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SURVEY

Survey of Strategies to Optimize Battery Operation to Minimize the Electricity Cost in a Microgrid With Renewable Energy Sources and Electric Vehicles

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ABSTRACT There is a rapid increase in the utilization of renewable sources such as solar and wind to provide power and electricity. The reason for this trend is to reduce costs and preserve the environment. However, the challenge is to efficiently use and store the energy from these sources. One approach is to optimize the decision when to charge or discharge a battery. The objective is to generate the greatest monetary gain. More charge/discharge cycles will reduce the life of a battery, thereby increasing the cost. A strategy to reduce the number of charge cycles while maintaining the effectiveness of electricity distribution from battery storage will improve battery life. With the inevitable proliferation of electric vehicles (EVs) in the market, strategies specific to electric vehicle battery profitability will be explored. An additional concern which threatens the financial feasibility of battery energy storage systems (BESSs) is the requirement of secure operation. There is currently little research study on strategies to detect cyberattacks on such systems. In this paper, we have presented a novel taxonomy for battery optimization, survey representative BESS utilization strategies, and classify these schemes within the taxonomy. Within our classification, we outline the battery optimization methods that have been discussed, analyze their ability to address issues that arise when implementing a BESS, and describe alternative research that could be explored. Future research could refer to this information to create unique battery optimization schemes to provide more efficiency and optimal revenue for a BESS when compared to current strategies.

INDEX TERMS Energy storage, battery management systems, renewable energy sources, microgrids, electric vehicles, machine learning.

I. INTRODUCTION

Distributed microgrids based on renewable energy sources provide a promising solution for rural areas and underdeveloped countries where electricity is not available [1], [2], [3], [4], [5], [6], [7], [8], [9]. Compared to fossil fuels, the cost is reduced making electricity more affordable. However, there are challenges inherent to the use of renewable energy sources such as the reduction in the quality of power, unstable frequency, and voltage instability, as well as issues related to security and reliability [1], [3], [4]. To stabilize the power source, reserved electricity can be acquired using a local power utility or an energy storage system. Power companies normally use fossil fuels that are hazardous to the environment. An advantageous alternative is a battery energy storage system (BESS), as shown in Fig. 1. A BESS can be installed quickly, is inexpensive to operate, responds quicker to disturbances and requires less space than other energy storage options such as pumped hydro or thermal energy [1]. With the decreasing cost of batteries [4], battery energy

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storage is also developing rapidly in commercial applications. Renewable energy microgrids can incorporate BESS in many applications to support utility companies such as peak shaving, load leveling, reserve energy, and voltage and frequency regulation [7]. Some disadvantages of BESS include a short lifespan and costly installation costs. Therefore, it takes a few years to break even financially, and hence its limited use in the power industry [10].

The number of charge/discharge events reduce the lifecycle and performance of batteries as well as the high temperatures, overcharges, and deep discharging. To stabilize the microgrid, coordination must exist between the BESS and the renewable energy sources. There has also been research related to energy management systems that use distributed BESS which can be effective in large commercial buildings. Other research has shown that the use of state of health (SOH) and state of charge (SOC) information can make BESS less expensive by deploying efficient battery management systems (BMS) [1], [2], [4].

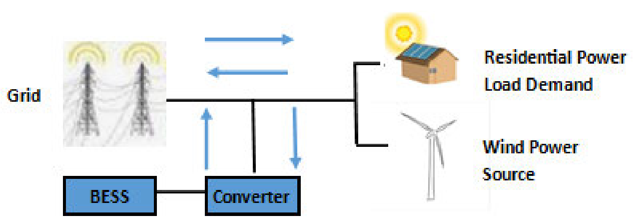

FIGURE 1. Solar-battery energy storage system topology.

One approach [1] discussed a strategy to control a microgrid that utilizes renewable energy with a distributed BESS to operate batteries that use SOH, SOC, and battery capacity to make decisions. The proposed method uses the battery SOH and loss of capacity in the control algorithm as well as the battery depth of discharge (DoD). Therefore, capacity loss is regulated by the decision to charge or discharge batteries.

The automobile industry is undergoing a paradigm shift from traditional exclusively gas-powered vehicles to electric cars which have improved reliability, efficiency, and environmental friendliness [6]. Research has shown that batteries in Electric Vehicles (EV) that are idle and grid-connected can provide electricity back to the grid. By combining EV battery power, electricity can be sent to the grid to provide demand services such as Volt-Amps Reactive (Volt-VAR) control, frequency regulation, and renewable energy integration using a distributed vehicle to grid (V2G) system [6]. V2G allows EVs to interact with the power grid and uses algorithms to decide whether to charge a battery to provide grid services. V2G applications include algorithms that can be incorporated into charging stations, control systems, EVs, and grid centers, as well as distribution and grid generation systems. V2G can also provide financial rewards by selling demand response services and renewable energy to the grid.

The use of renewable energy within the electric grid has increased dramatically over the last several years, but this trend has been undermined by its unpredictability [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24]. Because of the inherent nature of solar and wind energy, fluctuations cause the generated power to be inconsistent. This can lead to issues in the electric grid such as power quality, reliability, generation dispatch and ramp rates (speed of generator to change the amount of electricity production). Generation dispatch refers to power grid operators programming electricity sources based on the market demand. To confront these issues, an energy storage system can be added to a renewable energy system to smooth the power output. The Energy Storage System (ESS) has been found to provide an effective solution for the challenge of the fluctuation of the output of renewable power as it can provide energy when the renewable energy is low and can store power when it is high.

The BESS is the most common ESS and utilizes electrochemical cells. In power system applications, several cells are combined to satisfy the target voltage of the system. BESS has some advantages such as quick response time, energy efficiency, little maintenance, practical size, and simplicity of installation. Therefore, BESS is a prevalent application of ESS to balance renewable energy output power. Fig. 2a illustrates that the amount of electricity demand in the United States is projected to over 5000 terawatts by the year 2050. Fig. 2b shows that the forecasted battery storage capacity in 2050 will be over 150 gigawatts for the low-cost renewables case, which assumes a 40% reduction in the cost of renewables and energy storage compared with the reference case in the graph.

The projected growth and evolution of distributed energy resource deployment through solar, storage systems, and other environmentally friendly technologies could introduce cybersecurity threats to the public power grid infrastructure. Because the electrical grid and BESS sensing devices are connected to the Internet, BESS is vulnerable to cyberattacks. A false data injection attack (FDIA) can corrupt the values detected by sensors along with SOC measurements. Such attacks can lead to financial losses [25].

A. MOTIVATION

Currently, energy is mainly supplied by traditional resources. However, there is a limited quantity and constant increase in costs. Currently, there is a paradigm shift towards renewable energy sources. The most viable options are solar and wind energy, which are established technologies. At a lower cost to generate electricity, photovoltaic (PV) solar energy conversion systems are utilized in microgrid applications [21]. However, solar energy is inherently intermittent. To guarantee a steady power supply, battery storage technology is used as a component of the system.

In a microgrid environment, BESSs are widely used to balance the power generation supply and load demand. BESSs also address issues such as energy management, peak shaving, power quality, load leveling, supply stability,

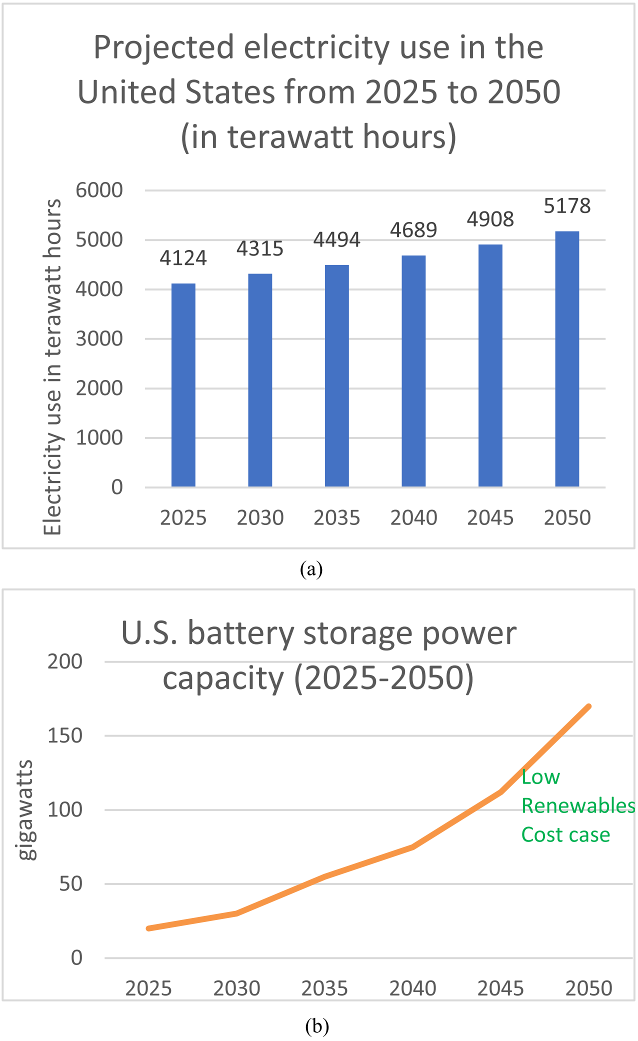

FIGURE 2. a. Forecasted U.S. electricity consumption. b. Predicted U.S. BESS capacity.

voltage regulation, and uninterrupted power supply. Along with microgrids, BESSs are also used in electric vehicles (EV). BESSs help address fluctuations in renewable energy sources.

The objective was to reduce the battery cost by extending its lifetime, enhancing the efficiency of the BESS, and minimizing the overall electricity cost for the consumer. This can be accomplished by providing an optimized strategy for charging and discharging the batteries. Excess charge/discharge cycles and maintaining a state of charge above or below a given threshold shorten the lifespan of the battery.

The BESS comprises two components: optimal battery utilization and revenue maximization. This is a critical issue for future research.

In this study, we address both topics. We also integrated renewable energy sources with the BESS. This is an area for further investigation. Many strategies should be explored in future research. Table 1 lists the cited publications related to battery charge optimization and opportunities for further research.

B. CONTRIBUTIONS

Our contributions are specifically:

1) A taxonomy that focuses on the highlighted surveyed approaches can be classified and categorized by the approaches and strategies for battery optimization.

2) A comparison of the various battery optimization algorithms that have been applied to BESSs.

3) Identification of current strategies and future trends that can be positively leveraged and applied to BESSs when deploying applications to provide power to the grid to maximize profit.

4) An overview of the problems and challenges faced and novel ideas to address these issues.

C. ORGANIZATION

The remainder of this paper is organized as follows. Section II provides a review of the related survey papers. Section III identified existing BESS publications relevant to our investigation. Finally, Section IV concludes the study and identifies potential directions for future research.

II. RELATED SURVEYS

Three representative studies were surveyed. A survey of related literature is presented in [14]. This paper provides a compilation of control strategies that utilize BESSs in conjunction with the power output from wind, which can be incorporated in solar power and other applications. The review concluded that many approaches use fuzzy, proportional-integral (PI), and MPC control strategies. However, there is a gap where little research has been performed on deep learning which is being used more frequently as a control technology with regards to wind energy.

Table 2 provides a summary of related surveys and their research topics.

Numerous strategies have been proposed to regulate the charging and discharging of the BESS, such as PI, PID, H-infinity, Model Predictive Control, Fuzzy logic, and non-linear prediction control, as shown in Table 3 along with the characteristics of each approach.

NLPC (non-linear prediction control) minimizes a cost function by finding the optimal control inputs and forecasting the behavior of nonlinear systems. H-infinity determines the highest increase from system output disturbances to create controllers that calculate the optimal performance of the system. MPC resolves an optimization issue for given time intervals to produce control input values.

Fuzzy logic uses heuristics, fuzzy rules, and linguistic parameters to formulate decisions. Proportional integral derivative (PID) performs system regulation by utilizing derivative, integral, and proportional terms. A subset is proportional integral (PI) that ignores the derivative term.

The advantages of NLPC are that is robust enough to enhance the performance of systems that are complicated and

TABLE 1. Comparison of related work and suggested enhancements.

Ref.	Year	Topics	Research Gaps	Suggested Enhancements
[15]	2013	Use larger batteries	Did not address increasing battery life	Increase life of large batteries
[5]	2018	Battery control	Cost/revenue optimization was not Addressed	Present BESS operation optimization
[18]	2019	Minimize cost of BESS	Weights in multi-criteria optimizations could be used to develop a robust design	Develop appropriate algorithm to address expense
[6]	2019	Grid management	Real data could be used in machine learning algorithms	Use historical data to train machine learning models
[25]	2019	Secure BESS	Simulated data used to detect attacks	Use actual data from known attacks
[1]	2020	Increase battery life	Only simulated data was used	Utilize real data
[14]	2021	Control for BESS	Not much research with deep learning	Apply deep learning methods
[27]	2021	Attack identification	IEEE test system was used, which is most representative of real-life environment	Test system generally lacks accurate and current data
[23]	2022	Predict demand	Only unsupervised machine learning was used [24]	Incorporate machine learning models with supervised learning
[22]	2022	Deregulated power	Demand must be determined a day in advance	Create adaptive algorithm using more current demand values
[26]	2023	Grid vulnerability	Simulated data used to detect attacks	Use actual data from known attacks

TABLE 2. Summary of related surveys.

Survey	Year	Topics	Machine Learning
Hybrid solar-electrical energy storage technologies for power supply to buildings [18]	2019	Minimize the cost of hybrid PV-BESS Application of various algorithms	None
Discussion of BESS applications [28]	2021	Technologies, optimization goals, constraints, approaches, and outstanding issues for BESS	None[29]
Control strategies to smooth wind power output using BESS [14]	2021	Fuzzy, PI, and MPC control strategies	Mentions deep learning for future research
Survey of strategies to optimize Battery Operation in a microgrid with renewable energy sources and electric vehicles [our survey]	2023	PV/BESS optimization and revenue maximization	Seven papers cited

nonlinear. However, it has issues with tuning and modeling. H-infinity is also robust and works best with time invariant and linear systems. But it is burdensome to apply to systems with a high degree of computations, tuning, and design. MPC is a powerful approach that addresses assumptions and limits while producing performance optimization. Its weakness is

TABLE 3. Comparison of major BESS charge and discharge regulation control strategies.

Strategy	Control Mechanism	Advantages	Pitfalls
NLPC	non-linear prediction control	Robust enough to enhance complex and nonlinear systems	Issues with tuning and modelling
H-infinity	controller	able to handle unpredictability of parameters	Not conducive to systems with many computations, tuning, and design
MPC	model predictive control	effective with parameter limitations	Handling high degree of modelling and computations
Fuzzy Logic	Controller	model complex systems	Not suitable for systems requiring preciseness
PI / PID	proportional integral controller	Quick deployment	Not effective for complicated or nonlinear systems

handling modeling and computations. Fuzzy Logic is flexible and simple but should not be selected for systems where preciseness is necessary. PI / PID can be used on many types of systems since it produces good results and is easy to implement. Another option may be better when it comes to nonlinear or very complicated systems.

Related surveys have contributed important work; however, we believe our survey is the first to present a detailed description of machine learning in BESS and study the relevance of the different approaches described. Our focus on machine learning has highlighted methods that address specific optimization issues related to BESS.

Other strategies are used to minimize the cost of hybrid Electrical Energy Storage systems [18]. Particle Swarm Optimization (PSO) and genetic algorithms (GA) were utilized to select the battery charge and discharge decisions in a PV-wind-BES system. A Harmony Search algorithm was used to calculate the charge schedule of the battery storage unit in the PV-BES system. Further research can include different strategies to make decisions regarding charging/discharging batteries using various weights to result in multiple criteria optimizations to develop a robust design. Also, [30] more analysis of optimization methods should be performed to determine the best application of each algorithm used to attain more accurate solutions for PV-EES systems.

The next survey [28] presents a review of BESS regarding optimal size goals, system limitations, models for optimal usage, and various strategies. This review also discusses BESS applications. The objective is to provide an effective, robust, and optimal BESS that utilizes renewable energy sources for environmental sustainability.

III. SURVEY OF BESS OPTIMIZATION SCHEMES

In this section we classify the existing BESS strategies into 11 classes. Relevant papers were added to each topic to classify the existing work into different subclasses.

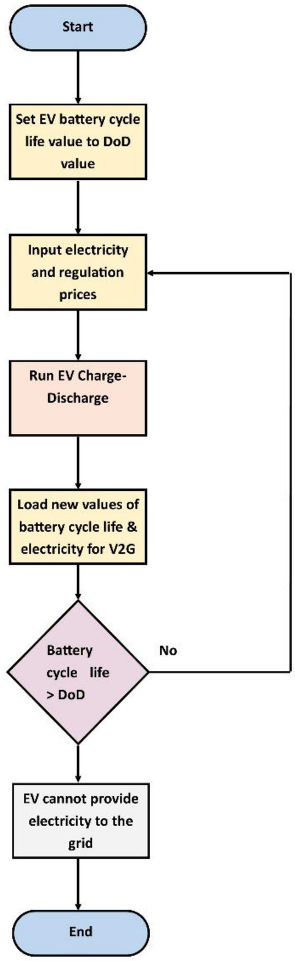

FIGURE 3. Flowchart of algorithm for decision to charge/discharge EV battery.

A. OPTIMIZATION SCHEMES UTILIZING DEMAND SIDE MANAGEMENT OF BATTERY ENERGY STORAGE TO REDUCE ELECTRICITY COST

In this class we surveyed 11 papers. In [15], an algorithm was proposed to distribute an increased amount of traffic into data centers with a reduced electricity price and charging the battery when the electricity price is low and discharging when the electricity price is high. The authors demonstrated that the larger the battery, the more cost-saving the proposed algorithm obtained. The algorithm was oversimplified and did not address the issue of increasing the battery life. They only commented that it was predicted that the battery cost would be reduced significantly in the next decade.

The authors of [13] created a hybrid optimization algorithm in which forecasting of the PV power and EV charging load is not needed. The algorithm calculates the optimum values using real-time data; therefore, the optimization procedure is less complex. The use of forecast data with machine learning algorithms can be compared to their results.

A method to control electric storage [20] was proposed based on predicting electricity prices to calculate the time required to charge the battery. An accurate forecast of electricity prices and demand would result in a charging schedule as follows: discharge during the highest price intervals and charge in the lowest price periods; reduce the use of energy during discharging periods until the battery runs out and increase energy consumption while the battery is charging.

Reference [4] describes the benefits of the proposed methodology to minimize the total cost of electricity with more efficient use of the BESS using constraints. The simulation results show that the power demand in a particular region can be met using BESS. However, the conservation of battery life is not considered to be a cost factor.

In [32] data from over 4000 homes with PV/BESS were modeled, trained, and tested using a machine learning algorithm. The results showed that smaller batteries generate better profits. It is interesting to note that the work in [15] produced directly conflicting results where larger batteries were found to provide better financial outcomes. The complexity of the model was reduced by simplifying the operation of the PV modules, inverters, and batteries. In addition, assumptions were made regarding the data sources that were input into the model.

The research in [33] produced effective strategies for private home battery storage by utilizing peak load shaving. The performance of the microgrid system was evaluated using a simulated PV energy source.

The authors in [34] presented a cost analysis of PV-BESSs using an improved Hybrid Optimization by Genetic Algorithms (iHOGA), but there was no discussion of the methodology used to implement the algorithms.

A mathematical model was proposed in [35] to determine the amount of energy consumed in which residential PV-BESSs become profitable: Several assumptions were applied to the model including the life span of the PV system to be 20 years and the ESS's lifetime to be 6 or 8 years.

In [36], the economic advantage of utilizing second-use batteries from electric vehicles was studied. As the use of EVs increases, the conservation of electricity demand from the grid becomes critical. One strategy for relieving the electricity grid is to charge the battery when the PV system generates power at its peak. Accurate forecasts are necessary for battery charge/discharge strategies to optimize grid use and maximize profitability. The authors developed a simulation model but did not specify a method for predicting solar energy production.

The research in [37] concluded that the technological advances in BESS and renewable energy sources affect the strategies for demand side management. In addition, governments provide a variety of financial incentives to encourage different aspects of demand side management. The authors studied and categorized the programs of several countries to promote the use of renewable energy and the corresponding ways that demand side management is utilized in those environments.

Our research shows that the economic implications of using solar or wind power sources significantly enhance profitability for EV users [38]. In addition, financial incentives are currently being offered by the U.S. government, for example federal tax credits of $7500 to purchase electric vehicles [39].

A new model was proposed in [40] for a shared battery station (SBS) to maximize the profitability of the SBS owner and replace the established battery swapping station (BSS) and battery charging station (BCS). Batteries deployed at the SBS can be charged, discharged, swapped, or run in sleep mode. The authors developed an objective function to optimize the number of active batteries at the SBS to maximize revenue. Simulations were conducted to validate the effectiveness of the model. The scalability of SBS can become an issue if peak shaving and valley filling are used to increase revenue. Machine learning can be utilized to predict demand and determine the optimum number of batteries used in the SBS at a particular time.

B. OPTIMIZATION SCHEMES BASED ON MAXIMIZATION OF SUPPLY SIDE REVENUE WITH A RENEWABLE ENERGY/BESS CONFIGURATION

In this class, we surveyed seven papers. Fluctuations in the generation of PV power were addressed using an optimization strategy to determine the most effective battery size. A randomized algorithm was used to increase the revenue of the PV/BESS [41]. There is no universal solution because of differing environmental conditions and electricity prices in different regions. The impact based on data from 415 households with EVs on hybrid PV/BESS showed that higher profit was realized for the self-consumption system [42]. However, the model results changed dramatically, based on assumptions regarding the prices of electricity and technology.

The study in [43] showed that standalone PV/BESSs that are not connected to the grid are economical for some households. Even with a grid, the connection electricity costs may be reduced. The authors utilized an oversimplified battery charge and discharge model that only included the degradation of the battery by artificially increasing the initial system size. Currently, the PV/battery system cost is high; however, the current trend shows a decrease in these costs [44]. Therefore, in the authors' opinion, PV/BESS will supplement the grid rather than replace it.

Not only are there economic benefits, but the environmental impact of PV/BESSs is also being scrutinized in current research. For example, in [45], simulations were performed to measure the lifetime and perform financial analysis of the PV/BESS in all 50 states. However, only the effects of the PV size and battery capacity on the performance and cost were analyzed. It was found that the cost of a PV/BESS system is like that of a standalone PV system.

The authors in [22] described a deregulated power network in which entities other than utility companies generate electricity. They mentioned that, in this scenario, the renewable energy source must submit its bid for electricity to be generated one day in advance. However, there has been no discussion on the methodology used to predict this value. We propose utilizing machine learning to accurately predict the solar irradiance produced by collocated solar panels.

In [23] a data-driven distributional robust optimization (DDRO) strategy was used, which was tested and verified using real data to predict day-ahead electricity demand. Upon reviewing the dataset, only the output variable solar irradiance was used. We present the use of supervised learning to predict the solar output based on atmospheric input variables. In addition, a weakness of their methodology is the need for more computational power which consumes both resources and time. This could cause a delay in real-time calculations, which could affect the accuracy of BESS operation.

C. OPTIMIZATION SCHEMES BASED ON PEAK LOAD LEVELING AND FREQUENCY REGULATION

For this class we surveyed 1 representative paper. Electric Vehicle (EV) batteries can be used to support several power grid services and to form a V2G system. In [6], the authors developed an objective function for an EV model to optimize charge and discharge decisions by utilizing the frequency regulation and electricity prices from both real and forecasted models. They presented a case study for the charge/discharge scheduling problem utilizing real and predicted frequency regulation and hourly electricity pricing for one month of data. They developed an optimization model and integrated the battery degradation cost into the charge/discharge scheduling of EVs. The input variables used during the simulation were SOC, end-of-charge voltage, cycle number, charge and discharge rates, operational temperature, and depth of discharge. Only simulated data were used in this study as well, and there is an opportunity to incorporate machine learning algorithms into real data to compare the results of battery charge/discharge strategies.

To accurately predict the battery cycle life, predictive data would be required for several years to cover the actual battery life. We can utilize machine learning algorithms on real data and compare the accuracy of the predictions with actual values.

D. OPTIMIZATION SCHEMES BASED ON DEMAND RESPONSE WITH FREQUENCY REGULATION

In this class we surveyed five papers. In [5], Fig. 3 was presented to predict the EV battery cycle life based on the use of static and dynamic electricity and regulation prices. The depth of discharge of the cycle loss can be compared to the value set by the EV owner to ensure that the life cycle is within an acceptable range of operation. The loop continues for the following charge/discharge cycles, while the set depth of the discharge limit has not been attained. Once the battery life cycle falls below the operational level, the loop is exited, and the EV is not allowed access to the vehicle-to-grid service.

The charge/discharge process considers day-ahead pricing, frequency regulation signals, and the predicted battery life. A case study was created for the charge- scheduling problem using hourly electricity pricing and actual frequency regulation. Overall, cost/revenue optimization was not addressed. Simulations were used in which machine-learning algorithms could be incorporated to compare the results.

In [46], the battery SOC and incoming current were used as parameters to control charge. The controller utilizes the PI for reference during the charging and discharging of the battery.

The authors of [47] presented an approach related to demand side resource bidding by using an aggregator to enter the market for frequency regulation. This addresses the uncertainty in markets for electricity and take advantage of the potential to earn revenue for demand response.

Another strategy was used to charge or discharge the battery using an H-infinity controller for high-frequency power fluctuation smoothing [48]. In [49], the approach to improve frequency regulation in a renewable energy microgrid is to incorporate a rule-based plan using the state of charge of the BESS and the frequency response of the energy system.

E. OPTIMIZATION SCHEMES BASED ON ENERGY EFFICIENCY OF ELECTRIC VEHICLES

We surveyed three representative papers in this class. The next paper [9] explained that there can be a major degradation of electric vehicles when the state of charge of the battery reaches its limits. The characteristics of the road can affect the EV battery charge/discharge sequences; therefore, energy management can benefit from a preview of road quality. During actual driving, the gradient of the road ahead can be assumed to be a random variable because the HEV controller does not always have information about the future route. A stochastic model approach was proposed using the location, direction, and road grade information of the EV area. Energy management is controlled using stochastic dynamic programming and Markov decision processes. The simulation was used for testing and comparing with the dynamic programming results and consumption minimization strategy. The results showed that the developed method can help maintain the state of charge within its limits and exhibit good performance in terms of energy consumption.

Reference [50] presented a view of optimizing the battery charge and discharge management for EVs in charging stations, power systems, and energy systems. By incorporating efficient methods, improved network operations and economic and environmental goals can be realized. The study also examined the major obstacles faced by EVs when using V2G applications.

The authors of [51] simulated three scenarios: base load, EV charging and both charging and discharging. An approach that uses optimal scheduling in a collaborative environment of EVs and renewable energy sources was found to reduce the charging costs for EV users, power generation, operating costs, and pollution costs. The model incorporates EV battery charging costs, pollution, air volume, generator costs, and EV V2G characteristics. The proposed strategy addresses the optimization of both the generation and load sides of renewable energy sources.

F. OPTIMIZATION SCHEMES USING A POWER DISPATCH REGULATION APPROACH TO IMPROVE THE UTILIZATION RATE OF A RENEWABLE ENERGY/BESS SOURCE INTEGRATED MICROGRID

For this class, we surveyed 10 representative papers. Owing to the variability in the price of energy and renewable power generation, a strategy using a model derived from stochastic programming to schedule the charge/discharge of the battery was presented in [12]. A BESS dispatch control algorithm based on rank was presented to produce the necessary power output for the dispatch. The simulation results show that the implementation of the strategy increases the reliability of the power supply and the net revenue. This strategy was used in a wind farm environment for power generation, which can easily migrate to a solar PV source. Real wind speed data from South Wales, Australia were used.

The next paper [2] proposed an integrated system of a BESS, an electric vehicle charging station (EVCS), and a PV system. An optimization model is presented for an electric vehicle/photovoltaic/battery energy storage charging station connected to the grid to size BESS and PV and to determine the charging/discharging pattern of BESS. The multi-agent particle swarm optimization (MAPSO) algorithm combines particle swarm optimization (PSO) and a multi-agent system (MAS). To simulate the EV charging patterns and calculate the EV charging demand at each time interval, a load simulation model is presented.

The PV data parameters are the rated power, investment cost, maintenance cost, Lifetime, Reduction factor of the panels, cell temperature, and PV temperature. The battery storage data parameters are the rated capacity, replacement cost, depth of discharge, investment cost, maintenance cost, self-discharge, and lifetime.

Most research can be categorized into three classifications using the following methods: software programming tools, artificial intelligence, and a programming solver. It is relatively simple to incorporate simulations using a software tool; however, the hardware specifications are generally fixed. Linear programming models are typically used to address optimization issues, and artificial intelligence algorithms can be used for linear and non-linear models.

In [52], a charge controller for a battery storage system that uses turbine tracking of the battery state of charge and the maximum power point was proposed to manage the decision to charge or discharge the battery. The control strategy was validated via simulation using MATLAB and SIMULINK.

The most common control strategies are PI and PID. A PI controller uses control-loop feedback, which calculates an error signal by subtracting the power discharged from the battery and the set point. Mathematical models of the control system are used. Research has been conducted regarding charging and discharging BESS with PI while remaining within the limits of the SOC. The authors in [52] proposed a battery charge/discharge control with maximum power tracking and battery SOC with PI. When the state of charge falls under the CC mode limit, the PI controller charges the battery. Otherwise, the battery charge remained the same.

The authors in [53] proposed a control strategy for battery power using the battery SOC and PI regulators to regulate the BESS discharge and charge decision. The state of charge is measured and when it is more than 50%, the battery can discharge to provide the power demand as necessary. When the battery's state of charge is less than 90%, the battery can charge. A MATLAB/Simulink platform was used to verify the results. A wind power source was used; however, the same strategy can be applied to a solar energy source.

In [17] a strategy was proposed for battery energy storage with double-stage variable rate limit control. The goal was to determine the optimum amount, rate, and time interval for the energy charged and discharged from the battery. Two different rate limits are used to charge or discharge the battery based on the load demand. The scheme also maintains the battery charge within an interval to increase battery life. The strategy was tested using real-time control hardware with dSPACE and an OPAL-RT. Because the authors utilized a simulation package, a different approach using machine learning to make predictions based on real data can be deployed and compared with their results. They also utilized a hybrid energy storage system composed of a supercapacitor and a battery. The price of a supercapacitor is very high making it impractical for the residential environment and an extraneous component of an energy storage system.

In [54] a dual BESS (DBESS) was proposed. The deployment of a DBESS causes the first BESS to charge, whereas the other is discharging. The SOC of both BESSs is maintained within the maximum and minimum bounds, whereas a control algorithm determines each BESS objective.

An approach to discharging and charging the BESS using a rule-based controller with a converter was described in [55] and [56]. The SOC and depth of the discharge limits were used as inputs for the converter.

In [57], the authors claimed that there is no way to effectively control the charge and discharge of the BESS without using data to predict the input from a renewable energy source a few hours in advance. To resolve this issue, their approach used a sliding time window and predicted the states of the variables, their limitations, and fluctuations.

In [58], the delayed battery response of a PV-BESS was studied, and simulation methods were utilized. The results showed that a faster response time from the battery resulted in greater savings for owners.

The BESS response time should also be measured from the perspective of the grid operator. There is also a demand for standard test procedures to determine the performance of grid-connected PV-BESSs. For a customer to compare various products, response-time measurements should be made available.

G. OPTIMIZATION SCHEMES USING A CONTROL STRATEGY TO HELP INCREASE THE LIFE OF BATTERIES

In this class, we surveyed four papers. Reference [1] presented a control strategy for distributed BESSs in a microgrid utilizing centralized control to increase the battery life. The strategy presented incorporates the SOC, SOH, and maximum capacity to regulate the discharging and charging of the batteries.

By incorporating the battery state of health and loss of capacity into the control strategy, the charging and discharging operation of batteries can control the depth of discharge and, therefore, the capacity degradation.

The control algorithm is validated using a MATLAB Simulink, which models a microgrid with a dynamic load, a backup diesel generator, a solar PV plant, and three battery energy storage systems.

When there is extra available solar power, batteries are charged, and to cover the power deficit during off-peak sun hours, the batteries are discharged.

The control variables that were fixed and contained assumed values were depth of discharge, upper and lower SOC limits, supplying capacity, power generation and load, state of charge, and state of health.

The results of the system simulation reflected a total improvement of 57% in the lifecycle of the BESS by utilizing the proposed algorithm as opposed to simple load sharing of the three BESSs.

A simulation was used to obtain measurable results. Actual data from the live sites were not used. Machine learning algorithms can be applied to real data to produce actual results for analysis. The option of selling excess electricity to utility companies has not yet been addressed.

An approach to minimizing the price of charging an electric vehicle is described in [16]. A model representing the battery lifecycle was developed which provides an estimate of the loss of both energy capacity and power fade based on the temperature, state of charge, and depth of discharge. The results were validated by comparing them with experimental data. The model was run using a MATLAB script to minimize the cost of charging. The results of a detailed model developed at the National Renewable Energy Laboratory were compared with those of the battery life model. When models of battery lifetimes are improved, the results of the details of the charge optimization will be different. No real data was used in the experiments.

The primary factors in extending the life of a battery are the charge and discharge depth. In [59] a two-layer neural network called the ADALINE (Adaptive Linear Neuron) was used to control the charge and discharge decisions of the battery. The characteristics of ADALINE include its accuracy, speed, and fast tracking.

An algorithm to control the battery power flow for a PV/BESS was presented in [60] to increase battery life and smooth the voltage.

H. OPTIMIZATION SCHEMES BASED ON MAXIMIZING OUTPUT FROM RENEWABLE GENERATION USING APPROPRIATE CHARGE/DISCHARGE CONTROL STRATEGY FOR BESSs

We surveyed two representative papers in this class. A strategy for BESS control is proposed in [61]. The predictive control of the model and layered optimization was combined to address energy fluctuations by optimally scheduling the BESS charge and discharge.

Regarding the system operation modes, two effective charging strategies for a hybrid PV-BESS were presented to improve the overall efficiency by modeling the PV panel and battery unit dynamically [62]. A simulation is performed to verify the methodology.

I. OPTIMIZATION SCHEMES BASED ON IMPROVING THE SMOOTHING PROBLEM OF WIND/PV/BESS HYBRID POWER GENERATION FLUCTUATIONS

In this class, we surveyed eight papers. In [63], a STATCOM was used to charge and discharge the BESS while sustaining the SOC of the battery within an interval of 30% to 100%. The authors analyzed a hybrid wind/solar power system using a simulation with PSCAD. The goal was to smooth the fluctuations in solar, wind, and BESS power sources. PSCAD (power systems computer-aided design) is software that is used to design and simulate electrical power systems. The results were obtained from the simulations and a simplified BESS model.

References [64] and [65] proposed a charge or discharge control strategy using the state-of-charge limitations of the BESS. A state of charge-based regulation approach for power fluctuation smoothing and adaptively controlling and updating the battery SOC in real time used adjustments based on the feedback and updated target outputs that were smoothed [66] to incorporate adjustments in real time for the battery state of charge.

In [67], a grid-connected doubly fed induction generator integrated with a wind energy conversion system was used to implement an optimization control strategy to smooth and maximize the power from wind and solar sources and stabilize the voltage from the DC link. Another strategy was used to charge or discharge the battery using an H-infinity controller to smooth the high frequency fluctuation of power [68].

Another approach was described in [69], which incorporated a BESS charge/discharge dual control strategy to supply power to the grid within a set maximum and minimum range. The primary control monitors the BESS so that it does not remain at full capacity. The output of the primary control is sent to the secondary control to determine how much power is sent from the BESS to the grid which is constrained by the combined power output from the renewable energy source and BESS.

NLPC uses an objective function to optimize BESS control. In [70] a system to control the voltage to charge the battery used NLPC, which ensured zero steady-state error.

A predictive control strategy using a model was presented for a PV-BESS for voltage stabilization and power balance [71].

J. OPTIMIZATION SCHEMES BASED ON CYBERSECURITY OF BATTERY ENERGY STORAGE SYSTEMS

In this class, we surveyed four papers. In [25], an approach using smart contracts with a battery charge/discharge control strategy within a distributed BESS network was presented to secure the systems. Simulated data were used to demonstrate that when the smart contract was deployed, it was more robust to cyberattacks. Blockchain technology is integrated into smart contracts. A blockchain is a peer-to-peer network model in which all nodes agree on the state of a shared digital entity. Every node only appends encrypted information, and all events are agreed upon per Distributed Ledger. These characteristics render it nearly impossible to alter the data. However, scalability issues exist in Blockchain networks. Therefore, more efficient peer-to-peer protocols must be utilized. An additional threat to BESS is ensuring that the sensor and actuator devices are physically secured. False data can be entered and transmitted across Blockchain networks. This causes the smart contracts to exhibit incorrect states. One solution is to utilize machine learning techniques to detect data anomalies.

The authors in [26] noted that because of smart power grids and a larger number of access points in these networks, there is a greater risk of intrusion. The resiliency of the electricity network was evaluated in relation to the cyberattacks. Both false data injection and DoS attacks were modeled using simulation methods. The test results demonstrated that charging the battery during low peak hours and discharging during peak times improved the resiliency against cyberattacks. Machine learning models utilizing actual data from real attacks can be used to test the robustness of the BESS. Further, more research can be performed using strategies related to the electricity market and other financial issues rather than focusing only on the technical aspects of cybersecurity.

To identify cyberattacks on smart meters, an intrusion detection system (IDS) was discussed in [27] which measures the strength of the signal received to categorize its source. An IEEE test system was used to validate the IDS performance.

In [72], the authors presented approaches for mitigating the effect of cyberattacks on smart grids owing to the presence of EVs. Both communication and physical threats can affect grid networks. Further research could include the implementation of a smart, adaptive defense mechanism to defend against such attacks.

K. STRATEGIES USING MACHINE LEARNING

In this class we surveyed seven papers. Artificial Neural Networks (ANNs) [19] have often been used in energy systems. ANNs allow for optimization, generalization, adaptability, data analytics, tolerance to failure, and minimal power consumption.

The next paper [3] proposed a strategy to control the management of demand for homes using smart grids that incorporate solar PV generation and energy storage. A system for decision making is proposed to reduce the electricity cost by managing the battery. The battery was assumed to be completely discharged as an initial condition for optimization. Fig. 4 shows a flowchart of the optimization process. A neural network that can be utilized at any home is implemented. Several combinations of consumption profiles and solar generation were used for validation. It was shown that the neural network system used to make decisions operates the battery effectively, resulting in a minimum electricity bill. The input data parameters used were the household power demand, maximum battery energy stored, PV power generation, electricity tariff, maximum power of the converter, and optimum battery power.

The cost of electricity to the customer is calculated. The minimum cost objective function is:

$$\text{Cost} = \sum_{k=1}^{k=M} T_{\text{energy}}(k) P_{\text{grid}}(k) dt \tag{1}$$

The variable k represents an interval of time, and the number of time intervals is M. T_{energy} is the value of the tariff for electricity. P_{grid} is the power supplied to or from the public utility. The time is dt.

The constraints are:

$$\begin{gathered} 0 < E_{\text{storage}}(k) < E_{\text{storage}}^{max} \\ -P_{\text{conv}}^{max} < P_{\text{storage}}(k) < P_{\text{conv}}^{max} \\ E_{\text{storage}}(1) = E_{\text{storage}}(M) \end{gathered}$$

$E_{storage}(k)$ is the energy storage of the battery at time k. $P_{storage}(k)$ is the battery power at time k.

In [8], the authors used machine learning to estimate charging and photovoltaic generation from data. The demo site has solar panels, batteries, and thermal storage. The focus was on EV and battery charging optimization and importing electricity from the network. The data from the demo site were processed using machine learning to identify EV charging events and overproduction, generate profits from PV energy production, time windows, energy requirements for EV charging and building energy demand. One year of data was used to implement supervised machine learning to predict the PV production and total electricity load to stop PV production after meeting the load and storage demand. Machine learning data were used as input to the optimization algorithm to minimize electricity cost. The gradient tree boosting ensemble method was used with the data obtained from a weather station. The variables used to train the model were brightness, temperature, wind speed, and precipitation with brightness having the greatest effect on predicting photovoltaic production.

Reference [7] proposed a BESS for peak-shaving and frequency regulation. Peak shaving occurs when the battery is

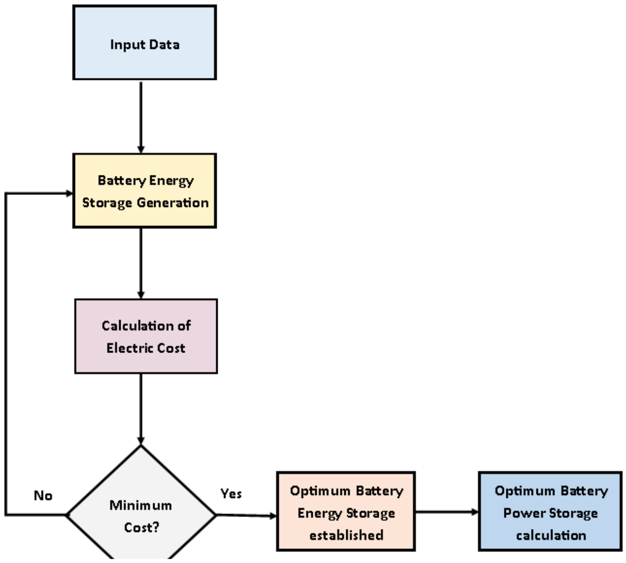

FIGURE 4. Flowchart of the optimization process.

charged when the electricity rates are at their lowest, which occurs during off-peak hours or when solar energy is free. These batteries were then discharged to avoid paying high prices during peak cost times of the day. The battery can discharge when demand is high.

This strategy uses uncertainties in customer load and regulation signals, battery degradation, and operational constraints. A simple threshold real-time algorithm was proposed. The peak demand charge is calculated for each month with 15-minute averages. Frequency regulation requires a decision of between 2 and 4 s. A formula was presented to calculate the total electricity bill.

They focused on lithium-ion batteries (LIBs). The degradation model for the battery proposed in this study is in a simplified linear form, applied to a specific battery operation constraint. For optimization, a more precise and general model of battery degradation can be used, such as a cycle-based degradation model.

Battery operation was limited to a depth of discharge range of 70% and a constant marginal cost was assigned for battery energy charging and discharging. The total electricity cost for the next day, including the energy cost, peak demand charge, and battery degradation cost, was minimized through the objective function.

They used a multiple linear regression model to predict the load one day in advance and used the 10-fold cross validation method to evaluate the MLR load prediction model. A real-time battery control algorithm for optimization was introduced. It only requires the measurement of the real-time state of the battery.

They performed a case study using half a year of power consumption data from the Microsoft data center and one year of data from the University of Washington EE and CSE building. The battery optimization horizon was assumed to be one day, and the time interval was 4 s. The electricity price, battery power capacity, battery power rating, energy capacity, and battery cell price are fixed. The annual bill and battery life expectancies were used for comparison with multiple scenarios.

Simulations were used to compare the results of the joint optimization to other scenarios. Real data could be used to verify these results. A scenario-based method was implemented using historical data to predict future frequency regulation signals where machine learning could be implemented using the same data.

The test sites were commercial buildings, which have the characteristics of a high load demand and large batteries. Batteries are also primarily used as backup resources. The inclusion of residential test sites with less demand and lower capacity batteries can be considered.

The BESS is vulnerable to security threats and can result in both physical and financial damage [73]. Little research has been conducted on methods for detecting cyberattacks in BESSs. The use of blockchain during the system design stage is suggested to secure the communication channels. In addition, the implementation of artificial intelligence and machine learning methods is explored to detect false data injection attacks (FDIA) while the BESS is operating. The analysis of the authors led to the use of data to forecast attacks utilizing methods such as clustering and state estimation using artificial neutral networks.

For owners of energy production facilities who want to add the option of renewable energy sources, calculations to maximize revenue from their BESS are of great importance. Reference [74] explored a deep learning methodology for the revenue prediction of a hybrid generation plant. By utilizing machine learning, more accurate revenue predictions were obtained on the order of a 4% average absolute error. In addition, the machine learning method reduced the computation time by more than 99%.

In [75], reinforcement learning was proposed to optimize the electric management system (EMS) and size of a PV/BESS microgrid. The Q-learning algorithm is used to determine the next actions for the EMS. The results showed higher utilization of PV energy, improved efficiency of the system, and lower cost of electricity.

L. OPTIMIZATION SCHEMES BASED ON META-HEURISTIC ALGORITHMS FOR BESS

Reference [78] uses metaheuristic algorithms to optimize a system consisting of a BESS, a renewable energy source, and an EV fast charging station (EVFCS). The goal is to calculate the optimal size of each component of the system and maximize the profitability of the EVFCS. There were 3 metaheuristic algorithms applied: the arithmetic optimization algorithm (AOA), salp swarm algorithm (SSA), and particle swarm optimization (PSO).

In [79], the objective is to determine the optimal allocation of the BESS. The metaheuristic algorithm Teaching

TABLE 4. Summary of surveyed strategies and suggested improvements.

Name	Year	Classification	Proposed Enhancements	Testing Method	Test Data
Minimize cost to charge EV [16]	2011	Battery lifecycle model	Use real data	MATLAB	None
Energy management of PV/BESS [19]	2012	Task scheduler for day ahead control	Distributed control system	Artificial neural network	Simulated
Reduce electricity cost [15]	2013	Battery size comparison	Increase battery life	Algorithm	None
Smoothing control [63]	2014	Smooth PV fluctuations	Control optimization	STATCOM	Simulated
BESS optimization [17]	2017	Dual charge/discharge rates	Analyze real data	Two stage rate limit control	Simulated data
Battery sizing [41]	2017	Determine most effective battery size	Increase revenue of PV/BESS	Algorithm	Actual data
Electricity consumption model [42]	2017	Market diffusion model	More profit for self-consumption system	Model simulations	Actual data
EV battery optimization [5]	2018	Demand Response	Optimize revenue/cost	Monitor signals	Simulated data
Maximize output from renewable source [62]	2018	System optimization	Charging strategy model	Algorithm	Simulated
Economic analysis of PV/BESS systems [45]	2018	Measure lifetimes of PV/BESS	Integrate BESS with PV system	Simulations	Actual data
Battery optimization in PV/BESS [3]	2018	Reduce energy cost	Decision making system	Artificial neural network	Actual data
Peak shaving and frequency regulation for BESS [7]	2018	Minimize electricity cost a day ahead	Day ahead electricity load prediction	Multiple linear regression model	Actual data
EV battery optimization [6]	2019	Frequency Regulation	Utilize machine learning	Optimization model	Simulated data
Secure BESS against cyberattacks [25]	2019	Use of blockchain technology	Use smart contracts	Simulated cyberattacks	Simulated
Optimization of PV/BESS [8]	2020	Minimize electricity cost	Predict electricity load and PV production	Supervised machine learning	Actual data
Cybersecurity of BESS [73]	2020	Forecast cyberattacks	Blockchain to secure communication channels	Artificial neural networks	Actual data
Energy management of PV/BESS [27]	2021	Detect cyberattacks	Intrusion detection system	IEEE 33-bus test system	Signal strength
Optimal operation of BESS [23]	2022	Uncertainty of scheduling PV/BESS	Predict electricity demand one day in advance	Optimization strategy	Actual data
Revenue prediction for PV/BESS [74]	2022	Find optimal revenue	Revenue prediction strategy	Deep learning	Simulated
Resilience of PV/BESS to cyberattacks [26]	2023	Smart grids and many access points are vulnerable	Charge battery during low peak hours and discharge during peak	Simulated cyberattacks	Simulated
Energy management for standalone PV/BESS [75]	2023	Reduce cost and increase PV utilization	Optimize energy management strategy	Reinforcement learning	Simulated

Learning-Based Optimization (TLBO) is used during the simulation. The electricity cost and loss of energy are the input variables for the objective function. The hourly power level of the BESS is the variable to be optimized. The results using TLBO were compared with several metaheuristic algorithms: The Cuckoo Search Algorithm (CSA), PSO, Gradient-Based Optimizer (GBO), SSA, and Barnacles Mating Optimizer (BMO).

Reference [80] presents a BESS control strategy which utilizes a metaheuristic algorithm, namely harmony search to determine the optimal smoothed BESS and solar energy limits by calculating the optimum filtering time constant to smooth PV intermittency by BESS. This metaheuristic optimization method uses stochastic random searches which result in fewer calculations and does not require the decision variables to be initialized.

M. OPTIMIZATION SCHEMES BASED ON SOH ENHANCEMENT FOR BESS

Reference [28] explains that the battery charge/discharge cycle can affect its lifecycle. The battery lifetime may be included in a cost analysis of the microgrid system. The current SOH of the battery can determine its power and capacity. BESS parameters may include SOH, cycle count, corrosion, and the degradation rate.

In [81], the authors stated that the lifetime of a battery is reduced if there is no consideration for factors leading to its degradation. The goal of the paper is to increase battery life and minimize the cost of electricity for a microgrid. A model of the battery representing its physical aging process is embedded into the algorithm. Dynamic programming is utilized for optimization with simulated data.

The next paper [82] states that the factors affecting the age of a battery are SOC, charge/discharge rate, depth of discharge, and SOH. One approach incorporated a strategy using Q learning with an aging model based on GA. Another method adopted adaptive droop control. The power variables related to the BESS in different scenarios determined the energy released by the Droop controller.

N. SUMMARY OF SURVEYED STRATEGIES AND SUGGESTED IMPROVEMENTS

Table 4 summarizes the strategies that we surveyed with their corresponding classifications included in our taxonomy. The table describes several battery optimization approaches with the suggested improvements. The testing methods and data used to validate the approaches for each study are also included in the table.

The table shows the classification of each strategy based on the topic, testing method, and test data. Improvements have also been suggested for each strategy. The new approaches include: utilizing machine learning, optimizing revenue/cost, analyzing real data, increasing battery life, using real data, charging strategy model, control optimization, increasing revenue of PV/BESS, more profit for a self-consumption system, integrating BESS with PV system, predicting electricity demand one day in advance, using smart contracts, charging the battery during low peak hours and discharge during peak, intrusion detection system, distributed control system, decision making system, predict electricity load and PV production, day ahead electricity load prediction, blockchain to secure communication channels, revenue prediction strategy, and optimize energy management strategy, revenue prediction strategy, and optimize energy management strategy.

For the 3 surveys cited in this paper, there are proposed enhancements to the research gaps described in each publication. For the survey in [18], the authors proposed that additional research can be performed related to integrating the control strategies for all elements of the BESS to achieve the optimal efficiency of the system. Machine learning algorithms can be applied to determine the strategy with the best results. The authors in [28] emphasized the need for further exploration of enhancing cybersecurity features to address the security vulnerabilities and weaknesses of both smart grid and microgrid systems for applications that run in real time. The review in [14] discovered that there has been no utilization of deep learning methods for BESSs deployed with wind power as an energy source. In the authors opinion, there is great future potential in the use of deep learning strategies to optimize the control mechanism of a BESS.

IV. CONCLUSION AND FUTURE DIRECTIONS

A. CONCLUSION

An optimized battery control system is critical in a renewable energy source/BESS system because of the potential for monetary gain from the BESS. A variety of control strategies for providing an optimum BESS are presented in this paper. Many studies have focused on regulating battery discharge and charge decisions. The major approaches described are PID, PI, H-infinity, MPC, and NLPC. The battery state of charge, life cycle, and other constraints are also presented. Other goals include environmental concerns, frequency regulation, consistent voltage levels, better quality of energy, and reducing microgrid costs.

The objective to incorporate a better and more adaptive strategy to maintain a cost effective, dependable, and high-performance BESS infrastructure is required. Several current studies have presented techniques to optimize the BESS by utilizing prediction schemes to enhance the results of the system. Currently, the most common approach is MPC.

This survey paper provides a summary of state-of-the-art strategies for smoothing renewable power output using a BESS. It also includes goals for optimization, limitations, different types of algorithms, and research gaps with suggestions.

It explains the various strategies and proposes ideas for further research to help researchers select an optimal control strategy for their respective systems [76].

B. FUTURE DIRECTIONS

The current state of research focuses on utilizing simulated data, stochastic methods, and algorithms for experiments to test different strategies. For future research, it is anticipated that more work will be done on machine learning.

A topic of great interest is the integration of revenue prediction with real data for cost and performance. This would allow for more accurate recommendations for BESSs to achieve optimal financial gains. In addition, the accuracy of the machine learning model can be improved by including a mixed-integer linear programming (MILP) model to create a hybrid strategy. The MILP model can adjust machine learning predictions that are not realistic owing to scenarios that are out of the sample. In addition, reinforcement learning can be implemented in conjunction with existing strategies to reduce costs and maximize the use of PV sources [77].

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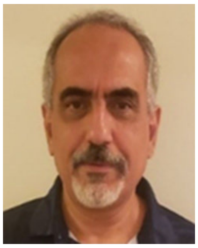

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