Advanced Energy Management System of Campus Microgrids

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Distributed generation connected with AC, DC, or hybrid loads and energy storage systems is known as a microgrid. Campus microgrids are an important load type. A university campus microgrids, usually, contains distributed generation resources, energy storage, and electric vehicles.

Keywords: smart grid ; energy storage system ; campus microgrid ; distributed generation

1. Introduction

Distributed generations (DGs) have the potential to overcome the problems of energy systems all over the world, such as power stability, system reliability, network overloading, greenhouse gas emissions, and high consumption cost. The energy management system of large commercial building microgrids has created problems to minimize the network load deviation and operational cost [1]. The energy management system (EMS) of the multi-energy microgrid (MG) can reduce the operational cost and is able to enhance energy utilization efficiency [2]. However, the distribution generations (DG) consist of renewable energy resources (RER) such as biomass, photovoltaic (PV), wind turbines (WT), fuel cells (FC) accompanied by non-renewable energy sources such as diesel generators (DiG), gas engines (GE), micro-turbines (MT) [3].

Microgrids have different types of systems, such as flexible load, DGs, and energy storage systems (ESS). The generic microgrid model is described as the model as illustrated in **Figure 1** that contains Solar PV, Diesel generator, grid, and energy storage company [4]. It also contains controllers that efficiently deal with the system by controlling the load to increase the solar output. This model is a bi-directional power flow as it takes the load from the homes, hostels, and academic departments [5].

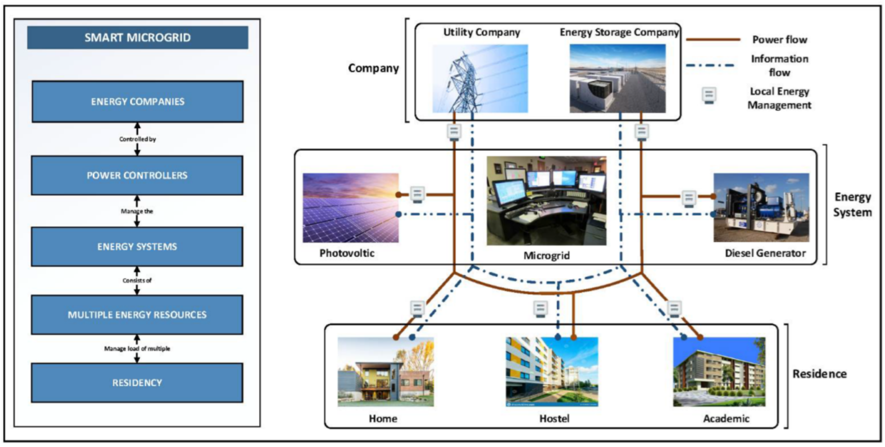

Figure 1. Generic Microgrid model.

In this model, those users who act as consumers and prosumers will be dealt with an intelligent energy management system. It is a generally understood that a microgrid that takes load from the user efficiently is a better maintained, reliable, and efficient microgrid system. One of the general microgrid models is also shown as an example in **Figure 1**.

The DG depends on the control of the distributed energy resources (DER) and the optimal scheduling of the microgrid. The optimal scheduling of power generation expressively affects the stability of the energy system [6]. Different scheduling techniques of the power system are used to improve the power quality and voltage control of microgrids based on the real microgrid solution with multiple implementation scenarios that aimed to get green energy and to make an efficient smart campus to achieve sustainable energy for the campus microgrid with the reduction in GHG emissions [7].

Microgrids face different types of problems due to the variation in demand side and fluctuations in voltages and frequencies. Energy management systems (EMS) normally face microgrid problems by the insufficiency of energy production sources. It aims to define the optimal usage of DG to feed the electrical loads [8]. EMS operates in centralized and decentralized modes. Centralize modes are those in which the power exchange of microgrids mainly bases on the price of markets. The decentralized mode is opposite from the centralized mode because of autonomy power exchange without the market price limitation [9]. Stability, efficiency, and energy protection are also the critical issues of microgrids due to reverse flow of power of generation units, voltage fluctuations, microgrid transient modes, drastic frequency variations in islanded operating mode, and supply-demand microgrid uncertainties in which high levels of angle droop are required for proper load sharing, especially under weak system conditions. EMS also contains multiple challenges.

2. Energy Management of Campus Microgrids with Distributed Generations

A microgrid mostly consists of an energy storage system (ESS), distributed generation (DG) resources, and load. Distributed generation has various types of technology for the generation of electricity, such as combine systems, solar panels [10]. To analyze the energy management of microgrids, researcher can discuss the self-resilience of microgrids as it makes the microgrids self-reliant [11]. In the centralized system, self-reliance provides communities with an efficient way to deal with the independent energy suppliers with the usage of fossil fuels. It provides remote community members an easy way to connect with the utility and to access the electricity more appropriately. Self-reliance helps the microgrid function as a self-reliant power producer [12].

On the other hand, a combined system consists of WT, DiG, FC, and PV is developed in **Figure 2** to show the self-resilience of microgrids and how they manage the AC or DC load in the communities.

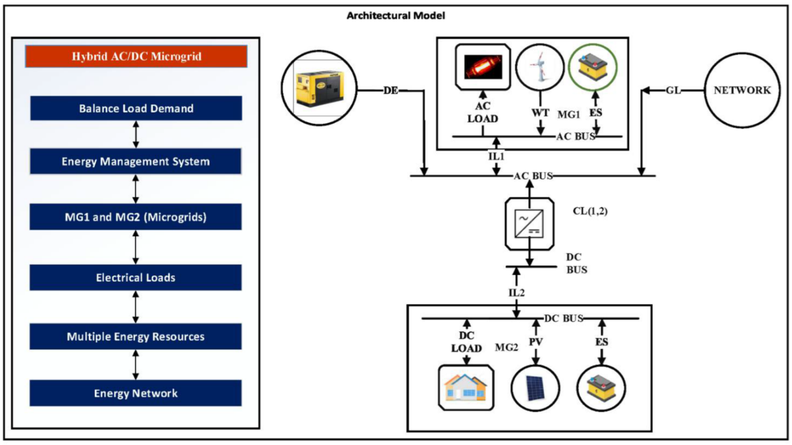

Figure 2. Architectural Model of an EMS Hybrid AC/DC Microgrid.

In **Figure 2**, Hybrid AC/DC microgrid units are connected to each other to balance the demand loads with the help of EMS. In MG1, battery, wind, and loads are connected with AC-BUS. Similarly, the components of the MG2 are connected with AC BUS (1–2), while CL (1–2) is the converter that is connected with the system. This model represented the microgrid systems connected with one another that aim to manage the load of the communities independently.

Now, researchers will discuss the microgrid systems with multiple solutions which have been presented for different EMS systems, optimization techniques, and various renewable energy resources. Several researchers have reviewed these distributed generations for different microgrid systems that are briefly described here:

Shahidehpour et al. [13] devised the energy management model to reduce the operation cost of the microgrid. For this purpose, the high-reliability distribution system technique was implemented in this Illinois campus (IIT). On the campus, the microgrid has distributed generation (DG), distributed energy resources (DER), controllable load, and energy storage systems (ESS). The proposed system was comprised of distributed generation. MG contains different HRDS switch for the reliability indices. Using this technique, the annual operation cost of campus microgrids reduce from 140,497 $/year to 119,236 $/year because the purchasing cost of energy fluctuates every hour. From this technique, it cannot focus on other parameters like uncontrollable loads, smart loads, and multiple energy storage systems at once. An effective solution with an improved distribution technique like soft computing techniques, fuzzy modeling techniques, or load flow techniques must be developed and implemented to further reduce the operational cost of the campus microgrid.

The prosumer campus microgrid is presented by Muqeet in [3] to financially save the consumer's operational cost with energy storage system (ESS) and distributed energy resource (DES). Three scenarios are present in this entry for the consumer:

- With only a grid attached;
- With photovoltaic (PV) source and ESS along with the grid source;
- With Wind energy, PV, and ESS along with the grid source.

MILP technique simulates the optimal schedule for the power system in MATLAB. After the energy management, the system's operational cost reduces 67.91% per day by integrating the Wind, PV, ESS, and grid energy. However, it lacks additional renewable energy resources which can be incorporated with the system such as Hydal and it can also be simulated with more advanced techniques like neural networks, deep learning, or any advanced technique. Various types of distribution generation is illustrated in **Figure 3** in which distributed generation [14] consists of two types of traditional and non-traditional generators which are also subdivided into further categories in which electrochemical devices such as fuel cells consist of polymer electrolyte membrane fuel cells (PEMFC), direct methanol fuel cells (DMFC), alkaline fuel cells (AFC), phosphoric acid fuel cells (PAFC), molten carbonate fuel cells (MCFC), solid oxide fuel cells (SOFC), and reversible fuel cells (RFC).

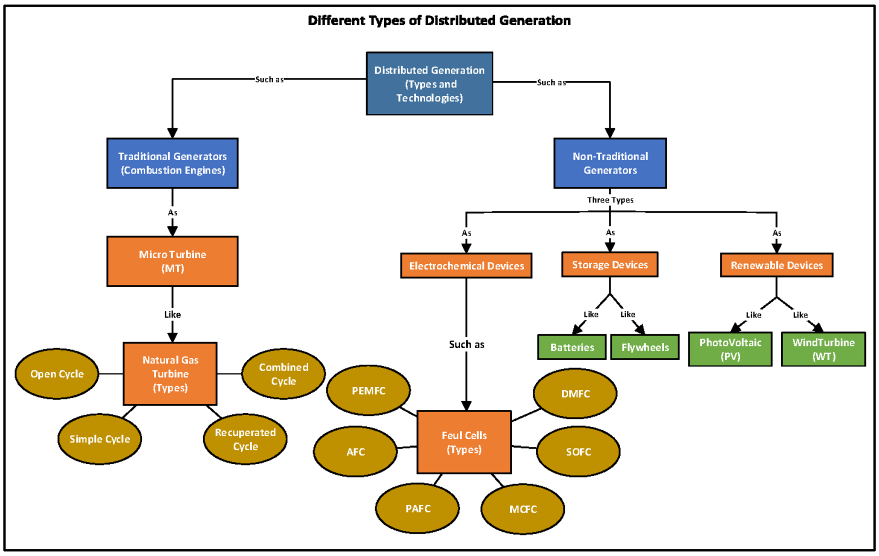

Figure 3. Architectural Model of an EMS Hybrid AC/DC Microgrid.

2.1. Solar PV in Campus Microgrids

PV systems are used to generate electrical energy with the help of solar energy. The PV system consists of more than one PV panel, electrical and mechanical connectors to produce an electrical output. Panels are connected to produce the required amount of current and voltage [15].

Some researchers have also reviewed PV systems of different campus microgrids and various energy systems.

Reyasudin et al. [16] devised the EMS (Energy Management System) model for the University of Kuala Lumpur, British Malaysian microgrid, which aims to reduce the operational cost of the microgrid. Energy storage systems (ESS) and Photovoltaic (PV) are used in the microgrid to meet the campus load demand. The HOMER software was used here to evaluate and analyze the environmental, economic, and electrical performance of the Hybrid Renewable Energy System (HRES). However, it can also be simulated with more advanced software like PVsyst [17], PVsol, or PV modeling software to achieve more accurate results.

Another energy management system is presented by Leskarac in [15] for the huge commercial building microgrid to reduce the network load variation and operational cost. It is proposed by the bi-level linear model that contains mobile storage (electric vehicle), stationary storage, microturbine, fuel cell, solar PV, and solved using the flower pollination algorithm (FPA) in MATLAB. The simulation results of the grid-connected mode and the isolated mode of the microgrid was studied and improved. However, the researcher does not address the frequency regulation or the power quality. It can also be solved with more advanced optimization techniques like Spiral optimization (SPO) 2013, Artificial swarm intelligence 2014, Golden Eagle Optimizer (GEO) 2020, and Jellyfish Search (JS) 2021, etc. [18].

An optimal system is introduced by Kumar in [19] on the (Nanyang Technological University (NTU), Singapore) campus microgrid (MG) includes photovoltaic (PV), natural gas micro-turbine (MT), Electric vehicles (EVs), and a fuel cell (FC).

Here, the researcher discusses how to manage the system's energy and elaborates on how to achieve the demand response (DR). They also describe how to achieve the output level of solar PV using the NTU campus' vehicle-to-grid technology using a PV system. On a typical day, the building serving transformer support an average of 17.3 kW of additional EV loads. Approximately MG 33% significantly supports the campus and EVs loads. However, it can also be addressed with the incorporation of wind and hydel resources, if possible. The researcher did not focus on the specific demand response programs like Incentive-based programs [20], Real-time pricing [21], Market-based programs [22], Price elasticity [23], and Price-based programs, etc.

Another system is devised by Esmaeili in [24] that enhances the optimal scheduling of multi-microgrids (MGs) in which the distribution system is enhanced by energy storage systems (ESS) and demand response (DR) programs. The microgrid and Distribution System Operators are the core objective discussed here because the upper level reduces the operational cost from DSO and the lower level increases the profit of MG with the help of energy management (EM). Mixed-Integer Second-Order Cone Programming (MISOCP) is formulated as an optimization problem which is conducted by the General Algebraic Modeling System (GAMS) language and resolved by the CPLEX solver. Market prices are relatively moving upward, so MG owners choose to install their distributed energy resources first, which includes microturbine (MT), Photovoltaic (PV), and responsive load, and then transfer the power with the others connected DSO and MGs. However, it focuses only on the market-based price demand response, and it can also consider other demand response programs like incentive-based programs or real-time pricing (RTP) schemes. Moreover, MISOCP can also be implemented on other modeling tools like AIMMS, AMPL, Mathematica [25] or APMonitor, etc. to get better results.

2.2. Wind Turbine in Campus Microgrids

Wind turbines (WT) generate electrical energy by wind power. Wind turbines are constantly dependent on airflow and their output vary according to the speed of air. Some researchers have also reviewed wind systems on different campuses and islanded microgrids:

Liu et al. [26] presented the ESS sizing technique with a comprehensive consideration of DGs, loads, and energy storage. DGs include wind turbines, Solar PV panels, electric vehicles, and combined heat and power (CHP) generation. A two-layered hybrid ESS (i.e., lead-acid battery). As shown in **Table 1**, several scholars have employed these optimization techniques to obtain the best solutions.

Table 1. Comparison of optimization methods considering advantages and disadvantages.

Techniques	Optimization Methods	Advantages	Disadvantages	Applications and Objectives
Deterministic Techniques	**MILP [27]**	**The problems are swiftly and completely resolved using mixed-integer linear programming (LP). Their linear constraint is located in the viable convex area, with the goal of locating the best global point and precise solution.**	**Economic and stochastic analysis are two types of analysis. It has limited capabilities for applications with objective functions that are not continuous or distinct.**	**For optimization challenges, MILP is often utilized. It's simple to operate with CPLEX Solver, that is a good piece of software. Unmanned aerial vehicles (UAVs) utilize it to design their flight trajectories.**
	Dynamic Programming (DP) [28]	**To divide the difficulties into smaller components and then optimizing them to obtain the best answer**	**It is time-consuming since it has a huge number of recursive routines.**	**It is also employed as an issue of optimization. It handles issues like dependability design, robots control, and navigation systems, among others.**
	MINLP [29]	**Solve issues using basic operations and has a large number of optimum solutions that outperform MILP.**	**It takes a long time.**	**Mixed-integer nonlinear programming (MINLP) is a method for solving optimization problems containing continuous and discrete variables in the optimization problem, as well as complex variables.**

Techniques	Optimization Methods	Advantages	Disadvantages	Applications and Objectives
Metaheuristic Techniques	Particle Swarm Optimization (PSO) [30]	Greater productivity while fixing optimization issues. Easy adaption for a variety of optimization issues and timely reporting of an optimal alternatives.	When addressing an optimal solution, complex calculation is required. In small optima/minima zones, the searching process may get entrapped.	Many optimization issues, such as power management, may be solved with PSO. It may also be utilized for video graphical effects.
	Genetic algorithms (GA) [31]	Focused on population evolutionary computation, which use mutation, selection, and crossover to find the best solution. They do also have a fast convergence rate and can rapidly adapt to different types of optimization techniques, providing near-optimal outcomes in a fair amount of time.	While resolving, the requirements for the selection, mutation, and crossover processes must be satisfied. It also does not ensure that the best solution will be found. Similarly to PSO, the search process may become entrapped in localized optima/minima areas.	In natural sciences, such as architectures, genetic algorithms can be used to find a comprehensive solution. It is employed in image processing as well as learning the robot's behavior. It is also utilized in distributed applications for data allocation.
	Artificial Fish Swarm [32]	High precision, few variables, flexibility, and quick convergence are all advantages. It also adapts well to a variety of optimization situations, producing near-optimal approaches in a fair amount of time.	It has the same benefits as genetic algorithms, but it has drawbacks because to the lack of mutation and crossover. It is also no assurance that you will find the greatest answer. Furthermore, similarly to GA, the searching may become entrapped in specific optima/minima areas.	Fault tolerance, quick convergence speed, outstanding adaptability, and great precision are all advantages of artificial fish swarms. It frequently uses the general technique to tackle a variety of issues, including prey, followers, and swarms. Neural network learning, color quantization, and data segmentation are some of the other uses of AFS.
Artificial Intelligence Techniques	Artificial Neural Network [33]	Its evaluation time is quicker than prior algorithms, and it solves difficulties such as obtaining target objective functions for real-valued, binary, and other values.	It supports parallel processing and is hardware technology dependent. It provides unexpected answers but no indication of how they were achieved.	Handwriting recognition, picture compression, and stock exchange predictions all employ deep neural networks.
	Fuzzy Logic [34]	Fuzzy logic's structure is simple to grasp, which makes it appealing to engineers who want to use it to operate machines.	It can be challenging to maintain precision while using fuzzy logic.	Fuzzy logic is widely utilized in spaceflight, the automobile industry, traffic control, and, most notably, in enhancing the transmission system's performance.
Special Techniques	Manta Ray Optimization [35]	When compared to alternative optimizers, the computing cost is lower, and the results are more precise.	Its fine-tuning for finding solutions for optimization is ineffective, and its convergence rate is extremely slow, finding it less useful.	The manta ray approach is a bio-inspired optimizing algorithm inspired by the exceptional behavior of gigantic manta rays recognized for their rapidity. It is popular because of its high accuracy and low computational cost.
	Harris hawks Optimization [36]	It is well-known for its good performance, reasonable convergence, and high-quality optimization outputs.	It can be tough to grasp at times, and the computing complexity adds to the difficulty.	HHO is still in its early stages for academics, but it offers good convergence, precision, and speed for addressing real-world optimization issues.

Li-ion battery Supercapacitor with three types of storage is built according to their power density, load classification, and Demand Response (DR), which is the main tool for attaining greater operational efficiency, reducing capital, and operational costs in MG resource size optimization. It uses different types of loads which are suitable for different kinds of energy storage systems that are hybrid and aim to improve energy storage systems' economy and reliability.

Moreover, huge differences in load variation during different periods are provided by many types of storage, while Lithium-ion batteries take priority over lead-acid batteries. This method reduces battery replacement time during the timespan of the MG. When the EV and DSM plan are taken into account, the load curve is smoothed, which results in a significant amount of profit, including the efficiency of the system. However, it lacks battery degradation cost with an economic analysis to predict the battery degradation according to time and it also focuses on a two-layered hybrid ESS system which also lacks the selection of some advanced energy storage systems such as Siemens Junelight Smart Battery SB–(3,3), Battery flex AC-1 1.3 (6.0 kW, 4.8 kWh) [37], or REACT2-5.0–12 kWh–AC or DC, etc.

On the other hand, MG performance was observed by Baron in [38], where the research aimed to increase the optimal scheduling of various types of grids. It included operational costs of the system and costs associated with the loss of energy storage. The researcher suggested this to avoid all the renewable energy transmission costs and cost of storage systems. It is noteworthy that this pattern has been observed in wind and solar energy production systems. Thus, this research provides the project operator with a tool to determine the best operational phase of the MG by considering various events of the batteries' useful life. However, it does not focus on providing the optimal battery size which may increase the operational cost of the microgrid. Thus, to reduce the operational cost and other costs, a sizing approach is focused on various renewable energy resources. To calculate optimal sizing approach for systems, various advanced optimization tools are available which can be used in this regard such as PVsyst, PVsol, or HOMER pro [39][40].

Another optimal scheduling model is proposed by Du in [41] that optimally schedules and operates the microgrid clusters of multi-microgrids' energy and establishes an optimal scheduling system to reduce the system operating costs for the microgrid (μG). The μG includes wind turbines (WT), combined heat and power (CHP), electric refrigeration (EC), photovoltaic (PV), electric boilers (EB), and other equipment. It is solved by the CPLEX solver for model optimization solutions under the GAMS platform. The total daily operation cost is calculated for case 1 is $29,033.6378 and for case 2 is $29,415.1206. Both the cases are analyzed to select the optimal system. However, the system can also be solved by a Gurobi solver to get better results and many other optimized renewable energy resources must be incorporated such as wind or hydro to further reduce the operational cost of the microgrids.

Now, Huang presented the microgrid configuration in [42] and introduce a power consumption schedule optimization by a Stackel-berg game which models the 2- rational decision-maker that relates among each other for the microgrid and can manage the energy consumption scheduling problem. It makes the decision for the microgrid, as the supreme leader, which leads to an advanced optimization problem to maximize the installed number of micro-turbines, photovoltaic (PV) units, wind turbines, and batteries. Microgrid configurations in residential buildings are used to validate the efficiency of two-level scheduling and two-level classified algorithms [43].

By comparing four two-tier algorithms, the experimental results show that the Stackelberg game model optimizes the timing of smart home and microgrid configuration simultaneously. Results show that the simultaneous optimization of power consumption and optimal scheduling of the microgrid configuration can significantly optimize the cost of configuration, even when there is little support for the public network [44]. Furthermore, the simulation results indicated that the proposed model is suitable for customer engagement to reduce consumption, such as changes in usage time and energy levels. However, the microgrid configuration can also be improved by implementing both Stackelberg and Cournot models together [45]. As the microgrid decision support system needs to be improved because it is the central brain of the system that controls everything [46].

2.3. Fuel Cell (FC) in Campus Microgrids

Fuel cells work like batteries, but they do not need recharging every time. It is an electrochemical cell that produces electricity from chemical energy. Most commonly used fuel cells are the PEMFCs (Proton exchange membrane fuel cells) which is common nowadays because it operates at very low temperature (−20 C) to (1000 C) and it can operate quickly in ideal condition to full load conditions [47].

Some researchers have also reviewed fuel cells that are installed at different campus microgrids and various locations:

Bouakkaz et al. [48] proposed an energy management approach that optimally improves batteries' lifetime by optimizing energy consumption at home with a unique fuel system connected to a fuel storage system consists of (photovoltaic, batteries, diesel generator, and wind turbine). Recently, optimization algorithms have attracted lots of attention to solve various engineering problems and some of them have high accuracy and lead to higher efficiency and promising results. The rain flow algorithm is used to compute the number of life cycles of the battery, but the problem is solved by the optimization technique called the PSO (Particle Swarm Optimization) algorithm. This optimization minimizes the number of battery cycles throughout the whole day by maintaining the charging/discharge process that aims to increase the battery's life cycle. The simulation results are obtained to show the efficiency of the proposed management approach to optimize the battery life cycle to more than 38%. However, the system lacks optimal sizing of batteries or battery degradation cost which also affects improving the battery life and reducing the cost of the energy storage systems. It can also incorporate more advanced techniques like Artificial bee colony algorithms, multi-swarm optimization, or Swarm intelligence, etc. [49].

The distributed energy storage system (DESS) is addressed by Kim in [50] to propose a low-cost planning method for the microgrid group. The proposed planning algorithm operates the community microgrids, which consists of large ESS & large-Scale Fuel Cells (LFC) that make the planning procedure while considering the variability of net load and CDESS market procedure is operated for the DESS system. In the LFC and LESS planning problem, the net load variation is formulated as a function of the amount of electricity exchanged with the external electrical grid. In the case of the Customer DESS market operation scheme, the market scheme is depending upon the price-signal market. The simulation results show that the LESS operation cost is reduced to operate the community microgrids. However, it can also focus on the expansion planning of the active distribution network while using enhanced heuristic optimization techniques. More, the system does not focus on the economic analysis and it can also focus on new market schemes to further reduce the operation cost of DESS.

A non-linear model is proposed by Mohsin [51] to optimize the energy management of emission-free ships (EF-Ships) with hybrid CI/ESS/FC as storage energy resources, focusing on the decaying life-span of fuel cells (FC), fuel systems, and energy storage (ESS). Aging factors and total operational costs of FC and ESS are analyzed. This entry presents an energy management scheme for EF-Ships with combined FC and ESS as power resources. The proposed method deliberates both the aging factors of the FC and ESS and the ship’s operation cost, and the problem attempts to find the optimal solution for the energy planning program that reduces the operating costs while taking into account the limitations of aging and decaying of the equipment [52]. The suggested SMPC method’s efficiency in processing rapid ups and downs in weather forecasting and the GAMS software tries to solve the suggested optimization problem calculated during the simulation process. The obtained simulation results indicate that the effectiveness of the recommended model to comply with the FC and ESS decaying/aging limitations while minimizing the operating costs of the system by 4.67%. However, it does not focus on the degradation cost of the energy storage systems and their optimal sizing approach. More, other tools are also available which can give better results than GAMS for modeling such as AIMMS, AMPL, APMonitor, or Mathematica, etc. [53].

However, a comprehensive EMS (energy management system) model is devised by Violante in [54] for a separate micro-grid that incorporates thermal energy resources, such as thermal storage systems (TSS), combined heat and power (CHP) units, heat pumps, boilers, and heat (HP), taking into account the thermal load model, is recommended in this entry. The advanced SMEs are verified and tested with an actual test bench micro-grid situated in Italy and Bari, which provides both the heat and electricity in a building located in Politecnico de Bari. The recommended EMS is intended to reduce the fuel costs of the microgrid system, and it models properly for cogeneration units. This model is optimized by the optimization problem called the (MILP) technique that is easily manipulated with viable solvers, making the EMS system suitable for online applications. MILP is an important technique in optimization methods utilized in various applications [55]. The simulations are performed for altered winter days that also have demonstrated the cost-effective benefits. Models of thermal systems in a micro-grid EMS, resultant in the profitability of the daily fuel costs. This significantly increased the total cost by more than 40% compared to the suggested EMS. Consequently, the incorporation of thermal systems into this micro-grid EMS has proved to be valuable. Moreover, it lacks the utilization of modern techniques like deep learning or artificial neural network, and it can also incorporate other thermal energy resources, if possible, like geothermal energy resources which give beneficial results.

Now, various number of fuel cell (FC) operated cars are reviewed by Alavi in [56] that can be seen as an energy production that is distributed within an islanded microgrid, and proper fuel cell power planning can keep up the power stability of the MG. The MM and DF MM methods are able to generate the FC incorporated power by reducing the operation cost of the system. Simulation results show that microgrids consider network topology with low-level control models, develop the distributed control architectures for the microgrids in grid-connected modes, and also considers the assembling of fuel cell vehicles using the ADMM technique. However, it can also be modeled by sequential quadratic programming, sequential linear programming, and sequential linear-quadratic programming and can also be simulated in Accord.NET (C# augmented Lagrangian optimizer), or ALGLIB (C# and C++ preconditioned implementations of augmented Lagrangian solver), etc. [57].

2.4. Diesel Generator in Campus Microgrids

Diesel generators convert the chemical energy to mechanical energy that contains diesel fuel, through combustion. The mechanical energy in the generator rotates the crank that can generate electricity. Electric charges are made in the electric wire by moving in a magnetic field, this is how a diesel generator works. Here, the Diesel generator (DG) is characterized based on efficiency and fuel consumption.

Some researchers have also reviewed diesel generators that are installed at different campus microgrids and various locations:

Rural areas of most developing countries are disconnected from electrical energy but not at all times, because without electrical power, it would not be possible to survive [58]. Therefore, Arthur introduces a more realistic model for the rural area appliances and the energy management optimized for the microgrid. Renewable energy resources, such as diesel generators and energy storage systems (ESS), fully support running a microgrid. However, the results are simulated in MATLAB software using the Linear Programming technique to maintain the load's demand response (DR). HOMER software can also calculate the fuel consumption of the running generator on an hourly basis that is also formulated in [59]. However, more advanced techniques must be utilized like MILP [60] or Deep learning [61], etc. Homer pro can also be utilized in this regard to effectively manage the microgrid [62].

On the other hand, an EMS (Energy Management System) model is developed by Krishnan in [63] for the industry microgrid (MG) to fulfill the industry's appliances' peak time that consumes power. Here, MG includes renewable energy sources (RES), diesel generators (DG), interruptible loads (IL), battery energy storage systems (BEES), and flexible loads (FL). The MILP (Mixed-integer linear programming) technique is used to simulate the energy management of industry load in MATLAB. Results show that optimal scheduling of the pump is improved, and system cost is reduced significantly while considering economic savings. However, smart loads, controllable or uncontrollable loads are not addressed here, and they must be addressed. Additionally, modern optimization methods can be utilized like the Flower pollination algorithm [64] or Harris Hawk's optimization [36] rather than MILP to further optimize the system.

However, an effective operative model for a utility grid is presented by Karimi in [65] that is attached with the microgrid considering different energy generation resources consists of Diesel Generator (DG), Energy storage system (ESS), Wind Turbine (WT), Photovoltaic (PV), and Demand Response (DR) which is implemented by a mixed-integer linear program (MILP) technique. The GAMS technique was also used to resolve the multi-tasking optimization problem for energy management. However, the researcher does not focus on the optimal power flow or optimal energy exchange among grids. Power quality and voltage regulation [66] must be focused on here to get a more effective approach for the given system.

Another power system is focused in [67] in which the BESS system is integrated into the MG to ensure a more sustainable and economical system. The operational cost of the remote microgrid is minimized by cost-effective planning during consideration of the optimal battery size. Although fast discharging results in battery life decaying: as further energy sources are expected to use the battery size with optimal lifetime and energy storage, economic consideration in the isolated microgrid must be considered to deliver reliable service to the customers. The present entry solved the economic planning problem between battery storage and diesel generators, considering battery degradation cost in real-time, ensuring reliable service. However, the selection of BESS must be addressed to find an optimal battery energy system for the MG to further reduce the energy cost for the system. The researcher mentions the optimal sizing approach for the BESS system but it lacks focus on high energy consumption usage from PV as it is the vital source to reduce the electricity cost for the microgrid [68].

Now, a smart charging program is proposed by Fouladi in [69] for the PHEVs (plug-in hybrid electric vehicles) to reduce GHG emissions of the utility grid, and it also reduces the high power consumption from the main grid by the increased usage of the RER/DER. Diesel generators, batteries, photovoltaic (PV) arrays and wind turbine (WT) are attached with the microgrid and properly integrated with the remaining grid, considering the system's overall operational constraints. The suggested power management scheme allows V2G (Vehicle-to-Grid) and G2V (Grid-to-Vehicle) operating systems to be used by the MG Aggregator PHEV for support services. Consequently, the effects of the V2G operation mode and G2V operation mode of PHEV (WEG) on microgrids are examined. The simulation results show that the V2G operation mode and G2V operation mode of the EV charging stations are studied thoroughly, which enables it to run as an efficient source for the EV. In this entry, two scenarios are planned to assess the suggested power management's efficiency and compare their results with those of the previously reported method. The proposed power management technique has proven to allow charging of PHEV depend upon the maximum integration of RER and DER; therefore, it reduces the power released from the utility grid even though the PHEV entry level is high. However, it does not focus on the price-regulated electric vehicle charging or discharging strategy for the V2G and G2V operation modes [70], and this must be addressed.

2.5. Energy Storage System in Campus Microgrids

An energy storage system is defined as the energy produced for later use that aims to reduce power energy imbalances between demand and power production. A device that stores electrical energy that is generated by any generator is generally termed a battery [71]. The microgrid that contains storage systems also contributes to the energy management of microgrids that provide the necessary information and efficient control system with essential functionality, which guarantees that both the generation side and distribution systems provide the electrical energy at nominal operational costs [72].

Some researchers have also reviewed energy storage systems that are installed at different campus microgrids and various locations:

Stina et al. [73] presented an energy storage solution for the Tezpur University based in NE (North-East) India. This entry consists of a DSM (Demand Side Management) system, an EMS (Energy Management System), and an ESS (Energy Storage system) with the integration of a Bio-mass power plant with a co-generating gas engine. The proposed system analyzed the cost minimization by reducing the usage of diesel engines and maximize the usage of PV-plant (1 MW) that was installed at the campus. Data were gathered to determine the economic analysis of the system so that profitability could be determined. By evaluating the data, an assessment has been developed that by a proper EMS, and an efficient ESS reduces the cost of electricity annually for the Tezpur Campus. Results revealed that the reasonable size for the lithium-ion batteries of BESS is 127 kWh at substation 4 and 90 kWh for the substation E4T microgrid. By this proposition, it is determined that it manages the campus load effectively and reduces the cost yearly. However, the proposed system lacks an optimal sizing of BESS which is an essential element in the energy storage system. To increase profitability, an effective sizing approach needs to be adopted and an applicable approach is needed to increase the high consumption of renewable energy resources [13].

In [74], the university installed a smart grid project at the MONASH campus, North Carolina, US. It consisted of 1 MW of Solar PV, 1 MWh of the energy storage system, and EV charging stations for 20 buildings. The main objective was to manage the bills of customers and to monitor the energy in real-time scenarios. However, Chongxin [75] overcomes the problems of a microgrid with multiple DER's by optimally applying day-ahead scheduling of active/reactive powers. It included EV, energy storage systems, wind systems, PV, gas turbines, and loads for the Nanjing University Microgrid. The researcher analyzed it with the TOU (Time-of-Use) price approach. Load and renewable resources were predicted and modeled with an Deep Q-Learning-based optimization technique. It decided on the interval variable that sets the active/reactive power for the system to mitigate fluctuations. It finally resulted in the optimal schedule of the microgrid with multiple DER. Both researchers have tried their best to install a smart grid project for the campus but they did not focus on the power quality [76] or voltage regulation [77] for the campus microgrid. An effective decision support system must be adopted that effectively manages the power flow among grids and a real-time pricing technique must be implemented.

Finally, Binod Koirala highlights key factors in [78] to improve the ICES (Integrated Community Energy Systems) with the consideration of power grid access, supportive incentives, voltage regulation, and structural design improvements. In this entry, several techno-economic perspectives are considered such as optimal energy storage devices, ancillary services, sustainability and flexibility, and cost-benefit analysis. Finally, it described the feasibility analysis of ICES technologies and the benefits of ICES in energy trends. However, the researcher did not focus on the optimal sizing parameters for the energy storage devices [79]. If such parameters are focused, it will improve the battery lifetime.

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