**OPTIMAL OPERATIONAL SCHEDULING OF A GRID CONNECTED SYSTEM BASED ON DEMAND RESPONSE**

**Seminar Report**

*A report is submitted in partial fulfillment of the requirements for the award of the degree of*

**Master of Technology**

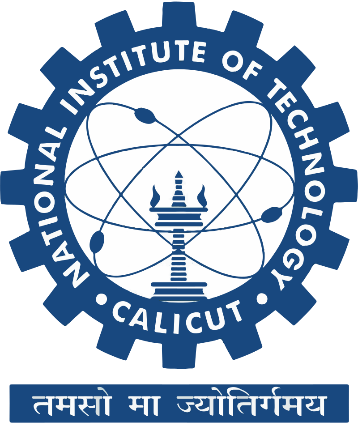
**in**

**Electrical Engineering**

**(Specialization: Power Electronics)**

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#### CERTIFICATE

**T**his is to certify that the report entitled **“Optimal Operational Scheduling of a Grid Connected System Based on Demand Response”**, submitted by **Antu Roy** (ROLL NO.-**M230635EE**) of the Department of Electrical Engineering, **National Institute of Technology Calicut**, in partial fulfillment of the requirements for the award of the degree in **Master of Technology** in **Power Electronics** is a bonafide record of carried out by him under my guidance during the academic year 2023-2025.

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### **ABSTRACT**

Microgrid is widely known for its reliability, robustness, and assimilation of renewable energy resources. A standalone microgrid is a good solution for the electrification of remote places. In this report, a smart standalone microgrid system has been designed optimally. Demand Response (DR) has been performed to manage the elastic loads considering the contributions of inelastic loads associated with this microgrid for economic operation. The optimal sizes of solar PV, wind turbine, diesel generator, battery energy storage (BES), and converter of this microgrid system have been decided. In the past few years, the transportation sector is shifting towards electric vehicle (EV) to reduce pollution. Therefore, the penetration of EV in microgrid has been considered for this work too. Two different DR schemes have been proposed and compared in terms of microgrid’s planning. Evolutionary based optimization techniques have been employed to solve the DR problem.

DR is indeed considered one of the best possible solutions to reduce peak demand and energy consumption in modern power grid. Both elastic loads and inelastic loads have been considered to optimize the economic operation of the power grid. The objective is to find out the most cost-effective way of managing electricity consumption by balancing the usage of elastic loads and ensuring the continuous operation of inelastic loads while minimizing overall costs. The consumers considered for the optimization model are residential consumers. The model provides recommendations on load scheduling, load shifting, or other strategies to minimize peak loads and reduce electricity costs specifically for residential consumers. DR programs aim to reduce this strain on the grid by encouraging customers to reduce their electricity consumption or shift their usage during peak periods through financial incentives or other means. This can help prevent blackouts, reduce the need for expensive new power plants, improve system reliability and lower consumer electricity costs. The work mentioned above, proposed the use of three soft-computing techniques, Differential Evolution (DE) to solve the problems. The results of the recommended algorithm demonstrate that it effectively reduces cost while simultaneously balancing the peak demand.

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**Abbreviations**

DR Demand Response

DE Differential Evolution

EV Electric Vehicle

AC Air Conditioner

CCHP Combined Cooling, Heat and Power

**Chapter 1**

**INTRODUCTION**

**1.1 Introduction**

The DSM is a mechanism used to manage electricity demand by encouraging customers to reduce their energy consumption during periods of high demand or when the grid is under stress. DSM is increasingly being implemented by utilities and grid operators as a way to manage peak demand and avoid the need for building new power plants or transmission lines, which can be costly and time-consuming. Price-based DSM models are commonly used to balance supply and demand in the electricity market by incentivizing consumers to reduce or shift their electricity usage during periods of high demand. In recent years, the pressure of the energy crisis and environmental pollution has prompted people to reconsider the existing modes of energy production, transmission consumption and storage. Nowadays, global energy demand is increasing rapidly and most of the load demand depends on conventional fossil fuel generation. Concurrently, the continuous improvement in the power market has enabled DSM technology to play a major role in the power grid [1]. DSM programs have become increasingly important in the operation of the electric grid, as they allow for more flexibility in managing peak demand and reducing the need for additional power plants or infrastructure. By offering financial incentives for consumers to reduce or shift their electricity usage during peak periods, demand side management programs help to balance the supply and demand of electricity in the grid. In addition to reducing the daily operating cost of the power grid, demand side management can also help to integrate renewable energy sources into the grid, as they often generate electricity intermittently and require more flexible demand management strategies. By incentivizing consumers to use electricity when renewable energy sources are available, demand side management can help to reduce the need for fossil fuel-based generation and support a more sustainable energy system. By providing consumers with information about these price fluctuations and the ability to adjust their electricity usage accordingly, price-based DSM models can help to reduce peak demand and smooth out the aggregated load in the system. This can help to improve the reliability of the electricity grid and reduce the need for expensive new infrastructure or power plants.

Price-based DSM models are an important tool for managing the electricity market and balancing the supply and demand of electricity in a more efficient and cost-effective way [2]. It seems like your goal is to achieve economic optimization by minimizing the cost of meeting the energy needs of users. Energy demand side management typically involves shifting energy use from one form to another, such as using a more energy-efficient appliance or shifting energy use from one time to another, such as running appliances during off-peak hours when electricity prices are lower.

DSM programs are increasingly being implemented by utilities and grid operators as a way to manage peak demand and avoid the need for building new power plants or transmission lines, which can be costly and time-consuming. By incentivizing users to shift their energy use, demand side management programs can help reduce overall electricity costs and improve grid reliability [3].

Load demand can be fulfilled by different forms of energy depending on the availability, cost, and efficiency of the energy sources [4]. DSM is a mechanism that allows consumers to adjust their electricity usage in response to changes in the price of electricity or other signals, such as grid congestion or the availability of renewable energy. This can include shifting electricity usage from peak to off-peak hours, reducing overall electricity consumption during times of high demand, or using on-site generation or storage to supplement grid power.

In this system, the energy market determines prices based on supply and demand. The energy market employs a dynamic pricing control strategy to adjust the price of electricity based on the preferred interests of various parties, including consumers and suppliers. This strategy allows for the best energy price to be determined through interaction between the consumer and the supplier [5]. In the case of a residential energy system with a 24-hour interval, the primary source of energy is typically power generating stations and gas-based power generating stations. These energy sources are referred to as the energy supplier. The goal of the system is to maximize consumer satisfaction while maintaining a minimum daily energy consumption level. DSM enables consumers to adjust their energy consumption based on dynamic pricing signals, helping to reduce energy consumption during periods of high demand. Energy storage technologies, such as batteries, can be used to store excess energy generated during periods of low demand and release it during periods of high demand, helping to balance the grid and reduce the need for fossil fuel-based peak plants. By employing these strategies, the system can help reduce energy costs, improve energy efficiency, and reduce greenhouse gas emissions.

In [6], a real-time demand-oriented temporal linear pricing technique is proposed as a way to optimize energy pricing and meet the objectives of different players in the energy system. The pricing strategy combines time-of-use pricing and real-time pricing to create a dynamic optimization pricing model that considers the unique characteristics of different energy system players. The goal of the pricing technique is to decrease supplier costs or increase supplier revenue, depending on the objectives of the energy system players. When the objective is to decrease supplier costs, the energy price is typically set at its lowest level. On the other hand, when the objective is to increase supplier revenue, energy prices are set to represent the upper limit of the goal's limitations. The proposed dynamic optimization pricing is different from traditional unified fixed energy pricing in that it can consider the unique characteristics of distinct energy system players. By using real-time demand-oriented temporal linear pricing, the energy system can achieve greater efficiency, reduce costs, and promote the use of renewable energy sources.

**Chapter 2**

**LITERATURE REVIEW**

[7] Tao Ding, Ming Qu, Nima Amjady, Fengyu Wang, Rui Bo and Mohammad Shahidehpour, *“Tracking Equilibrium Point Under Real-Time Price-Based Residential Demand Response,”* IEEE TRANSACTIONS ON SMART GRID, VOL. 12, NO. 3, MAY 2021.

The problem of tracking the equilibrium point of the real-time LMP-based residential demand side management program. The model assumes that the residential demand is elastic and is modeled as a monotonously decreasing linear function of the LMP. To verify the effectiveness of the proposed demand side management model, numerical results on the IEEE 30-bus system were presented. The results show that the model is effective in tracking the equilibrium point of the LMP-based residential demand side management program. Overall, this letter presents a promising approach to addressing the challenge of real-time LMP-based residential demand side management program tracking, and its effectiveness is demonstrated through numerical results.

[8] Shahab Bahrami, Yu Christine Chen, and Vincent W. S. Wong, *“Deep Reinforcement Learning for Demand Response in Distribution Networks,”* IEEE TRANSACTIONS ON SMART GRID, VOL. 12, NO. 2, MARCH 2021.

The DE algorithm that is specifically designed for residential users, with a focus on addressing the uncertainties that can arise from load demand and electricity price fluctuations, privacy concerns of users, and power flow constraints imposed by distribution networks. The actor network selects the optimal actions for the residential users, while the critic network evaluates the value of these actions based on the current state of the system. Overall, the proposed demand side management algorithm has the potential to be an effective tool for load aggregators to motivate residential users to reduce electricity demand during peak time periods while taking into account uncertainties and user preferences. The use of the DRL algorithm with an actor-critic method is a promising approach to achieving this goal.

[9] Xin Chen, Yingying Li, Jun Shimada, and Na Li, Member, *“Online Learning and Distributed Control for Residential Demand Response,”* IEEE TRANSACTIONS ON SMART GRID, VOL. 12, NO. 6, NOVEMBER 2021.

The critical challenge of uncertain and unknown customer responses to load adjustment in incentive-based residential DSM programs, specifically in relation to regulating AC loads. Overall, the proposed approach offers a promising solution for managing AC loads in incentive-based residential DSM programs by addressing the challenge of uncertain and unknown customer responses. The use of machine learning techniques such as the Gaussian process and logistic regression enhances the accuracy and reliability of the approach and could be useful in designing effective DSM programs.

[10] Mostafa Vahedipour-Dahraie, Homa Rashidizadeh-Kermani, and Amjad Anvari Moghaddam*, “Risk-Based Stochastic Scheduling of Resilient Microgrids Considering Demand Response Programs,”* IEEE SYSTEMS JOURNAL, VOL. 15, NO. 1, MARCH 2021.

A risk-constrained stochastic framework for joint energy and reserve scheduling of a resilient microgrid that incorporates demand-side management. The optimization problem is formulated to schedule the system operation in both normal and islanding modes, taking into account the prevailing uncertainties of islanding duration, as well as prediction errors of loads, renewable power generation, and electricity prices. To solve the optimization problem, the authors propose a two-stage stochastic programming approach that considers both the first and second-stage decision-making problems. In the first stage, the microgrid's optimal energy and reserve schedules are determined, while in the second stage, the decisions are adjusted based on the actual system conditions. Overall, this article provides a valuable contribution to the development of resilient microgrid systems that can operate under uncertain and dynamic conditions.

[11] Peyman Afzali, Masoud Rashidinejad, Amir Abdollahi and Alireza Bakhshai*, “Risk-Constrained Bidding Strategy for Demand Response, Green Energy Resources and Plug-In Electric Vehicle in a Flexible Smart Grid,”* IEEE SYSTEMS JOURNAL, VOL. 15, NO. 1, MARCH 2021.

The increasing need for flexibility in smart grids due to the growing penetration of uncertain energy resources such as renewable energy and virtual power plants. The authors propose a stochastic decision-making model for the coordinated operation of renewable resources and virtual power generation, incorporating DSM programs and PEVs to resolve the uncertainty of power generation from renewable resources. Overall, this paper highlights the importance of incorporating DSM programs and PEVs in the coordinated operation of renewable resources and virtual power plants in smart grids and presents a valuable contribution toward the development of flexible and resilient smart grids.

[12] A. Pal, S. Chatterjee, A. Bhattacharya and A. K. Chakraborty, "Optimal Design of Microgrid with Demand Side Management in Presence of Electric Vehicle," 2020 IEEE FIRST INTERNATIONAL CONFERENCE ON SMART TECHNOLOGIES FOR POWER, ENERGY AND CONTROL (STPEC), NAGPUR, INDIA, 2020, PP. 1-6, DOI: 10.1109/STPEC49749.2020.9297705.

The proposed system aims to optimize the energy resource scheduling in internet data centers by considering the use of CCHP and various demand side management techniques. By incorporating CCHP into the system, the energy efficiency of the data center can be significantly improved, leading to reduced electricity costs. The system is designed to incorporate multiple energy sources, including the power grid, solar photovoltaic panels, CCHP systems, and battery energy storage systems. Overall, the proposed system provides a comprehensive approach to optimizing energy resource scheduling in Internet data centers. By incorporating CCHP and demand side management techniques, the system can significantly reduce electricity costs while improving energy efficiency and sustainability.

**Chapter 3**

**OPTIMIZATION TOOLS UESD**

**3.1 Introduction**

Differential Evolution (DE) is a robust, stochastic, and population-based optimization algorithm developed by Storn and Price in 1996. Primarily used for solving numerical optimization problems, DE efficiently addresses real-world issues across various scientific and engineering disciplines. The algorithm distinguishes itself through its simple yet powerful operations: initialization, mutation, crossover, and selection. These operations collaborate to iteratively improve a population of candidate solutions toward an optimum, making DE an excellent choice for complex optimization tasks where traditional methods falter.

**3.2 DIFFERENTIAL EVOLUTION (DE)**

The DE is a popular optimization technique used to find the minimum or maximum of an objective function. It is a stochastic, population-based algorithm that works by maintaining a population of candidate solutions and iteratively improving them. The algorithm was introduced by Storn and Price in 1996. DE is an evolutionary algorithm commonly used for solving numerical optimization problems. It employs four main operations: initialization, mutation, crossover, and selection. Let's briefly describe each of these operations:

**3.2.1 Initial population**

Typically, the initial population is generated randomly between the lower and upper bound of the problem. Each candidate solution, also known as an individual or a member of the population, represents a potential solution to the optimization problem. These random solutions are also known as targeted vectors. The values of the decision variables in the candidate solutions are initialized randomly, ensuring that they fall within the feasible range defined by the problem constraints.

= + rand \* () (3.2.1)

*i = 1, 2, 3*....*N*

*j = 1, 2, 3*....*D*

Where,

* rand is the function that typically generates random values uniformly in the interval [0, 1]
* *N* is the size of the population
* *D* is the number of decision variables
* is the lower bound of the variable
* is the upper bound of the variable

.

After the initial population is generated, the DE algorithm evaluates the fitness of each individual by applying the objective function or evaluation metric specific to the optimization problem. The fitness evaluation assesses the quality of each candidate solution and guides the search process toward better solutions in subsequent generations.

**3.2.2 Mutation**

A mutation operation is applied to each candidate solution to generate a new candidate solution. This creates a mutant vector. The mutation operation randomly selects three candidate solutions from the population and generates a new candidate solution by adding the difference between two of them multiplied by a scaling factor to the third candidate solution. This generates a new candidate solution that is a linear combination of the selected candidate solutions.

In DE, the mutation operator is responsible for creating mutant vectors by perturbing the existing population. The mutant vector is created by combining the difference between two randomly selected vectors, and at the iteration, as per the following equation:

= + () (3.2.2)

*i = 1, 2, 3*....*N*

Where,

* is the mutant vector, representing a potential solution in the population.
* is the randomly selected vector from the current population. The superscript 'a' denotes that this vector is selected as a base vector for mutation.
* and two other randomly selected vectors from the current population. These vectors are different from and are used to calculate the difference for perturbation.
* F The scaling factor, which is a constant that controls the amplification of the difference between and . It is typically a value between 0 and 2.

The mutation operator introduces random perturbations to explore different regions of the search space. By combining the difference between and , scaled by the factor F, with , a new mutant vector is generated.

**3.2.3 Crossover**

The crossover operation is employed after the mutation operation to produce trial vectors, which helps to maintain population diversity and explore the search space more effectively. The trial vectors are generated by combining the information from the parent vectors and the mutant vectors, which explores new regions of the search space while retaining some characteristics of the parent vectors. This helps to maintain diversity in the population and prevent premature convergence to local optima. The trial vectors are used in the selection process according to the following equation:

*=*  (3.2.3)

*i = 1, 2, 3*....*N*

Where,

* , and are the individual of the target vector, mutant vector and trial vector respectively
* is an integer random number between [1, D]
* is the element of the donor vector entering the trial vector with recombination probability

The crossover operation is typically implemented using a binomial crossover scheme, which is performed on each component whenever a randomly picked number between 0 and 1 is less than or equal to the , the is a user-specified constant within the range [0, 1], which controls the fraction of parameter values copied from the mutant vector.

**3.2.4 Selection**

In the selection procedure described for the minimization problem, each solution in the population, including the trial vectors and the updated target vector, has an equal chance of being selected as parents. The selection is based on comparing the cost function values of the target vector and the trial vector. If the trial vector has a better value (lower cost) of the cost function compared to the updated target vector, it replaces the target vector in the next generation, as per Equation (2.4).

After the mutation and crossover operations, the greedy selection strategy is employed to determine whether the trial vector or the target vector will survive in the next generation. The selection process can be expressed as follows:

= (3.2.4)

If the fitness of the trial vector is better (lower or higher, depending on the optimization problem) than the fitness of the corresponding target vector, the trial vector replaces the target vector in the next generation. The new trial vector yields a solution equal to or better than the target vector, it replaces the corresponding target vector in the next generation; otherwise, the target is retained in the population.

Mutation, Crossover and Selection continue until some stopping criterion is reached.

**3.3 Conclusion**

In conclusion, Differential Evolution stands out as a versatile and effective optimization method capable of tackling a wide array of numerical problems. Its core mechanisms—initialization, mutation, crossover, and selection—work synergistically to explore and exploit the solution space, driving towards the optimal solution with remarkable efficiency. The adaptability and straightforward implementation of DE make it a valuable tool in the arsenal of modern computational optimization, with applicability ranging from engineering design to economic forecasting. As computational demands evolve, DE continues to be a relevant and powerful approach to solving complex optimization challenges.

**Chapter 4**

**PROBLEM FORMULATION AND PROPOSED SOLUTION METHODOLOGY**

**4.1 Introduction**

This section outlines the problem formulation and the proposed solution methodology tailored to address the specific challenges identified in the study. We begin by defining the parameters and constraints of the problem, establishing a clear and quantifiable objective. Following this, we introduce the Differential Evolution (DE) algorithm as the chosen method for seeking optimal solutions. The suitability of DE for this problem is justified by its proven efficacy in handling similar complex optimization scenarios. This section will detail the implementation nuances of DE, including population initialization, mutation strategies, crossover techniques, and selection criteria, tailored to the specifics of the problem at hand.

**4.2 To Solve the DR Problem by Load Shifting**

DSM is a mechanism that allows consumers to adjust their electricity usage in response to changes in the price of electricity or other signals, such as grid congestion or the availability of renewable energy. This can include shifting electricity usage from peak to off-peak hours, reducing overall electricity consumption during times of high demand, or using on-site generation or storage to supplement grid power. In the work, the loads are categorized into two types: elastic loads and inelastic loads. The scheduling of loads has a direct influence on both the peak load and the energy cost for end users. By strategically managing the timing of load operation, residential consumers can effectively control their electricity consumption patterns and achieve benefits in terms of peak load reduction and cost savings.

**Elastic loads:** These are the loads that can be scheduled and shifted to different time slots based on requirements. An example of elastic loads such as water pumps, washing machines, and vacuum cleaners, can be easily adjusted to take advantage of lower electricity prices during off-peak hours and EVs that can be charged at different times without affecting its operation. This type of load is known as a transferable load, as it can be shifted from one time period to another without affecting the overall demand for electricity.

**Inelastic loads:** These are the loads that are called non-transferable loads, on the other hand, are those that cannot be easily shifted in time, such as lighting, refrigeration, and heating. Inelastic loads typically have rigid time requirements and cannot be rescheduled without compromising their functionality.

DSM is performed to schedule the elastic loads effectively. The goal is to find an optimal schedule for the elastic loads that minimizes costs and maximizes the utilization of available generation resources while maintaining a balance between the generation capacity and the load demand of the power grid. By considering the flexibility of elastic loads, the DSM program aims to achieve economic operation and improve the overall efficiency of the power grid.

By applying DE to the optimization problem within the DSM program, the objective is to find the optimal scheduling solution for the elastic loads that minimize the COE of the power grid. The algorithms search the solution space iteratively to find the best combination of load scheduling and generation utilization, considering the constraints and objectives of the DSM program.

**4.2.1 PROBLEM FORMULATION**

1. **Objective Function**

The objective function [12] F, which represents the goal of the DSM program, is to minimize the total tariff of the customers over a 24-hour period. The mathematical expression of this objective function can be represented as follows:

Min (F) = ) (4.2.1)

Where,

* F is the objective function to be minimized. It represents the total tariff of the customers
* t is the 1-hour time slot of a 24-hour period
* is the price weight at hour period. It represents the cost or price of electricity at each specific time within the 24-hour period
* are the elastic load and inelastic load respectively at hour period. It represents the amount of electricity used by the customers at each specific time within the 24-hour period

The objective is to find a scheduling solution for the elastic loads that minimizes the total tariff incurred by the customers over the 24-hour period. By minimizing the objective function, the DSM program aims to optimize the electricity usage of the customers in a way that reduces their overall tariff cost. This can be achieved by adjusting the customers' power consumption patterns to align with lower-priced periods or by implementing other demand side management strategies to optimize the electricity usage and reduce costs.

1. **Constraints**

The following constraints to ensure that the total required energy by the elastic loads is fulfilled and that the load remains within the peak supply capacity.

The equality constraint (3.2) ensures that the sum of the elastic loads over 24-hour period intervals equals the total required energy for the day. It guarantees that the total energy demanded by the elastic loads is met.

(4.2.2)

The inequality constraint (3.3) ensures that the total load (elastic + inelastic) for each time interval remains within the specified upper and lower limits. It ensures that the load does not exceed the peak supply capacity or fall below a certain minimum level.

(4.2.3)

With these equality and inequality constraints in the optimization problem, you can ensure that the total required energy is fulfilled, and the load remains within the prescribed limits.

Where,

* is the total energy requirement by the elastic loads in the power grid
* is supply capacity of the grid connected power network at hour period
* and are the lower and upper bound of the respective elastic loads

**4.2.2 PROPOSED SOLUTION METHODOLOGY**

DE optimization techniques commonly used in solving power system network optimization problems, including DSM programs. Typical steps for DE have been shown with flowcharts in Fig. 4.2.2



**Fig. 4.2.2 Typical steps of the DE to solve the load scheduling problem**

In a practical scenario, when considering the implementation of a DSM program, it is common to treat all loads, including domestic loads, as AC loads. This assumption allows for a simplified representation of the power consumption patterns in the system. Figure 3.2. presents the daily average load profile of different loads over a 24-hour period. This load profile represents the initial state or baseline before the implementation of the DSM program.

The load profile indicates the average power consumption or demand for each hour of the day. It provides insights into the overall load pattern, including peak demand periods, variations throughout the day, and potential opportunities for load shifting or optimization. By comparing the load profile before and after the implementation of the DSM program, it becomes possible to evaluate the effectiveness of the program in modifying the load pattern and achieving the objectives of cost reduction, peak demand management, and overall load optimization.

**Fig. 4.2.3 Daily average 24-hour load profile [12]**

The daily average 24-hour load profile refers to the average power consumption or demand for each hour of the day, considering all loads within a specific system or area. It provides a representation of the typical load pattern observed over a 24-hour period.

**Input Data for DSM Program**

The numerical information concerning the work's constraints is shown in Table 3.1. To provide input data for a DSM program, typically need information related to energy consumption, facility or equipment characteristics, and operational parameters. While the specific requirements may vary depending on the program and utility provider, here are some common data points might need:

**Table 4.2.2 Limits of elastic load**

|  |  |  |
| --- | --- | --- |
| **Energy Requirement/Day** | **Lower Limit of Elastic Load** | **Upper Limit of Elastic Load** |
| 636.42 kWh | 0 kW | 66 kW |

**DSM with Dynamic Price**

In DR programs, where the objective is to cut peak load demand, it is common for participants to follow the dynamic price weight provided by the utility company. Dynamic pricing involves adjusting electricity prices based on the level of demand at a given time, with higher prices during periods of high demand (peak hours) and lower prices during periods of low demand (off-peak hours). Hourly price weight has been given in Fig. 3.3.

**Fig. 4.2.4 Hourly price weight [12]**

**4.2.3 RESULTS AND DISCUSSIONS**

In the mentioned case, the problem of shifting the elastic load is based on hourly price weights. DE optimization techniques that have been used to solve the problem. The outcome load profiles, as depicted in Figure 3.4, indicate the resulting load curves after applying the optimization techniques. These load profiles tend to exhibit a flatter shape, suggesting that the load-shifting strategy has been successful in redistributing the electricity consumption and reducing the peak load demand. Flattening the load curve helps in reducing stress on the power grid during peak periods and can lead to more efficient utilization of electricity resources.

**Fig. 4.2.5 Hourly residential scheduled load values with DE using dynamic price**

**Table 4.2.3 Cost of energy consumed by the for consumers**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Optimization Technique** | **Number of Runs** | **No. of Hits to Best Solution** | **Minimum**  **Cost ($)** | **Maximum**  **Cost ($)** | **Average Value**  **($)** | **Standard Deviation** |
| DE | 10 | 10 | 2221.13 | 2221.13 | 2221.13 | 0.0299 |

The minimized cost of energy consumed by the for consumers achieved using DE 2221.13. This indicates that DE have been able to find a load-shifting strategy that results in a slightly lower cost of energy, which could correspond to either reduced costs or better peak load reduction.

Figure 3.5. is the convergence characteristics of DE, providing insights into the optimization progress and the convergence behaviors of the three algorithms. Convergence curves show how the objective function values evolve over the iterations or generations of the optimization process. Generally, a steeper decrease in the objective function value indicates faster convergence and better performance.



**Fig. 4.2.6 The convergence characteristics of DE**

**Conclusion**

In summary, the problem was meticulously defined with clear objectives and constraints to ensure an accurate evaluation of solution strategies. The Differential Evolution (DE) algorithm, customized for this specific application, has been proposed as the solution methodology. This approach leverages DE's adaptive mechanisms, which are expected to be particularly effective given the problem's complexity and the solution space's characteristics. The methodology's design aims to exploit DE's strengths in convergence and exploration capabilities, promising a robust search for optimal solutions. Future steps will involve fine-tuning the DE parameters through empirical testing and potentially integrating hybrid strategies to enhance performance further. This structured approach is anticipated to yield significant insights and satisfactory solutions to the problem.

**Chapter 5**

* 1. **CONCLUSION**

#### 5.1.1 Conclusion

In this work, the scheduling of elastic loads has been performed using the DSM program. In the proposed DSM strategy, the optimization problem has been addressed using both DE algorithms. The objective function used in the optimization problem has been formulated to incorporate both hourly and daily limits of elastic loads. The COE analysis has been conducted to compare the economics of a power grid with and without DSM. The proposed approach in the paper provides a basic idea for a DSM strategy that can be applied to any distribution system with both simple elastic and inelastic loads.

The interests of both suppliers and customers were considered when building an optimization model. This model represents the operating characteristics of both sides and aims to balance their needs in a way that is beneficial to both. By reducing peak load demand through effective load scheduling, the proposed strategy contributes to enhancing the capacity and reliability of the distribution network. The objective optimization model of a system considering both supplier revenue and consumer cost is constructed to represent the operating characteristics of the opposing sides with interest in supplier and consumer.

* + 1. **SCOPE OF FUTURE WORK**

Load shifting can help to minimize the cost of energy consumption by shifting electricity usage to off-peak hours when electricity prices are lower. Overall, load shifting has the potential to play a significant role in the future of grid connected power network. By encouraging energy consumers to shift their electricity usage to off-peak hours, load shifting can help to balance the energy supply and demand, reduce energy costs, and promote the integration of renewable energy sources. The load scheduling strategy based on DE can be employed in the future Smart Grid.

A grid connected power network that minimizes the cost of the demand side and maximizes revenue on the supply side has the potential to be a game-changer in the energy industry. By effectively balancing energy supply and demand, a grid connected power network can improve grid reliability, reduce energy costs, promote renewable energy integration, and enhance the customer experience. As technology continues to evolve, the scope and benefits of a grid connected power network will continue to expand, making it an exciting area for future development. Energy resources such as Renewables (Photo Voltaic cell) and Electric Vehicles (EV) will be integrated with the present formulation to make the problem statement more robust.

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