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Original Article

Enhanced Genetic Algorithm for Optimal Demand-Side Control of Time-of-Use Pricing in the Live Central University Building

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Abstract *- The energy auditing process collects data on the type and quantity of connected loads, their ratings, energy consumption, and the amount of money spent on power. Identifying sites with high energy demand and waste in academic buildings, hostels, food courts, and other facilities. Solutions for energy-efficient and cost-effective ways to conserve energy and reduce electricity prices. The demand response based, balancing the energy supply and demand, creates a grid with greater economic and environmental advantages. This was made possible by an academic building that reduced electricity costs and optimized power. An energy audit includes observations, measurements, system surveys, data collection, and analysis. Demand-side management is used to balance supply and demand. We then determine and create a demand response program that emphasizes the potential to lower energy costs and increase efficiency by employing a methodical process for measuring the current energy use. The early convergence problem in the process is resolved by the suggested Enhanced Genetic Algorithm, which employs Fitness Distance Balance selection (FDB). When the weather changes or there is a power outage, demand is met by renewable energy. The best time to use renewable energy is when it is most economical. The three objective functions for optimization are energy efficiency, the overall cost per hour for the electrical power supply (computer, water, lights, fans), and the motors' carbon dioxide emissions. By using an enhanced genetic algorithm to optimize power and lower electricity bills, an academic institution backed this. Reduce costs and peak demand by managing consumer energy usage patterns to preserve customer comfort and maximize the use of renewable energy sources.*

Keywords *- Enhanced Genetic Algorithm (EGA), Peak to Average load Ratio (PAR), Demand Side Management (DSM), Renewable energy, Electricity.*

1. Introduction

Rather than concentrating only on supply-side enhancements, Demand Side Energy Management (DSEM) refers to tactics and technology intended to regulate and lower energy use from the customer side. The primary objectives are optimizing energy use, cutting expenses, and promoting grid stability [1]. This demand-based study suggests using energy audits of appliances and academic buildings to save energy and money. In order to control energy, we then test solar and wind power, focusing on sustainable energy [2]. We offer a weighted Enhanced Genetic Algorithm selection and an organizational structure in the current study to boost the population variety of the algorithm [3].

Enhancing the efficacy and efficiency of optimization procedures is the goal of the Enhanced Genetic Algorithm (EGA), a variant of the conventional Genetic Algorithm (GA). 4]. The algorithm works well for complicated energy management scenarios because of its exploratory nature, which enables it to locate high-quality answers throughout a wide search area [6]. Techniques for lowering peak energy use are usually redistributing use to off-peak hours or cutting back on consumption altogether [7].

This work uses the Enhanced Genetic Algorithm to create a new kind of power optimization that reduces consumption. Governments and organizations are preparing to deal with the expanding urban population, which is expected to reach 70% of the population by 2050 [8]. The overall goal of energy management in academic buildings is to provide a comfortable and effective learning environment while balancing cost-effectiveness, environmental stewardship, and operational efficiency [9].

2. Literature Survey

Ejaz and colleagues [10] developed a proposed energy management system, one of the most crucial paradigms for implementing complex energy systems in smart cities.

Proposed effective energy management of residential structures was developed in 2020 by Hafeez et al. [11] in order to lower electricity costs, enhance Peak-to-Average Ratios (PAR), and accomplish the intended trade-off between power costs and user annoyance in the smart grid.

Ali et al. [12] proposed in 2019 that a server's power consumption costs will exceed the cost of its hardware throughout its lifetime. Clusters, grids, and clouds—which include thousands of diverse servers—have significant power input issues. Constant attempts have been made to lower the amount of electricity consumed by these large-scale. With Smart Grids (SGs), consumers can configure their home appliances to respond to Distribution System Operators' (DSOs') Demand Response programs (DRs). This was the idea put up by Rehman et al. for 2021 [13].

In 2020, Han et al. [14] created a plan for short-term energy use, facilitating effective communication between energy distributors and consumers. In 2020, a broad range of energy-related topics was proposed by Moustakas et al. [15], incorporating waste-to-energy technologies, wind energy, biomass, biorefineries, biofuels and bioenergy, life cycle assessment studies, integrated waste management strategies, and energy and materials recovery from trash.

According to a 2019 study by Qazi et al. [16], renewable energy sources, including solar, wind, and biomass, will not reduce their supply. The ever-increasing demand for energy is met by sunlight, a steady energy supply. In order to maximize power extraction and operation, in 2020, Babatunde et al. [17] developed an amalgam energy system that generates electricity by combining many energy sources, either renewable or driven by fossil fuels.

A variety of possible studies were carried out in almost or net Zero Energy Buildings (nZEBs) in 2018 by Hannan et al. [18] to optimize building energy usage economically and sustainably. Sarkar et al. [19] suggested that in 2020, the pollution levels from traditional power generation methods sharply rise, leading to negative environmental effects and problems. The following are the project's primary contributions:

- The EGA algorithm makes the management of energy easy to use and efficient.
- By applying to the EGA, the population's variety is increased, it breaks out of local optima, looks for better possibilities, and enhances their ability to investigate the academic building's cost-effective and ecologically beneficial benefits.
- The EGA approach uses this idea to reduce energy expenses and increase efficiency, provided that the target of the study is in a state of hydrostatic force equilibrium.

3. Research Methodology

The following three elements lower peak demand (kW) and energy usage (kWh).

1. Energy Efficiency
2. Demand Response
3. Strategic Load Growth

3.1. Energy Efficiency

It strongly emphasises lowering peak demand and overall energy usage over several years. The process of employing less energy to accomplish the same level of output, comfort, or performance.

3.2. Demand Response

Energy maintains system efficiency and stability in reaction to outside signals, such as shifts in electricity prices or grid conditions. It focuses on lowering peak demand during brief intervals on a few days of the year. Numerous academic buildings have used time-of-use pricing as the default rate structure as it is one of the price-based Demand Response (DR) schemes with lower control expenses.

3.3. Strategic Load Growth

The procedure for controlling and guiding the rise in energy demand is to promote resource efficiency, sustainable development, and grid stability. The focus is on steadily lowering peak demand throughout the season. In order to guarantee that grid dependability, environmental sustainability, and infrastructure development all keep pace with rising energy demands, strategic load growth is a proactive approach to energy demand management.

3.4. DSM- Energy Efficiency

The term "energy efficiency" describes using less energy to accomplish the same task. As seen in Figures 1 and 2, it is a gauge of how effectively we can employ energy to produce the intended result. Energy-efficient renovations and technology can be expensive initially, but the long-term benefits frequently outweigh them. Performing energy audits offers suggestions for enhancements and assists in locating locations where energy is wasted. Both business and residential premises may be the subject of these audits.

3.5. Role of DSM in Energy Efficiency

Demand Side Management (DSM) plays various roles in energy efficiency and is essential to maximizing energy use and lowering demand in general. DSM, or demand-side management, is a crucial component of energy efficiency. The idea of DSM is to control energy use by affecting demand rather than supply, which is economical and environmentally beneficial. By actively controlling energy demand during peak times, DSM helps lessen the need for peak power plants, which are usually less effective and more costly. Both the environmental effect and overall energy prices may decrease as a result. By modifying demand in real-time, DSM assists in balancing the unpredictable nature of renewable energy sources, such as wind and solar. Reduced energy use, enhanced grid dependability, environmental advantages, and cost-effectiveness of the academic building are all made possible by DSM.

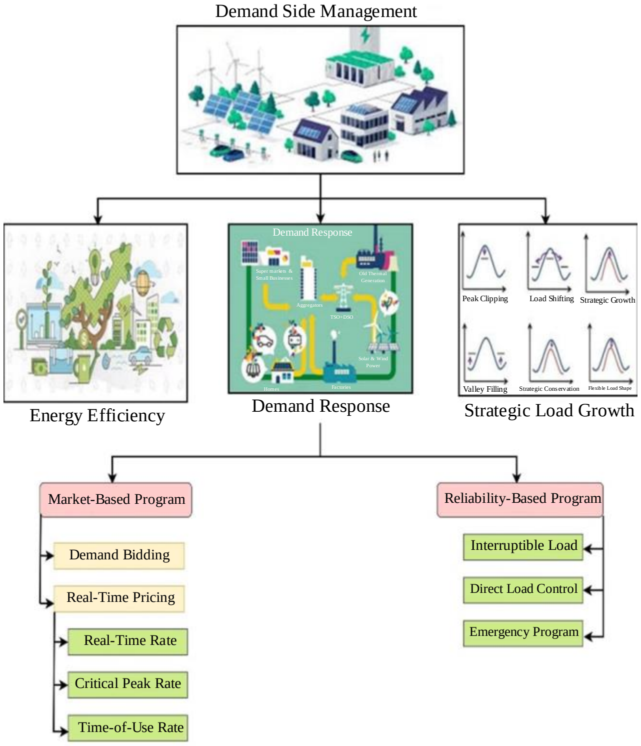


Fig. 1 Various DSM techniques

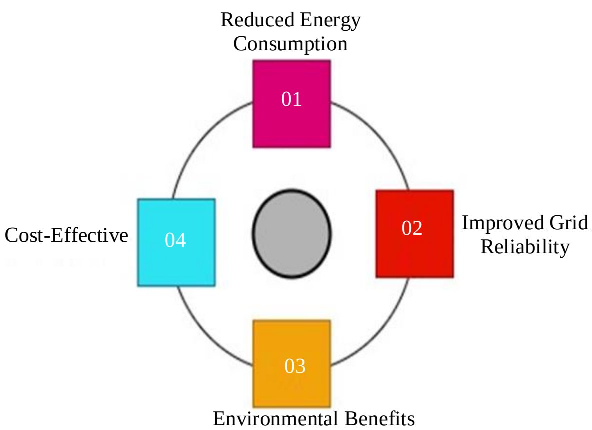


Fig. 2 The role of demand side management in energy efficiency

3.5.1. Energy Efficiency

Permanent demand reduction occurs when high-efficiency equipment is used to do the same activity while using less energy. Modernization of equipment leads to lower power consumption and higher equipment efficiency.

3.5.2. Demand Response

By efficiently controlling distributed renewable power generation by wind or solar, demand response systems lower the cost and demand for electricity during peak hours. Due to high demand, the daytime is typically regarded as peak hours; however, solar power generation also peaks, causing demand response to use alternate solar power generation to fulfil peak demand. Demand response programs are short-term load manipulation initiatives that calculate the demand as the total load less the amount of renewable electricity generated. They aim to lower peak consumption and change the load or generation pattern.

3.5.3. Dynamic Demand

Dynamic demand primarily aims to screen grid power calculations and other power framework characteristics. The dynamic nature of demand capacity conveys the widely accepted belief that decisions about power value are influenced by prior behaviour. In order to create a range of burden sets, hardware functional patterns are delayed by a few seconds. During peak hours, the loads are distributed separately to control the overall structure load and prevent major power outages.

3.5.4. Distributed Energy Resources

Another demand-side management strategy is the use of distributed energy resources. In this case, the demand side generates the power, which lowers the peak demand. DERs are tiny, grid-connected renewable energy sources that enable decentralized, variable power generation and conservation. A point of interaction within a smart electric grid may be used to facilitate and control the DER. Dispersed generation and capacity enable the consolidation of power from multiple sources, reducing the impact of natural disasters and promoting production safety.

4. Enhanced Genetic Algorithm (EGA)

Darwin's idea of evolution, which holds that natural selection drives evolution through the survival of the fittest, is the main source of inspiration for EGA. Encode all search criteria into the binary and decimal word stream's chromosome to practically solve optimization challenges. The chromosome is then the best option. On the other hand, chromosome-based genes serve as the problem's control variables. After that, each chromosome is sent into a crossover pool based on its fitness level, known as duplication. Next, crossover and mutation operations are carried out to produce sub-generations with higher fitness capabilities. Finally, the chromosome is decoded back into its original value, which it originally represented. This process is repeated until the best solution is obtained. If not, fitness is determined by re-decoding the chromosomes, which repeats until convergence. An elitist number of 2 over an average of 500 generations and a dispersed cross-over proportion of 0.8 were also encoded.

The Enhanced Genetic Algorithm uses the fitness function to determine the optimal solution based on DSM's goal parameter for load shaping.

$$Minimize\ \sum_{i=1}^{t}\sum_{k=1}^{L} l_k p_i \tag{1}$$

where t represents the total number of time steps, L represents the number of different types of loads (device types), l represents the total number of devices in each load type, and p represents the power of each load expressed in kWh.

$$Fitness\ function = 1 + \frac{1}{\sum_{i=1}^{t}\sum_{k=1}^{L} l_k p_i} \tag{2}$$

The genetic algorithm's objective function is represented by Equation (1), and its fitness function by Equation (2). The FDB selection procedure seeks to quickly and systematically identify the candidate or candidates who will contribute most to Pbest and the search process, and the design variables x1, x2, and xm have optimal values. Finding the solution candidates' scores is necessary when using the FDB selection procedure. Scores are determined by utilising the solution candidates' normalised fitness (normFPi) and distance (normDPi) values.

$$\forall_{i=1}^{n}, P_i \neq P_{best}, D_{Pi} = \sqrt{(X_{1Pi} - X_{1Pbest})^2 + (X_{2Pi} - X_{2Pbest})^2 + \dots (X_{mPi} - X_{mPbest})^2} \tag{3}$$

$$D_p = \begin{bmatrix} d_1 \\ . \\ . \\ . \\ d_n \end{bmatrix}_{n\times 1} \tag{4}$$

$$\forall_{i=1}^{n} P_i, S_{FDB^1 Pi} = \omega * normF_{Pi} + (1-\omega) * normD_{Pi} \tag{5}$$

$$\forall_{i=1}^{n} P_i, S_{FDB^2 Pi} = normF_{Pi} * normD_{Pi} \tag{6}$$

$$S_p = \begin{bmatrix} S_1 \\ . \\ . \\ . \\ S_n \end{bmatrix}_{n\times 1} \tag{7}$$

The Enhanced Genetic Algorithm flow chart is displayed in Figure 3. Among the parameters are the 24-hour electricity price weight, the average electricity price curve, the 24-hour inelastic load, and the utility company contract load. The client party includes the following: number of generations, crossover rate, mutation rate, elitism rate, population size, total elastic load limitation, and lower and upper elastic load constraints.

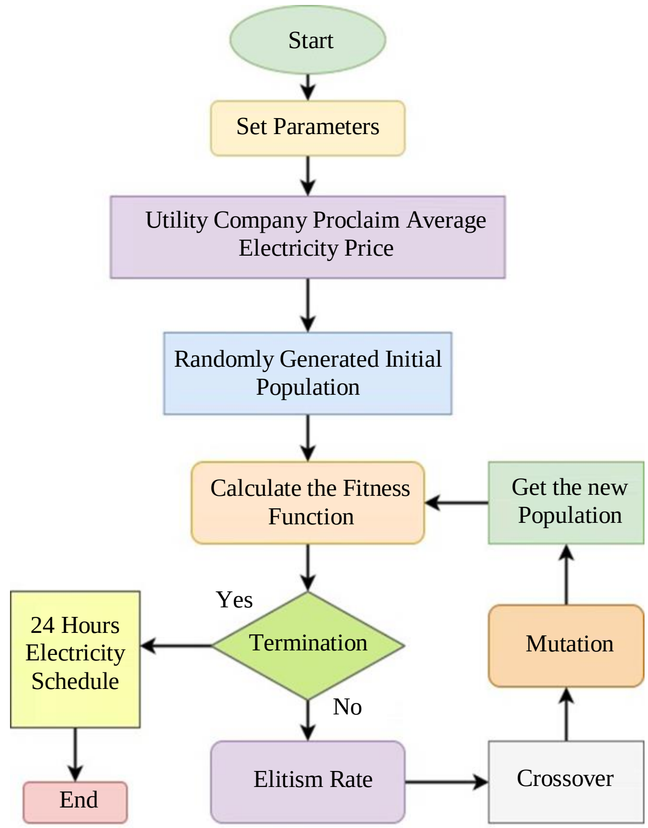


Fig. 3 24-hour electricity schedule by Enhanced Genetic Algorithm

The utility firm publishes the average power price curve with the electricity price weight to its customers. Population produced at random initially creates the initial parent chromosome at random based on the population size.

Compute the fitness value. It employs the aim function of minimizing client tariffs, as illustrated in (1,2). Assess if the termination requirement was met. List the customer's ideal 24-hour electricity scheduling if the answer is yes. If not, go to step 6. The maximum generation was obtained as the termination condition in this paper. Parents pass on their chromosomes to their children based on the elitism rate. Select a parent generation chromosome using fitness values and roulette wheel selection to perform duplication, crossover, and mutation. Treating the chromosome collected in steps 6–7 as a new parent generation is necessary to proceed to step 4.

4.1. The Fitness-Distance Balance (FDB) Selection

The FDB selection method was developed to consistently and efficiently identify applicants or candidates from an application pool who will contribute most to the search process. This suggests that a balanced approach will be taken to the variation management, which allows the exploration of various areas of the space, and an increased process guarantees the use of prior knowledge regarding the exercise environment for the Enhanced Genetic algorithm.

Finding the distance between the solution candidates and the most effective solution (Pbest) is the first stage in the FDB technique. A modular approach was used to complete the building energy bills, electrical supply and distribution systems, lighting systems, air conditioning systems, water pumping systems, building envelopes, harmonic assessments, and data collection and analysis of the building's energy system. Estimating the prospects for peak load savings computation of load work can be made easier with a tariff audit. The Predicted Mean Vote (PMV) at gross metering (the entire facility) was used to establish a baseline for applying several energy-saving techniques in a structure.

FDB selection method

begin

Select a total number of matrices

Generate a random number of devices to the w-weight coefficient

for i = 1: n do

Calculate distance between the P_i and P_{best} using (3)

Create or update the distance vector as given in (4)

end

for i = 1: n do

Normalize distance and fitness vectors based on minimal during peak hours

Calculate the score for each solution candidate as given in (5, 6)

Create the FDB-based score vector as given in (7)

End

Same process is repeated for each load and the best optimal fitness function is chosen

End

The separation between the best solution (Pbest) and the solution candidates is computed in the first stage of the FDB approach. The solution candidates' scores were determined in the second stage of the FDB approach. The score was calculated using the candidates' normalized distance and fitness values (normF and normDP, respectively). The greedy technique chooses the solution candidate with the highest fitness value in the ecosystem, Pbest. Pi represents the solution candidates chosen from the ecosystem using the incremental selection process according to their index. The values were normalised to prevent these two characteristics from controlling the score calculation. These factors were used to assign a score to each candidate in the P population, with 0 w = 1. This investigation used a value of 0.5 for w. The FDB selection procedure aimed to identify the candidate or candidates that would be most beneficial to Pbest and to carry out the recruiting process in the most effective and targeted manner possible. The ability to appropriately preserve variation and avoid premature convergence as the process of search lifespan draws to a close is described by this FDB attribute.

5. Results

Fig. 4 Current waveform

Simulations were carried out using MATLAB. Switching to LED lighting might result in savings of up to 52.36 %. In the previous three years, metal halides and fluorescent bulbs have mostly supplanted LED lights. The people in charge of maintenance prefer LED over normal bulbs, as their lifetime is longer. The chiller plant was also quite efficient. When employing a chiller plant, up to 43 %of the energy is saved, and by using the same amount of energy as conventional sources, the chiller plant can offer nearly double the number of rooms that conventional ACs do with current, as depicted in Figure 4. The management has conserved energy and can now supply more rooms with air conditioning by investing in the chiller plant.

Table 1. Energy consumption unit for academic institution building

Energy Unit Consumption					
2017		2018		2021	
Month	EBUNITS	Month	EBUNITS	Month	EBUNITS
Jan	17759	Jan	19667	Jan	18336
Feb	23598	Feb	20225	Feb	31210
Mar	32181	Mar	31254	Mar	39000
Apr	40611	Apr	41973	Apr	45083
May	37193	May	13262	May	12085
Jun	13286	Jun	12166	Jun	30588
Jul	27440	Jul	26846	Jul	28852
Aug	35580	Aug	39562	Aug	29655
Sep	35983	Sep	39772	Sep	31866
Oct	26420	Oct	35889	Oct	31461
Nov	29080	Nov	27748	Nov	29208
Dec	23441	Dec	23968	Dec	16185
Total	342572	Total	332332	Total	363529

Figure 5 depicts the power generation with a time graph that, in accordance with the EGA algorithm with the simulation model, displays a sharp variation in the amount of power created. Figures 6, 7 and 8 show the precise time-lapse of the electricity consumption base in 2017, 2018 and 2021. The graph makes it evident that there was a significant spike in electricity use in 2021 from July to October. The peak average ratio is crucial in DR.

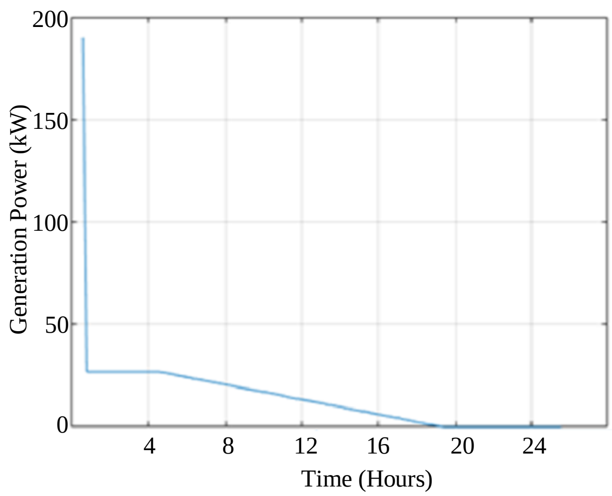


Fig. 5 Power Generation effects

Figure 9 shows that the median of 2017 to 2018 and 2018 to 2021 by July to October produced the biggest surge in the demand response overall. Figure 10 also discusses the PV wind utility factor at a rate ranging from 10 to 25% in relation to renewable energy. The difference in DR rates between offshore wind capacity factor and all other RES is substantial, ranging from 25% to 75%. This simulation provided the overall status using the same algorithm as the analysis.

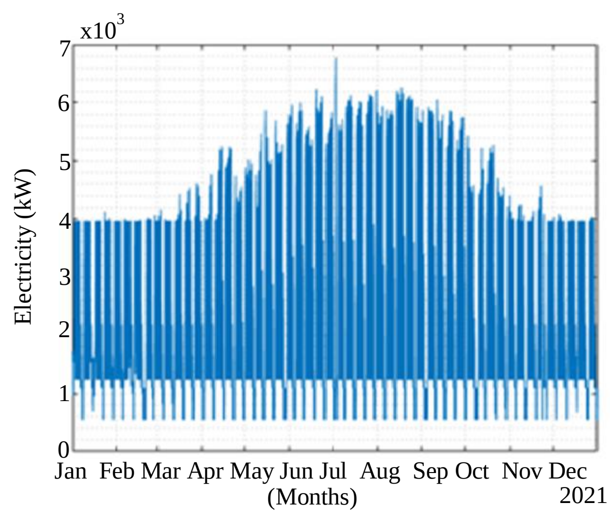


Fig. 6 Consumption for the year 2021

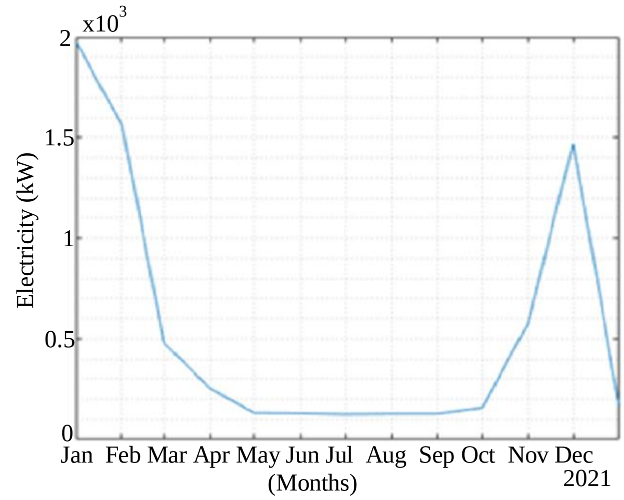


Fig. 7 Peak value evaluation for 2021

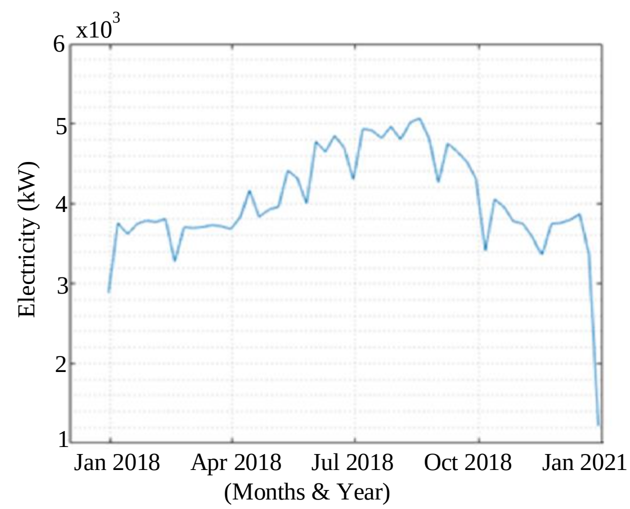


Fig. 8 Variation for the electric consumption from Jan 2018 to Jan 2021

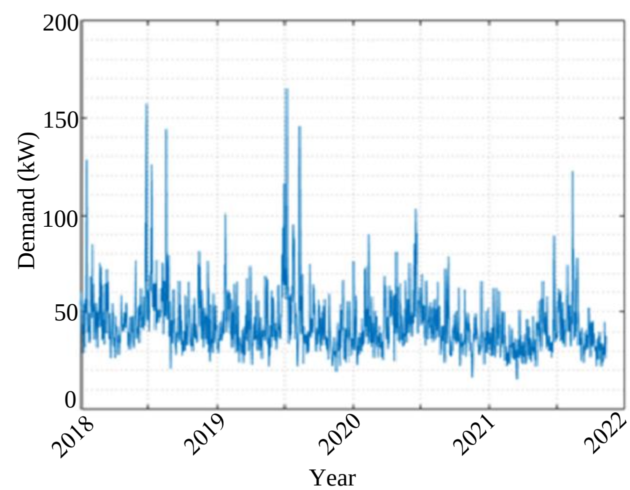


Fig. 9 Overall yearly comparison of the demand response

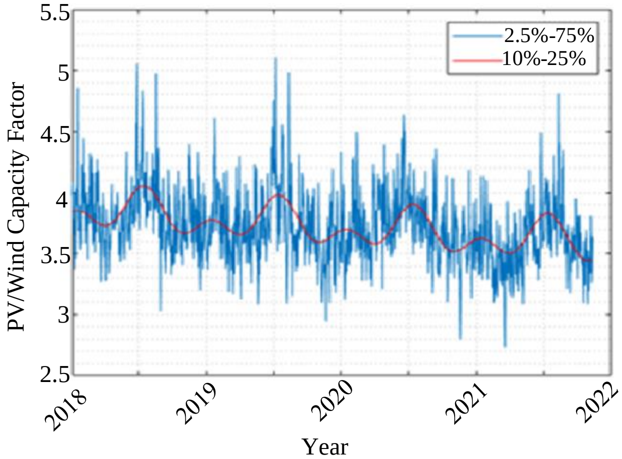


Fig. 10 Yearly changes in the wind capacity

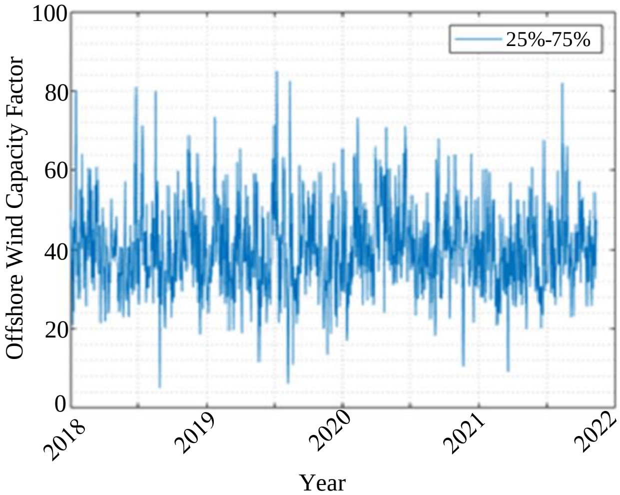


Fig. 11 Offshore wind capacity factor from 2018 to 2022

A general academic building has a large server storage capacity that can be moved to online cloud-based enterprises. This removes the requirement for physical servers to be maintained with the energy spent on cooling.

Solar panel installation has been incredibly effective, and because newer structures are quite vast and tall, solar panels may be mounted on top of them. In addition to these structures, 30% of existing panels may be placed.

Making healthy behaviors engrained and providing opportunities for many passive savings may be seen. Students can turn off the computers after each class since most of them are now left on and only the display is turned off. The offshore wind capacity factor from 2018 to 2022 is shown in Figure 11. Food waste is significant in the general academic building process; thus, investing in a biodigester would assist in the reduction of LPG gas cylinders.

This unit can be designed to generate electricity, although it is more efficient to use it primarily as a fuel supplier. Table 2 displays the electricity bill for the academic institutions in terms of rupees.

Table 2. Total electricity bill amount in academic institutions

Electricity Bill Amount in Rupees					
2017		2018		2021	
17-Jan	148709	18-Jan	162899	21-Jan	161956
17-Feb	188205	18-Feb	170118	21-Feb	246643
17-Mar	246202	18-Mar	277067	21-Mar	399581
17-Apr	304802	18-Apr	316769	21-Apr	344131
17-May	267892	18-May	117431	21-May	122940
17-Jun	119270	18-Jun	115565	21-Jun	80560
17-Jul	216919	18-Jul	215978	21-Jul	174319
17-Aug	270931	18-Aug	301087	21-Aug	347171
17-Sep	272190	18-Sep	302492	21-Sep	357748
17-Oct	212480	18-Oct	275391	21-Oct	252842
17-Nov	226076	18-Nov	221094	21-Nov	240234
17-Dec	188301	18-Dec	195382	21-Dec	156977
Total Bill Amount	2661981		2671278		2885109

Many studies have observed that the water entering the chiller plant consumes even less energy when cooled. However, such experiments could not be conducted because of time constraints. Before BLDC fans are brought in to replace existing fans, they have to be tested in terms of efficiency.

Hence, they must be replaced gradually rather than once. Space availability for solar panel installation is decreasing, as some places must be left vacant for future building construction. Making everyone aware of the energy situation is the most effective energy-saving strategy. If money is saved by conserving energy, an incentive system may be devised to produce greater performance.

The energy saving analysis is shown in Figure 12. Residential structures' low carbon emission and energy-saving capabilities are being used for further optimisation. Renewable resources contribute to energy conservation and process cost-effectiveness by lowering needless energy consumption. By comparing the EGA optimisation method to other optimisations, it is possible to estimate the cost and energy savings in academic institutions' buildings.

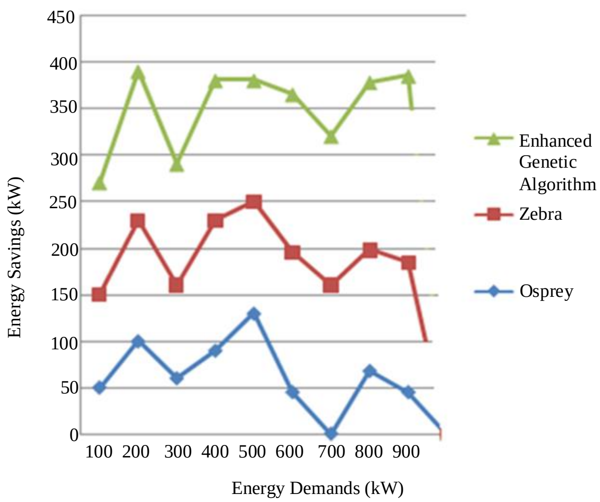


Fig. 12 Energy consumption analysis

Based on the comparative study, the proposed method outperforms existing methodologies and is validated with appropriate results. It may be inferred that the suggested method is more effective at lowering expenses. The simulation findings for our proposed power consumption scheduling arrangement are extremely successful at minimising peak load demand, recording management adjustments, comparing the changes' efficacy, and providing an applicable solution to boost efficiency and reduce power consumption.

The simulation reveals that the proposed strategy lowers peak load demand, resulting in considerable customer savings. The electrical system of the general academic building was originally sketched up by observing substations, transformers, and power lines.

Table 3. Comparison of unit energy consumption with various optimizations

Optimization	Electricity Bill Amount	
	Year	Amount (Rs)
Osprey Optimization	2017	2381971
	2018	2476278
	2021	2586100
Zebra Optimization	2017	2461781
	2018	2591298
	2021	2795407
Enhanced Genetic Algorithm	2017	2661981
	2018	2671278
	2021	2885109

During this time, there was little to no rain. Water shortage was a major concern during that period because the increased usage of air conditioners, fans, and water coolers consumed the most power compared to the rest of the year in 2017. Rather than sticking to regular academic schedules, the administration cancelled vacations from December through May. Consequently, cooling and air-conditioning systems used significantly less energy and water throughout the summer.

Figure 13 and Table 3 compare the unit energy consumption with various optimisations. A slight shift during the semester vacation from mid-November to December to May and June substantially impacted the decrease in energy use from 2017 to 2021.

Based on the comparative study, the proposed fitness balance distance algorithm outperforms Osprey and Zebra methodologies and has been validated with appropriate results. Utilization of solar power reduces reliance on grid electricity, leading to lower EB bills. An energy audit examines energy-consuming locations and loads to develop ways to minimise consumption while evaluating the return on investment from energy-saving methods.

5.1. Comparative Analysis

To Compare the three algorithms, a few metrics are considered, which are listed below:

1. Energy saving
2. Objective attainment
3. Control level
4. Progression estimation
5. Optimization complexity

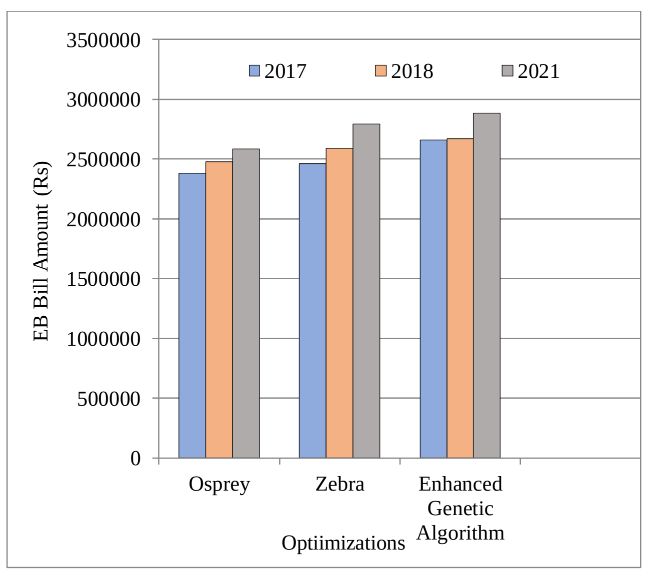
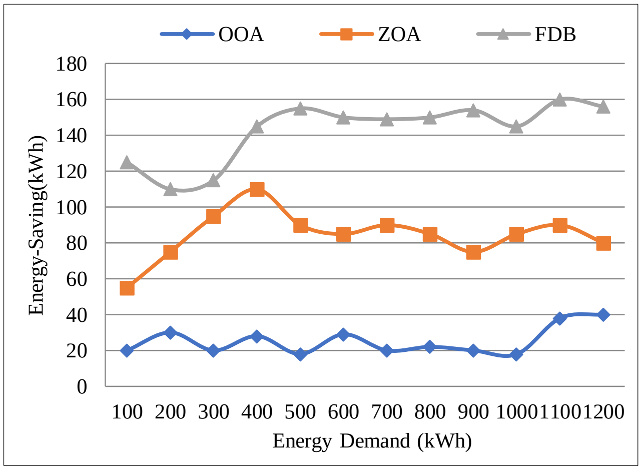
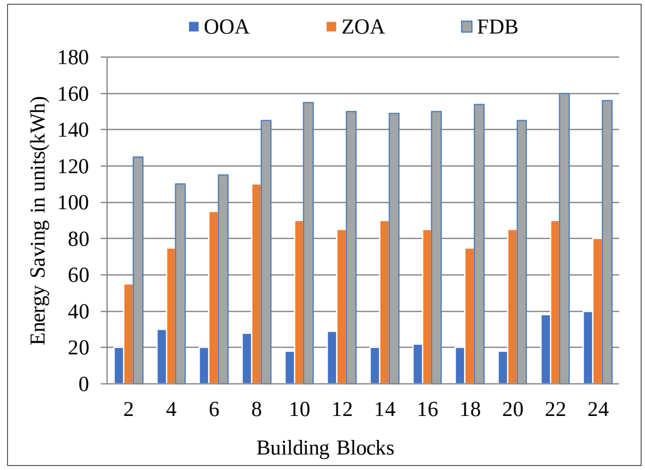


Fig. 13 Comparison of energy consumption with various optimizations

5.1.1. Energy Saving Analysis



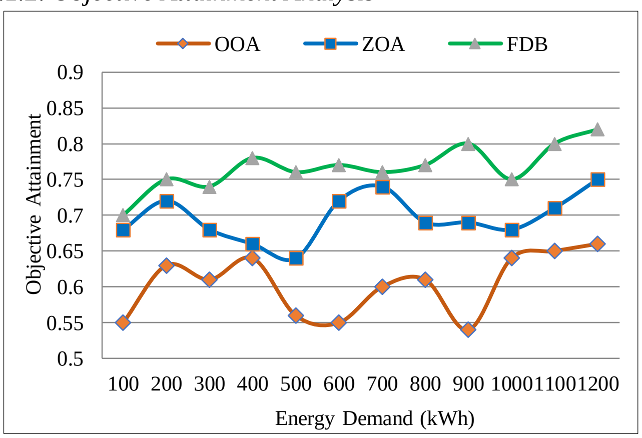
(a) Energy demand



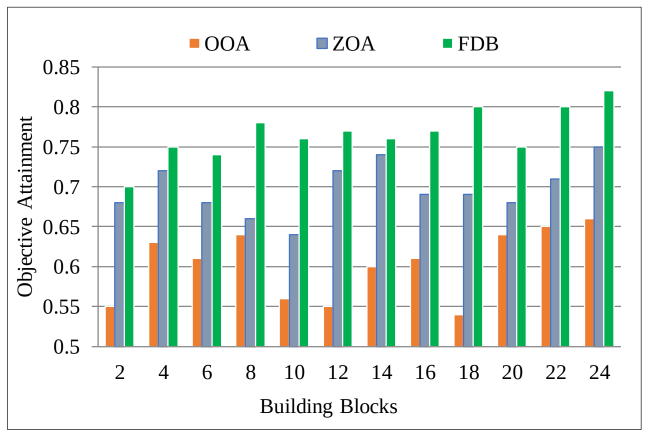
(b) Buiding blocks

Fig. 14 Energy saving analysis

5.1.2. Objective Attainment Analysis



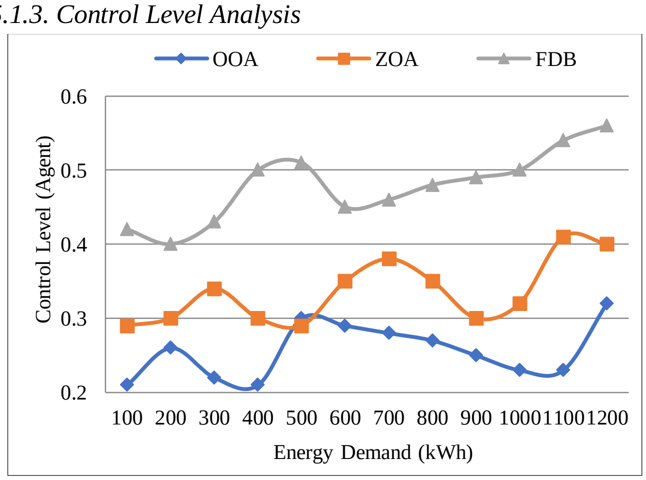
(a) Energy demand



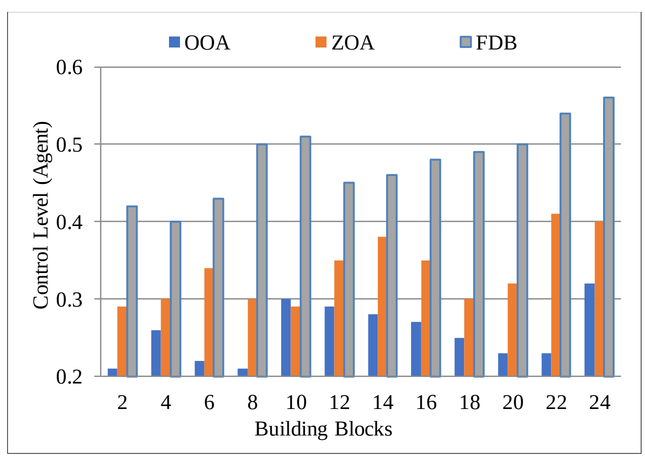
(b) Buiding blocks

Fig. 15 Objective attainment analysis

5.1.3. Control Level Analysis



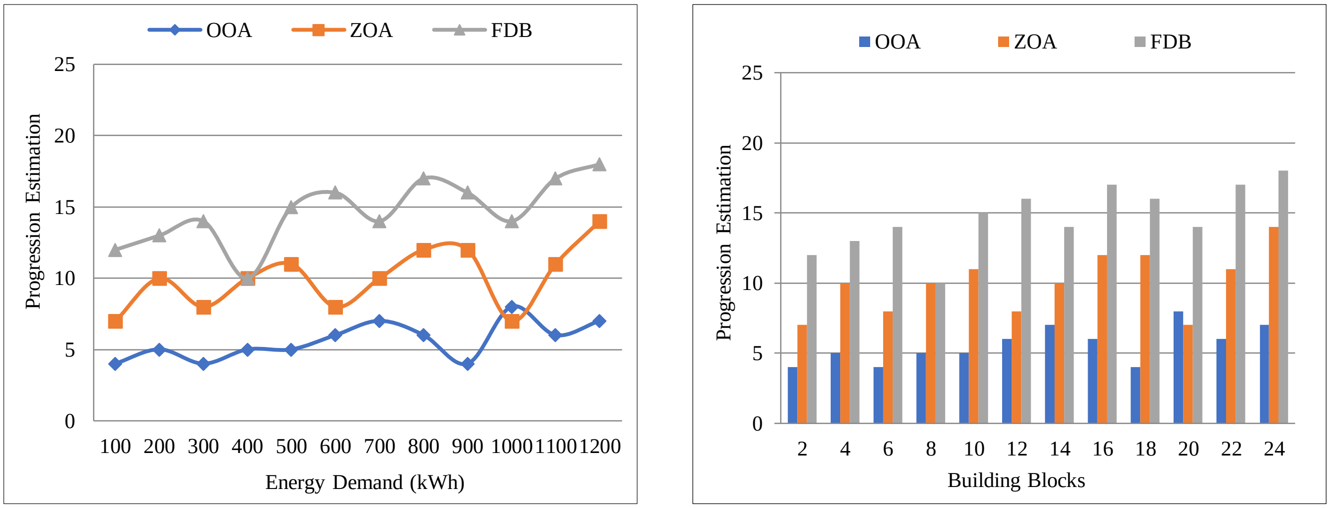
(a) Energy demand



(b) Buiding blocks

Fig. 16 Control level analysis

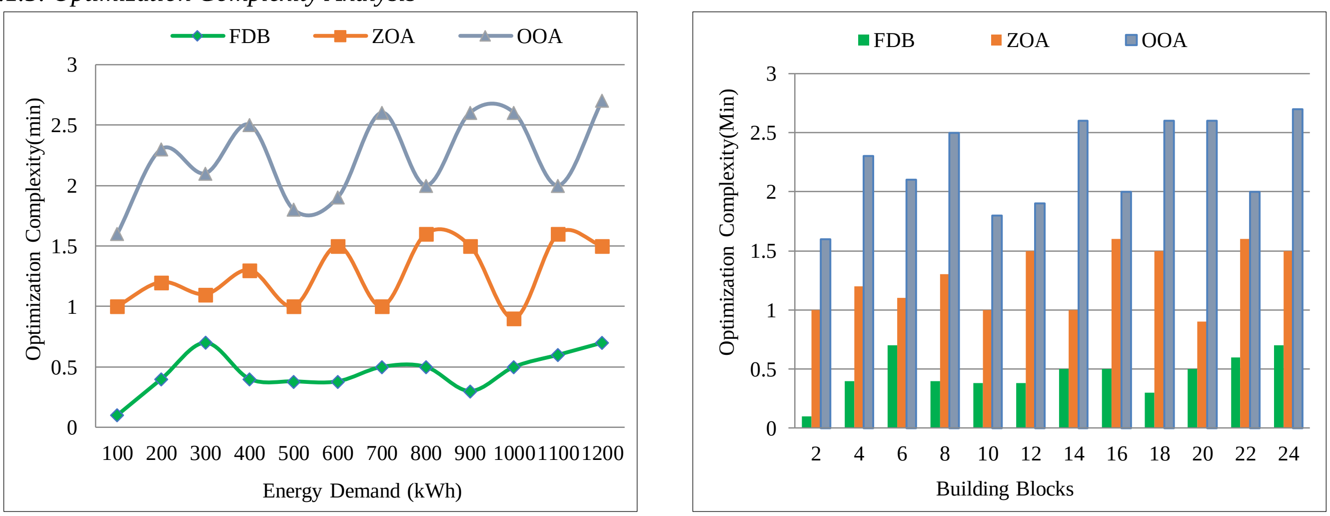
5.1.4. Progression Estimation Analysis



(a) Energy demand **(b) Buiding blocks**

Fig. 17 Progression estimation analysis

5.1.5. Optimization Complexity Analysis



(a) Energy demand **(b) Buiding blocks**

Fig. 18 Optimization complexity analysis

6. Conclusion

The academic institutions building energy audit an understanding of the electrical structure, data collection, data analysis and data completion were performed. By utilizing the Enhanced Genetic Algorithm, a photovoltaic subsequent generations system can be integrated with other potential power sources, such as solar power, which has the benefit of being efficient day and night, winter and summer, with a perfect production during the times when the PV is limited (generally winter & night), and vice versa. This execution was performed on the MATLAB platform, and the findings were acquired and fully supported by the provided for the research. Detailed analyses were performed to determine the focusing area of unwanted energy consumption.

A detailed analysis includes understanding the past 5 years' plans and actions of the past five years on energy management. The proposed EGA algorithm is validated for an academic institution's building-based research examining the best way to grow the university's power supply, considering the institution's electric motor, engine, and lighting. The Multi-Objective Enhanced Genetic Algorithm method is an iterative search algorithm with a simulation mechanism that combines the benefits of genetic evolution and natural selection. It may do constraint processing by combining constraint processing technology with the efficient search features of evolutionary algorithms, successfully resolving multitask constraint problems. Future research can lower costs and peak load demand by utilizing various dynamic optimization techniques. Integrating renewable energy sources identifies cost reduction and energy savings in academic institutions. Compared to the different optimization algorithms for energy-efficient building, the Enhanced Genetic algorithm is more effective in lowering expenses.

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