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Modeling Framework For Optimizing Microgrid Operation With Ev And Responsive Load Profile

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Abstract: In this thesis, a thorough modeling framework is presented for the purpose of optimizing the functioning of a microgrid that is integrated with electric vehicles (EVs) and load profiles that are responsive. Because of the growing incorporation of electric vehicles and renewable energy sources into the power grid, it is essential to manage energy resources in an effective manner in order to improve grid stability, lower operational costs, and guarantee the utilization of energy in a sustainable manner. Demand-side management tactics, optimizing energy storage, and the dynamic charging and discharging of electric vehicles are all incorporated into the framework that has been presented. This framework also takes into account the unpredictability of load demand and the generation of renewable energy. The model seeks to minimize energy expenditures and maximize the use of renewable energy while ensuring system reliability by utilizing advanced optimization techniques such as mixed-integer linear programming (MILP) and machine learning algorithms. These techniques are utilized in order to reduce the overall cost of energy. It is possible for the microgrid to adjust to fluctuating energy demands thanks to the incorporation of responsive load profiles, which in turn promotes efficient energy utilization. In order to illustrate the usefulness of the framework in terms of enhancing operational efficiency, lowering grid dependency, and offering economic and environmental benefits, simulation results from case studies have been shown to be beneficial. The findings of this study contribute to the creation of micro grids that are both sustainable and intelligent, and that are able to manage the complexities of current energy systems in the presence of electric vehicles and dynamic load behaviors'.

I. Introduction

The advancement of shrewd grids expects to upgrade energy the board and efficiency while tending to worldwide difficulties looked by power grids. A vital part of streamlining load reaction programs is giving consumers real-time energy pricing information, empowering them to settle on informed choices that lessen network costs because of cost fluctuations. For these models to succeed, it is fundamental to guarantee client responsiveness to pricing signals, precise interpretation of discount costs into retail rates, and admittance to client information. By adjusting retail rates with discount fluctuations, these models energize off-peak utilization, assisting consumers with setting aside cash and further developing in general grid efficiency.

A new approach to meeting these complex challenges is raised in this article. It addresses problems of energy production and transmission within gas and electricity networks. Optimizing profitability for energy hubs remains a challenging problem since there are many uncertain energy sources. The analysis of micro grids and power system designs indicates the increasing role of energy hubs in such systems. This study combines economic issues with the effort of pollution reduction across micro grids using a multi-objective approach. Advanced energy storage systems, E-fuel, and renewable sources include solar and wind energy.

This paper presents research on ESS and the importance of ESS in smart grids, its critical role for security and reliability.

The integration of electric vehicles into shrewd grids furnishes amazing open doors alongside challenges. Smart charging systems for streamlining the usage of sustainable power and investigating further potential outcomes of involving EVs as versatile energy stockpiling units are key foci. The research study underlines the inherent nature of hourly variability of load demand in basic systems of micro grids. Utilities balance this through time-of-use (TOU) pricing to shift the rates corresponding to the shape of the load demand curve. The paper contributes in three dimensions: techno-economic impact due to participation in grids, dynamics of electricity pricing, and integration of renewable energy.

The uncertainty present in the renewable energy generation output was incorporated into the optimization for microgrid energy management in the proposed model. The idea was to have efficient scheduling schemes with less operating cost for storage as well as renewable energy sources while simultaneously assuring the performance of the grid. Simultaneously, they studied state-of-the-art control techniques such as artificial intelligence algorithms, fuzzy logic, and model predictive control by trying to stress the stability characteristics of the grid and improve energy management.

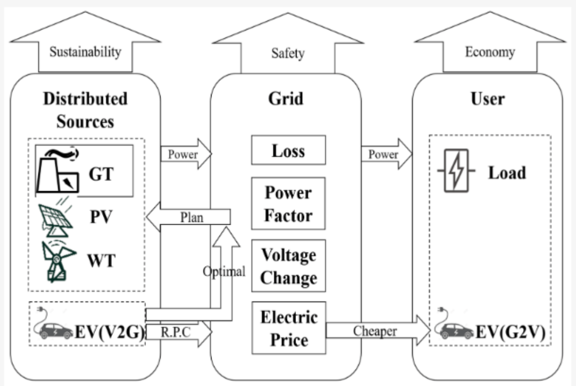

Figure 1.1: Structure of Source-Grid-User

In the paper, the investigation of the potential brought by VPPs to savvy grids was investigated. A portion of the issues in the review comprised of the plan and streamlining of VPPs for the coordination and collection of circulated environmentally friendly power assets. Expanding accentuation on VPPs raises the viability of usage of environmentally friendly power inside a grid and of the adaptability and unwavering quality. The other commitment made was in fostering a control methodology for islanded miniature grids working with environmentally friendly power. The point in planning the improvement was to upgrade energy the executives in microgrid systems such that will guarantee steady activity and smooth changes between grid-associated and islanded modes.

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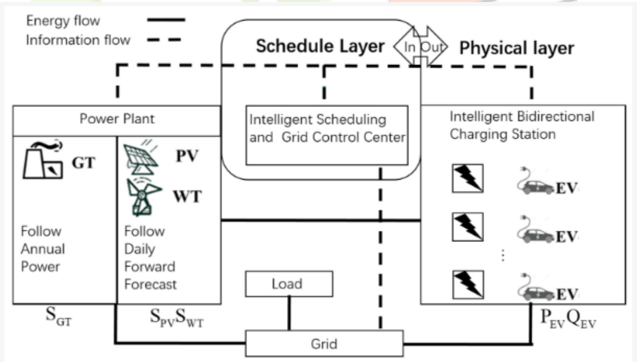

Figure 1.2: Layered System Scheme

Mixed-integer particle swarm enhancer was proposed as a solid streamlining structure that gives an answer for the unit responsibility issue. To delineate the robustness and unwavering quality of the technique, six distinct cases were tackled, each addressing a unit responsibility issue: vulnerabilities, and battery debasement. With the rising use of sustainable power sources by networks to diminish the energy charges, there is a need to moderate the fancies of climate subordinate RES. In such manner, another technique for exchanging enhancement inside microgrid activity in light of RES integration was proposed.

1.1.MICROGRID COMPONENTS AND ARCHITECTURE

The four essential pieces of a microgrid are generally energy the board, loads, energy storage, and energy age. In Figure 4, the microgrid engineering is shown.

1.1.1. Architecture of the Microgrid

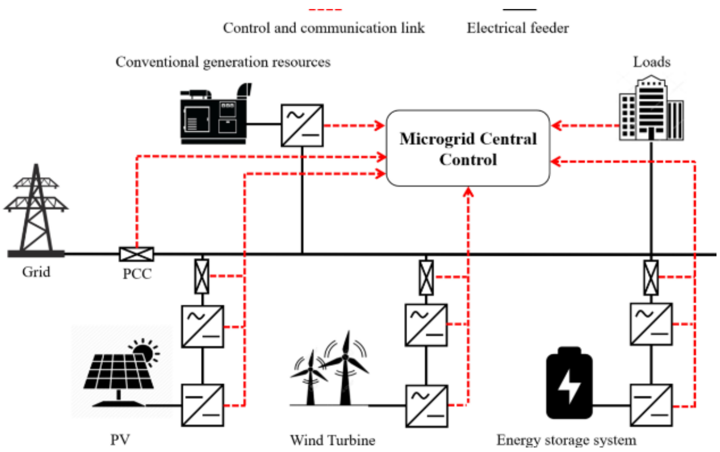

Figure 1.4: Architecture of microgrid

- **Energy Generation**: A microgrid is a hybrid of traditional energy assets like diesel generators and elective sources like sun based and wind energy. The synthesis may change relying on the particular necessities of the microgrid that is extraordinary to that area.
- **Energy Storage**: One of the most important contributions the energy storage devices, such as batteries, make in the microgrid is the ability to make it possible to store energy that is made available for use during periods when generation is low. This capability goes to ensure supplied energy assurance and sustainability independent of the source being renewable.
- **Energy Management**: The optimal utilization of energy in the microgrid would need a strong system designed to handle the flow of energy appropriately. For example, it deals with monitoring and coordinating different sources of energy while appropriately balancing supply and demand for energy.
- **Loads**: Loads refer to electrical systems and devices in a microgrid that consume electricity including household homes, business buildings, public facilities, etc. Therefore, proper load management is also important to the total functionality of the microgrid ensuring wise and responsible energy consumption.

1.2.OPTIMIZATION OBJECTIVES IN MICROGRID OPERATION

Energy is essential to human society's survival and advancement. It is shaping national economies, livelihoods, and strategic competitiveness around the world. Throughout recent many years, petroleum products, like oil, coal, and flammable gas, has overwhelmed worldwide use because of a remarkable leap in world energy demand. Long haul reliance on these conventional wellsprings of energy has prompted serious energy and natural issues around the world that oblige financial turn of events and debase everyday environments. Burning of petroleum derivatives, like coal and oil, is delivering barometrical carbon dioxide and different gases into the environment, however in this process; it has become one of the most remarkable causes for a worldwide temperature alteration and environmental change.

Figure 1.6: Optimize Microgrid

1.3.MODELLING TECHNIQUES FOR MICROGRID OPTIMIZATION

The greatest sources of energy on Earth are fossil fuels-natural gas, oil, and coal. And with the increasing global consciousness that these resources are few, many scientists worldwide explore other energy sources. Among the renewable energy resources, hydro, wind, and solar power are ranked as the most available. Below is a list of the operational challenges and controls that arise from micro grids.

- Maintaining a balance between active and reactive power while ensuring high power quality.
- The microgrid must operate effectively in both grid-connected and standalone modes.
- A robust energy storage system is required to serve as a backup.
- Effective energy scheduling, monetary burden dispatch, and enhanced power stream activities are essential for guaranteeing financially savvy activity and keeping up with system security.
- Accurate load and generation forecasting should be implemented to minimize short-term discrepancies between energy generation and demand.

1.4.RESEARCH OBJECTIVES

- ➢ Integrate Electric Vehicles (EVs) and Responsive Loads into Microgrid (MG) Modeling Based on Real-Time Power System Dynamics.
- ➢ Simulate Microgrid Performance Considering Renewable Energy Source (RES) Uncertainties with Integrated EVs and Responsive Loads.

1.5.RESEARCH METHODOLOGY.

The following is the suggested algorithm for scheduling responsive loads and electrical vehicles at the same time to ensure micro grids operate as efficiently as possible:

1) Statistics about the input problem, such as load demand, generation statistics, etc.
2) The following formula can be used to calculate the grid load mean:

$$PL_{Mean} = \frac{\sum_{t=1}^{T} PL(t)}{T}$$

3) Where T is the total number of study hours and $PL(t)$ is the load that the grid needs at hour t.
4) t = 1.
5) If $PL(t) \geq PL_{Mean}$ electric vehicles can be discharged.

Thus,

$$PL(t) = PL(t) - V2G(t)_{dischar}$$

6) If $PL(t) < PL_{Mean}$ electric vehicles can be charged.

Thus,

$$PL(t) = PL(t) + V2G(t)_{char}$$

7) To supply the load $PL(t)$, turn on the generators; if the load is successfully supplied, move on to the next phase; if not, go back to step 6 and recalculate reserve power to support wind and PV sources as best as possible.

$$P_{reserve} = \big(WT(t) - WT_{LB}(t)\big) + (PV(t) - PV_{LB}(t)$$

where $WT_{LB}(t)$ and $PV(t)$ are the scheduled wind and PV powers at time t, and $WT_{LB}(t)$ and $PV_{LB}(t)$ are the lower limit of wind and PV powers at time t.

8) To provide the required reserve, turn on the generators and responsive loads; if the reserve is present. Subsequently, compute the pollution of units at time t and ascertain the startup, power generation, and reserve expenses. Time is increased by one (t = t + 1); if $t \le t^2$, return to step 4; if not, terminate the procedure.

II. LITERATURE REVIEW

Harsh et al. (2022) It highlighted the challenges posed by electric vehicles (EVs) and other non-EV loads that contribute to increased energy consumptions within microgrids, complicating energy scheduling for operators. The authors proposed an alleviation of this workload of the operator by considering a demand response (DR) program in the micro grid's operational planning by underscoring the requirement of the aggregators in facilitating effective communication between operators and several potential DR participants.

Guzzle et al. (2022) the work here explored smart charging strategies' potential to improve grid reliability by exploiting PEVs load ability flexibility. It developed a method for real-time stochastic control of single and finite time horizons with personalized PEV models. The authors use Kernel Density Estimation to compute driver load models and observed that such personalized models help smart charging algorithms. Such algorithms are enhanced because the scheduling algorithms are able to track future random data, and the time distribution to charge has become fairer.

Mansouri et al. (2023) The creators have dissected the prerequisite for imaginative planning of a microgrid (MG) taking into account a rising number of smart buildings (SBs) and electric vehicles (EVs) in a distribution system (DS). They proposed a technique established on a three-layered risk-loath game-hypothesis structure to facilitate the planning of SBs and EV armadas with MG tasks. The primary level is where SBs engage in a DRP in view of supporter use designs, which present powerful impetus duties. In the second level of decentralization, the planning among SBs and whole armadas of EVs is dealt with by cooperation in the DRP. In the last level, MG administrators get power trade data about SBs, in this manner empowering them to plan their exercises as per set functional standards.

Mohseni et al. (2023) According to the literature, the problem of MG planning and optimization that is resilient in nature falls into a class of NP-hard problems. The authors proposed using metaheuristics, high-level algorithms inspired by different natural and physical processes, to arrive at near-optimal designs for MGs. This approach underlines huge potential through advanced metaheuristics to make capital-intensive, 100% renewable grid-isolated MGs economically viable enough for implementation.

Rahman et al. (2019) Such a high-level V2M architecture is explored in this chapter that can cope optimally with the distributed management of electric vehicle storage within a commercial environment behaving like a hybrid AC-DC microgrid. The proposed scheme thus enables bi-bus voltage regulation: both the AC bus and DC bus voltages are regulated at their point of delivery. Real commercial networks and loads are used in case studies to prove the efficacy of the proposed architecture. Experimental results show that the system can handle generation-demand variations commendably and function efficiently under islanded grid tie-in modes, user-preferrd EV disconnection, and acceptable time-delays.

Rezaeimozafar et al. (2021) This established there is an urgent need for management solutions to minimize the impact of rising numbers of electric vehicles on the performance of distribution grids while charging. However, most of the methodologies existing are based on laboratory-scale research with hypothetical data thus cannot be applied to real networks. In this work, therefore, the authors have proposed a two-stage scheduling technique to manage huge fleets of electric vehicles within microgrids without dynamic monetary systems. The day-ahead scheduling was first optimized in line with large-scale EV behavior forecasting to reduce energy supply costs and minimize EV battery degradation. An improved K-means clustering method was adopted, which classified vehicles based on classes, handling the challenges of computational dimensionality. Online coordination through the best scoring system was achieved to encourage driver compliance with the initial scheduling model in the second step. The methodology was assessed involving real information in light of extended improvements in the Ontario energy network throughout the following decade, on a grid-associated microgrid coordinated with photovoltaic systems. Brings about all examinations the proposed approach precisely executed ideal charging and releasing timetables in huge scope systems.

Gupta et al. (2022) Examines at the microgrid as one coordinated controlled substance, consolidating energy storage gadgets, controllable loads, and both sustainable and non-renewable power age sources. The major objective behind was minimizing operation costs on the same turn with technological constraints. This aim has been addressed by taking a layered stochastic optimization algorithm to compute optimal incentive values of an incentive-based demand response program along with the battery dispatch mechanism and generation schedule. The effects of different hybrid electric vehicle charging modes on system execution were broke down, and the ideal integration of the energy the board plan with a voltage control smart transformer-based system was likewise explored. Recreation tests hung on a 33 transport test system showed the efficiency of the calculation, principally through a decline in the working expenses by 17.53% to 17.74%, other than lessening the complete system misfortunes from 29.49% to 31.36%.

Sedighizadeh et al. (2020) The paper focused on the critical role of demand-side management in improving the operation of efficient microgrids and distribution networks. For this reason, their research aimed to examine how responsive loads and the uncertain nature of electric vehicles may potentially impact the performance of a grid-connected microgrid relying on combined heating, cooling, and electricity systems as demand-side management tools. Integrating electric vehicles and responsive loads into the system could reduce operations costs by 18.12% and emissions by 4.91% with results such as arrival and departure times and charge levels from simulation runs.

Rana et al. (2022) Community microgrids were widely studied as one promising solution towards smart grid operational resilience, where most of these come into the fore where an increasing set of eco-friendly electric vehicles is seen within the microgrid systems. The authors highlighted that uncontrolled charging may dominate these electrical networks with such electric vehicles. In that direction, the authors propose a strategy for efficient demand response based on dynamic pricing to improve the prospects of an upgrade in the microgrid's efficiency about harboring a large number of EVs in safety. A two-level hierarchical optimization framework was developed to structure the DR system; the top level optimized dynamic pricing for the DR participants, while the lower level adjusted each user's energy consumption based on top-level price signals. In the present formulation, the optimization problems at the lower level were solved with a mixed-integer linear programming model, while the evolutionary method was utilized for the upper-level optimization. A key advantage of the approach is that user energy scheduling challenges can be solved in a distributed manner, thus scalability. Numerical experiments on an IEEE European low-voltage distribution network microgrid system validate the DR strategy as proposed against benchmark pricing models available in the literature.

Srilakshmi et al. (2022) Conducted research on improved management techniques for community microgrids supplied with electricity from EVs, ESS, and PV panels as primary sources of backup power. They also considered the possibility of using the electric vehicle as a gateway of stored energy that can be shared between houses and the grid through the technologies of bidirectional flow of power. By far, one of the salient features of this control strategy is the variation of the charging/discharging rate from EV to ESS, which varies based on the availability of EVs, transformer loads, and day-ahead pricing. The paper introduces the Markov model-based approach in using real, hourly vehicle utilization data to forecast the supply of EV. This work aims at minimal battery degradation with maximum economic benefits for prosumers.

Rajamand et al. (2020) Feasibility of using MSUs in EV-powered MGs to meet peak loads for sustaining stable voltage and power profiles. The researchers found that at EV peak hours, the augmented demands from EVs along with other loads started to degrade the microgrid's performance. In order to overcome these challenges, the authors of this research provide a power scheduling strategy for EV, which would help in facilitating the profit profile of the microgrid and help to alleviate problems associated with demand support as well as cost issues. The paper discusses two strategies which are V2L, i.e., electric vehicles to loads, and V2G, that is, electric vehicles to the main grid, both of which are designed to reduce costs and decrease dependency on the main grid. It usually had to buy electricity at the peak periods, which meant high costs. A demand response program was another technique adopted to reduce the load when demand was increasing or spreading it to off-peak hours. Through this, the microgrid saved costs and raised profits with the help of demand response and EV scheduling software. The proposed work introduced an optimization method for microgrid operation related to scheduling of EVs and DR programs, based on the Lagrange methodology and Bender decomposition. Simulation results obtained from the study demonstrate that the cost profile can be reduced up to 14.67% against traditional DR programs and optimal scheduling can be done of EVs.

III. MICROGRID SIMULATION UTILIZING OPENDSS

3.1.INTRODUCTION

The greater the complexity issues facing distributed power generation, RES, and energy storage devices when entering the electricity system network, the more challenging it is to evaluate the performance of these components efficiently. The key is to perform load flow, short circuit, transient, and other analyses. A real asset in simulation tools is to deal with assessments of virtual scenarios to help analyze system behavior within various situations. Out of all these options of this category, OpenDSS is the most used software applied to the distribution systems and microgrids with efficiency in both balanced and unbalanced cases.

3.2.OPEN-SOURCE SOFTWARE

Open-source simulations: This is usually available free of charge and is available. Students in the classes can use the tool if proprietary simulation licenses are not accessible. There are a plethora of simulation packages in existence, but yet to one's surprise, none of them fit all investigations. This implies that some are more suited for transient studies, others better for load analyses, or have optimized transmission over the distribution system.

Since the focus of this study is based on microgrids or distribution systems modeling, some open-source software packages have been reviewed with regard to their strengths and weaknesses. The following section elaborates on these tools in more detail, discussing the features and limitations offered by them.

3.2.1. Internet-based power system simulator (InterPSS)

Researchers from China, the United States, and Canada worked together to create InterPSS, an open-source web platform for software development. Its primary purpose is to facilitate the use of internet-based tools for the study, modelling, and creation of solutions to practical engineering problems. There are two editions of InterPSS that you may choose from: desktop and web. To improve overall efficiency, the DE version includes a graphical editor that allows users to run transient stability and load flow simulations simultaneously. It is hence directly accessible through web browsers for performing load flow and short circuit studies. InterPSS is based on Java, which enables the following high-level features: forecasting, CIM6 modeling, and cascaded failure analysis. Also, it integrates intraplatform components. On the other hand, it is limited due to a dependency on languages that are less efficient than Fortran, C, or C++.

3.3.SIMULATION USING OPEN-SOURCE SOFTWARE: OPENDSS

The primary objective of OpenDSS is to model microgrids of renewable energy sources with unbalanced systems, demand response, and electric vehicles. In addition, it works with optimisation connections in MATLAB. Lines, transformers, capacitors, reactors, loads, generators, voltage sources, current sources, and storage devices are all modelled by its modelling engine. In addition, it has sensors and meters for energy, voltage, and ammeter. OpenDSS supports communication with other software: Excel, VBA, and MATLAB to make the application much more workable and integrable.

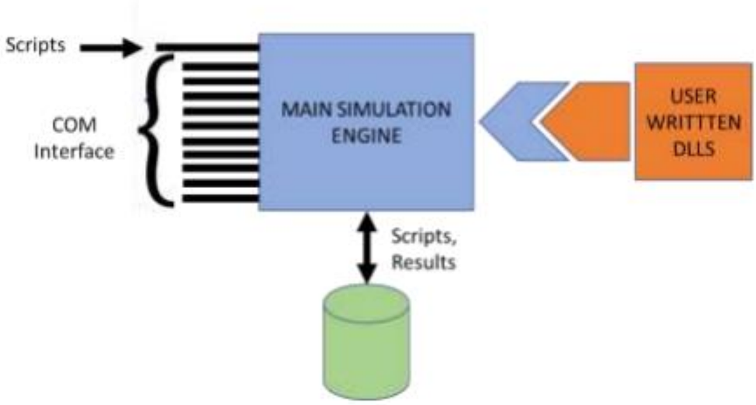

Figure 3.1: Structure of OpenDSS

As mentioned before, OpenDSS is a solid choice for microgrid and distribution system modeling.

3.3.1. Test cases for simulation

The IEEE 13-node system is used for simulating the distribution system under three different scenarios, namely the first without distributed generation, the second with conventional generators, and the third with a combination of conventional generators and renewable energy. Based on this study, the unbalanced IEEE 13-node circuit is used as a test case, and the relevant dataset for this system can be obtained from specific sources. This has thirteen nodes in the configuration, as presented in Figure 3.3, where capacitors are connected to nodes 673 and 611.

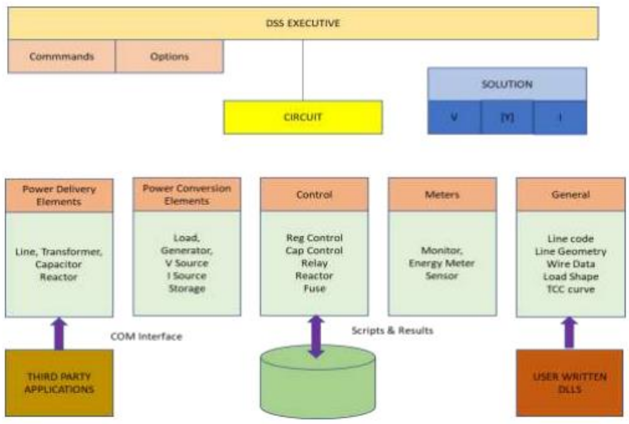

Figure 3.2: Detailed simulation engine of OpenDSS

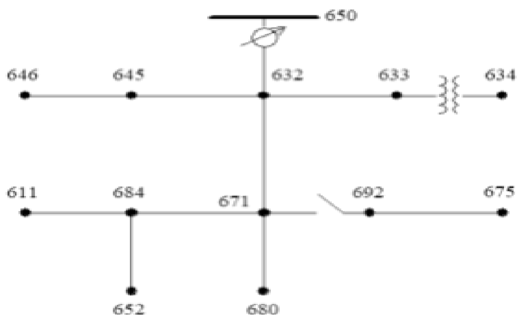

Figure 3.3: IEEE 13 node Feeder

As can be seen in Figure 3.4, node 680 is one of the nodes allocated with distributed generator. The wind and solar generators' daily outputs are determined by multiplying their rated kW values with duty schedules obtained from historical data files. It can be observed that generation by the solar source is off-peak for full days and, thus is always variable for the wind source. Further, in Figure 3.5, redesigned feeder configuration is given.

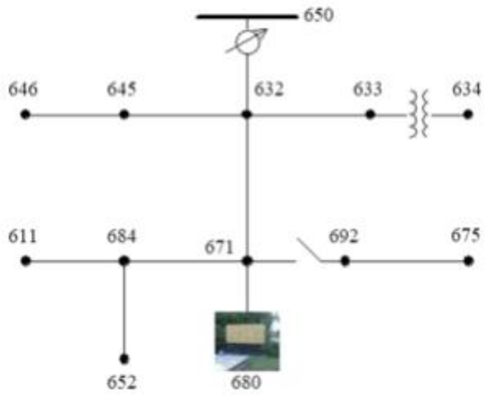

Figure 3.4: IEEE 13 node Feeder with the distributed generator at node 680

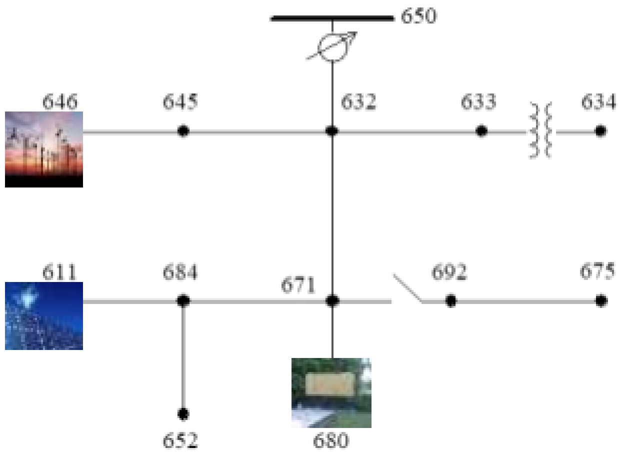

Figure 3.5: IEEE 13 node Feeder with RES and distributed generator

IV. RESULTS AND DISCUSSION

- **IEEE 13 node system**

To solve the power flow in IEEE 13-node feeder circuits, 38 devices are employed with 16 OpenDSS buses and 3 controls with iterations. Total Vp.u voltage profile is at 1.056 and 0.96083. The calculated values of Q=1.7369MW and P=3.56721MW for the network. The reactive losses of the system will remain at 0.327912 MVAR, and the active loss will stand at 0.112409 MW, at 3.15%.

- **IEEE 13 node system with conventional generators**

The addition of the conventional generator to bus 680 of the IEEE 13-node feeder analysis involves 39 devices and 3 iterations of control. Voltage ranges 1.0499 to 0.96708, within which both minimum and maximum voltage points approach unity. The calculated network's active power is 2.5311 MW, and the reactive power calculated was 1.60015 MVAR, showing a rise in the level of reactive power within the network. If the network is computed using OpenDSS, the active power losses calculated are 0.717954 MW, which accounts for approximately 2.837%, and the reactive power losses are calculated to be 0.196112 MVAR, which is 12%. Connection of the conventional generator reduces the active and reactive power losses suitably.

- **IEEE 13 node system with conventional generator and renewable energy sources**

When combined with solar, wind, and a dispatch able generator on the IEEE 13-node feeder, OpenDSS requires 4 iterations to reach convergence for the simulation using 41 reading devices. The maximum voltage achieved by Vp.u. is 1.0501 while the minimum point has a value of 0.98125 and also close to unity. Table 3.1 lists some static power flow results provided by OpenDSS for different test cases.

Table 3.1: Load Flow Results Obtained by Opendss for Different Test Cases for Static Power Flow

Parameter	Max p.u. Voltage	Min p.u. Voltage	Total Active Power	Total Reactive Power	Total Active Losses	Total Reactive Losses
IEEE 13 node circuit	1.112	0.95968	3.57148 MW	1.74152 MVAR	0.111265 MW	0.330125 MVAR
IEEE 13 node circuit with conventional generator	1.0501	0.97014	2.4985 MW	1.59264 MVAR	0.0721545 MW	0.195847 MVAR
IEEE 13 node circuit with conventional generator and solar and wind generator	1.501	0.98125	1.90263 MW	1.55124 MVAR	0.0529458 MW	0.139256 MVAR

Table 3.1 OpenDSS load flow results for the test scenario on IEEE 13-node circuit: the voltage levels and power losses Case Conventional Max and Min p.u. voltages per phase Voltage deviation (Vmax and Vmin) Active Power (MW) Reactive Power (MVAR) 3.57148 MW 1.74152 MVAR In the conventional configuration, the maximum and minimum p.u. voltages are recorded at 1.112, 0.95968 with active and reactive power measurements of 3.57148 MW and 1.74152 MVAR, respectively. This configuration gives minimum voltage up to 0.98125 and the voltage reaches 1.501. The active and reactive power occur at their minimum value 1.90263 MW, 1.55124 MVAR with negligible losses at 0.0529458 MW, 0.139256 MVAR. It has been observed that including renewable energy resources improves the voltage stability with minimum loss in a power system.

3.3.2. Simulation test cases

In this chapter, a ten-unit control framework for 24 hours is analyzed, taken into thought since it considers the impacts of 50,000 enlisted electric vehicles and renewable vitality sources on the power framework. This ponder is based on an normal private power utilization of 1,500 kWh per month, producing to an hourly request of 2.0833 kW. Of generated power for residential users at 30%, and with an all-time minimum of 700 MW hourly demand, a total of around 100,800 residential electric consumers exist. Assuming each household owns one EV, and 50% of these vehicles participate in bidirectional power flow, 50,000 active EVs exist. All the EVs have on average a capacity of 15 kWh as well as a consumption of 8.22 kWh per day, hence at any given time, the sum total daily charging power requirement amounts to 411 MWh. Figure 3.6 Load demand over the 24-hour period that has been assigned for charging of EVs to occur during off-peak hours (1 AM to 9 AM and 10 PM to midnight) while the energy surplus is fed into the grid during peak hours (10 AM to 9 PM).

- **Case I: Calculation of cost and emission considering only 10-unit systems without PEVs and RES**
- **Case II: Calculation of cost and emission considering 10-unit system with PEVs charging only**

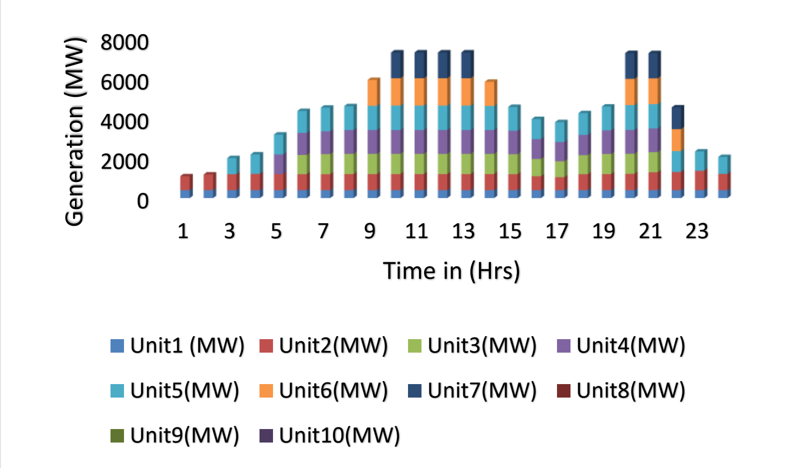

Figure 3.6: Power generation by generators without electric vehicles and RESs

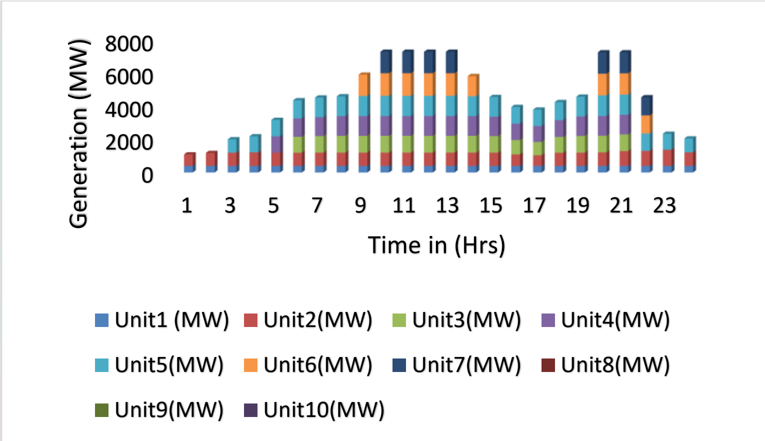

Figure 3.7: Power generated by generators with EVs charging only

- **Case III: Calculation of cost and emission considering 10-unit system with RESs and PEVs charging and discharging**

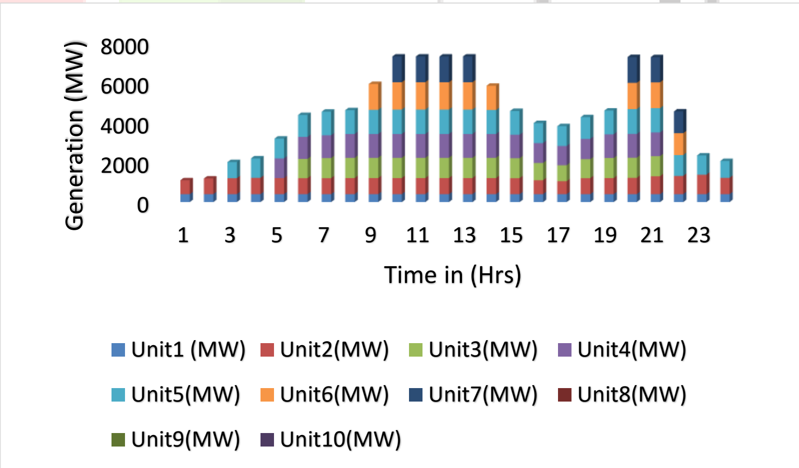

Table 3.2: Producing Electricity Through Ten Units Ignoring EVs and Res

Time (H)	Unit1 (MW)	Unit2 (MW)	Unit3 (MW)	Unit4 (MW)	Unit5 (MW)	Unit6 (MW)	Unit7 (MW)	Unit8 (MW)	Unit9 (MW)	Unit10 (MW)	Demand (MW)
1	460	250	0	0	0	0	0	0	0	0	695
2	460	300	0	0	0	0	0	0	0	0	745
3	460	400	0	0	0	0	0	0	0	0	845
4	460	500	0	0	0	35	0	0	0	0	945
5	460	460	0	0	0	85	0	0	0	0	995
6	460	460	0	0	125	55	0	0	0	0	1095
7	460	460	0	0	125	105	0	0	0	0	1145
8	460	460	0	125	125	155	0	0	0	0	1195
9	460	460	125	125	125	157	0	0	0	0	1295
10	460	460	125	125	125	157	0	73	0	0	1395
11	460	460	125	125	162	157	75	43	0	0	1445
12	460	460	125	125	162	157	75	73	0	0	1495
13	460	460	125	125	162	157	78	60	0	0	1525
14	460	460	125	125	125	157	78	0	0	0	1495
15	460	460	125	125	125	157	78	0	0	0	1495
16	460	460	125	125	125	125	78	0	0	0	1445
17	460	460	125	125	125	125	78	0	0	0	1395
18	460	460	125	125	125	125	78	0	30	0	1345
19	460	460	125	125	125	125	78	30	0	0	1345
20	460	460	125	125	125	125	78	60	0	0	1395
21	460	460	125	125	125	97	78	0	0	0	1345
22	460	460	125	125	125	73	78	0	0	0	1295
23	460	460	125	125	125	0	78	0	0	0	1095
24	460	350	0	0	0	0	0	0	0	0	795

Table 3.3: Power Generation By 10 Units with Electric Vehicles Charging

T (H)	Unit1	Unit2	Unit3	Unit4	Unit5	Unit6	Unit7	Unit8	Unit9	Unit10	Demand
1	460	278.9	0	0	0	0	0	0	0	0	733.88
2	460	328.5	0	0	0	0	0	0	0	0	783.15
3	460	403.8	0	0	0	30	0	0	0	0	883.26
4	460	403.4	0	0	0	0	0	0	0	0	983.29
5	460	423.7	0	125	0	30	0	0	0	0	1028.62
6	460	445.1	0	125	125	30	0	0	0	0	1128.35
7	455	455	0	125	125	38.88	0	0	0	0	1190.6
8	455	455	0	125	125	118.7	0	0	0	0	1229.35
9	455	455	125	125	125	157	0	0	0	0	1328.36
10	455	455	125	125	125	157	30	15	0	0	1398
11	455	455	125	125	125	157	37	15	0	0	1445
12	455	455	125	125	125	157	37	37	0	0	1498
13	455	455	125	125	125	157	28	30	0	0	1448
14	455	455	125	125	125	157	30	0	0	0	1398
15	455	455	125	125	125	157	30	0	0	0	1398
16	455	455	125	125	125	125	30	0	0	0	1398
17	455	455	125	125	125	125	30	0	0	0	1298
18	455	455	125	125	125	125	30	0	0	0	1298
19	455	455	125	125	125	125	30	0	0	0	1298
20	455	455	125	125	125	157	50	0	0	0	1398
21	455	455	125	125	125	118.8	0	0	0	0	1398
22	455	455	125	125	125	49.2	20	0	0	0	1298
23	455	455	125	125	125	0	0	0	0	0	1128.36
24	455	353.8	0	0	30	0	0	0	0	0	828.65

Table 3.4: Power Generation By 10 Units with Electric Vehicles Charging/ Discharging and With Ress

T(H)	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10	PV	WIND	EV	Demand
1	460.0	271.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.7	-18.0	708.3
2	460.0	306.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	21.8	-23.1	752.8
3	460.0	379.2	0.0	0.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	30.5	-20.7	835.2
4	460.0	460.0	0.0	0.0	50.1	0.0	0.0	0.0	0.0	0.0	0.0	30.5	-17.2	953.7
5	460.0	399.2	0.0	125.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	30.5	-20.2	998.7
6	460.0	370.2	125.0	125.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	30.5	-22.5	1088.0
7	460.0	420.1	125.0	125.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	30.5	-19.1	1143.5
8	460.0	460.0	125.0	125.0	30.0	0.0	0.0	0.0	0.0	0.0	18.2	30.5	33.3	1133.7
9	460.0	460.0	125.0	125.0	81.8	0.0	30.0	0.0	0.0	0.0	32.3	30.5	27.1	1267.9
10	460.0	460.0	125.0	125.0	110.0	15.0	30.0	0.0	0.0	0.0	42.0	30.5	18.8	1308.7
11	460.0	460.0	125.0	125.0	110.0	15.0	30.0	0.0	0.0	0.0	37.8	30.5	17.6	1357.9
12	460.0	460.0	125.0	125.0	110.0	15.0	30.0	0.0	0.0	0.0	36.3	30.5	68.1	1357.8
13	460.0	460.0	125.0	125.0	110.0	15.0	30.0	0.0	0.0	0.0	37.2	30.5	20.0	1319.7
14	460.0	460.0	125.0	125.0	49.3	0.0	30.0	0.0	0.0	0.0	32.3	25.2	21.8	1231.8
15	460.0	430.7	125.0	125.0	30.0	0.0	0.0	0.0	0.0	0.0	10.1	21.3	20.1	1148.5
16	460.0	283.1	125.0	125.0	30.0	0.0	0.0	0.0	0.0	0.0	13.6	15.6	-17.4	1037.9
17	460.0	233.8	125.0	125.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	30.5	-42.3	1009.8
18	460.0	339.5	125.0	125.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	20.0	-21.3	1095.2
19	460.0	433.8	125.0	125.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	30.5	19.3	1160.2
20	460.0	460.0	125.0	125.0	110.0	15.0	30.0	0.0	0.0	0.0	0.0	19.0	51.8	1329.2
21	460.0	460.0	125.0	125.0	60.2	15.0	30.0	0.0	0.0	0.0	0.0	30.5	30.0	1253.5
22	460.0	460.0	0.0	0.0	158.3	15.0	30.0	0.0	0.0	0.0	0.0	20.8	-20.2	1088.2

23	460.0	460.0	0.0	0.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-40.2	940.2
24	460.0	349.8	0.0	0.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	2.8	-61.3	848.7

Table 3.5: Comparative Results of PSO And Priority Method

Sr. No.	**Test Case Description**	**Cost of Generation (USD)**	**Emission of Generation (tons)**
1	Case I: 10-unit system without PEVs and RES	By PSO: $560,401.12	By PSO: 26,102.612
		By Priority Method: $548,395.93	By Priority Method: 30,912.5251
2	Case II: 10-unit system with PEVs charging only	By PSO: $670,737.88	By PSO: 27,915.603
		By Priority Method: $558,995.90	By Priority Method: 30,415.095
3	Case III: 10-unit system with RESs and PEVs charging/discharging	By PSO: $549,168.03	By PSO: 23,848.705
		By Priority Method: $528,514.05	By Priority Method: 30,594.296

Table 3.6: Comparative Results of Percentage Reduction of Cost and Emission of PSO And Priority Method

No.	**Description**	**PSO (%)**	**Priority Method (%)**
1	Percentage decrease in Case III's generation costs in a single day when compared to Case I	0.88	3.69
2	percentage of Case III's generation's emissions that were reduced in a single day compared to Case I	4.51	2.58
3	percentage decrease in Case III's generation costs over a single day compared to Case II	2.70	5.47
4	percentage of Case III's generation's emissions that were reduced in a single day compared to Case II	7.58	0.69

IV. DESIGN OF THE ARCHITECTURE FOR RESPONSIVE LOAD

In order to nullify this problem, the authors in this chapter introduce the concept of responsive load management. With this, consumers' load can be altered according to the number of units generated; when the generation is more than what is required, the load is not cut, but when the deficit arises, it is reduced. To avoid any inconvenience to the consumers, a priority list is developed for load management. The high-priority loads must always be satisfied while the low-priority loads may be curtailed at times and reinstated when surplus generations are available.

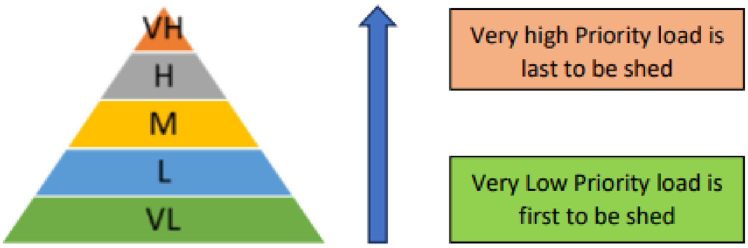

Figure 4.1: Hierarchy for Priority of load

4.1.PROPOSED ARCHITECTURE FOR RESPONSIVE LOAD

Responsive load is the flexible load that responses for the commands of the dispatch center of the load which commands load points to modify their behavior depending on the availability of the power supply. The proposed architecture takes advantage of the intelligent grid technology by managing the ON/OFF turning of smart devices at the load point. Therefore, the mechanism will cut load when the demand is high and outweighs generation capacity, increase load in areas of surplus electricity, and even reschedule loads for the utility's benefit as well as the customer's. Thus, responsive load helps minimize spinning reserves while still ensuring stability in supply. Besides, it flattens peak-hour load curves and maximizes load usage. Because of this, utilities invest little in costly spinning reserves to meet peak loads, and consumers benefit from a reliable supply to meet the large part of their priority loads. Figure 4.2 Responsive load architecture. The responsive load integrates electricity management with communications, depicting the power system network, starting from the load points down to the generating station.

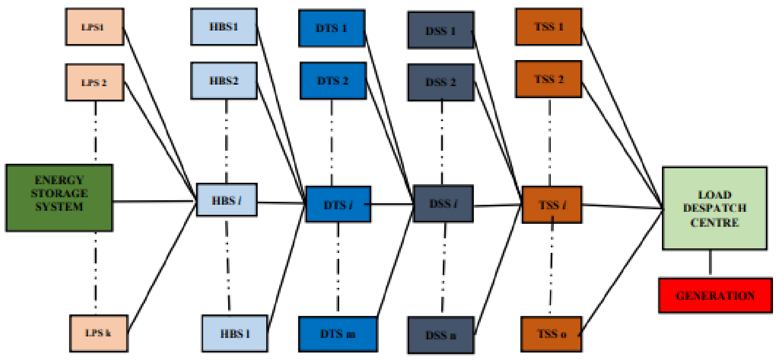

Figure 4.2. Design of the architecture for the responsive load

Figure 4.2 Responsive Load Structure: The responsive load architecture is depicted above, where it is assumed that for every home base station (HBS), 'k' number of load points exists. Several HBS units are connected with a single distribution transformer station (DTS) per station and each DTS is connected to its localized HBS. Only one connection per station is shown in figure 4.2 as space constraints do not permit more.

Figure 4.3 also depicts the structure design architecture's communication and power flow. A solid line indicates the power flow from generating units towards LPS while a dotted line indicates two-way communication flow between generation units and LPS relating to available power and power required.

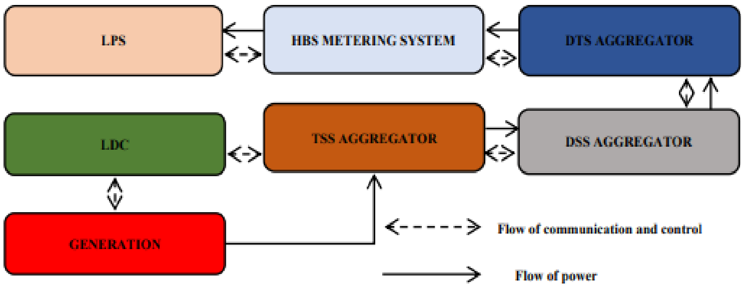

Figure 4.3 Block diagram for flow of communication and power

The information reaching the home base station (HBS) includes an address ID and time stamp of the load point switches' (LPS), along with more data from the other LPS units. As a simplification for calculation, it was assumed that there are 200 HBS in total. The data collected from these several HBS is further summarized at the DTS and forwarded to the LDC through DSS and TSS but with each node transfer that encompasses the address ID for tracing purposes.

.

Table 4.1: Payload from HBS to DTS

Field	Size (bytes)	Description
SYNC	2	Synchronization Byte
SOC	4	Second of century time-stamp
ANALOG	8	Active power flow, reactive power flow
PRIORITY	2	VL, L, M, H, VH (Priority Levels)
ID CODE	2	Address ID of HBS

Table 4.2: LPS Information Report Collected by HBS Table 4.2 shows the data received by the Distribution Transformer Station from the Home Base Station based on the information collected by all Load Point Switches, as discussed in Table 4.1. HBS processors differentiate LPS values into five priority levels: VH, H, M, L, and VL. The payload for these levels is reported in Table 4.2.

Table 4.2: Payload from Web-Server at LDC To LPS

Field	Size (bytes)	Description
SYNC	2	Synchronization Byte
ID CODE	2	Address ID of station
SOC	4	Second of century timestamp
ANALOG	8	Change in active power and reactive power (2*4)
PRIORITY	2	VL, L, M, H, VH (Priority Levels)

The web server will communicate with the TSS and provide details about the number of load levels that have to be switched off. From there, DSS will then process the requirements for each DTS and relay that information. Each HBS will receive the update on the DTS's load and which LPSes to turn ON or OFF. This is summarized in Table 4.3 where the actual data sent from the LDC web server to the LPS are presented:

4.1.1. Case I: Constant Communication between LPS and LDC

Table 4.3: Summary of Communication Technologies

From	Technology	Max. Theoretical Data Rate	Coverage Range	Latency	Reliability (%)	Payload Throughput (bps)	Channel Efficiency (%)	Time Required to Send Data (in seconds)
50 LPS to HBS	ZigBee	250 Kbps	Up to 100 m	Sec	>98	14.8	44.19	0.05436
	Wi-Fi	2 Mbps	Up to 100 m	Sec	>98	14.8	9.00	0.04106
	Power Line Carrier	14 Mbps	Up to 200 m	Sec	>98	14.8	1.39	0.03943
	Bluetooth	721 Kbps	Up to 100 m	Sec	>98	14.8	21.54	0.04443
	Ethernet	10 Mbps	Up to 100 m	Sec	>98	14.8	1.94	0.03954
200 HBS to DTS	ZigBee Pro	250 Kbps	Up to 1600 m	<5 s	>99.5	138	163043.48	0.41046
	PLC	10 Kbps	Up to 3 Km	<5 s	>99.5	138	9791.12	3.86646
	WiMAX	75 Mbps	Up to 50 Km	<5 s	>99.5	138	465838.51	0.26694
	Cellular (4G)	100 Mbps	Up to 50 Km	<5 s	>99.5	138	466562.99	0.26682
	DSL	1 Mbps	Up to 5 Km	<5 s	>99.5	138	319148.94	0.30246
	Coaxial Cable	172 Mbps	Up to 28 Km	<5 s	>99.5	138	467475.99	0.26667
20 DTS to DSS	WiMAX	75 Mbps	Up to 50 Km	<5 s	>99.5	13.5	465838.51	0.02696
	Cellular (4G)	100 Mbps	Up to 50 Km	<5 s	>99.5	13.5	466562.99	0.02694
	DSL	1 Mbps	Up to 5 Km	<5 s	>99.5	13.5	319148.94	0.03051
	Coaxial Cable	172 Mbps	Up to 28 Km	<5 s	>99.5	15.7	467475.99	0.02693
5 DSS to TSS	Fiber Optic	155 Mbps	Up to 100 Km	<0.1 s	>99.9	3.7	467336.68	0.00748
	WiMAX	75 Mbps	Up to 50 Km	<2 min	>99.9	3.7	465838.51	0.00749
	Cellular	100 Mbps	Up to 50 Km	<2 min	>99.9	3.7	466562.99	0.00748
	Satellite	1 Mbps	100-6000 Km	<2 min	>99.9	3.7	319148.94	0.00837
1	Fiber Optic	155 Mbps	Up to	<0.1 s	>99.9	0.68	467336.6	0.00149

TSS to LDC			100 Km				8	
	WiMAX	75 Mbps	Up to 50 Km	<2 min	>99.9	0.68	465838.51	0.00149
	Cellular	100 Mbps	Up to 50 Km	<2 min	>99.9	0.68	466562.99	0.00149
	Satellite	1 Mbps	100-6000 Km	<2 min	>99.9	0.68	319148.94	0.00167

4.1.2. Case II: Occasional Communication between LPS and LDC

The network will be better powered if information is communicated periodically, rather than every second. For example, if data are transmitted every 15 minutes, instead of consistently each second as in case I, the number of possible hubs at each aggregation point is much greater. This case has the total time to relay data from one hub to a single aggregator as 90 seconds. The number of hubs increases approximately multiple times with data being sent every 15 minutes. Table 4.7 depicts the maximum number of nodes from each point to the aggregator.

Table 4.4: Maximum Admissible Hubs When There Is Occasional Communication

Type of Station	Network Type	Technology	Permissible Nodes
LPS to HBS	HAN	Power Line Carrier	108,098
HBS to DTS	NAN	Wi-MAX	68,395
DTS to DSS	NAN	Wi-MAX	67,695
DSS to TSS	WAN	Wi-MAX	59,112
TSS to LDC	WAN	Wi-MAX	59,101

4.1.3. Case III. Necessity based Communication between LPS and LDC

This method entails recalculating the raw data every 15 minutes if the difference in the actual values is ±5% or higher than the base values. The online software "getdatagraphdigitizer 2.26" was used to develop the characteristic load curves for this mathematical analysis. The evaluated loads are commercial, industrial for one shift, industrial for two shifts, and residential loads. The load pattern of Figure 4.8 (a-d) shows a sampling period of 15%.

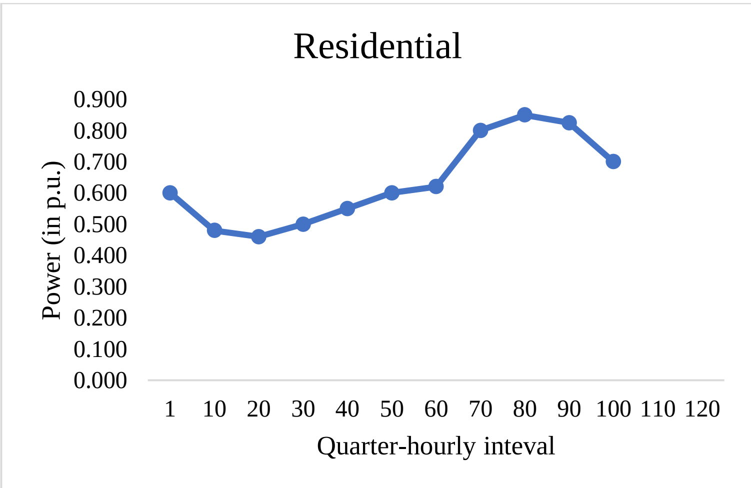

Figure 4.5a: Load profile for residential load

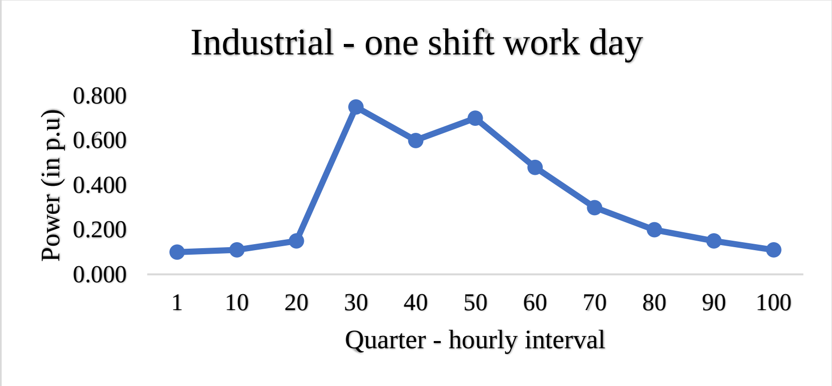

Figure 4.5b: Load profile for Industrial- one-shift workload

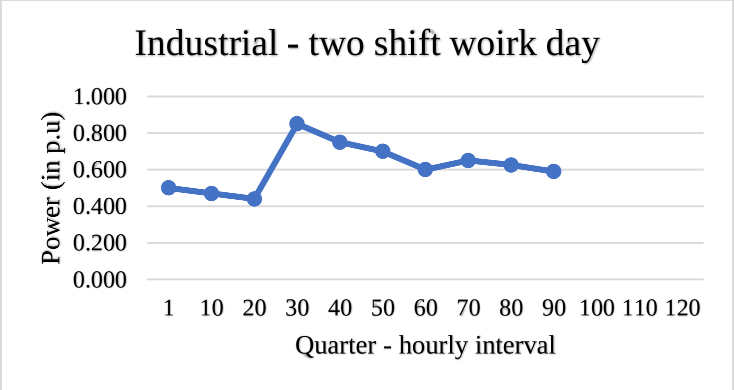

Figure 4.5c: Load profile for the Industrial- two-shift workload

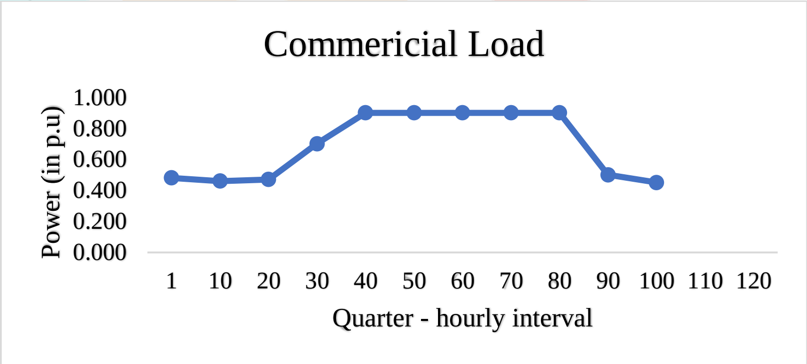

Figure 4.5d: Load profile for the commercial load

Table 4.5: Maximum Admissible Hubs for Different Types of Loads with Change in Information of More Than ±5%

Type of Station	Communication Technology	Residential Load	One Shift Load	Two Shift Load	Commercial Load
LPS to HBS	Power Line Carrier	159,112	180,195	192,265	238,513
HBS to DTS	Wi-MAX	94,205	108,138	115,415	137,911
DTS to DSS	Wi-MAX	93,301	105,215	113,295	138,516
DSS to TSS	Wi-MAX	85,812	88,618	95,501	132,214

5.1.CONCLUSION

It is found that within power networks, various communication strategies interplay with load control at a complex level. This analysis illustrates how the frequency and technology of communication maximize the number of nodes possible within the sections of a power network. This is done by the authors who modelled three cases of communication: continuous, intermittent, and necessity-based, varying the condition and time for transmitting data on different networks in order to enhance capacity and efficiency in networks.
In the first scenario, where data was transmitted constantly, the experiment demonstrates that a periodic flow of data highly limits the number of nodes allowed in the system. However, if switched to periodical

transmission—transmitting data every 15 minutes—a significant amount of allowed nodes present itself. Therefore, periodically transmitting data may help enhance the capabilities of the network and reduce congestion. The high jump from allowable nodes at 240 to over 114,000 clearly illustrates how the timed communication will provide a better designed network.

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