Introduction of Campus Microgrids

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Campus Microgrids are a scattered group of power sources and electrical loads that are usually synchronous with the primary grid, called the utility grid. 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.

Keywords: campus microgrids ; energy management system

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. Campus 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.

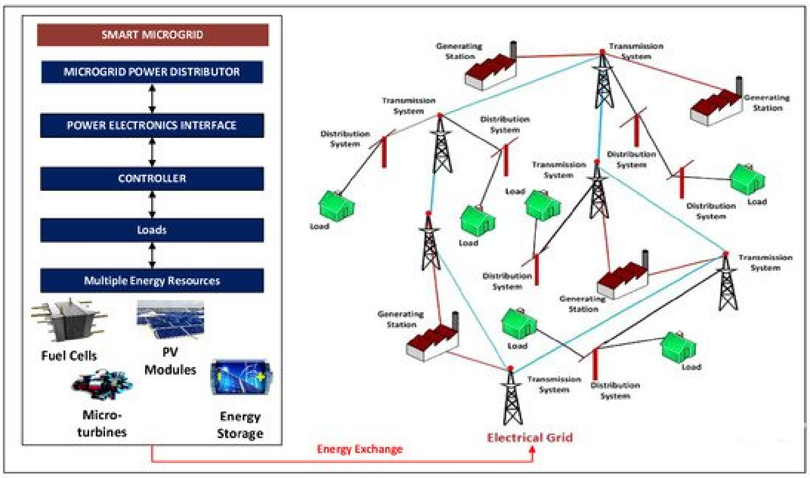

Figure 1. Schematic diagram of a microgrid.

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 developing 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**.

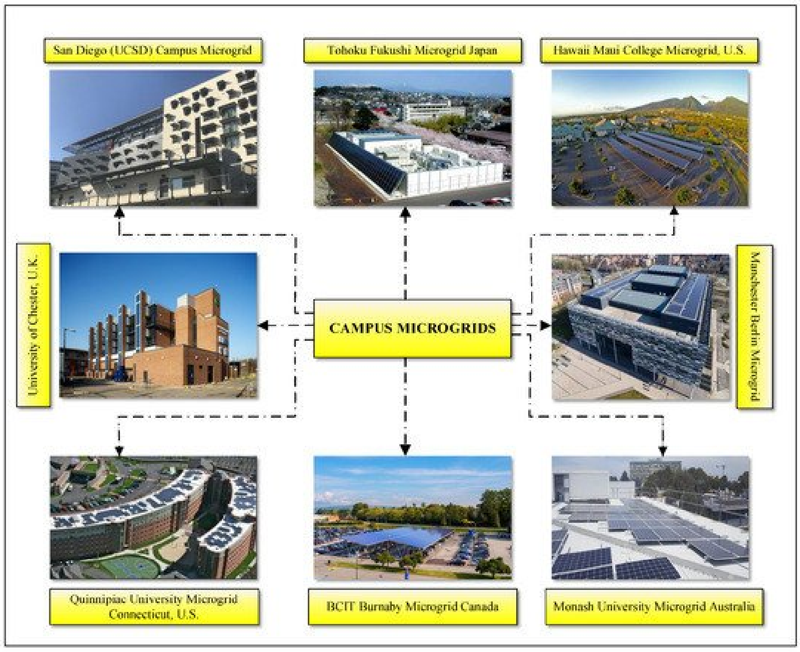

Figure 2. Overview of campus microgrids at different locations.

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**.

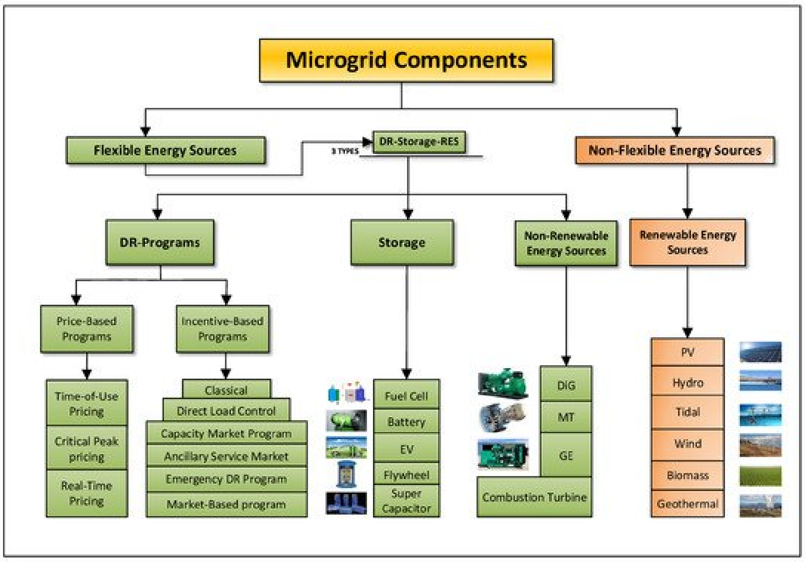

Figure 3. Microgrid components.

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**.

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

Refs.	Campus	Technical Aspects										Load Type
		Components										
		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

Refs.	Campus	Technical Aspects										
		Components										Load Type
		PV	BESS	Wind	Biomass	DG 1	MT 2	EV 3	SC 4	FC 5	CHP 6	Campus/Building
[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
[37]	Yuan Ze University, Taiwan	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	Campus Building
[14]	Chalmers University of Technology, Sweden	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus
[38]	Federal University of Pará, Brazil	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	Campus

Refs.	Campus	Technical Aspects										Load Type
		Components										
		PV	BESS	Wind	Biomass	DG [1]	MT [2]	EV [3]	SC [4]	FC [5]	CHP [6]	Campus/Building
[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.

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.

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.

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.**

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

Ref.	Location	Components	Optimization Techniques for Energy Management	Economic Analysis
[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.**

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.
[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.

Existing Literature Reviews of Microgrids	Objectives
[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.**

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