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An energy management system of campus microgrids

State-of-the-art and future challenges

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Review

An Energy Management System of Campus Microgrids: State-of-the-Art and Future Challenges

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Abstract: The multiple uncertainties in a microgrid, such as limited photovoltaic generations, ups and downs in the market price, and controlling different loads, are challenging points in managing campus energy with multiple microgrid systems and are a hot topic of research in the current era. Microgrids deployed at multiple campuses can be successfully operated with an exemplary energy management system (EMS) to address these challenges, offering several solutions to minimize the greenhouse gas (GHG) emissions, maintenance costs, and peak load demands of the microgrid infrastructure. This literature survey presents a comparative analysis of multiple campus microgrids' energy management at different universities in different locations, and it also studies different approaches to managing their peak demand and achieving the maximum output power for campus microgrids. In this paper, the analysis is also focused on managing and addressing the uncertain nature of renewable energies, considering the storage technologies implemented on various campuses. A comparative analysis was also considered for the energy management of campus microgrids, which were investigated with multiple optimization techniques, simulation tools, and different types of energy storage technologies. Finally, the challenges for future research are highlighted, considering campus microgrids' importance globally. Moreover, this paper is expected to open innovative paths in the future for new researchers working in the domain of campus microgrids.

Keywords: campus microgrids; energy management system; prosumer market; renewable energy; energy storage system; renewable energy resources; smart grid

1. Introduction

Over the years, the surge in demand for electricity has directly led to reducing reserves of fossil fuels such as petroleum, natural gas, and coal. This affects the environment through the direct increase in greenhouse gas (GHG) emissions. Power systems worldwide integrate renewable energy resources such as solar–PV, tidal energy, biomass energy, and wind energy to alleviate the problems mentioned earlier [1]. Microgrids provide an opportunity to offer a solution to reduce greenhouse gas emissions while providing reliable power to fulfill the load demand. Microgrids are a scattered group of power sources and electrical loads that are usually synchronous with the primary grid, called the utility grid [2]. Residential electrical energy sources strongly assist microgrids, and the distribution of

energy from the primary grid is performed at long distances and is difficult to achieve. Microgrids that are autonomous and self-reliant are called stand-alone, autonomous, or isolated microgrids [3]. A microgrid can operate in isolated mode and grid-connected mode and handles the transitions between both modes. In isolated mode, both the real and reactive power are produced inside the microgrid, and the electrical energy storage systems (ESSs) can stabilize the local load demand. In the utility grid or grid-connected mode, ancillary services are offered in such a scenario, considering the trading activity between the utility and the microgrid [4]. Microgrids provide a proposition with respect to extreme events and natural hazards such as earthquakes, floods, hurricanes, tornadoes, storms, etc., with the advantages that they utilize the latest technologies and techniques to overcome the system's daily challenges, such as the need for power in an emergency [5].

Institutional campuses or universities typically fulfill the main requirements to convert their energy supply into campus microgrids. Their operations are monitored from a central controller, as shown in Figure 1, to manage the loads and generation units for every campus building [6]. In Figure 1, multiple sources are connected to the electrical grid in which the power electronics interface receives the power from the microgrid power distributor and converts the power to the voltage and frequency required. The main role of the current survey paper was to analyze different types of campus microgrids with multiple resources that are installed on various campuses, including conventional energy resources, renewable energy sources, demand-side management (DSM), and energy storage systems (ESSs). Campus microgrids are reviewed based on the optimization techniques, objective functions (OFs), and modeling techniques. Different types of solutions are provided in the current survey paper for multiple campus microgrids.
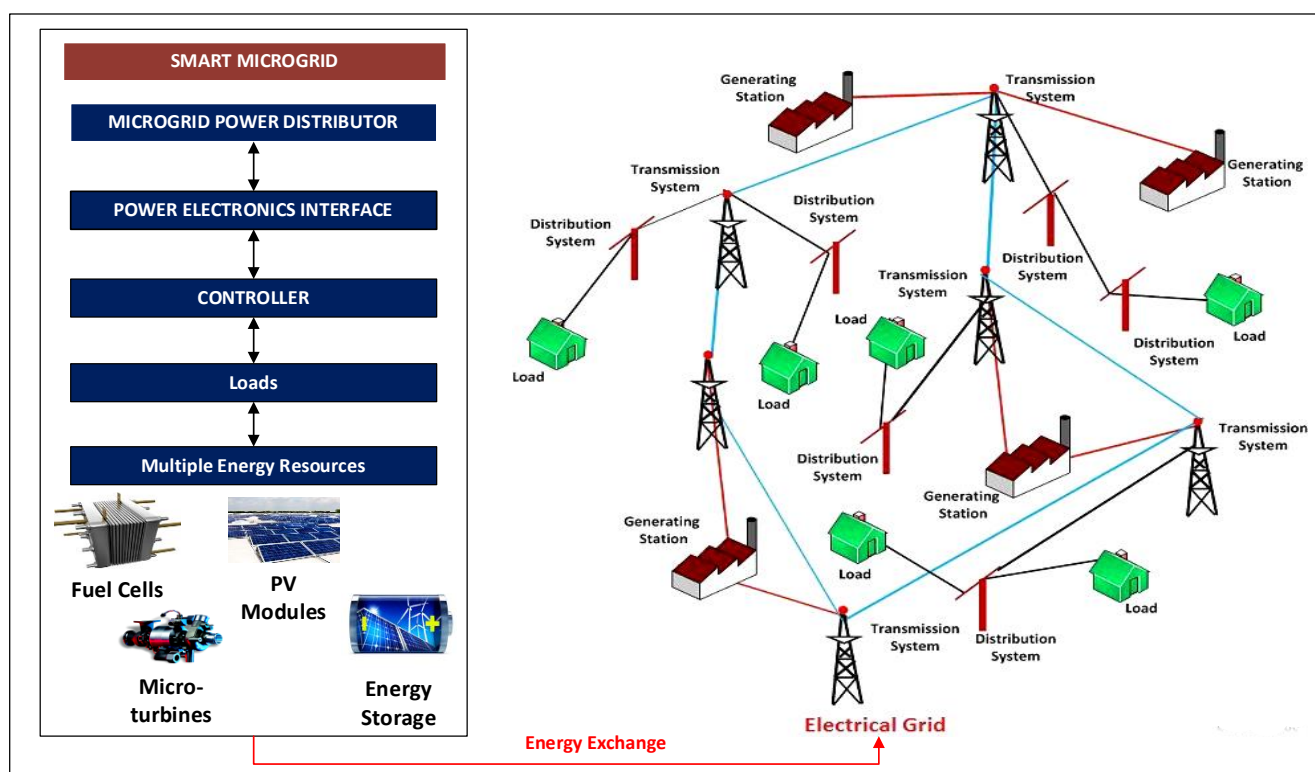

Figure 1. Schematic diagram of a microgrid.

Numerous campus microgrids have been installed globally to serve as a testbed and reveal the economic benefits and profits of utilizing such a system in the utility grid.

In this paper, some campuses are discussed as actual microgrids, and some are discussed as simulated microgrids. Those for which the authors mentioned develop-

ing the model of a microgrid or proposed a microgrid are the simulated microgrids. Various campus microgrids installed at multiple locations are discussed here.

Nemanja et al. [7] presented a microgrid model for the University of Novi Sad, Serbia. This overall microgrid model consists of two solar–PV, two wind-generating microturbines, biogas-based turbines, a BESS, an EV system which are acting as a prosumer, a microcontroller that connects it to the primary grid, and consumers. They also analyzed the feasibility and economics in which the installation cost, energy generation cost, and GHG emissions were reduced, although not considering a risk assessment for the campus microgrid. Figure 1 shows the general model of a microgrid that contains PV modules, wind generators, controllers, and an electrical grid; an overview of campus microgrids at different locations is shown in Figure 2.

Figure 2. Overview of campus microgrids at different locations.

Similarly, Stefano et al. [8] presented research on smart microgrids and the energy management of multiple campuses, efficient and innovative designs, and operating and nonoperating grids in grid-connected and islanded modes. This study was presented at the University of Genova, Savona Campus, Italy. It aimed to improve the grid system, maintain efficiency, and overcome energy efficiency and sustainability issues, but did not address issues such as frequency regulation for the campus microgrid. However, a feasibility and techno-economic analysis was also developed in [9] by Kritiawan for a PV integrated power plant at Sebelas Maret University, Indonesia, to mitigate the issues of

energy management in the Sebelas campus microgrid; however, the power quality [10] and voltage regulation [11] were not addressed, although were also needed for the project. On the other hand, the Pulau Ubin daily operated microgrid based in Singapore was examined by Valentina in [12]. This testbed consisted of an ESS, a solar–PV system, and three biodiesel generators. A system was developed to improve the power factor and voltage deviation. The main objective was to reduce the operational cost of the MG and the voltage variation of the network, but it did not focus on power improvements, the P2P trading mechanism, or frequency regulation for the campus.

Some of the related studies, especially the energy management structure of the microgrid, have considered optimal scheduling, an ESS, and PV. Many researchers here have also investigated the integration of an ESS in a microgrid while also checking the feasibility of solar–PV; however, some other researchers merely focused on the cost savings of PVs and optimum scheduling of the ESS.

Distributed generation (DG), on the other hand, is known as on-site generation and can also be called decentralized generation [13]. It can be defined as on-site electricity generation facilities to transmit the power over large distances from grid-like coal power plants. It can be utilized to minimize the effects of GHG emissions and to improve system efficiency and reliability. However, DG consists of photovoltaics (PVs) [14], wind turbines (WTs) [15], biomass [16], and fuel cells (FCs) [17] as renewable units, whereas other sources such as diesel generators (DiGs) [18], microturbines (MTs) [19], and tidal and geothermal gas engines (GEs) [20] are the sources of conventional units [21]. The microgrid component model is depicted briefly in Figure 3. This generic model consists of flexible and nonflexible energy sources. The flexible energy sources comprise three types: DR-programs, energy storage, and conventional energy resources [22]. The flexible energy sources contain storage systems that comprise fuel cells, batteries, flywheels, supercapacitors, and batteries. Flexible energy sources also contain conventional energy resources such as microturbines, diesel generators, and combustion turbines. Moreover, they also contain the DR programs, further categorized into price-based programs and incentive-based programs, as shown in Figure 3.

The non-flexible energy sources include renewable energy resources such as PV, wind, biomass, and tidal energy sources, as shown in Figure 3. The analysis has been evaluated based on the literature of some campus microgrid review papers which describes which type of campus load is connected with components such as those mentioned in Table 1.

The main contributions of this survey paper are:

- Campus microgrids are studied to depict the different types of sources installed at various campuses, including conventional energy resources, renewable energy sources, demand-side management (DSM), and energy storage systems (ESSs);
- Campus microgrids are reviewed based on optimization techniques, objective functions (OFs), and modeling techniques;
- Campus microgrids are studied as innovative campus microgrid scenarios that serve as smart decision approaches for university campuses.

Table 1. A review of the literature of campus microgrids with multiple sites.

Refs.	Campus	Technical Aspects										Load Type
		Components										Load Type
		PV	BESS	Wind	Biomass	DG [1]	MT [2]	EV [3]	SC [4]	FC [5]	CHP [6]	Campus/Building
[4]	University of Cyprus (UCY)	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus
[6]	University of Malta	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus
[7]	University of Novi Sad, Serbia	✓	✓	✓	✗	✓	✗	✓	✗	✗	✗	Campus
[23]	Chalmers University of Technology, Sweden	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus Building
[24]	American University of Beirut (AUB), Lebanon	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	Campus
[25]	Tezpur University, India	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	Campus
[26]	Valahia University of Targoviste, Romania	✓	✓	✓	✗	✗	✗	✗	✗	✗	✗	Campus Building
[27]	Seoul University, South Korea	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus
[28]	Griffith University, Australia	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus
[29]	Federal University of Rio de Janeiro, Brazil	✓	✓	✓	✗	✓	✓	✗	✗	✗	✗	Campus
[30]	University of Southern California, USA	✓	✓	✗	✗	✗	✗	✗	✗	✓	✗	Campus Building
[31]	Nanyang Technological University (NTU), Singapore	✓	✓	✗	✗	✗	✗	✓	✗	✗	✗	Campus
[32]	Illinois Institute of Technology, USA	✓	✓	✓	✗	✓	✓	✗	✗	✗	✗	Campus
[33]	Eindhoven University of Technology, The Netherlands	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus
[34]	Al-Akhawayn University, Morocco	✓	✓	✓	✓	✗	✗	✗	✗	✗	✗	Campus
[35]	University of Genova, Savona Campus, Italy	✗	✓	✗	✗	✗	✗	✓	✗	✗	✗	Campus Building
[36]	University of Central Missouri, USA	✓	✓	✓	✗	✗	✗	✓	✓	✗	✗	Campus

Refs.	Campus	Technical Aspects										Load Type
		Components										Campus/Building
		PV	BESS	Wind	Biomass	DG [1]	MT [2]	EV [3]	SC [4]	FC [5]	CHP [6]	
[37]	Yuan Ze University, Taiwan	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	Campus Building
[14]	Chalmers University of Technology, Sweden	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus
[38]	Federal University of Pará, Brazil	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus
[39]	Clemson University, South Carolina	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	Campus
[40]	University of Connecticut, Mansfield, Connecticut, USA	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus Multiple Buildings
[41]	University of Science and Technology, Algeria	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	Campus
[42]	University of Wisconsin-Madison, USA	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus
[43]	De Vega Zana, Spain	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	Campus
[44]	Aligarh Muslim University, India	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	Campus
[45]	North China Electric-Power University, Beijing, China	✓	✓	✓	✗	✗	✗	✓	✗	✗	✓	Campus

[1] DG denotes distributed generation. [2] MT denotes the microturbine. [3] EV denotes the electric vehicle. [4] SC denotes super capacitor. [5] FC denotes fuel cells. [6] CHP denotes combined heat and power.
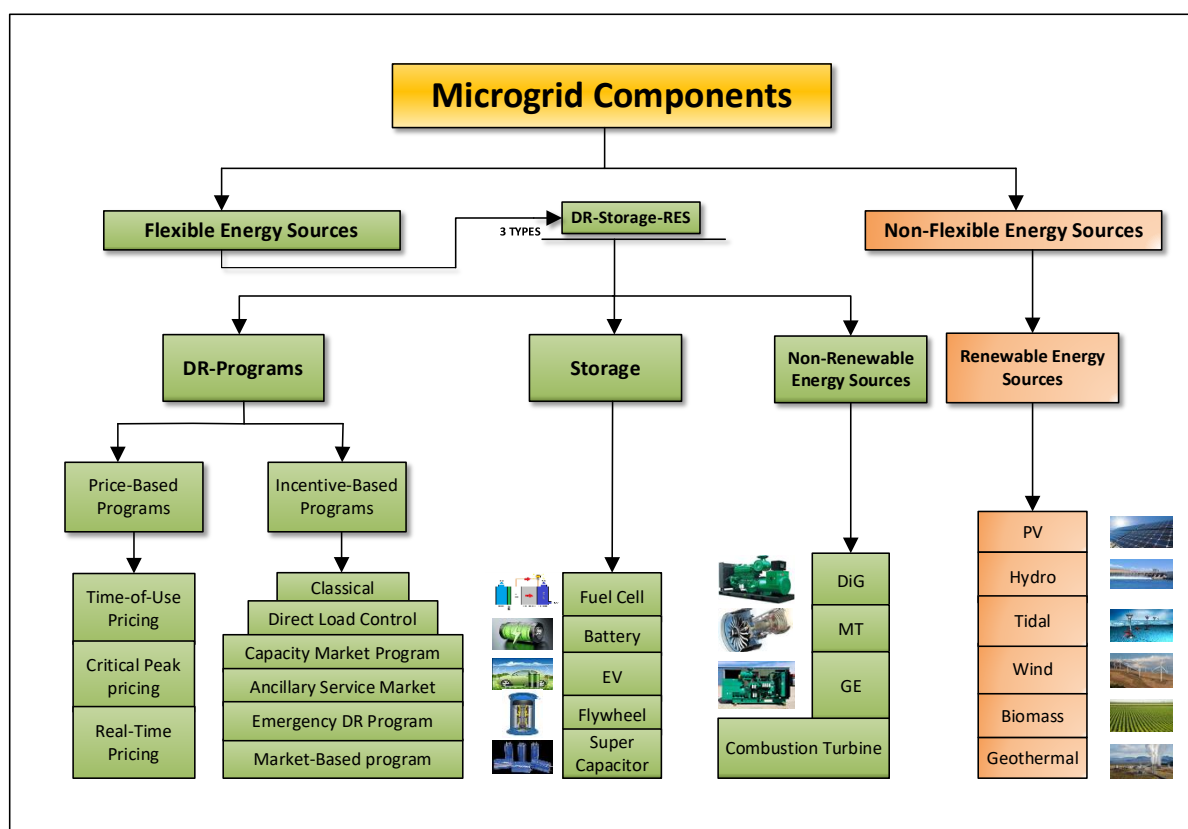
Figure 3. Microgrid components.

The review methodology of the paper aims to present various energy sources for different types of campus microgrids. This will also facilitate researchers in their respective areas and optimize the microgrid with the updated energy management systems [46]. The methodology monitored the power flow information in real time, monitored energy consumption, and stabilized the campus microgrid's energy [47]. It also covered a timeline of 5 years of technological development, including aspects from 2014 up to the latest microgrid developments. It also provides a new solution for a microgrid that operates for different power plants. This paper discusses various power plants and microgrids' architectural designs, techniques, operations, and reliability. These were analyzed with many optimization algorithms, fuzzy logic algorithms, and ANNs (artificial neural networks) [48].

This paper delivers the literature review on the campus microgrid EMSs by classifying the remaining articles into the following categories:

- Campus microgrids: optimization techniques;
- Renewable energy utilization in campus microgrids;
- Modeling techniques of campus microgrids;
- Resilient power system using campus microgrid;
- Role of energy storage systems in campus microgrids;
- Simulation tools for campus microgrids.

The remainder of the survey paper is structured as follows. In Section 2, the campus microgrid optimization techniques are discussed briefly. A survey on the utilization of renewable energy resources in campus microgrids is presented in Section 3. Resilient power systems using campus microgrids and the role of energy storage systems in campus microgrids is introduced in Section 4. The suitable simulation tools used for campus microgrids are described in Section 5. Finally, the research challenges and conclusions are presented in Section 6.

2. Campus Microgrids: Optimization Techniques

Campus microgrids' energy management involves some automatic systems that aim to schedule the resources optimally. It comprises the latest information technology, manages the energy storage system, and distributes energy sources with optimum conditions. Campus microgrid optimization typically involves the following points to improve the generator power to the maximum value and reduce the microgrid's operation cost and environmental cost. The main objective of the optimization techniques is to increase the efficiency of the power system [49].

Many standard optimization methods include mixed-integer linear programming (MILP) and non-linear programming [50]. Well-known deterministic mathematical methods are MILP, MILNP, and dynamic programming, which deal with and resolve the complications quickly and comprehensively, whereas metaheuristic mathematical models [51,52] include the artificial bee colony (ABC), particle swarm optimization (PSO), simulated annealing (SA), genetic programming (GP), differential evolution (DE), genetic algorithm (GA) and many multi-objective problems that involve contradictory spatial objectives in the process of decision making. The constraints and objective functions used in linear programming are special linear functions having a whole and real-valued decision variable. Dynamic programming is also termed the DP programming method used for many complex problems sequenced and discretized. To deal with such issues, they can be categorized as sub-problems that can be solved optimally. These results are then covered to create an appropriate solution to solve the main problem [53] optimally.

The metaheuristics approach is another effective alternate in the optimization of microgrids. Heuristic methods are combined to find an adequate solution using genetic algorithms, statistical mechanisms, and biological evolution to achieve the optimal control and operation of microgrid power [54]. Predictive control methods are used to forecast electricity generation and effectively manage the energy stored already. This method classically associates both control and stochastic programming. The most notable among these methods are predicting the weakening of elements in the grid, especially energy storage systems [55]. Optimization techniques based on multi-agent approaches allow the proper decentralized management of campus microgrids. These multi-agents include various loads, storage systems, and distributed generators linked with one another to achieve minimal cost of the microgrids [49].

A detailed literature review on multiple campus microgrids with various techniques, components, and results are summarized in Table 2. This represents a detailed analysis of campus microgrid topics with the addition of their illustrated results, techniques, and components. Presenting this type of analysis benefits various authors who contribute to the field of smart grids. Table 2 is helpful for those researchers who search for optimization techniques or algorithms in different literature reviews. The detailed analysis is presented in Table 2.

Table 2. A survey of optimization techniques used in campus microgrids.

Ref.	Location	Components	Optimization Techniques for Energy Management	Economic Analysis
[56]	Oregon State University, Corvallis, Oregon, USA	Smart meters 2 Solar–PV arrays	Linear optimization	Energy management and voltage-regulated
[57]	Al-Akhawayn campus, Morocco	RER [1]* Smart meters Sensors	Energy management system	Minimize energy losses and GHG emissions
[9]	Sebelas Maret University, Indonesia	RER Solar–PV Energy Storage	HOMER analysis	NPC cost: USD 153,730 IRR value: 4.9%
[58]	Purdue University, Indiana, USA	Solar–PV grid 3 lead–acid batteries	EMS technique	Annual ROI: USD 602.88 Payback period: 13.38 years.

Table 2. *Cont.*

Ref.	Location	Components	Optimization Techniques for Energy Management	Economic Analysis
[11]	Eindhoven University of Technology, The Netherlands	RES Distributed Generators Storage systems	Generic algorithm	400 kWh energy production
[59]	(Illinois Institute of Technology), Chicago, USA	(DERs) (DG) (ES) resources	Energy scheduling optimization problem (ESOP)	Power balance Reliability Sustainability
[60]	McNeese State University, Lake Charles, Louisiana, USA	15 kW PV system 2/65 kW CHP generators	Fast Fourier transform (FFT) algorithm	Controlling water flow resulted in higher thermal recovery
[61]	AMU (Ali Garh Muslim University), India	PV Grid wind	HOMER analysis	NPC (Net Present Cost): USD 17.3 million/year CO_2 emissions: 35,792 kg/year.
[62]	Jordan University of Science and Technology, Irbid, Jordan	PV plant Utility grid	Charging/discharging algorithm	Reduce the energy consumption from 622.4 MWh to 6.3.87 MWh
[63]	METU (Middle East Technical University) campus and NCC (Northern Cyprus Campus)	RES ESS	Generalized reduced gradient (GRG) algorithm	Increased the RES fraction by 91.8% Demand and supply fraction by 89.4% COE calculated 6.175 USD per kWh
[64]	Massachusetts Institute of Technology, Cambridge, Massachusetts, USA	Grid Battery	Forecasting method	Reduces the peak energy consumption by 11%–32% and saves USD 496,320 annually
[13]	Chonnam National University Yongbong Campus, Gwangju, South Korea	500 kW ESS PV Load controllers Power load-bank	P2P trading mechanism	Maximized the performance of every interlinked microgrid
[65]	Guangdong University of Technology, China	BESS PV system	NSGA-2 (Non-dominated Sorting Genetic Algorithm-2)	To maximum PV consumption and to minimize the operational cost
[66]	Nanjing University, China	EV [2]* Wind system PV	Interval optimization	Transmission loss is reduced
[67]	Multiple Microgrids location such as Nanjing University Microgrid	(PV) Wind turbines Energy storage units (EV) Diesel generators Gas turbine	OPF (optimal power flow) technique Auction algorithm CPLEX solver	Achieved a minimal USD 8616 operation cost
[68]	University of Connecticut, Mansfield, Connecticut, USA	Wind turbine Fuel cell PV Energy storage system Hydro-kinetic systems	HOMER analysis	The final selected microgrid consisted of solar–PV (203,327 kW), wind turbine system (225,000 kW), and energy storage systems (730,968 kWh)
[69]	Nnamdi Azikiwe University, Nigeria	Solar–PV Diesel generator	HOMER analysis	The NPV and LCOE were calculated as USD 1,738,994 and USD 0.264
[70]	McNeese State University, Lake Charles, Louisiana, USA	CHP NG microturbine PV plant	HOMER analysis	A CHP-PV-based hybrid system is efficient
[71]	University of Coimbra, Portugal	PV [3]* plant Li-ion batteries EV Controllers	LabVIEW analysis	Lower energy consumption and it met electricity demand for the campus by 22.3% yearly
[72]	Proposed University based in India	Wind system PV system Energy storage Biomass	Newton–Raphson technique Swarm intelligence approach	It improved the energy exchange among grids, and also enhanced power quality

[1]* **RER** denotes renewable energy resources. [2]* **EV** denotes electric vehicle. [3]* **PV** denotes photovoltaic.

Various optimization methods have also been applied to improve power efficiency, reduce electricity costs, and take full advantage of improved storage systems [73]. Various researchers have applied multiple methods such as MILP, dynamic programming, MINLP, particle swarm optimization (PSO), genetic algorithms (GAs), an artificial bee colony, artificial fish swarm, and bacterial foraging algorithm. MILP is the latest to be implemented into microgrid systems, similarly to the other latest techniques such as artificial neural networks, artificial intelligence, or machine learning. The assurance of searching for the global optimal point in the linear problem makes the MILP method more attractive among commercial solvers, and its limitation is the impossibility of dealing with the nonlinear effects and the main risk of facing a high-dimensionality problem. Several other methods have been established to challenge these types of limitations, such as rolling horizon methods, piecewise linearization approaches, and high-dimensionality reduction by clustering algorithms. Dynamic programming, on the other hand, splits the problems into their following parts and then finds the optimal solution; its main advantage is the computational saving over complete enumerations, but it also has high-dimensionality problems similarly to MILP because it faces issues in dealing with multiple states. MINLP, on the other hand, solves problems with simple operations and contains many optimal solutions that take positive benefits over MILP because it also deals with nonlinearity optimization problems. However, the main problem is that it performs more complex iterations than MILP and is hard to understand. Particle swarm optimization (PSO), developed in 1995 by Kennedy and Eberhart, has greater efficiency than MILNP, but it has complex computation while solving an optimization problem. Genetic algorithms, on the other hand, developed in 1975, support multi-objective optimization, but the usage of population size, the finding of the main parameters such as the rate of mutation and crossover, and the choices of the new population should be made carefully.

Many researchers have used these algorithms to find optimal solution, as seen in Table 3.

Table 3. Comparison of optimization methods considering advantages and disadvantages.

Methods	Optimization Methods	Advantages	Disadvantages	Objectives and Applications
Deterministic Methods	MILP [74]	Mixed-integer linear programming (LP) resolves the complications quickly and comprehensively. Their linear constraint lies in the feasible convex region, aiming to find the optimum global point and an exact solution.	Economic and stochastic analysis. It contains limited capability for applications which do not have continuous and differentiable objective functions.	MILP is commonly used for optimization problems. It is easy to use with CPLEX Solver, which is good software available. It is used for unmanned aerial vehicle (UAVs) in planning their flight paths.
	Dynamic Programming (DP) [75]	Splitting the problems into their sub-sequent parts and then optimizing them to find the optimal solution.	It contains a large number of recursive functions; therefore, it is time-consuming.	It is also used as an optimization problem. It solves problems such as reliability design problems, robotics control, and flight control.
	MINLP [76]	Solves the problems with simple operations and contains many optimal solutions that take positive benefits over MILP.	It is time-consuming.	Mixed-integer nonlinear programming (MINLP) deals with an optimization problem involving discrete and continuous variables, as well as nonlinear variables in the objective function.

Table 3. *Cont.*

Methods	Optimization Methods	Advantages	Disadvantages	Objectives and Applications
Metaheuristic Methods	Particle Swarm Optimization (PSO) [77]	Greater efficiency while resolving the optimization problems. Easy adaptation for various kinds of optimization problems and reporting near-optimal solutions in a reasonable time.	Complex computation while solving an optimization problem. The search process may face entrapment in local optima/minima regions.	PSO can be used for many optimization problems, such as energy-storage optimization. It can also be used for visual effects in videos.
	Genetic algorithms (GA) [78]	Based on population-type evolutionary algorithms that comprise mutation, selection, and crossover to search for an optimal solution for a particular problem. They also have a suitable convergence speed and can adapt easily for various kinds of optimization problems with reporting near-optimal solutions in a reasonable time.	The parameters must be met for the operations of mutation, selection, and crossover while solving. It also has no guarantee of attaining the best solution. The search process may face entrapment in local optima/minima regions, similarly to PSO.	Genetic algorithms have several applications in natural sciences such as in computer architecture to find an extensive solution. It is used to learn the robot's behavior and is also used in image processing. It is also used for file allocation in distributed systems.
	Artificial Fish Swarm [79]	High accuracy, contains few parameters, has flexibility, and fast convergence. It also adapts easily for various kinds of optimization problems with reporting near-optimal solutions in a reasonable time.	It has the same advantages as genetic algorithms, but it has disadvantages without mutation and crossover. Attaining the best solution is also no guarantee. Moreover, the search process may also face entrapment in local optima/minima regions, similarly to GA.	Artificial fish swarm is used for fault tolerance, fast convergence speed, good flexibility, and high accuracy. It commonly uses the general method to solve all types of problems such as prey, follows, and swarms. Other applications of AFS are neural network learning, global optimization, color quantization, and data clustering.
Artificial Intelligence Methods	Artificial Neural Network [80]	Its evaluation time is faster than previous algorithms; it deals with problems to obtain the target function values for real-valued, discrete values, etc.	It is hardware-dependent and requires parallel processors. It gives untold solutions, does not give a clue for the solution how it has been done.	Artificial neural networks are used in handwriting recognition, image compression, and stock exchange forecasting.
	Fuzzy Logic [81]	The structure of fuzzy logic is easy to understand, which highly encourages developers to use it for controlling machines.	Maintaining the accuracy with fuzzy logic is quite difficult sometimes.	Fuzzy logic is commonly used in spacecraft, automotive industries, traffic control, and especially in improving the efficiency of the transmission system.
Other Methods	Manta Ray Optimization [82]	Computational cost is comparatively less compared to other optimizers and also has good precision in solutions.	It is not effective in fine-tuning for providing solutions for optima, and it has a slow convergence speed, making it less usable.	The manta ray technique is a bio-inspired optimization technique idealized from the excellent behavior of large manta rays, which are known for their speed. It is widely used for its solution precision and computational cost.
	Harris hawks Optimization [83]	Commonly known for its excellent performance, acceptable convergence, and quality of results generated for optimization problems.	Sometimes difficult to understand and has computation complexity, which makes it more difficult.	HHO is in the initial stages for researchers, and it has acceptable convergence, accuracy, and speed for solving various optimization problems in the real world.

3. Renewable Energy Utilization in Campus Microgrids

Microgrids have progressed as a critical technology to aggregate and harness the existing renewable energy sources (RESs) to increase network reliability, reduce energy costs, and reduce the carbon footprint. Many researchers have discussed renewable energy utilization among various campus microgrids by employing different approaches and

methods. However, all methods have focused on determining the most efficient and optimal solution for the microgrid operation. The respective sub-sections discuss the renewable energy utilization among various grids.

Navid presents an optimal solution in [84] to optimize the system's size and reduce the net present cost (NPV) for a campus grid that consists of PV, wind, integrated converters, and a BESS system. The university grid was connected with 100% RERs to reduce the LCOE (levelized cost of energy) by half that of an urban university which buys electricity from a utility company. The proposed RES also included a tracker system, which aimed to reduce the LCOE by a further 50%, although an economic analysis needs to be performed to better understand the COE for the campus.

A DSS (decision support system) was developed by Vangelis in [85] to manage the energy power flow for three cities in Spain, Italy, and The Netherlands. This approach scheduled the temperature set-points, ON/OFF heating system, and PV system for the public and private sectors. The results conclude that it maximized RER production by 10% with cost minimization and reduced GHG (greenhouse gas) emissions, but an optimal solution needs to be focused on by regulating the power quality for the respective cities. Moreover, a more developed DSS approach is needed to effectively manage the load data. On the other hand, a comparative scenario is presented by Walter in [86] to use RER types in nearly 50 universities worldwide. In this study, three different approaches were developed to optimize the university microgrid, in which macro-, medium- (meso), and macro-level cases have been discussed. Universities consume electricity at a maximum of 700 kWh/m^2, with a 20 kWh/m^2 average consumption level among many universities. Results revealed that 70% of PV/solar renewable energy is a vital source among different universities, but an effective solution needs to be implemented to reduce the operational cost for the university energy, such as with a high penetration of RERs in the campus.

A harmonic model was developed by Alessandro in [87] for the University of Genova, Savona Campus Microgrid, to overcome the transient-based issues present in the system. This proposed model can control and manage the microgrid that is connected with RERs in grid-connected mode and islanded connected mode, but it can also reduce the transients by adding or subtracting generation assets, generator inertia, adding electricity storage, or with dedicated demand response. However, different university microgrids are reviewed in [88], in which UCM is implemented to reduce the operating cost of RESs (renewable energy sources). UCM aims to find an effective techno-economic analysis for other university microgrids. For Jiangan University, 8.3 MW and 11.6 MW are installed on rooftops, covering 33% to 46% of load demand from the PV system. In another scenario, the DUTH University Microgrid gives an annual saving of EUR 8258. The results showed that the increased photovoltaic solar capacity reduced the campus's energy consumption by 2.8% annually. Moreover, it can represent an effective economic solution for the given universities. An effective approach can also be utilized, such as a smart support solution for campuses to further reduce energy costs.

In [63], Murat suggests a sizing method of renewable energy sources and ESSs (energy storage systems) for the METU (Middle East Technical University) campus and NCC (Northern Cyprus Campus) Microgrid. This methodology compares the performance of the PV system and wind energy system by technical–economic feasibility analysis under four ESS conditions:

(1) No ESS conditions;
(2) HFC (hydrogen fuel cell) conditions;
(3) PHS (pumped hydrogen storage) conditions;
(4) Combination of PHS and HFC.

This system optimally configures the RES by comparing it with the national grid tariff with the COE (cost of electricity) calculation. Results show that it increases the RES fraction to 91.8% from 62.6%, maximizes the demand and supply fraction to 89.4% from 46.5%, and LCOE is calculated as 6.175 USD per kWh. Furthermore, with COE, the NPC (net present

cost) can also be calculated to enhance the technical–economic feasibility analysis, and more conditions should be focused on optimizing the system more economically.

A power-sharing energy market was established by Javad in [89] for commercial buildings in Portugal. These commercial buildings consist of ESS on-site and EV charging stations. The proposed method aims to increase the PV output, which covers the demand profile for the communities. Results show that it maximizes the self-consumption of renewable energy for commercial buildings and communities and reduces the total electricity cost by 27%. However, to increase the self-consumption of renewable energy, more resources should be incorporated to further move towards RER self-consumption with the consideration of techno-economic analysis.

An efficient microgrid system is presented by Reyasudin in [90] that included solar–PV and BESS, which were implemented in HOMER software. The battery storage system had various load ranges connected with μG that had a range of 1 kW to 500 kW capacity. Results show that both the systems, grid-connected only and grid-connected with battery storage, are feasible. Both can be used at the proposed campus. An approach also needs to be focused on analyzing the BESS optimal sizing, which could be the best possible solution for the microgrid system.

Dimitrios developed another approach in [91] to deal with the electric power losses in a microgrid with optimal scheduling of generating resources. The two-stages platform devised this integrated approach. At first, it used an EMS approach (energy management system) that calculated the system's economic dispatch and load dispatch. The second stage applied a strategy to meet the standards of power quality at the distribution side level. The results showed that this tool effectively used voltage regulation, unbalancing conditions, and harmonics deviations with the minimum cost. The system can also focus on frequency regulation. If demand-side frequency response is focused, then it will mitigate problems for the power losses.

However, the related work focused here presents a review on renewable energy utilization for multiple microgrids, presenting solutions to improve network reliability, reduce the cost of energy, and reduce the carbon footprint. Many researchers have also investigated efficient and optimal solutions for the microgrid operation; however, this manuscript gives appropriate solutions for the campus microgrids which are approaches that can be further utilized to improve the reliability and sustainability for power systems to give customers a good level of confidence that the provided solution is effective.

Therefore, this study focused on the recent literature on campus microgrids that also covered a brief comprehensive analysis of the different microgrid models worldwide with the techniques and energy systems used.

A comparison has been developed to better analyze existing review papers and our survey paper, as shown in Table 4.

Table 4. Comparison between existing studies of campus microgrids and our survey paper.

Existing Literature Reviews of Microgrids	Objectives
[30]	A DR (demand response)-based software architecture is highlighted in the literature to optimize the microgrid of the USC (University of Southern California) campus, LA (Los Angeles). It comprises the data collected under machine learning models to effectively schedule the load demand for peak hours.
[32]	A system of the establishment of microgrids is proposed at IIT (Illinois Institute of Technology), Chicago. In this system, reliability, sustainability, and efficiency are concerned.
[33]	A smart design of smart grids is proposed for the Eindhoven University of Technology, The Netherlands. It provided some solutions to convert the existing distributed system into an intelligent grid system.
[34]	An EMS (energy management system) approach is presented in the literature for Al-Akhawayn University in Morocco, which can efficiently control the energy for this smart microgrid.
[36]	A microgrid model is proposed, and a solution is given to handle the UCM campus load, manage the EV (electric vehicle) connections, and mitigate problems related to peak campus demands.

Table 4. *Cont.*

Existing Literature Reviews of Microgrids	Objectives
[45]	The power management and scheduling problems are addressed in this study with hybrid renewable microgrids in the North China Electric-Power University, Beijing.
[57]	An overview is presented for the topics of smart campuses, EMSs (energy management systems), CBSs (control-based systems), and stability solutions for campus microgrids. This paper introduced energy management for the Al-Akhawayn campus microgrid.
[86]	A comparative scenario is explained to use RERs (renewable energy resources) in almost 50 universities as sample case studies worldwide. In this paper, three different approaches were developed to optimize the university microgrid, in which many macro-, medium- (meso), and macro-level cases were discussed.
[92]	The latest research is reviewed in the literature on DERs (distributed energy resources), which aim to train students with in latest courses of microgrid technologies. This project was undertaken as a MERMET Project, which over the lifespan has trained almost 11,012 students with 154,432 credit hours lectured to trainees.
[93]	The GridEd project is discussed among seven universities based in different cities. This GridEd project aims to modernize the education curriculum with improved training for future engineers.
[94]	A solution is presented for the Santa Rita Jail in which a microgrid is installed 70 km away from the current operating location.
[95]	An EMS system is presented for the University of Genova, Savona campus, which aims to effectively manage the energy, reducing the generation costs of the smart polygeneration grid.
[96]	An analysis is developed to improve the power demand for Gachon University, South Korea. It consists of distributed energy resources with an energy storage system. The system improves the efficiency and sustainability of the university microgrid.
Current survey paper	In the current survey paper, the main objective is to organize, review, and present a comparative analysis of all the existing campus microgrid systems with the consideration of multiple optimization techniques, simulation tools, and different types of energy storage technologies.

3.1. Renewable Energy Resources in the Stochastic Environment

When renewable energy sources are installed in a stochastic environment, it means that there is uncertainty in the next state. It is difficult to determine what type of environment there will be in the next 24 h or the next stage [97]. When adopted, stochastic programming can handle the random nature of demand by using numerous trajectories created from the scenario generation tool [98]. Various authors have contributed to dealing with power energy inefficiencies in the stochastic environment; some are mentioned below:

Yuanming et al. [99] analyzed multiple distributed operations to manage the energy and schedule the power for the Tsinghua campus microgrid, China. In this paper, the authors describe the energy management of campus microgrids in three sections:

1.　First, it optimizes the operation for the campus buildings with a two-stage stochastic programming technique:

　　i.　In the first stage, it schedules the charging and discharging of batteries according to day-ahead timing;

　　ii.　In the second stage, it decides to distribute power in real time.

2.　Secondly, it handles the uncertainties and converts the problem into a stochastic MILP technique;

3.　Thirdly, it considers Tsinghua University as a case study.

Results show that the proposed technique effectively schedules the energy efficiency for the microgrid, but it can be further improved by implementing a stochastic genetic algorithm to additionally enhance the system or by incorporating more renewable energy resources into the system that will support the campus microgrid to reduce further electricity cost.

An MPC (model predictive approach) method is presented by Zhenya in [100], using a stochastic and robust model that manages the energy efficiency and minimizes the MG's operation cost. This study uses a stochastic model to present the predictivity analysis and analyze electricity prices in real-time-based scenarios. At the same time, robust models represent electric vehicle charging loads. The obtained results show that the proposed energy management (EM) system satisfies the consumers and improves the microgrid's performance. It can also add a DSS (decision support system) or more advanced approaches such as artificial neural networks to further reduce the microgrid operating cost.

The related work mentioned here focuses on renewable energy resources implemented in the stochastic environment that deal with the random nature of demand and with the help of wind trajectories created from the scenario generation tool. Various authors have contributed to dealing with power energy inefficiencies in the stochastic environment, which aim to improve the efficiency and reliability of the system.

3.2. Renewable Energy Resources in the Deterministic Environment

When renewable energy resources are incorporated in a deterministic environment, it means that the forecasting of the environment can be determined earlier. Some authors who have contributed to dealing with energy inefficiencies for the deterministic environment are mentioned below.

An optimal solution is proposed by Saritha in [72], who aimed to install a renewable energy resource to a campus microgrid that was also connected to the utility grid. The proposed model was installed in a deterministic environment that consisted of a wind system, photovoltaic system, energy storage, and biomass. It calculated the electrical distribution network simulation by PSAT MATLAB and analyzed the power flow calculations using the Newton–Raphson technique. Results show that it improved the energy exchange among grids and improved the microgrid system's power quality and stability. Moreover, the advanced approach can also be utilized similarly to neural networks or artificial intelligence to improve the power flow more effectively. However, in peer-to-peer energy transaction, presented by Wang in [101], and consisting of a double auction market, the model is utilized as distributed energy management; this model sets the targeted price to maximize the profit. Urban community microgrid system (UCMSs) can be used to assign energy resources that are presented for a deterministic environment. This concludes that adopting this strategy and participating in the market will maximize the economic profit of prosumers. Results show that overall daily cost, peak-to-valley difference, and the renewable energy self-consumption ratio were increased by 72.74%, 48.94%, and 30.31% in a sunny scenario, and 14.45%, 40.63%, and 27.18% in a cloudy scenario. Additionally, for UCMS, the power quality or voltage regulation can be improved to reduce the daily energy cost. Another energy trading strategy is also proposed by Yuan in [102], between prosumers in an MG (microgrid). Prosumers choose either utility, purchase the electricity from the grid, or run in island mode. Island mode relies on self-DERs and self-energy storage devices. Prosumers can also export energy with other prosumers in cases of excess energy or surplus energy. The main objective is to maximize renewable energy utilization and minimize the ESS and generation costs, which affect the prosumer economically; however, a more effective energy trading mechanism is needed because it lacks less utilization of renewable energy resources. An effective approach should be implemented in campuses to further reduce the operational costs of the system.

The related work presented here is comprehensively analyzed with the deterministic approach perspective, which means that environment forecasting was observed earlier. Renewable energy resources incorporated in the deterministic environment analyzed the forecasted energy and observed the energy trading among grids. Many authors have comprehensively analyzed energy management in the deterministic environment and presented multiple solutions for campus microgrids, aiming to maximize renewable energy utilization and reducing energy generation costs.

3.3. Electric Vehicle Integration in Campus Microgrids

Osama performed a feasibility analysis in [62] to use an electric vehicle as a temporary energy storage source in the Jordan University of Science and Technology, Irbid, Jordan. It consisted of a PV (photovoltaic) plant, load, and the utility grid. This microgrid system was installed with a charging station at the JUST campus, aiming to determine the available electric vehicles in the system and reduce the energy consumption drawn from the utility. Results show that it reduced the energy consumption from the utility (from 622.4 MWh to 63.87 MWh), but it lacked power quality or demand response; thus, an effective approach is needed to improve the energy for the campus.

An efficient approach is presented by Morris [103] to charge electric vehicles (EVs) in different charging scenarios for the University of Genova, Savona campus microgrid. This paper discusses different EV types with various capacities, different driving ranges in kilometers, energy consumption, and respective maximum speeds. Results aimed to improve the charging times and to prevent overcharging. However, the study did not focus on EV charging planning and operation services, which could be effective if utilized to improve the charging time for the campus further.

However, Stefano et al. [35] presented an improved system for the electric vehicles of the Genoa campus microgrid. This project aimed to renovate the storage system of EVs that may reduce the operational cost for EVs' energy storage systems, although the microgrid lacked a grid-to-vehicle energy trading mechanism or vehicle-to-grid energy trading mechanism, which should be the focus for enhancing the system further, as well as improving service stability. Yang [37] focuses on determining the actual installed capacity of an electric scooter in which the charging station is organized in such a way to determine the actual energy power quality and service stability for the EV in the YZU campus (Yuan Ze University). The main objective of this contribution is to make the campus microgrid suitable for charging the electric scooters and determine the voltage change during the power flow, but it lacks the economic evolution of EVs, which is needed for the campus, and does not focus on electric vehicle charging strategies for the campus.

Many researchers have also investigated the efficiency of electric vehicles (EVs) in different charging scenarios for the different campus microgrids. Various EV kinds are discussed with different capacities, multiple driving ranges, respective maximum speeds, and different energy consumptions. Overall, the focuses are on improving the charging time, and providing solutions to prevent overcharging.

3.4. Storage Systems in Campus Microgrids

Various storage systems have been deployed across the institutes. From the microgrid point of view, various authors have contributed to campus microgrid energy management using batteries, fuel cells, flywheels, different battery storage systems, etc. Some are mentioned here.

A solution is presented for the Santa Rita Jail Microgrid by Chris in [94] for a microgrid that is to be installed 70 km away from the current operating location. It includes 8-year-old solar–PVs and 5-year-old battery storage systems aiming to reduce the peak for the utility by around 15%. With the installation of battery storage of 2–4 MW, the system's total peak reduction is 18%, minimizing the bill cost for the Santa Rita Microgrid, although it lacks a sizing approach for the campus; optimal sizing is also an effective method to further reduce the bills for campus microgrids.

Another solution is presented by Yasha in [55] to optimally charge the SC (supercapacitor), lead–acid batteries, and lead-ion batteries. This was achieved by applying CC, CP, CV, and CC-CV charging strategies and using these strategies on different ESSs (energy storage systems). For comparison among several scenarios, efficiency analysis was carried out. In the first scenario of a lithium-ion battery and a supercapacitor (SC), the CC strategy was the optimal and final strategy for charging. In the second scenario, the CP strategy was used for the SC (supercapacitor) case, although was not an optimal solution and would be less efficient. In a lithium-ion battery scenario, both the CC and CP were

optimal strategies. In the lead–acid battery scenario, the optimal charging strategy was more efficient and optimal compared with the CC and CP charging strategies. Results show that the optimal charging strategy proposed here is the most efficient charging model for energy storage systems, but it can also incorporate a double-layer optimal charging strategy or choose a voltage-based multistage constant current (VMCC) optimal charging strategy as an effective method to find an optimal solution.

For some of the related work mentioned here, a comprehensive analysis has focused on different storage systems in campus microgrids, and an optimal solution has been presented while focusing on the improvement of battery charging/discharging times as well as for fuel cells, flywheels, and various battery storage systems. However, some other researchers have merely focused on the cost-saving of PVs and optimum scheduling of ESSs. This work also focused intensely on the research areas mentioned before and gave a brief comprehensive model of the energy management structure of a campus microgrid.

3.5. Energy Management and Energy Trading in Campus Microgrids

Energy management and energy trading are key topics for attaining minimal carbon footprints, efficient energy consumption, and reductions in the expenditure of consumer energy [104]. Various authors have contributed to energy management and energy trading for campus microgrids; some are explained below.

An efficient energy management system was developed by Young in [105] for the Gwanak campus, Seoul, South Korea. It was developed and organized by LSIS (LS Industrial System). The Seoul University building consists of three fuel cells—normal cells, virtual cells, and premium cells—that save up to 21% energy costs during the whole year. The results also show that they reduced energy consumption by 11% and 110 TOE GHG emissions; however, a more effective solution has been presented for the campus in [106] to further reduce the energy consumption. On the other hand, a microgrid concept has been presented on the American Website [2] that represents the New York State University campus microgrid, mainly consisting of a BESS system and hybrid solar–PV system. At the same time, the SUNY hybrid microgrid produces energy locally and integrates it with the utility grid. It successfully manages the energy among the prosumer grid and utility grid. The result obtained was 217 kW from the solar–PV system, which is economical for the New Paltz campus, although did not address the solar–PV predictive maintenance, which can also improve solar–PV generation or the active power management needs to be focused to further improve the performance of the solar–PV. However, Alireza reviewed energy management research for the microgrids in [107] based in San Diego, California, and New York. The author suggested that maintaining an energy supply is crucial for every campus microgrid. It also maintains the power supply during a grid outage. It was reviewed that some microgrids in North America would reach 1.2 GW energy production by 2024 with a USD 4.2 billion installation cost. The energy market solution concludes that Hitachi is optimal in North America, but more optimal solutions could be utilized in the future to use advance renewable energy resources with an advanced approach.

Many researchers mentioned above investigated energy management and energy trading to attain efficient energy consumption and to minimize carbon footprints. However, some solutions have been presented which can benefit some authors to improve their systems further. The work presented above gives a brief comprehensive analysis on the topic of energy management and energy trading to efficiently manage the energy of campus microgrids.

4. Resilient Power Systems and Energy Storage Systems in Campus Microgrids

A campus microgrid consists of limited power generation, users (or consumers), and a storage system. An electrical consumer purchases electricity from the utility and pays for the units consumed. On the other hand, a prosumer both consumes and produces electricity at once, while a prosumager consumes, produces, and can store that energy to be used at any other time. Figure 4 briefly describes the comparison between the consumer,

prosumer, and prosumager. It illustrates the power consumption from the user end and prosumer end.
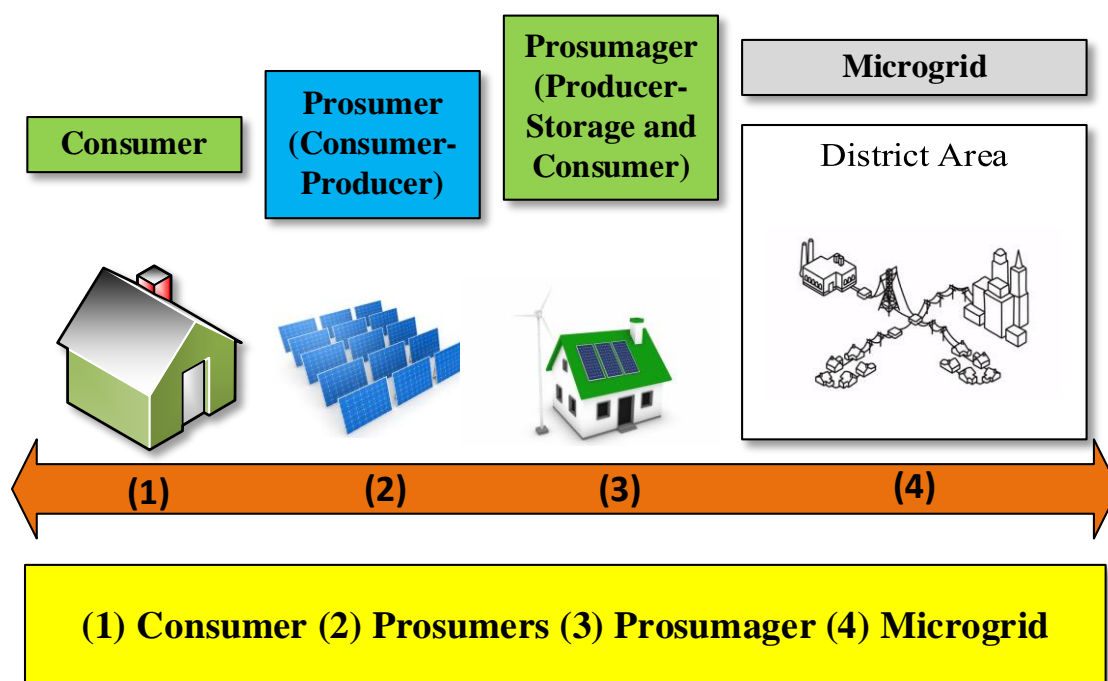

Figure 4. Comparison of Consumer vs. Prosumer vs. Prosumager vs. Microgrid.

It means the consumer takes power from the microgrid, the prosumer acts as a producer and consumer, whereas the prosumager acts as power producer, consumer, and stores the energy for future purposes. A simple comparison among microgrids is shown in Figure 4, describing the general comparison with a consumer, prosumer, prosumager, and district area microgrid.

The resiliency in the power system specifies the capable response that the system withstands the faulty conditions and must not fall back to blackout conditions. It recovers the system from the faulty state and turns it into the normal state [108]. It also introduces the term level of resilience (LoR), evaluating multiple MG topologies to eradicate the faulty scenarios for microgrid operation [109]. It can be determined by reducing the served load, voltage percentage, and recovery time of the fault. It can also be determined by the time needed to reach the normal state of the system [110].

When campus microgrids are used as a resiliency source, it means that the infrastructure conditions must be fully met. Some of the major infrastructure parts include lines, switches, cables, transformers, and breakers, which connect multiple microgrid elements [111]. Such a microgrid that involves a resilient backup source maximizes the efficiency of the power system. It also reduces power losses in the system because it detects faulty lines and operates them according to maintaining the system's reliability [112]. Resilience-enhancing methods can be regarded as:

1. Enhancement of the capability to adapt;
2. Enhancement of the capability to recover.

The resilience planning stages and particular actions are summarized in Figure 5. During a disaster, the microgrid enters the first stage of planning and decides whether to operate further or move towards the off condition, which is the disconnection mode. Then, it starts the operation again and responds to the crises that occur in the system; finally, after the clearance of the fault, it undergoes the recovering stage and normalizes the grid [109].
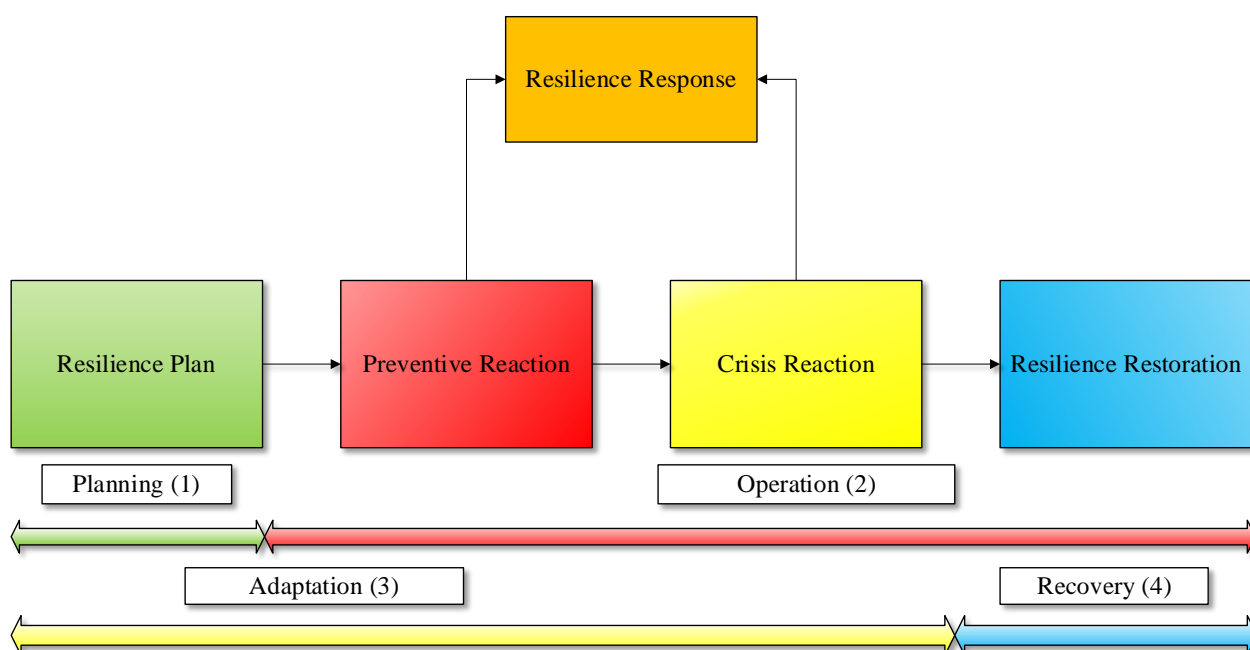
Figure 5. Resilience stages in campus microgrids.

A campus microgrid becomes resilient only through long-term reinforcement and effective short-term operations [109]. These characteristics help improve the power system structure in times of disaster, and it can prevent crises by implementing quick restoration or applying islanded mode.

A microgrid adapts to difficult situations such as blackouts or brownouts and then takes preventive actions according to the condition of the system. To eradicate severe problems, it applies corrective actions such as shutting down the system by tripping. Protection schemes help in this scenario because they make the system more efficient and reliable. This helps the system to tackle the problems that cause issues after blackouts.

Once the problem is analyzed, the system makes a resilience plan and takes preventive action, reacting to the crisis according to the problem; in the end, it restores the system to the original state, as shown in Figure 5 [113].

Resiliency in the power system specifies the capable response that a system can withstand faulty conditions, but must not deteriorate to blackout conditions. It recovers the system from the faulty state and returns it to the normal state [108]. It also introduces the term level of resilience (LoR), which evaluates multiple MG topologies to eradicate faulty scenarios for microgrid operation [109]. This can be determined by reducing the served load, voltage percentage, and recovery time of the fault. It can also be determined by the time needed to reach the normal state of the system [110].

When campus microgrids are used as a resiliency source, it means that the infrastructure conditions must be fully met. Some of the major infrastructure parts include lines, switches, cables, transformers, and breakers, which connect the multiple microgrid elements [111]. Such a microgrid that contains resilience as a backup source maximizes the efficiency of the power system. It also reduces the power losses in the system because it detects faulty lines and operates them whilst maintaining the system's reliability [112].

Figure 6 describes the planning and hardening measures that involve power conversion systems and underground lines, whereas Figure 7 describes the effective short-term operations that include preventive and corrective actions.

Resilience is an important topic in power systems; therefore, much adaptive focus (high precision) is needed to operate them more efficiently. Long-term or short-term reinforcement takes short-term goals or long-term goals to adopt the corrective actions to solve difficult situations. However, the resilience of power systems effectively takes the

negative results and creates positives, which means it effectively takes preventive actions to correct faulty sections of the power system [114].

Figures 6 and 7 briefly described the disciplinary actions and steps taken to eradicate the problems and return the system back to a normal state [113]. A campus microgrid is a decentralized electricity power grid that contains many small-size energy sources that can operate in islanded and grid-connected modes [115].
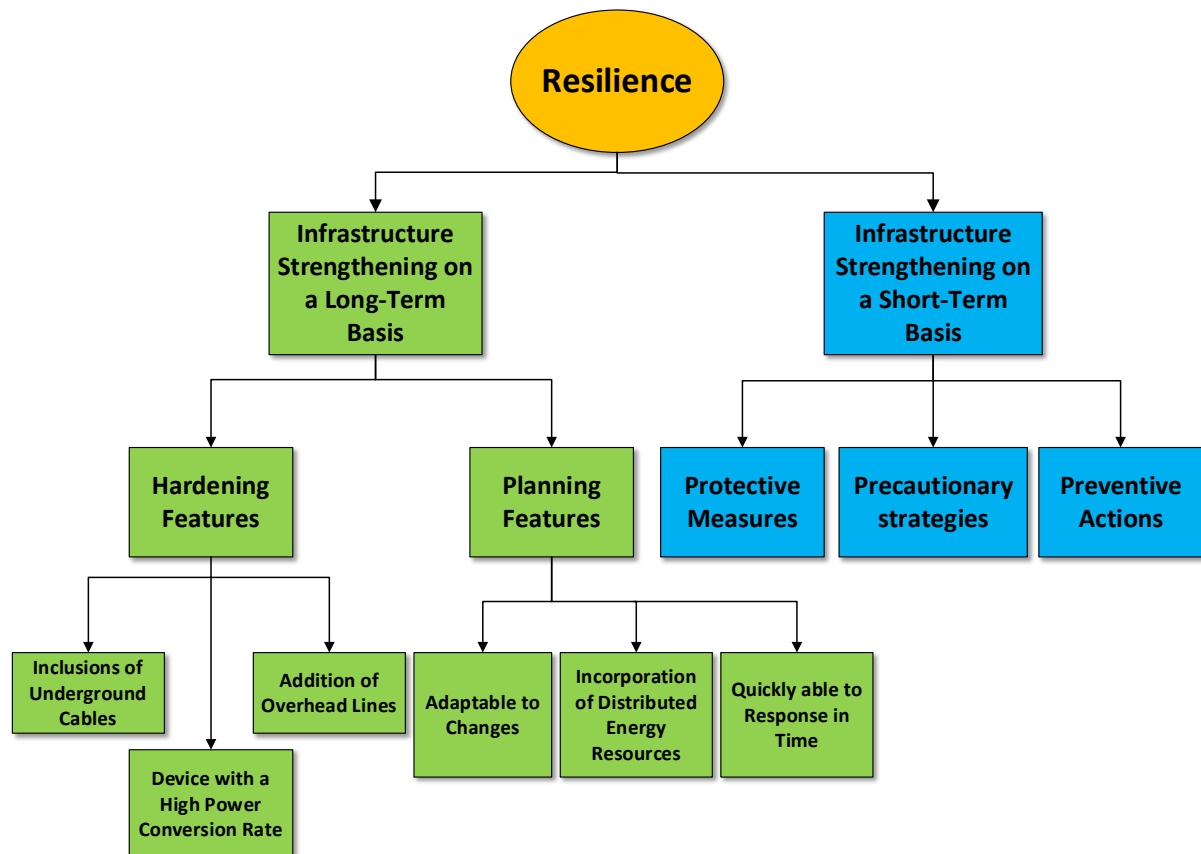

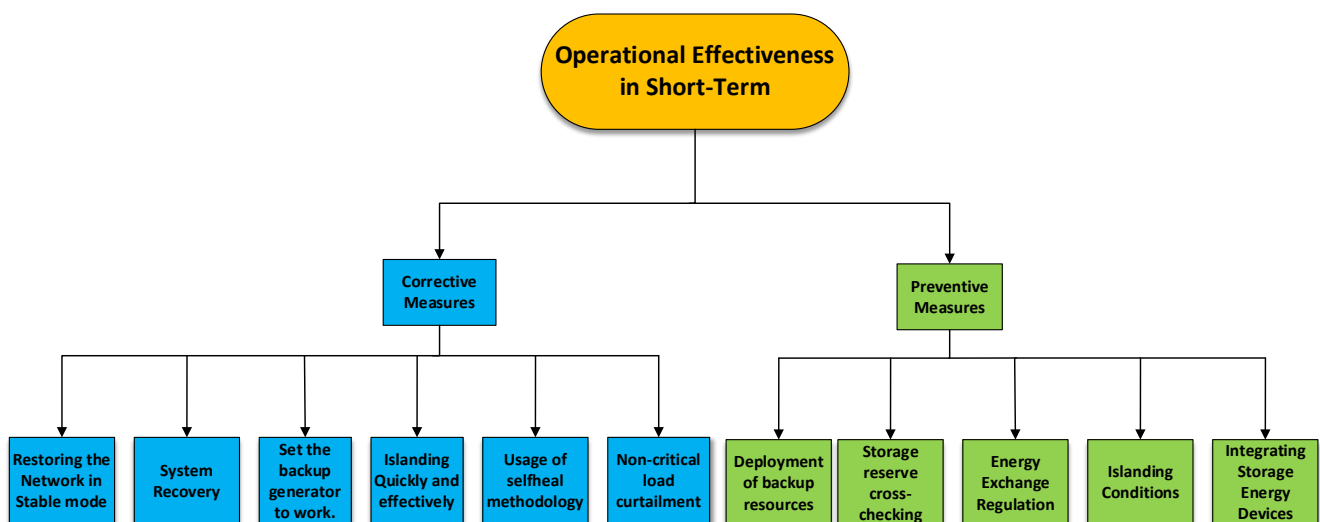**Figure 6.** Resilience infrastructure.

Figure 7. Short-term measures of Resilience.

The main objective of campus microgrids is to attain an efficient and reliable energy supply [116]. Emi et al. [117] contributed to the research and technological development of community microgrids, considering socio-economic benefits, appropriate power flow solutions, and community microgrid investment [118]. In a campus microgrid, resilience represents a considerable impact to deal with the disruption problems quickly and effectively [119]. As seen in Figure 8, it restores the system by dealing with the problem of continuing supply during disruptions [120].
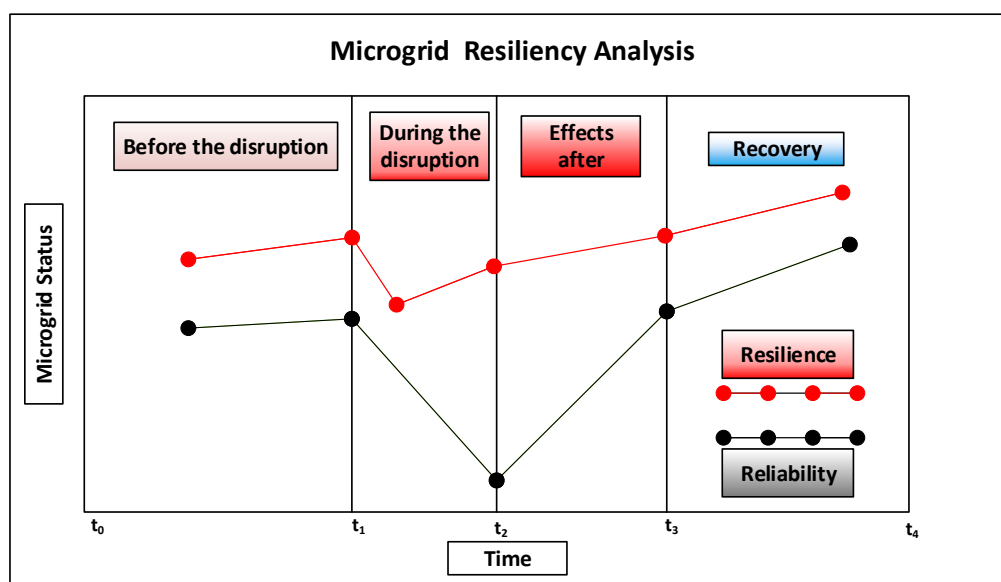

Figure 8. Microgrid Status vs. Time Comparison (Resilience vs. Reliability Comparison).

Once a disruption occurs, the system enters the pre-fault analysis of the fault in the t_0 time period for the microgrid. The resilience solves the disruption problem and enters the recovery phases accordingly for the faults in the t_0, t_1, t_2, t_3, and t_4 periods (hours). It shows the disruption stages that illustrate before, during, and after the disruption stages in the MG. It has to ensure that the non-stop supply of energy has been delivered to the system [121]. The microgrid status is shown in Figure 8 versus time comparisons.

Microgrids which are installed at campuses with energy storage systems create 100% clean, renewable energy which can be utilized in another campus or grid. Energy storage systems in campus microgrids generates clean electricity for the system [122]. Some energy storage systems, such as fuel cells, batteries, flywheels, ESS and SSS, etc., are reviewed here.

From the microgrid point of view, various authors have contributed to campus microgrid energy management using batteries, fuel cells, flywheels, different battery storage systems, etc. Kamal et al. [36] proposed a grid model and a solution to handle university campus microgrid loads, presenting a solution to manage EV (electric vehicle) connections, and mitigate problems related to campus peak demands. In this paper, the UCM campus included a three-phase 208 V distributed system with a 300 kW PV system, 100 kWh battery storage system, 130F SSS (super-capacitor storage system) 15 kW fuel cells. Results conclude that using an NOP-optimized algorithm minimizes the operating cost by around 117% for the UCM campus, but it can be further enhanced by giving various solutions to improve power quality, voltage, and frequency regulation or to implement an optimal EV charging strategy.

The BESS system installed by Niklas in [14], based at the Chalmers University of Technology in Sweden, was probably the best possible location and was determined with the consideration of profit for the campus microgrid. This scenario determined the BESS location in the grid-connected scenario and island-connected scenarios. In this paper, the microgrid-OPF technique was used to calculate the profit:loss ratio for the BESS system. The results aimed to show the benefits of the microgrid and locate the BESS system's best

possible location, but it lacked optimal BESS sizing. An optimal approach is needed to be developed to improve the system further. Multiple approaches can be implemented with OPF techniques such as GAs (genetic algorithms). However, another efficient system was proposed by Angelim in [38] to effectively manage energy for the Federal University of Pará, Brazil. The proposed system consisted of PVs and a BESS system. It minimized the consumption cost of energy using the annealing algorithm technique. Results compiled from the simulation showed that case 3 (PV + BESS) was the most effective scenario, which effectively managed the energy and reduced the campus energy usage costs. However, it also lacked BESS sizing; as mentioned for [14], multiple approaches such as GAs can be used to reduce the energy consumption costs.

However, an optimal solution model is presented in [4] to effectively manage energy for the Cyprus University Microgrid. In this proposed model, an optimal solar–PV and BESS system was installed at the campus microgrid. In this way, simulation analysis was performed to calculate the NPV and IRR price calculations for electricity. Calculated results show the pricing for the first scheme of DSOs (distribution system operators)—NPV obtained was EUR 4,061,332, and pricing for the second scheme was EUR 1,252,853, although with the use of DR (demand response) schemes or real-time pricing schemes, it could be further improved, also improving the NPV or IRRs cost for the Cyprus University microgrid.

On the other hand, a campus microgrid's structural design, operation, and controllability are discussed in [123] based at Clemson University, South Carolina. The proposed microgrid model fulfilled IEEE standard 1547.7. This study considered the applicability of conversion from grid-connected to island-connected mode. Results show that the overall system which used DG [124] represented a USD 2000 profit, the solar–PV system represented a USD 74,000 profit, and the BESS system represented a USD 5400 profit. A miscellaneous system represented a USD 5000 profit, whereas the overall profit calculated for the microgrid was USD 72,400; however, it lacked an optimal economic analysis for different types of DGs, BESS systems, or PVs used in the system. Thus, economic analysis can be useful for finding an optimal solution.

An economical and optimal solution is given by Rahim in [125] that aimed to reduce the cost of operation for isolated microgrids with optimal battery sizes. It consisted of RERs, diesel-operated generators, and a BESS system. The firefly algorithm proposed in this paper determined the optimal dispatch for the microgrid system to calculate the power production cost. However, it also considered the battery DOD (depth of discharge) to analyze the battery performance and operation cost. The results showed that the PSO (particle swarm optimization) method calculated the operation cost of the microgrid (USD 404.46), artificial bee colony (USD 393.10), and firefly algorithm (USD 325.68). Firefly algorithm is an effective method that saves the costs of operation of the microgrid, but the whale optimization approach, dragonfly algorithm, or modern approaches such as neural networks can also be incorporated, because sometimes the artificial bee colony method lacks precision; therefore, more advanced techniques should be utilized to find optimal solutions for the campus microgrid. On the other hand, a hybrid BESS system was proposed by Mazidi in [106] that included fuel cells as the main component and battery storage as a complementary component. In this study, the droop-based dynamic control strategy was implemented to quickly improve the fuel cells' power transition. The proposed control strategy was intelligent enough to manage frequency fluctuations among the SAMGs (standalone microgrids). It was simulated in Simulink-MATLAB to evaluate the performance of the fuel cells and battery by using time-domain digital simulation. Results showed that using this droop control strategy improved the lifespan of the FC battery system and developed an efficient hybrid battery BESS system, but to improve efficacy or efficiency, this model could also be implemented in HOMER pro to further enhance accuracy and precision, and robust control strategies should be adopted to further improve the SAMG energy.

A BESS and DR-based PV system was also introduced by Zhang [65] for the Guangdong University of Technology microgrid, based in China. It was implemented with an improved NSGA-2 (Non-dominated Sorting Genetic Algorithm-2) that mainly focused on

the annual profit and maximum PV consumption. The main objective was to calculate the total cost of BESS, minimize the operational cost, satisfy the consumers, compensate for power fluctuations, and achieve maximum economic benefits. The obtained results show that BESS operation cost is too expensive at the start, but it reached the breakeven point in almost ten years, although it needed to enhance more economic benefit for the microgrid by applying more advanced algorithms such as NSGA-III, random weighted genetic algorithms (RWGAs) or weighted genetic algorithms (WGAs).

In [126], another study was performed to help different entities improve factors such as participation in the market, the degradation of BESS, and the annual replacement of BESS through realistic CAISO data. Results show that it achieved an increment of 4–5-fold in the NPV compared with the day-ahead energy market. For NAS batteries, it effectively managed the degradation of batteries under a 1 MWh/MW power-to-energy ratio and a 20% improvement in NPV, but it lacked optimum solutions as for which type of BESS system needed to be adopted. An effective solution should be given by conducting an economic analysis for the batteries.

Different types of fuel cells, batteries, flywheels, ESS and SSS, etc., are reviewed here, as shown in Figure 9.
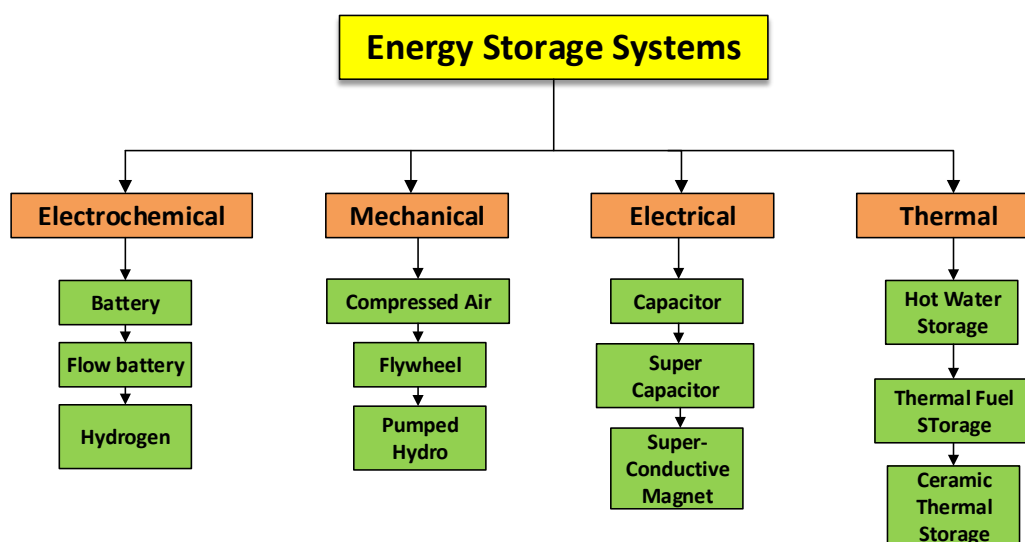

Figure 9. Different types of energy storage systems.

5. Simulation Tools for Campus Microgrids

These simulation tools are used as an optimization tool or to effectively estimate the performance of a campus microgrid. MATLAB/Simulink (MathWorks) is a mathematical computation program which using a fourth-generation high-level language. It can integrate with other programming languages such as C, Java, C++, Fortran, C#, and Python.

MATPOWER [127], on the other hand, is an open-source simulation tool which utilizes the Monte Carlo technique to optimally balance power flows among grids, which can practically assess the performance of a campus MG. Many tools are used for the energy management of campus microgrids, as indicated in Figure 10.

GAMS [128] is as an optimization tool for mixed programming, both linear and nonlinear. Various authors used it to resolve uncertainty problems for microgrids that effectively managed the energy and aimed to maximize the output.

CPLEX [129] is another tool which is compatible with Java, Python, and C++. HOMER PRO software is used by most contemporary authors in different kinds of studies.
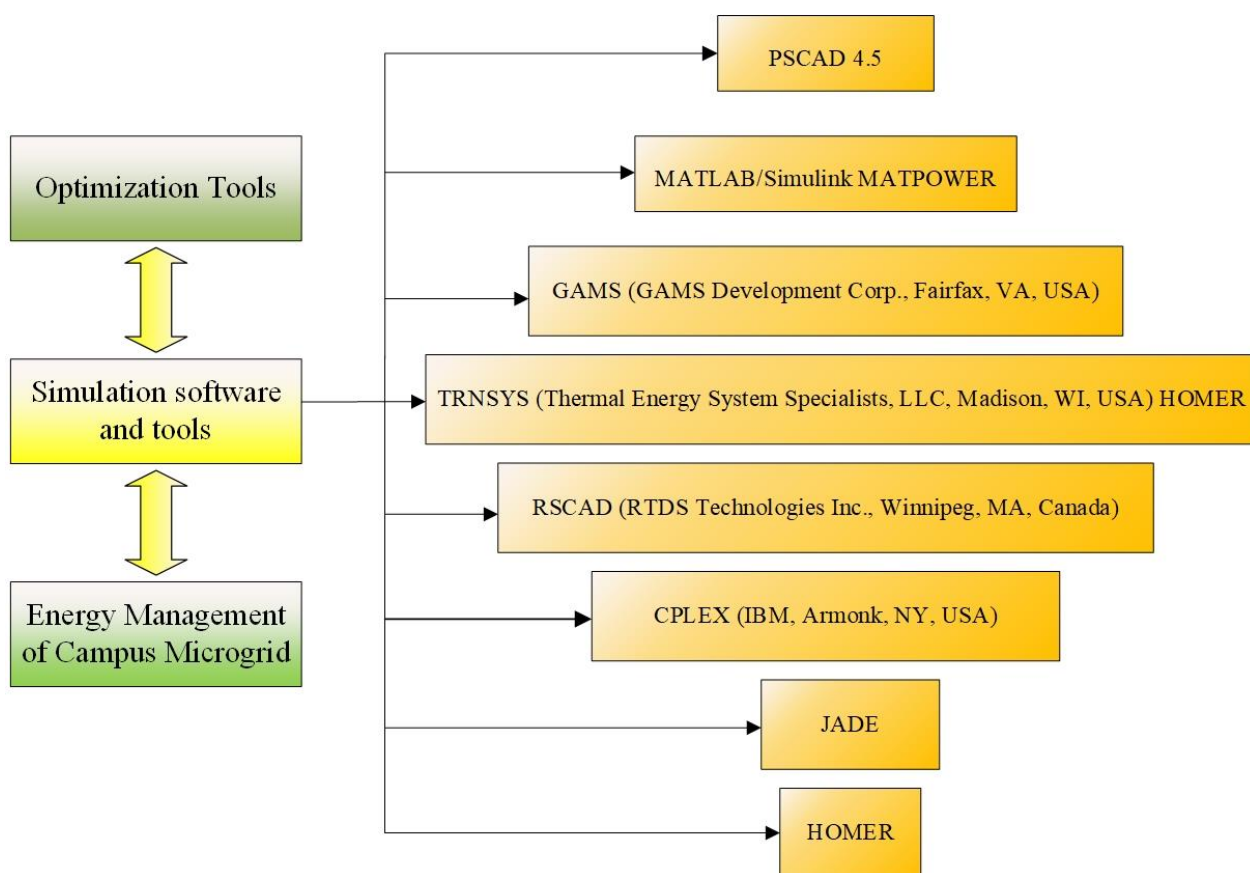
Figure 10. Simulation tools used in the energy management of campus microgrids.

In contrast, PSCAD 4.5 [130], TRNSYS [131], and JADE [132] are also employed at other campus microgrids, although HOMER, MATLAB, and CPLEX Solver are mainly used as optimization tools for campus microgrids.

Some of the simulation tools used in various microgrids are reviewed in Table 5.

Table 5. Simulation software used in the energy management of campus microgrids.

References	Tools	Objectives and Applications
[2,33,67,72,133–137]	MATLAB/Simulink	MATLAB is a high-performance, highly computational language. It incorporates visualization, computation, and programming, where solutions of the problems are found in the mathematical notation. It also includes mathematical calculations, modeling simulations, data analysis, visualization, and exploration. It is highly compatible with different programming languages (C++, Fortran, and Java).
[9,44,61]	HOMER	It is a simulation software that can model hybrid systems of power generation. It is used to design on-grid and off-grid power systems for stand-alone, remote, and distributed generation applications.
[138]	CPLEX Solver	It is an optimization tool that is compatible with C, Java, C++, and especially Python languages. It has multiple applications such as web development, game development, artificial intelligence, machine learning, data visualization, and data science.

Some of these software programs which have been used for optimization and simulation in different kinds of literature are illustrated below.

Muqeet et al. [135] presented three different scenarios for prosumers, integrating the energy market and benefiting prosumers economically. Three different scenarios were observed:

1. A system connected to grid power only;
2. A system connected to ESS and PV generation as well as the connected grid;
3. A system connected to the energy storage system, PV, and grid integrated with the grid.

In this system, the MILP technique was used in MATLAB, which optimally scheduled the energy storage. The proposed approach was scheduled in a high renewable penetration time to gain highly efficient results. Similarly, it scheduled the discharging for batteries in the off-peak period, which aimed to benefit prosumers. Results show that by installing the PV, Grid, and Wing power generation with ESS, a 67.91% reduction in the total operation cost was observed, from 631.93% to 202.724%. It was analyzed with the MILP technique, but it could also be analyzed with GA, PSO, or more advanced techniques such as artificial neural networks to obtain better results for campus microgrids, and more renewable energy resources can be incorporated, such as wind or hydro energy, to reduce the electricity bill for the U.E.T Taxila campus microgrid.

However, another model was developed by Kim in [139] to improve BESS systems, which was hybrid in classification. This model delivers specific behavior for the operation of lithium-ion batteries. It was validated on Simulink in MATLAB under various circumstances with the consideration of temperature and currents. This was then compared with the T. Kim hybrid model, which exhibited accuracy and improved Li-ion cells' running-time behavior. However, it lacked optimal BESS sizing for a hybrid system, which would give more precision and accuracy.

Saleh proposed a microgrid design in [140] for the Hawija Campus, Iraq. This MG consisted of a solar–PV generation system, controllable loads [141,142], and a BESS system [143]. In this paper, the simulation was implemented on Simulink in MATLAB using Droop controllers, which regulate the voltages in the MG. Results were obtained to reduce the operation costs and GHG emissions for the Hawija campus microgrid. However, for an integrated management system, smart loads should be included for demand responses to effectively manage the energy for campus microgrids.

Another algorithm is proposed by Shukur in [133], which improved the firefly algorithm (IFA) for the Connecticut microgrid. This improved algorithm optimized the generation cost, daily energy consumption, and generated the microgrid system's limits. It consisted of three generators in the first system and seven generators, two wind turbines, two diesel generators, and three fuel cells. This system was implemented in MATLAB. The results showed that this improved firefly was more appropriate and suitable than the other algorithms, CSA (Cukoo Search algorithm) and DE (Differential Evolution). The firefly algorithm can also be improved with the integration of machine learning. Moreover, renewable energy resources can also be incorporated to further reduce the daily energy consumption for the microgrid system [144].

Another system is proposed in [138] in which prosumers behind the meter resources are aggregated. This proposed system was solved in a multi-dimensional advance solver, CPLEX 12.6.3, an MILP solver. The technique was solved mathematically and tested on a 14-bus microgrid system, which minimized the complexity of constraints by replacing the variables of decisions with dummy variables. It aggregated the prosumers, generating electricity in one place and providing ancillary services to the respective grids. Two scenarios were concerned here to attain the final results: ramping rate and deferable loads. When the curve of the ramping rate increased, the cost was reduced [145]. On the other hand, when deferable load windows were extended, the cost was reduced. It lacked advanced approaches such as neural networks or advanced algorithms, but it could be enhanced further by solving it with a CPLEX solver in GAMS to improve the results.

Some of the related work was comprehensively analyzed with many optimization tools used in various campus microgrids to effectively estimate the performance and reliability. Various authors have used it to resolve uncertainty problems for microgrids, and

multiple solutions have been presented in the current paper to find optimal solutions more appropriately, which effectively manage the energy and maximize the output. This work focused intensely on the research areas mentioned above and gave a brief overview of the latest optimization tools such as CPLEX solver, HOMER PRO software, PSCAD 4.5, TRN-SYS, and JADE, which are used at many campus microgrids, although HOMER, MATLAB, and CPLEX Solver are mainly used as optimization tools for various campus microgrids.

6. Research Challenges and Conclusions

This paper also studied the research challenges which are essential in optimizing microgrid structures, which help in their planning, control, and operation. It also performed techno-economic analysis by implementing smart grid solutions into the power system. It studied various factors that harness energy and increase the utilization of renewable energy resources. Some of the challenges for the campus microgrid are mentioned here:

- To harness the potential of campus energy;
- To boost the campus's renewable energy utilization;
- To minimize the operational cost of the campus microgrid;
- To maintain the stability and reliability of the system;
- To minimize the utilization of utility energy by providing RE resources;
- To make the system reliable by implementing advanced optimization techniques into the system;
- To improve the system by reducing power fluctuations such as voltage or frequency fluctuations;
- To make the system more efficient, an advanced EMS (energy management system) should be developed;
- To make the electricity unit pricing efficient, a reliable, improved time-of-use pricing scheme is mandatory;
- To achieve economic benefits, an efficient techno-economic analysis was calculated;
- Developing the system more sustainably requires an effort to maintain an efficient framework for sustainable campus microgrids.

In this paper, brief comparative research has been analyzed and recommended based on various optimal approaches for various types of campus microgrids, and they were investigated with multiple optimization techniques, simulation tools, and different types of energy storage technologies.

It was analyzed that various campus microgrids worldwide lack efficient energy management with old-fashioned techniques because there are many effective solutions which are available that can further enhance their systems into smart ones. Many microgrids lack the optimal sizing of BESS, deficiencies of power quality in their systems require voltage regulation, and many of them are using outdated methods and techniques to their campus microgrid's energy costs. This literature review is summarized to give researchers, policymakers, and campus microgrid owners a proper and up-to-date solution by providing recent updates on the trends in campus microgrid energy management worldwide. This was analyzed with multiple tools and techniques used in various campus microgrids, so an efficient energy system could be developed.

The feasibility and techno-economic analysis of the campus microgrid have also been focused on here. The recent literature aims to minimize the cost, maximize available resources, and minimize the energy trading among microgrids for the HEC higher education universities. Many different campuses analyzed had innovative microgrid approaches to help improve energy efficiency and reduce energy loss and GHG emissions.

The energy management schemes of multiple campuses such as Eindhoven Campus, University of Genova (Savona campus), YZU campus (Yuan Ze University), Connecticut Microgrid Campus, USTO (University of Science and Technology) Algeria campus, University of Novi Sad, Clemson University, South Carolina, and Tsinghua campus microgrid China were analyzed. The literature also provides some of the latest research for innovative researchers that aim to convert the existing conventional microgrids into an intelligent grid system.

The main objective of this study is to present a brief overview of the recent studies on campus microgrids that cover both the operating costs and the utilization of the energy systems. It also covers some topics on EMSs (energy management systems), CBSs (control-based systems), energy trading, energy management of the campus microgrid, and systems which can stabilize campus microgrid systems. It also contributes to the research and technology for the development of smart campus microgrids, considering socio-economic benefits, appropriate power flow solutions, and smart campus microgrid investments.

It also focuses on the campus microgrid systems such as wind, energy storage, solar–PV, EV charging/discharging scenarios at these institutes. These topics were based on real microgrid systems with multiple solutions and implementation scenarios aiming to harness green energy, develop an efficient smart campus, and achieve sustainable energy for campus microgrids to reduce GHG emissions.

It also analyzed the energy trading policies in the recent literature between prosumers and consumers. Prosumers have a choice: either to choose utility and purchase electricity from the grid, or run in islanded mode. The aim is to maximize renewable energy utilization and minimize the ESS cost and generation cost, which affects the prosumer economically.

The solution for these problems is to invest in smart grids that will make the existing conventional microgrids into smart microgrids. It is suggested that maintaining energy supply is crucial for every campus microgrid, especially during a grid outage. This will achieve greater efficiency for the whole microgrid system. Prosumers will also take benefit from their improved electricity generation and load flow management. It will be crucial to reduce GHG (greenhouse gas) emissions and global warming, especially through CO_2 reduction. Moreover, this latest research will be helpful for those researchers who are aiming to explore the field of energy management, energy trading, smart grid, and microgrids with multiple optimization techniques, simulation tools, and different types of energy storage technologies.

Finally, advancements will be needed in demand response management on the utility side, where utility cost reduction will be concerned. More progressive approaches will be required in the future that aim to maintain the stability issues, transient issues, load variations, and the sustainability of microgrids. In the future, advanced approaches should be utilized for campus microgrids such as artificial intelligence, deep learning, peer-to-peer energy trading using blockchain, and neural networks. These are the modern research trends for the campus microgrid that needs to be focused on to develop more efficient methods to manage the energy in this digital age.

Nomenclature and Acronym

The following acronyms and nomenclature are used in this manuscript:

DSM	Demand-side management
DG	Distributed generation
DERs	Distributed energy resources
DG	Distributed generator
DER	Distributed energy resources
DiG	Diesel generator
DSM	Demand-side management
DR	Demand response
EMS	Energy management system
FIT	Feed-in-tariffs
FC	Fuel cell
GAMS	General algebraic modeling system
GHG	Greenhouse gas
GE	Gas engine
MILP	Mixed integer linear programming
MPC	Model predictive control
MT	Micro turbine
μG	Microgrid
PV	Photovoltaic
PSO	Particle swarm optimization
VPP	Virtual power
WT	Wind turbine

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