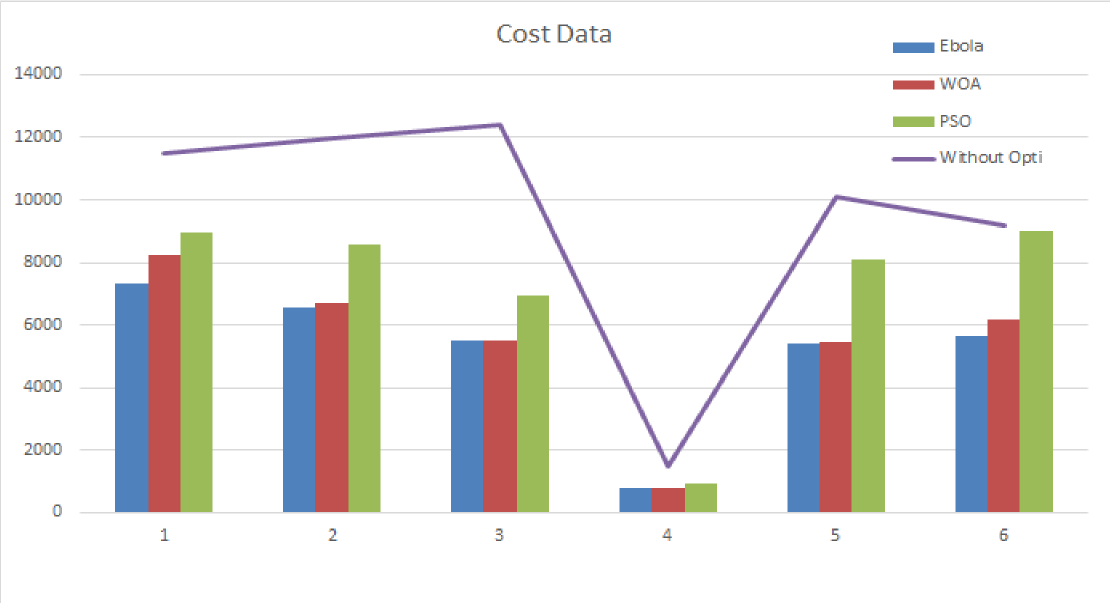

Figure 11: Total energy cost in different residential buildings

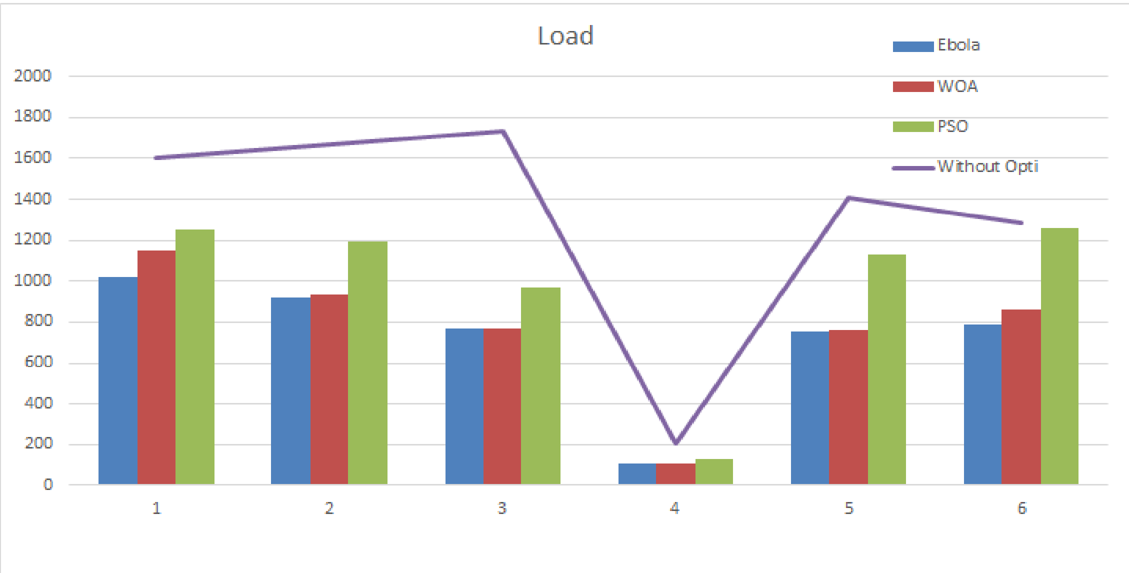

Figure 12: Average energy use in residential buildings

Table 1: Load deviation details

	Ebola	WOA	PSO	Without Opti
Res1	1021.11344	1148.367568	1251.13721	1605.81637
Res2	915.825936	935.5921706	1197.26014	1671.11429
Res3	766.851814	768.0132902	971.683811	1733.61429
Res4	105.936192	107.3506002	129.642271	206.957923
Res5	755.555163	762.3223439	1132.13498	1410.30189
Res6	788.990599	859.1931291	1256.02551	1284.81429

Table 2: Cost deviation details

	Ebola	WOA	PSO	Without Opti
Res1	7310.71108	8220.57811	8955.38102	11491.3371
Res2	6557.90544	6699.23402	8570.16003	11958.2171
Res3	5492.74047	5501.04503	6957.28925	12405.0921
Res4	767.193771	777.306791	936.692239	1489.49915
Res5	5411.96942	5460.35476	8104.51514	10093.4085
Res6	5651.03278	6152.98087	8990.33241	9196.17214

Load deviation with respect to proposed optimization technique with the Whale optimization and PSO technique is shown in Table 1. An average load deviation for six residential buildings of 45% from the actual load is made possible with the proposed technique, which is 3% more from Whale optimization also 20% more improvised results from PSO.

Cost deviation details are shown in Table 2. An average cost deviation of 45% from the overall cost for six residential housed which is 20% more improvised compared to PSO technique and 3% improved compared to Whale optimization. Whereas whale optimization has 42% reduction from the overall cost which is 3% less than the Ebola optimization technique, with PSO at 25% deviation from the overall cost.

Conclusion

Sharing of load in six residential buildings depending on the load priority with optimal load shifting strategy is discussed in this paper. Real time data collected over the internet for six residential buildings is studied to reschedule the operating time for optimal usage of power equipment's and to reduce the cost. Overall price reduction of 45% in average with respect to the operational cost without DSM in six residential buildings and an average reduction in load is about 45% is made possible with the proposed Ebola optimization technique by scheduling the electrical appliances based on fixed loads, power flexible loads and time controllable loads. Proposed technique bought an average of about 20% improvement compared to PSO technique and around 3% average improvement from Whale optimization Technique.

Abbreviations

Nil

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Author contributions

All the Authors contributed equally in experimental work and simulation and writing the paper.

Conflict of interest

The authors declare no conflict of interest.

Ethics approval

All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

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