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Use of Forecasting in Energy Storage Applications: A Review

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ABSTRACT During the last decade there has been a major shift towards renewable energy sources to fulfill the increasing demand for energy in a sustainable manner. However, a major challenge with renewable energy generation is its dependency on weather conditions. Energy storage is deemed instrumental to harness renewable energy by providing a means to overcome stochasticity in renewable generation. Nonetheless, the operation of energy storage is not trivial due to its energy limitation and degradation behavior. Many works in literature consider forecasts as a cornerstone for effective management of energy storage for various grid applications. However, little work has been devoted to studying the actual value of forecast for energy storage management, which is highly dependent on the use case. This paper presents a review of the state of the art in the use of forecasts for energy storage management, identifying the estimated value of forecast with respect to baseline management approaches that do not rely on forecasts. The paper also discusses research pathways that would focus on improving forecast only on the energy storage applications that can benefit from it.

INDEX TERMS Energy storage, energy forecasting, control, battery.

I. INTRODUCTION

Global energy consumption has been growing in the past few decades and is projected to grow even further in the future. Electricity demand has been traditionally met by fossil fuels, but sustainability concerns have driven a shift toward renewable sources of energy. Renewables are expected to grow by 2.3% each year [1], posing major operational challenges due to their stochastic nature [2]. Researchers and industry agree that energy storage can help overcome these challenges by storing excess energy and releasing it when demand is high [3], effectively increasing the dispatchability of a resource mix. Powered by this perception, as well as regulatory incentives and other major industry drivers, energy storage deployment has grown drastically and its cost has decreased making it a feasible grid resource. The most common energy storage technologies based on batteries exhibit high flexibility and speed. This results in added grid flexibility and increased ability to integrate high penetration of renewables [4]. Flexibility also implies that storage can be deployed for a variety of applications on different levels of the power system, providing services for transmission, distribution, and end-users. Demand-charge reduction [5], energy arbitrage [6], frequency regulation [7], peak reduction [8], renewable energy curtailment reduction [9], transmission congestion relief [10] are widely studied and analyzed in feasibility studies, as well as offered by technology vendors and integrators. A study conducted by Rocky Mountain Institute [11] identifies thirteen fundamental services that can be provided by energy storage devices for customers, utilities, or independent system operators. It also identifies the benefit of stacking multiple services to maximize the value provided by the storage system. Apart from the flexibility that energy storage systems provide, several studies have identified the economic value of deploying storage [12], [13]. As a result, energy storage adoption is on the rise and is expected to grow further in the near future [4].

However, the key to cost-effective storage projects lies in operation, this is, knowing when to charge and discharge to increase the benefit to the grid and storage operator. There has been extensive research on management of energy storage systems, and the majority of approaches rely on energy, load, solar, or price forecasts as inputs to operational strategies. Extensive review studies on forecast methodologies and their

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accuracy can be found in the literature. A detailed review of solar power forecasting is presented in [14]. The paper presents a complete review on solar forecasting techniques, its economic impact, probabilistic and deterministic forecast, as well as error metrics used in literature. Another detailed review of solar forecasting techniques as well as their applications is presented in [15]. A comprehensive review of load forecasting is presented in [16]. A review on wind speed and wind power forecasting has been presented in [17]. The paper discusses different methods of wind power forecasting found in literature, however it does not discuss the impact of forecast accuracy. In [18], the authors present the use of wind power forecasting for onshore and offshore wind power farms and their economic value. It presents a detailed analysis of various methodologies found in literature for wind power forecasting. Even though many studies present a state-of-the-art of forecasting techniques, not many quantify the effect of forecasts and forecast quality on the performance of energy storage operation. This creates a detachment between the storage operation research and the forecast research regarding the types of forecast that are more useful, and whether improving them does generate actual value.

In this work, the goal is to explore the existing literature in control and optimization applications of forecast, to understand the benefits of using forecast for decision-making and control, compared to more standard, less sophisticated approaches. This work looks into various energy storage applications found in the literature and how the authors address the use or impact of energy forecasts. This paper does not present a forecasting methodology, rather, it presents a review of the impact of forecast accuracy on the performance of energy storage applications. We start by identifying a broad range of works on energy storage control and optimization for different applications. Then, after grouping the papers in different buckets according to their application, we identify whether a value analysis of the use of forecast is being carried out. Based on the value analysis presented in the reviewed papers, we identify the general benefit of applying forecast with respect to baseline scenarios that do not rely on forecast, and whether forecast can be useful to improve the performance of each storage application. This paper is organized as follows. In Section II, an introduction to forecasting is presented. In Section III, the importance of forecasting in energy storage control is highlighted. Section IV, presents a review of energy storage papers with a focus on the impact of forecast. Section V presents a detailed analysis of the findings and Section VI summarizes and contributions of the work.

II. INTRODUCTION TO FORECASTING

Forecast is the process of predicting an unknown signal, e.g., electric demand [16], [19], generation [20]–[22], electricity prices [23], natural gas [24], among others, for the next hour/day/week/month etc. Predicting a value in future requires a well defined methodology that takes into account the historical values, trend, and other variables that can impact the value at a future time step. Figure 1 shows

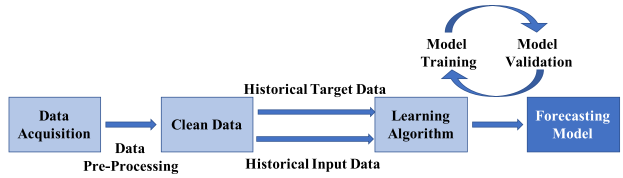

FIGURE 1. Forecasting methodology.

a general methodology used for forecasting. The first step in forecasting is to understand the application of the forecast. This will define the data collection process and the methodology to be used. It is important to understand the forecast horizon and forecast resolution based on the application. Forecast horizon is the duration for which the forecast is to be made. This can be very-short-term (minute ahead), medium-term, or long-term (annual). Forecast resolution is the granularity of the data, defined as the period of time covered by each sample of the forecast signal, for example, per-minute, hourly, daily, weekly, etc. One hour granularity is the most used one in the industry. Once this is decided, the first task is gathering the data. This step involves approaching agencies and getting hold of reliable data. The length of the data should be enough for training and validating any forecasting approach of interest. Also, the quality of the data will impact the accuracy of the forecasting model. Next, the data must be preprocessed. This task involves feature extraction, cleaning and scaling the data, detecting and removing outliers, among others. Finally, the learning stage of the model must be carried out using the preprocessed training data. Once the training is complete, the model performance is evaluated according to some performance or error metrics. Validation process is an optional phase for such data-driven forecast models. The most common performance metrics used to evaluate energy forecasting models are Mean Absolute Percentage Error (MAPE) and Root-Mean Square Error (RMSE). Based on the model performance and the desired outcome, the model is tuned. This process of training and validating the model is repeated until a "good-fit" is achieved in the learning process.

III. IMPORTANCE OF FORECAST IN ENERGY STORAGE CONTROL

The value of a storage system depends on how it is operated. Given that storage is an energy-limited resource, present actions affect the ability to carry out potentially more valuable actions in the future. Forecast becomes a critical part of storage management in the process of deciding the course of action over the lifetime of the system. To maximize the economic benefits of storage control, the storage operator may also need energy price forecast to compute (dis)charging schedule for the storage system. However, on system operator/utility side, the load forecast would be needed to manage supply and demand at a given node. If no overload is expected, the system can be used for other applications, being able to accrue more value. Without forecast, the storage system would be operated sub-optimally without realizing

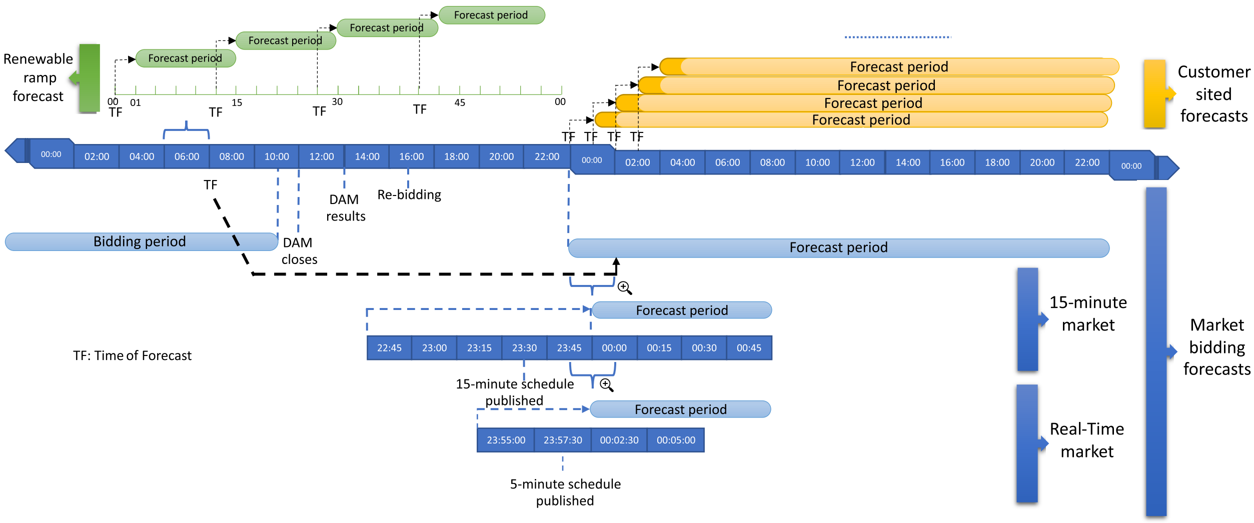

FIGURE 2. Forecasting timeline for different use cases.

its full potential, unable to provide additional services to the grid. Renewable generation forecast allows the operator to optimize charging times, getting maximum benefit from renewable generators.

As discussed in Section II, depending on the storage application, forecast of market prices, load, or renewable generation can take different forms. These forms are mainly determined by the time granularity (step size) and forecast horizon. For example, it has been theorized that a sufficiently accurate forecast at a high time granularity and short time horizon (1-minute step size for the next 15 minutes) could be used to predict renewable ramping [25], making it easier for the storage system controller to dispatch and correct undesirably large variability. Moreover, energy storage used for customer tariff management can benefit from 15 or 30-minutes step size to perform real-time charge/discharge, trying to reduce the customer's demand charge, which applies to the peak load of the month. An accurate forecast may help an optimization algorithm to calculate the maximum demand charge reduction possible, and the charge/discharge profile needed to achieve it. In this case, the forecast horizon is generally longer than one period of the load signal, typically one day. In both of the mentioned applications, the forecast for a given time period can be generated using the latest measurements of the signal, which should help increase the forecast accuracy.

Strategies for market participation use market price forecast, and the forecast type depends on the market structure. If the storage system participates in a Day-ahead (DA) market, the forecast generally has 1-hour time step and a time horizon of one day. If the resource participates in the Real-time (RT) Market, the time step is generally between 5 and 15 minutes time-step and between 15 minutes and one hour time horizon. It is worth reminding the reader that the forecast for market applications is generated for a time period relatively distant in the future (e.g., for DA market the forecast must be generated several hours before midnight, and for RT market it must be generated more than one hour before the performance hour). In this case, latest samples of the forecasted signal at the time of performance are not available when forecast is generated, which may lead to inaccuracy. Figure 2 shows the different timelines for forecasts for different applications.

The key to determine the benefit of using forecast is the concept of "sufficiently accurate." For many applications that could have great benefits from sufficiently accurate forecasts, it is unclear if the actual attainable forecast is sufficiently accurate to improve the control performance. Load and renewable generation can be very difficult to predict if one tries to capture short-term changes, or for small loads or generators. For example, estimating a renewable generation ramp from two power samples collected one minute apart can act as a derivative filter, which is known for amplifying high-frequency noise, and can lead to a wrong estimation of the ramp and a deteriorated control performance. In the case of demand charge reduction, when dealing with small loads, even if one tries to use forecast with 15-minutes step size, it can fail to foresee the maximum demand, yielding a detrimental effect in the customer's bill.

IV. ENERGY STORAGE USE CASES

There is a consensus in industry about the flexibility of energy storage as a grid asset capable of supporting a broad range of grid tasks that operators need to cover in order to provide safe, reliable, and affordable electricity to customers. For example, battery storage exhibits a fast response to power setpoint changes, which translates in a more effective response to supply/demand imbalances. This leads to battery storage to be theoretically more beneficial for frequency response applications than traditional resources with slower response time. The (Pennsylvania, New Jersey, and Maryland)

TABLE 1. Summary of the energy storage applications addressed in this review.

Energy Storage Application	*Description*
Energy Arbitrage	Energy arbitrage or load shifting refers to charging the energy storage system when the price of electricity is low and discharging it when the price is high.
Energy Storage as Operating Reserves	Operating reserves are the additional generation capacity that act as backup in case demand cannot be met by the current generation units. Due to their ability to respond quickly, energy storage devices have the potential to provide as operating reserves.
Renewable Integration	Renewable sources of energy such as wind and solar are dependent on weather which make their generation highly intermittent and variable. This makes their integration into the power grid challenging. Energy storage systems can help address this issue by storing energy during high generation and discharging during low generation hours.
Microgrids	Providing service reliability to electricity customers with highly sensitive loads, e.g., military bases, airports, and other critical infrastructure, is a major application of battery storage reflected in the growing interest for microgrid deployment, mainly comprised of storage and renewable generation.
Behind-the-Meter	Increasing number of electricity consumers are starting to produce a portion of their electricity needs independent of the utility. Consumers store energy during high generation hours and use it to lower their demand charges and subsequently their electricity bills.
Market Application	Energy storage systems can be designed to participate in the energy market for revenue. This can be done by energy arbitrage, providing generation capacity in congestion, peak load shifting for regions with varying TOU rates, etc.
Degradation Management	The health of the battery deteriorates over time and the rate of degradation depends on the charging-discharging cycles and the way the battery is operated. More accurate forecasts can help optimize the charging-discharging cycles of the battery and improve the longevity of the battery.
Storage Sizing	Sizing of the energy storage system depends on the application. However, with more accurate forecasts, the uncertainty can be reduced and consequently lower capital costs.

PJM market pioneered the inception of battery storage for secondary frequency response exploiting its flexibility through the development of the REG_D signal. Another high-value application is providing capacity for generation, transmission, or distribution. Southern California Edison (SCE) has deployed large battery systems to replace a gas peaker in the aftermath of a major gas leak in Southern California [26]. Other utilities intend to use battery storage to manage power overloads in transmission and distribution equipment to avoid expensive infrastructure upgrades. On the electricity customer side, the acquisition of battery systems is mainly driven to supply power in the event of an outage, while reducing the customer cost of electricity via energy arbitrage, demand charge management, and participation in demand response programs.

This section will extend on different applications of energy storage in the literature where forecasts have been used. We will analyze the forecast methodology, the storage control and management approach, and the benefits associated with the use of forecast. The review is divided into distribution applications, degradation management, storage sizing, storage as operating reserves, renewable integration, microgrids, and behind the meter(BTM) storage. The various energy storage applications are summarized in table 1.

A. ENERGY ARBITRAGE/LOAD SHIFTING

Energy arbitrage refers to using a storage system to collect energy when the price of electricity is low or there is an energy surplus, and discharging this energy when prices are high or energy generation is scarce. Typically in the U.S system, demand varies during the day, reaching its lowest during the night, and reaching a peak sometime around 6 pm. Consequently, shifting the load can help accommodate the changing demand as well as change in generation. Load shifting can be done for intraday load as well as for seasonal load [27].

In [28], the authors propose an offline planning-based control for energy storage for peak demand reduction in a low voltage distribution network. The paper uses day ahead forecasts to plan the charging discharging of the energy storage device. However, the authors do not incorporate real-time adjustments or control. The idea is to rely on day-ahead planning based on day-ahead forecasts which are preprocessed using historical load data to save on added costs due to real-time control. The proposed methodology reduces the peak demand by 19%, which is compared to a case with perfect forecast, which reduces the peak by 24%. On a 5-week testing period, the peak-demand is reduced 97 times out of 100. The methodology is also tested on a larger data set which consisted of 500 aggregations. The results show that the system does not reach its maximum demand-reduction capacity due to multiple peaks in the system. The uncertainty in low-voltage system is very high as the demand is difficult to forecast. In certain situations, a negative demand reduction was seen where a peak was caused due to the storage system charging. The offline model is also compared to a set-point control algorithm with the same forecasts and the offline system resulted in more negative peaks. ***Forecast methodology:*** Since the authors did not have access to the location of the data, they could not find numerical weather prediction data to develop traditional forecasting methodologies. The paper uses multiple weekly profiles to generate forecasts. The forecast is obtained by using half-hourly data from the same day of the previous weeks. The model was trained on 14 weeks of data and tested on 5 weeks. The paper presents a pre-processing step to minimize the impact of forecast error. The preprocessing stage uses a set of rules to tries to search for a filter to widen and increase the magnitude of the forecast peak to increase the robustness.

In [29] the authors propose an online control-based methodology for load-shifting using real-time load forecasts. The day-ahead stage of the control algorithm uses average load curves from similar days for planning and the real time on-line stage uses linear regression to predict the load based on real time data. The average load curve, the real-time regression-based load forecast, SOC, and battery inputs are used to optimize the battery dispatch using dynamic programming. The average load curve based on historically similar days yields a MAPE of 0.36 for a day while the on-line forecasting model yields a MAPE starting from around 0.12 for the first hour of the day and reduces to 0.01 by the end of the day. In terms of variance, the similar-day average load curves have a variance of 42.32 at the beginning of the optimization period while the forecast from on-line model has a variance of 15.29. If the system uses only the average forecast, there is over charging and over-discharging due to error in forecast, and the variance of the peak-shifted load curve is 4.85 while the peak-shifted load curve variance after using regression is decreased to 4.18. ***Forecast methodology:*** Weighted least squares based linear regression is used to forecast load. Historical load as well as real time load is used in the forecasting model. Days are categorized based on whether it is a weekday, weekend or a holiday as well as based on weather if it is a sunny day or a cloudy day.

In [30] the authors propose a Model Predictive Control (MPC) based control strategy to smoothen the overall load at a substation with energy storage and Renewable Energy Sources (RES). The MPC controller uses day ahead and short-term RES forecasts to optimize the dispatch from the energy storage system (ESS). The day-ahead RES forecasts are updated once a day for day-ahead planning while short-term RES forecasts are updated at each iteration of the MPC loop. Three cases have been discussed in the paper. In the first case, short-term RES forecasts are assumed to not be available, thus only relying on day-ahead forecasts. In this case, the day-ahead forecast uncertainty is modeled using a Gaussian curve with a variance of 4. Since this is an artificial forecast, it could miss out on some of the real world scenarios. The mismatch in forecast is partly covered by ESS by discharging and charging, but mostly by the grid, and it may cause a large power exchange at the node. In the second scenario, short-term RES forecasts are made available to the system. Perfect short-term RES forecasts along with 1000 different short-term forecasts with varying errors are simulated. It is observed that due to the availability of short-term forecasts, the changes in RES generation are met by the storage system rather than the grid. RES forecast outperforms the benchmark scenario where short-term forecasts are not considered. In the third case, real data along with real forecast has been considered to analyze the system. A case with large forecast error is considered, where the actual RES generation is less than the forecast. The results show that the proposed control strategy is able to cope with the skewed forecast uncertainty and absorbs the fluctuation in generation. ***Forecast methodology:*** The forecasting strategy used in the work is not explained in the paper. The paper considers day ahead as well as short-term RES forecasts, but there is no discussion as to how the forecasts are done.

In [31], the paper presents four different strategies to smoothen the demand of a small electricity network consisting of residential customers, each with PV and energy storage. The first strategy, used as a base case for comparison, is a rule-based approach to set the charge-discharge dispatch of the battery based on PV generation and demand. The following three approaches make use of load and PV forecasts and proper optimization algorithms to control the battery. The second strategy is a centralized MPC control strategy. A central hub runs the control algorithm using information such as each household's load forecast, PV generation forecast, etc with the aim to reduce the overall variation in demand. Next, a decentralized MPC-based strategy is presented where each individual household runs the optimization algorithm to reduce its variation in demand. Fourth, a distributed control approach is presented. In this scenario, each customer runs the optimization problem and communicates that information to a central hub termed as the market maker. The market maker looks at the overall load profile to update the prices and broadcast them to all customers. This process is repeated until the distributed optimization algorithm converges. Since each customer's load and PV forecasts are fixed, the overall demand from the algorithm's perspective is also fixed. To assess the performance of the proposed strategies, the prediction horizon and the accuracy of forecasts are varied. Root-mean-square (RMS) deviation and peak-to-peak (PTP) variation from the average demand are used to evaluate the performance of the system. As the prediction horizon is varied from 3h to 24h, the accuracy of forecasts deteriorates. In general, the centralized approach and the distributed approach have similar RMS deviations and perform better than the decentralized approach. Shorter forecast horizons (3h and 6h) have significant effect on the performance, while the system performance is almost the same for 12h and 24h horizons. The accuracy of the forecast is varied by introducing noise to the forecast time series. The performance is compared to the base case and the results show that the proposed control strategies are not very sensitive to forecast accuracy. ***Forecast methodology:*** The paper does not discuss the process of obtaining the forecasts.

The accuracy of the forecasts in terms of any error metrics is not discussed.

The effect of forecasting uncertainty on peak shaving and time-of-use applications for battery storage system has been studied in this work [32]. First an Artificial Neural Network (ANN) based load forecasting model is developed. Next, four scenarios are modeled to understand the effect of forecast accuracy on the system. First, a scenario without any forecast is modeled. Next a scenario using the proposed ANN with 10.02% mean absolute error (MAE) is simulated. Two more scenarios with 2% and 0.02% MAE are also simulated. The more accurate forecasts are generated by adding white noise to the actual load. It is observed that all the scenarios with predictions performed better than the one with no prediction. The proposed ANN model with high MAE performed better than the no prediction scenario 64% of the time whereas scenarios with lower MAEs performed better every time. Hence, it has been concluded that improving the forecasting accuracy has a significant effect on designing a reliable battery dispatch strategy, especially on days where the actual load does not follow a smooth curve and is abrupt. ***Forecast methodology:*** ANN has been used as the learning algorithm in this work. A two-layer feed-forward ANN is trained using Levenberg-Marquardt backpropagation algorithm, with one hidden layer containing 6 neurons. Historical load along with dummy variables such as day of the week are used to train the model.

B. ENERGY STORAGE AS OPERATING RESERVES

The paper [33], puts forth an operation technique for a distribution load aggregator that provides an improved energy storage management strategy. Furthermore, a communication and control structure has been provided to supplement the functioning of ESS in an event of loss of load in bulk power system, improving the overall reliability of the power system. Finally, a structure to analyse impacts of energy storage reliability on bulk power system based on sequential Monte Carlo simulation has been presented. The author highlights the fact that this study can provide with better business model strategies for the deployment of energy storage. Even though the study uses perfect forecasts, the authors discuss the effect of forecast on the optimality of the operation. ***Forecast methodology:*** Forecasts are used in the proposed system, however, the forecast information is assumed to be available without any discussion on the methodology used to obtain the forecasts.

In [34] the authors assess the value of energy storage in the context of electric system security. The work studies the cost of operating a system with significant intermittent generation covered by standing reserves. In the proposed model, a priority ranking method for generating unit commitment is developed using wind profiles and net demand forecast. Imbalances are introduced in wind forecasts and realized wind using random walk method with the resulting forecasting errors representing forecast uncertainties. Furthermore, allocation of spinning reserve is established to forecast uncertainties using statistical methods. Various studies were developed using the method and it was concluded that storage adds value to the overall operation of the system for all levels of wind penetration. Different wind penetration levels are assessed ranging from 16 GW to 56 GW. Using storage reduces the need for additional reserves that comes from the additional renewable penetration and the ensuing power balance uncertainty. C02 emissions also follow a similar trend, thus emphasising the benefit of storage in wind uncertainty. ***Forecast methodology:*** Forecasts are made by introducing a random normal distribution to the historical wind time series.

The work in [35] explores the impact of forecast error and uncertainties in wind power generation on storage-based standing reserves considering high wind penetration. ***Forecast methodology:*** Importance of wind power forecasts has been discussed in detail. The paper focuses on the effect of forecast horizon on the accuracy of the forecast and its effects on standing reserves. A random-walk methods is used to model the imbalance in net forecast (demand and generation).

C. RENEWABLE INTEGRATION

Renewable sources of energy such as wind power and PV power are highly dependent on weather conditions. The major challenge for the integration of renewable sources of energy is their intermittent and variable generation. From the grid operational standpoint, this challenge can be observed in two different time scales. First, the fast variation of renewables leads to fast power imbalances that translate into a higher need for frequency response reserves. To mitigate these effects, storage systems are used for smoothing and ramp rate control of renewable generation, ensuring that the generation seen by the grid is slow-varying enough that frequency response reserves can act more effectively. The other side of tackling intermittent renewables is the ability to use them as firm capacity when offering energy to the bulk system. Storage systems are used in this case to compensate for sudden power drops ensuring than a firm amount of power is delivered during a market period.

In [36], the authors propose to use wind power forecasts to determine when frequency deviation will occur and regulate the energy storage dispatch accordingly. The inaccuracy in wind forecasts is handled by a feedback loop to take care of the steady state frequency deviation based on real-time information. The proposed methodology is tested on a real-time digital simulator (RTDS). ***Forecast methodology:*** The paper comments on the importance of wind power forecasts and the uncertainty associated with it. They also introduce additional steps in their methodology to incorporate the error in wind power forecasts. However, they do not discuss the methodology used to produce the wind power forecasts, nor do they mention the quality of the forecasts in terms of error metrics.

In [37], the authors look into the effect of stochastic forecast error on the state of charge (SOC) of ESS, i.e., the overcharging and undercharging of the ESS with RES in the form of wind and solar. An MPC based strategy with two hierarchies, one to deal with small forecast errors and another to deal with larger forecast errors along with a real-time feedback loop to constrain the SOC to stay within limits. ***Forecast methodology:*** In this work, the authors concentrate on stochastic forecast error (SFE), which is described using a probability distribution function with normal distribution. Load, solar and wind forecasts for day ahead are calculated mathematically. They are combined to get the net load of the system. The variance of the individual forecasts is summed to get the variance of the net load. In order to test the system under different levels of SFE, the system is injected with small and large SFE based on confidence bands. The authors observe a significant impact on SOC, operation costs and lifetime of ESS due to SFE.

D. MICROGRIDS

Providing service reliability to electricity customers with highly sensitive loads, e.g., military bases, airports, and other critical infrastructure, is a major application of battery storage reflected in the growing interest for microgrid deployment, mainly comprised of storage and renewable generation. This has become especially important since natural events (hurricanes in the U.S. east coast and fires in the west coast) have led to periodic and prolonged outages. Forecast plays a fundamental role in the operation of microgrids for longer time periods. Adequate predictions of the critical load and the available renewable resource allows a better use of the storage system capacity, potentially reducing the DER size needed to meet the critical load, while allowing to address more extended outages. Tertiary microgrid control would perform economic dispatch using decision-making algorithms informed by the forecast to decide if it is beneficial to run a diesel generator or discharge the battery system, given the availability of solar resources and the magnitude of the critical load for the following few hours. Improved forecasts would reflect in less capacity needed to address uncertainty and reduced renewable curtailment.

In [38], the authors present the influence of the load forecasting error and the availability of energy storage in a microgrid with a wind turbine, photovoltaic plant, diesel engine and a microturbine. This work presents a Stochastic Programming Unit Commitment (SUC) model to optimally operate isolated microgrids in short term. A three-stage methodology is proposed where a demand forecast is obtained from historical demand data using ARMA technique, followed by solving the SUC problem by taking spinning reserves into account to offset the uncertainty associated with demand. Finally, a case study has been provided where an optimization problem is solved to study the power flow from generators and battery management by simulating the demand estimation error. Minimization of the microgrid's total operation cost has been observed by the authors. ***Forecast methodology:*** Renewable generation is assumed to be known or in other words a perfect forecast is considered for wind and solar power. An ARMA based 24 hours ahead load forecasting approach is used in this work. Two years of hourly historical load data is used to determine the p (order of the Auto-Regressive part) and q (order of the Moving-Average part) coefficients. The found values for p and q are 6 and 5 respectively.

In [39], an MPC controller is deployed to dispatch an ESS to reduce the overall cost, which includes electricity and natural gas consumption costs. The first scenario considers forecast uncertainty in the load forecast while the solar forecast is assumed to be perfect. The second scenario considers uncertainty in renewable forecast. The effect of both the scenarios are observed and it is seen that an MPC controller between the day-ahead planning stage and real-time dispatch stage helps reduce the cost of operating the system. The impact of forecast error is addressed by deploying an MPC to control the dispatch of an energy storage device as and when needed to compensate the error in forecast. The paper presents the impact of forecast uncertainties on the system by inducing different levels of load forecast errors (5%, 10% and 15%). As the forecast error increases, it is observed that the average cost of operating the system increases. ***Forecast methodology:*** The paper does not present a traditional forecasting methodology. Forecast error is obtained by adding a normal distribution on to the base load or renewable profile with varying standard deviation and percentage.

The work in [40], proposes an energy management system operation strategy for a single family home with PV and battery storage. The paper presents an MPC based model considering probabilistic forecasts and the uncertainties associated with them. A deterministic optimization problem is formulated considering the quantiles from the probabilistic forecasts. Considering energy storage as a manageable source, a mathematical model was proposed for deterministic optimization using probabilistic predictions where the dependency on current state and operating point of the energy storage device is evaluated and obtained a guaranteed band to compensate for the forecast errors. ***Forecast methodology:*** Demand and PV time series data is injected with a randomly generated time series with normal distribution, zero mean and 0.2 standard deviation to mimic probabilistic forecast.

In [41], using a forecast of the microgrid's net electricity demands, a linear optimization model is introduced for coordinated optimal dispatch of energy storage units in a grid tied microgrid with renewable assets to reduce the electricity costs. The electricity cost was calculated considering local and grid components of microgrid net power with respective local and grid electricity rates. Results of numerical calculations were carried out for various energy sharing strategies on a rolling horizon basis with real electricity and solar production data and demonstrated the coordinated optimal energy storage dispatch can significantly minimize the microgrid electricity costs. ***Forecast methodology:*** There no discussion on the methodology used for forecasting in this work.

E. BEHIND THE METER STORAGE

Electric utilities are building tariff rates that encourage electricity customers to modify their load shapes to reduce the stress on the power grid. This is done through time of use (TOU) energy charges that encourage consumption via low prices when system capacity is high and discourage consumption via high prices when capacity is scarce. In addition, for some commercial and industrial customers, tariffs are endowed with a demand charge that penalizes the highest demand in the billing period. This encourages customers to reduce their load factor making their load flatter. Managing BTM resources, including flexible loads, and storage, provides electricity customers the ability to reduce their electricity bill. However, this management needs knowledge of the customer's load and site generation, which is generally renewable. Moreover, as some storage resources have been deployed with the primary goal of providing backup to critical loads, secondary use for bill reduction requires advanced prediction of the critical load to ensure that the secondary use does deplete the energy reserve needed for backup.

The study in [42] looks into a BTM case with Photovoltaic (PV) and storage. The authors present a methodology for load and PV forecasting that is fed into a linear optimization problem that outputs an optimal schedule for the battery to maximize economic benefits by buying less when the price is more and buying more when the price is low. The model considers PV, grid, load, and battery parameters. The paper very well demonstrates the effect of forecast accuracy on the system. ***Forecast methodology:*** Artificial neural network (ANN) based load and PV forecasting models are developed. The forecasts are made for 24 hours ahead with hourly resolution. Two separate models are trained, one for PV forecasting and one for load forecasting. The ANN model for PV prediction is made up of one input layer with three input neurons namely, air temperature, global irradiance, and relative humidity, one hidden layer, and one output layer. The load forecasting model is also made up of three layers but with a single neuron in the input layer. Both models use sigmoid as the transfer function. The forecasts are made on a 24-hour rolling horizon. The authors have used forecast skill (s) and relative RMSE as the error metrics to validate the models.The models are compared with other models found in literature which use the same data.

In [43], the authors propose an electricity price forecasting methodology with BTM energy arbitrage. The aim is to use electricity price forecasts as an input to an optimization algorithm that aims to maximize economic benefits by charging the battery during off-peak hours and discharging during peak hours to save energy costs. The optimization routine gives the battery schedule for each hour. The experiments are run with different number of market clearing prices. ***Forecast methodology:*** The authors present an interesting approach to conduct electricity price forecasts. Unlike the commonly used rolling horizon, the authors propose an intra-hour rolling horizon approach, where they consider the time taken to create the forecasts. Thus, a fraction of the hour is used to get the forecasts. The forecasting steps starting from data preprocessing, feature selection, and model selection used in the paper are explained in great detail. An auto-regressive model with exogenous variables (ARX) is used as the forecasting model. The model is validated on the basis of Spike Prediction Accuracy (SPA). One model is created for high-resolution data and another one for low-resolution data. The high resolution model gives one hour ahead forecast whereas the low-frequency model provides hourly forecasts for the day.

The work in [44] proposes a methodology for BTM energy storage with PV to reduce demand charges. The authors propose a two-level control strategy with different timescales to deal with uncertainties and error in forecasts efficiently. The first control algorithm runs on a 15 minute timescale and suggests optimal energy storage operation to reduce demand charges. The second control part considers real-time data and tries to reduce the error caused by forecast inaccuracies. Three different scenarios are studies, namely, low PV penetration, medium PV penetration, and high PV penetration. ***Forecast methodology:*** For this control strategy, day-ahead PV generation and electricity demand at the feeder are forecasted. An auto-regressive moving average (ARMA) is used to build the forecasting model with one year of training data. However, the paper does not talk about the accuracy of the forecasts developed in the work.

In [45], the authors present an interesting approach whereby the forecast error metric is customized to improve the output of the control algorithm. The controller's objective is to minimize the monthly electricity bill. An MPC based controller is designed to schedule the charge-discharge times for the battery to reduce demand charges by reducing peak demand. The authors point out issues with commonly used forecast error metrics and propose two error metrics, namely, Parametrized Earth Mover's Distance (PEMD), and the Parametrized Forecast Error Metric (PFEM). Forecasts are created by minimizing traditional as well as proposed error metrics. It is observed that the controls provided with the best forecast by minimizing the proposed error metrics have better performance than the ones that get forecasts minimized with traditional error metrics. ***Forecast methodology:*** Feed forward neural network (FFNN), Seasonal Auto-Regressive Moving Average (SARMA) and naive daily periodic model are used to build the forecasting models. The hyperparameters of the models were found by grid search by testing the performance of the models on validation data. For the SARIMA model, it was found that AR of order 3 and a seasonal component of order 1 gave the best results. For the FFNN model, it was found that a network with one hidden layer with 50 neurons over a training period of 200 days gave the most accurate results.

F. MARKET APPLICATION

In [46] the authors propose a way for the owners of ESS to increase their revenue by participating in the day ahead market using a two-levell model, with arbitrage in one level and market market-clearing process simulation in the other level. The paper proposes to use the prices generated in the lower level to adjust the energy storage operation in the upper level, instead of price forecasts. Different wind uncertainty scenarios are generated and the arbitrage revenue is calculated for the proposed bi-level model as well as the conventional model. The bi-level model is able to smoothen the effect of forecast uncertainty and yield less revenue than the conventional model for all scenarios. ***Forecast methodology:*** A Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is used to get wind power forecast along with a forecast-bin based error model to create different wind scenarios. The forecast errors in terms of MAPE or RMSE have not been calculated.

The work in [47] proposes a methodology for reducing the generation peak, while satisfying the load requirements. The proposed system is tested on a testbed consisting of a generator, secondary storage, and load. The storage device charges prior to the peak hours and supplies power during peak hours to reduce the peak at the generator. Generation power is kept in a specific band and the power is optimized by taking the shortest path within the energy band. ***Forecast methodology:*** Load profile is assumed to be known, thus no forecasting methodology has been discussed.

The work in [48], proposes an operation scheme to minimize energy purchasing costs for a distribution system load aggregator using price and renewable forecast information. An MPC based operation strategy using load forecast, renewable forecast and price information is proposed and implemented on both grid-tied mode and islanding mode to evaluate the impact of reliability and economy and provided insights on how it can be impacted by energy storage capacity and power limits. ***Forecast methodology:*** The paper assumes perfect forecasts, hence no forecasting methodology is provided.

The work in [49] presents an operating strategy for load aggregator with electric energy storage to minimize their electricity cost in day-ahead and real-time markets under load and price forecast uncertainty. The paper presents an MPC based operating framework which makes use of forecast information as well as real-time information to minimize the operating cost of the system under different price and load uncertainties. For the day-ahead price uncertainty, three scenarios are generated with 5%, 15% and 30% maximum deviation from the day-ahead price. Since load forecasts are generally more accurate than price forecasts, 2%, 5% and 10% maximum deviation from the actual load in the day-ahead forecast is considered. Real-time price and load forecasts are fed into the model as well. The proposed strategy is compared with a no storage strategy and a day-ahead scheduling strategy. It is observed that as the uncertainty in load and price increases, the cost of electricity goes up drastically for the two strategies, while the proposed MPC-based strategy is able to cope with the increase in price and load uncertainty. With the increase in price uncertainty and fixed load uncertainty, the MPC-based strategy is able to leverage energy arbitrage opportunities and reduce the cost. ***Forecast methodology:*** The day-ahead forecasts are modeled by adding error to the actual time series. Real-time forecasts are generated by multiplying the actual value by the maximum forecast error percentage and a random number. Since the forecast in the near term is more accurate then long-term, the maximum forecast error percentage is low for short-term forecasts and higher for long-term forecasts.

G. DEGRADATION MANAGEMENT

Managing degradation is a major need for economically feasible battery storage projects. The health of a battery deteriorates with time [50], but also according to how the battery is operated. The depth and number of charge/discharge cycles have a significant impact on the capacity retention of the battery [51]. In optimized operations, therefore, it is important to determine the value of executing each cycle, to understand whether it exceeds the cost of degradation. The role of forecast for this application is to allow a more accurate estimate of the operational value of an action before it is carried out, avoiding ineffective cycles.

The work in [52] presents a two-layer energy management system with the upper layer minimizing the operating costs and the lower layer minimizing the fluctuations caused by forecast uncertainty in a microgrid with a hybrid ESS made up of battery and supercapcaitors. The model considers a degradation cost model to take into account long-tern costs associated with battery degradation. An MPC based framework with a feedback to compensate forecast uncertainty is proposed with the upper layer running every 1 hour and the lower layer running every 5 minutes. The effect of forecast horizon is presented and it is observed that as the forecast horizon increases from 6 h to 96 h, the operational costs almost remain the same, however, there is significant decrease in the battery degradation cost. Next, the effect of forecast accuracy on the system is simulated. The forecast error is increase 10% to 40%. It is observed that the effect of forecast is less on the battery operation and more on the supercapacitor as it is responsible to take care of the fluctuations caused by the forecast error. Since most of the fluctuations caused by the forecast error are taken care by the supercapacitors, no significant effect of forecast uncertainty is observed on the total operational cost and the battery degradation cost. ***Forecast methodology:*** The authors discuss the impact of forecast horizon and forecast accuracy on the proposed system and model different forecast errors but do not discuss the methodology used to obtain the forecasts.

H. STORAGE SIZING

The size of an energy storage system directly depends on the application of interest, and it greatly affects the economics of the storage project. All factors that affect the operation, including load, renewable resources, pricing, and power constraints, also affect the optimal size of a storage system [53]. Sizing also involves dealing with the uncertainty in operation which is driven by load, renewable generation, or electricity prices. With design methodologies that optimize the size of a storage system either to meet a capacity requirement or maximize owner's benefit, uncertainty leads to requiring increased size to accommodate uncertainty. If the forecast helps reduce the unstructured uncertainty in modeling a use case of storage, it will lead to reduced capacity and consequently to lower capital costs.

In [54], the authors present an optimal battery sizing problem using dynamic programming that aims to reduce the customer's demand charges by performing peak shaving. The idea is to reduce the peak or peak-shaving for industrial customers whose demand peaks for short time intervals, which increases their demand charges. The optimization algorithm maximizes the profit from peak shaving. The impact of forecasts and the forecast accuracy is not discussed in the paper. The study could have benefited from using demand forecasts to understand the impact of forecast error on the system. ***Forecast methodology:*** No forecast methodology is used. It is assumed that demand for the next day is available. In [55], the authors employ a two-stage stochastic programming approach for optimal sizing of energy storage device for intra-hourly economic dispatch. The wind forecast errors are included in the optimization problem as a chance constraint, with a selected level of probability of error. Using the output obtained from the 2 stage optimization problem, the amount of distribution lying beyond the energy storage limits was calculated and ensured to be between the chanced constraints. ***Forecast methodology:*** Wind forecast is simulated using normally distributed random variables.

In [56], the authors solve the problem of ESS sizing by formulating a chance-constrained optimization problem, where wind power constraints, loading shedding constraints, power balance constraints and network constraints are one-sided chance constraints. The ESS is deployed for hourly dispatch to the power system. They concluded that consideration of forecast errors was necessary for high operational reliability in ESS sizing problems. The total optimal energy capacities and the total optimal power capacities sized considering uncertainties are larger ***Forecast methodology:*** For wind power constraints, forecast wind power is modeled using PDF with a multivariate normal distribution. The correlation of forecast errors of different wind farms is also considered. Similarly, the load demand is modeled using a multivariate normal distribution at different buses.

V. ANALYSIS

This section analyses and summarises the findings from the work. One of the more significant findings to emerge from this study is that forecast and its accuracy play an important role in energy storage applications. However, it is of interest to analyse how forecasts are generated in different energy storage applications found in literature. Improvements in machine learning and artificial intelligence techniques have been applied to improve forecasts in energy applications [57], [58]. Contrary to expectations, we have not found a significant number of studies that deploy the state-of-the-art energy forecasting techniques for energy storage applications. Several studies mention the importance of forecast accuracy and the effect of forecast uncertainty but fail to report the forecast methodology used in their work. For example in [52], the authors discuss the effect of forecast uncertainty without mentioning the forecast methodology. Some papers such as [47], [48] assume the forecast to be known or perfect, which never happens in reality, making their assumption and any conclusion coming from the studies unreal. A widespread practice found in the papers studied, is the use of artificial forecasts [34], [40], [49], [55]. Artificial forecasts are forecasts made by synthetically inducing random noise to the actual data or persistence to mimic a forecast. In [49], the authors go into great detail to simulate artificial day-ahead load and price forecast. Random noise is added keeping in mind the fact that error is less for recent hours and more for later hours, since the short-term forecasts are, in general, more accurate than long-term forecast. However, they do not use actual forecasts. Artificial forecasts mimic the uncertainty caused by errors in forecasting to some extent, however they are not a true representation of actually forecast uncertainty. For example, a load forecasting model can perform fairly well in general but not so well on holidays due to the unpredictable behaviour of customers during holidays. The forecast can be off on the day of the holiday, the previous day as well as the next day. This could greatly affect the performance of the system in a month with more holidays (e.g. December) compared to another month (e.g. January). This real-life scenario could be completely missed if the forecasts are generated artificially using random noise. Few papers present real forecasting methods [29], [32], [38]. Figure 3 shows a pie chart with the various forecasting methodologies found in this study. Around 31% of the papers use artificial forecasts for their studies while 15% do not do any forecasts and assume perfect forecasts. Approximately 35% of the papers use either a statistical or a machine learning based forecasting technique. Around 19% of the papers do not mention any forecasting technique.

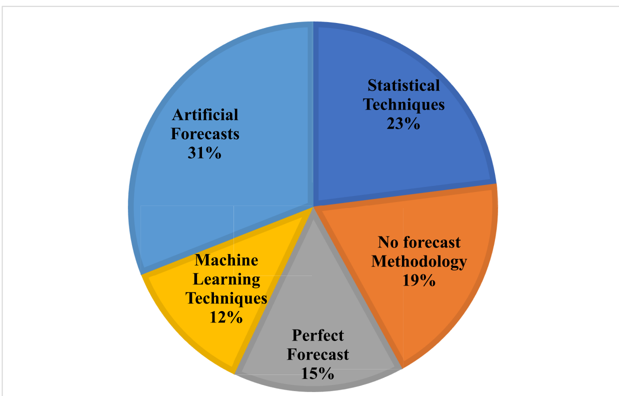

FIGURE 3. Pie chart showing the forecasting methodologies used.

Another important factor to take into consideration apart from the forecasting technique is the effect of different levels of forecast uncertainty in the energy storage application. Few studies present such an analysis [30], [39], [49], [52]. [32] is a good example of a paper that considers all the important points considered in this study. The authors first present

TABLE 2. Table shows the summary of the papers reviewed in the study.

Author and ref.	Application Summary	Forecasting Technique	Uncertainty Analysis	Forecast Horizon	Forecast Resolution
[28]	Off-line planning based control for energy storage for peak demand reduction in a low voltage distribution network	Pre-processing with historical weekly profiles to generate forecasts.	Yes	Day-ahead	Hourly
[29]	On-line control based methodology for load-shifting	Weighted least squares based linear regression	Yes	Day-ahead	Hourly
[30]	MPC based control strategy to smoothen the overall load at a substation	No forecasting methodology discussed	Yes	Day-ahead+short-term	
[31]	Smoothing the demand of a network of residential customers with PV+Storage	No forecasting methodology discussed	Yes	3h, 6h, 12h, 24h ahead	Hourly
[46]	Energy storage for increasing the revenue by participating in the day ahead market	Generalized Auto-regressive Conditional Heteroscedasticity (GARCH)	Yes	Day-ahead	Hourly
[54]	Optimal battery sizing for peak shaving and demand charge reduction	Perfect forecast	No	Day-ahead	Hourly
[47]	Reducing the generation peak	Perfect forecast	No	Day-ahead	Hourly
[48]	MPC based control strategy to minimize energy purchasing costs for distribution system load aggregator	Perfect forecast	No	Day-ahead	Hourly
[49]	MPC based operating strategy for load aggregator to minimize electricity costs in day-ahead and real-time markets.	Artificial Forecast	Yes	Day-ahead + Real-time	
[32]	Peak shaving and time of use applications for battery storage systems	ANN+artificial forecast	Yes	Day-ahead	Hourly
[52]	MPC based energy management system to minimize the effect of forecast uncertainty on operation costs degradation	No forecasting methodology discussed	Yes	6 h to 96 h ahead	5 min and 1 min
[55]	A stochastic programming approach for optimal sizing of energy storage.	Artificial forecast	No	hour-ahead	10 minute
[56]	ESS sizing by formulating a chance-constrained optimization problem	Artificial forecast	No	Not mentioned	Not mentioned
[33]	ES management system in an event of loss of load in bulk power system, improving its overall reliability.	Perfect forecast	No	Day-ahead	Hourly
[34]	Value of energy storage in context of electric system security and reserve allocation with wind generation uncertainty.	Artificial forecast	Yes	Not mentioned	Not mentioned
[35]	Impact of forecast uncertainties in wind power generation on storage based standing reserves considering high wind penetration.	Artificial forecast	No	Not mentioned	Not mentioned

TABLE 2. *(Continued.)* Table shows the summary of the papers reviewed in the study.

Author and ref.	Application Summary	Forecasting Technique	Uncertainty Analysis	Forecast Horizon	Forecast Resolution
[36]	Frequency deviation and regulation of the energy storage dispatch based on wind power forecasts.	No forecasting methodology discussed	No	Not mentioned	Not mentioned
[37]	An MPC based strategy to deal with small and large forecast errors to constrain the SOC to stay within limits.	Artificial forecast	Yes	Multiple	Multiple
[38]	Effect of load forecasting error in a microgrid with storage, wind turbine, photovoltaic plant, diesel engine and a microturbine	ARMA	No	Day-ahead	Hourly
[39]	MPC based control strategy to control the energy storage dispatch for overall cost reduction in a microgrid with solar + storage	Artificial forecast	Yes	Day-ahead + Real-time	Hourly
[40]	Energy management system operation strategy for a single family home with PV and battery storage	Artificial forecast	No	Not mentioned	Not mentioned
[41]	A linear optimization model for coordinated optimal dispatch of energy storage units in a grid tied microgrid with renewable assets to reduce the electricity costs considering net-demand forecasts.	No forecasting methodology discussed	No	Not mentioned	Not mentioned
[42]	A linear optimization based methodology that outputs an optimal schedule for the battery to maximize economic benefits with load and PV forecasts.	ANN	No	Day-ahead	Hourly
[43]	BTM energy arbitrage	Auto-Regressive model with eXogenous variables (ARX)	No	Hour-ahead + Day-ahead	Intra-hourly + Hourly
[44]	Demand charge reduction for BTM energy storage with PV.	ARMA	No	Day-ahead	Hourly
[45]	MPC based control for demand charge reduction.	Feed forward neural network (FFNN) + Seasonal Auto-Regressive Moving Average (SARMA) + Naïve model	Yes	Day-ahead	Hourly

a real forecasting model using ANN. In-order to analyse the performance of the system under varying forecast errors, the authors use artificially created forecasts with varying accuracy. They also present a case which simulates the system without forecast information. Such a well presented study helps understand the effect of forecast on energy storage applications in detail.

One of the most significant findings to emerge from this study is that forecast and its accuracy play an important role in some energy storage applications. Our main interest is to understand how forecasts are generated in different energy storage applications found in the literature, and what impact those forecasts have on the operation of storage assets, according to the results presented by different authors. Multiple factors affect the impact of forecast accuracy on a given system. Some papers also design the system in a way that it is capable of absorbing the impact of forecast uncertainty and still function efficiently. Nevertheless, from the papers reviewed in this study, it can be concluded that forecasts are useful for most energy storage applications. In the case of energy arbitrage or load shifting, the ESS is used to store energy during low cost or off-peak hours and use it during peak hours. Forecasts such as load forecast and electricity price forecast are critical in designing control systems for energy arbitrage. It can be concluded that for energy arbitrage, forecasts are crucial and add value. Moreover, the accuracy of forecasts directly impacts the performance of the system [29], [31], [32]. The authors in [32] compare the performance of their proposed system with forecasts of varying accuracy as well as a case with no forecasts to highlight the benefit of using forecasts. As operating reserves, energy storage offers great potential in terms of flexibility and reliability. Reserve requirement is estimated based on the difference between the forecast and the actual power and generation. The papers reviewed in this study identify the importance of using forecasts, however, they fail to quantify the value of forecasts for energy storage as operating reserves. In the case of using energy storage devices for renewable integration, forecasts play an important role in estimating future renewable generation and operating the system accordingly. The work in [37] highlights and quantifies the importance of using forecasts for RES integration. The authors observe the significant impact on SOC, operation costs and lifetime of ESS due to forecast accuracy. In microgrids, forecasts play a fundamental role in the control of energy storage devices. The authors in [38] study and highlight the value of forecasts with a case study.

Forecasts play an important role in the control of BTM energy storage devices. Load and BTM generation forecasts provide prosumer control over their energy storage devices as well as their electricity bill. The study in [42] looks into a BTM case with PV and storage. The paper very well demonstrates the effect of forecast accuracy on the system. In market applications of energy storage devices, forecasts of electricity price, renewable generation and load are used in the optimal control of storage devices, however, from the papers reviewed in this study, the value of forecasts in market applications could not be quantified. Forecasts play an important role in the sizing of storage devices. The authors in [56] conclude that the consideration of forecast errors was necessary for high operational reliability in ESS sizing problems.

Table 2 shows a summary of each paper reviewed in this study. It presents a summary of the application, forecast methodology, forecast horizon, and forecast resolution, and whether the authors conduct an uncertainty analysis,

Based on the work reviewed, the following recommendations are made to assist future research:

- Use a standard performance metrics: Depending on the application or use case of the ESS, different parameters can be used to evaluate the performance of the system. However, when using forecasts, Mean Absolute Percentage Error MAPE) and Root Mean Square Error (RMSE) should be used as the error metrics. MAPE and RMSE are the most common error metrics used to evaluate energy forecast models.
- Benchmark forecasting models: When presenting a forecasting methodology, the authors should use benchmark forecasting models available in literature to compare and assess their models.
- Use real forecasting methodology if applicable: In any work that evaluates the uncertainty caused by forecasts and its impact on the entire system, at least one analysis of the uncertainty caused by a real forecasting model should be considered.
- Use a realistic forecast horizon based on the use case: The use case will dictate which forecast will be used, from one hour ahead to day-ahead, which will vary the uncertainty in the forecast.
- Authors must present a complete overview of the forecasting methodology used in the work. This includes any preprocessing done to clean the data, the inputs used to train the forecasting models, and the hyper-parameters of the models.

VI. CONCLUSION

Joint use of energy forecasting and ESS provides promising opportunities as enabler technologies for creating new forms of flexibility options. The use of energy and pricing forecast for energy storage management applications has the potential to enable the use of energy storage flexibility and optimization of its value. Realistic uncertainty analysis of forecasts play an important role to determine the value of ESS usage, quantify the operational risks, and create new next generation business models. The present study has been one of the first attempts to thoroughly examine the impact of forecast uncertainty on energy storage applications found in literature. The papers present a comprehensive overview of the state-of-the-art of energy storage applications and how they incorporate energy forecasts into their study. It is expected to observe new combined utilization of ESS and energy forecasting while both domains are evolving. Distributed, federated and hierarchical energy forecasting using new AI algorithms like explainable or responsible AI can be considered among the most promising new dimensions in the field.

REFERENCES

[1] I. Mead, ''International energy outlook 2017,'' US Energy Inf. Admin., Washington, DC, USA, 2017.

[2] B. N. Stram, ''Key challenges to expanding renewable energy,'' *Energy Policy*, vol. 96, pp. 728–734, Sep. 2016.

[3] J. P. Barton and D. G. Infield, ''Energy storage and its use with intermittent renewable energy,'' *IEEE Trans. Energy Convers.*, vol. 19, no. 2, pp. 441–448, Jun. 2004.

[4] W. Gorman, A. Mills, M. Bolinger, R. Wiser, N. G. Singhal, E. Ela, and E. O'Shaughnessy, ''Motivations and options for deploying hybrid generator-plus-battery projects within the bulk power system,'' *Electr. J.*, vol. 33, no. 5, Jun. 2020, Art. no. 106739.

[5] J. Neubauer and M. Simpson, ''Deployment of behind-the-meter energy storage for demand charge reduction,'' Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-5400-63162, 2015.

[6] D. Krishnamurthy, C. Uckun, Z. Zhou, P. R. Thimmapuram, and A. Botterud, ''Energy storage arbitrage under day-ahead and real-time price uncertainty,'' *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 84–93, Jan. 2018.

[7] U. Akram and M. Khalid, ''A coordinated frequency regulation framework based on hybrid battery-ultracapacitor energy storage technologies,'' *IEEE Access*, vol. 6, pp. 7310–7320, 2018.

[8] M. Faisal, M. A. Hannan, P. J. Ker, A. Hussain, M. B. Mansor, and F. Blaabjerg, ''Review of energy storage system technologies in microgrid applications: Issues and challenges,'' *IEEE Access*, vol. 6, pp. 35143–35164, 2018.

[9] P. Denholm, "Energy storage to reduce renewable energy curtailment," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2012, pp. 1–4.

[10] A. D. Del Rosso and S. W. Eckroad, "Energy storage for relief of transmission congestion," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1138–1146, Mar. 2013.

[11] G. Fitzgerald, J. Mandel, J. Morris, and H. Touati, "The economics of battery energy storage: How multi-use, customer-sited batteries deliver the most services and value to customers and the grid," Rocky Mountain Inst., CO, USA, 2015, p. 6.

[12] D. Zafirakis, K. J. Chalvatzis, G. Baiocchi, and G. Daskalakis, "The value of arbitrage for energy storage: Evidence from European electricity markets," *Appl. Energy*, vol. 184, pp. 971–986, Dec. 2016.

[13] W. A. Braff, J. M. Mueller, and J. E. Trancik, "Value of storage technologies for wind and solar energy," *Nature Climate Change*, vol. 6, no. 10, pp. 964–969, Oct. 2016.

[14] J. Antonanzas, N. Osorio, R. Escobar, R. Urraca, F. M. de Pison, and F. Antonanzas-Torres, "Review of photovoltaic power forecasting," *Sol. Energy*, vol. 136, pp. 78–111, Oct. 2016.

[15] R. H. Inman, H. T. Pedro, and C. F. Coimbra, "Solar forecasting methods for renewable energy integration," *Prog. Energy Combustion Sci.*, vol. 39, no. 6, pp. 535–576, 2013.

[16] T. Hong and S. Fan, "Probabilistic electric load forecasting: A tutorial review," *Int. J. Forecasting*, vol. 32, no. 3, pp. 914–938, 2016.

[17] M. Lei, L. Shiyan, J. Chuanwen, L. Hongling, and Z. Yan, "A review on the forecasting of wind speed and generated power," *Renew. Sustain. Energy Rev.*, vol. 13, no. 4, pp. 915–920, 2009.

[18] Ü. Cali, *Grid and Market Integration of Large-Scale Wind Farms Using Advanced Wind Power Forecasting: Technical and Energy Economic Aspects*, vol. 17. Kassel, Germany: Kassel Univ. Press GmbH, 2011.

[19] R. Ramanathan, R. Engle, C. W. J. Granger, F. Vahid-Araghi, and C. Brace, "Short-run forecasts of electricity loads and peaks," *Int. J. Forecasting*, vol. 13, no. 2, pp. 161–174, 1997.

[20] V. Sharma, U. Cali, V. Hagenmeyer, R. Mikut, and J. Á. G. Ordiano, "Numerical weather prediction data free solar power forecasting with neural networks," in *Proc. 9th Int. Conf. Future Energy Syst.*, Jun. 2018, pp. 604–609.

[21] U. Cali and V. Sharma, "Short-term wind power forecasting using long-short term memory based recurrent neural network model and variable selection," *Int. J. Smart Grid Clean Energy*, vol. 8, no. 2, pp. 103–110, 2019.

[22] S. S. Soman, H. Zareipour, O. Malik, and P. Mandal, "A review of wind power and wind speed forecasting methods with different time horizons," in *Proc. North Amer. Power Symp.*, Sep. 2010, pp. 1–8.

[23] A. J. Conejo, M. A. Plazas, R. Espinola, and A. B. Molina, "Day-ahead electricity price forecasting using the wavelet transform and ARIMA models," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 1035–1042, May 2005.

[24] B. Soldo, "Forecasting natural gas consumption," *Appl. Energy*, vol. 92, pp. 26–37, Apr. 2012.

[25] H. Zareipour, D. Huang, and W. Rosehart, "Wind power ramp events classification and forecasting: A data mining approach," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2011, pp. 1–3.

[26] P. Fairley, "The troubled link between gas and electricity grids [news]," *IEEE Spectr.*, vol. 53, no. 6, pp. 11–12, Jun. 2016.

[27] K. Bassett, R. Carriveau, and D. S.-K. Ting, "Energy arbitrage and market opportunities for energy storage facilities in Ontario," *J. Energy Storage*, vol. 20, pp. 478–484, Dec. 2018.

[28] M. Rowe, T. Yunusov, S. Haben, C. Singleton, W. Holderbaum, and B. Potter, "A peak reduction scheduling algorithm for storage devices on the low voltage network," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 2115–2124, Jul. 2014.

[29] G. Bao, C. Lu, Z. Yuan, and Z. Lu, "Battery energy storage system load shifting control based on real time load forecast and dynamic programming," in *Proc. IEEE Int. Conf. Automat. Sci. Eng. (CASE)*, Aug. 2012, pp. 815–820.

[30] A. Di Giorgio, F. Liberati, A. Lanna, A. Pietrabissa, and F. D. Priscoli, "Model predictive control of energy storage systems for power tracking and shaving in distribution grids," *IEEE Trans. Sustain. Energy*, vol. 8, no. 2, pp. 496–504, Apr. 2017.

[31] K. Worthmann, C. M. Kellett, P. Braun, L. Grüne, and S. R. Weller, "Distributed and decentralized control of residential energy systems incorporating battery storage," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1914–1923, Jul. 2015.

[32] V. Papadopoulos, T. Delerue, J. Van Ryckeghem, and J. Desmet, "Assessing the impact of load forecasting accuracy on battery dispatching strategies with respect to peak shaving and time-of-use (TOU) applications for industrial consumers," in *Proc. 52nd Int. Univ. Power Eng. Conf. (UPEC)*, Aug. 2017, pp. 1–5.

[33] Y. Xu and C. Singh, "Power system reliability impact of energy storage integration with intelligent operation strategy," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1129–1137, Mar. 2014.

[34] M. Black, V. Silva, and G. Strbac, "The role of storage in integrating wind energy," in *Proc. Int. Conf. Future Power Syst.*, 2005, p. 5.

[35] M. Black and G. Strbac, "Value of bulk energy storage for managing wind power fluctuations," *IEEE Trans. Energy Convers.*, vol. 22, no. 1, pp. 197–205, Mar. 2007.

[36] L. Wu, W. Gao, Z. Cui, and X. Kou, "A novel frequency regulation strategy with the application of energy storage system for large scale wind power integration," in *Proc. 7th Annu. IEEE Green Technol. Conf.*, Apr. 2015, pp. 221–226.

[37] Y. Chen, C. Deng, D. Li, and M. Chen, "Quantifying cumulative effects of stochastic forecast errors of renewable energy generation on energy storage SOC and application of hybrid-MPC approach to microgrid," *Int. J. Electr. Power Energy Syst.*, vol. 117, May 2020, Art. no. 105710.

[38] L. Alvarado-Barrios, Á. R. del Nozal, J. B. Valerino, I. G. Vera, and J. L. Martínez-Ramos, "Stochastic unit commitment in microgrids: Influence of the load forecasting error and the availability of energy storage," *Renew. Energy*, vol. 146, pp. 2060–2069, Feb. 2020.

[39] M. Arnold and G. Andersson, "Model predictive control of energy storage including uncertain forecasts," in *Proc. Power Syst. Comput. Conf. (PSCC)*, Stockholm, Sweden, vol. 23, 2011, pp. 24–29.

[40] A. Arnoldt and P. Bretschneider, "Model predictive control considering forecast deviation in local districts," in *Proc. 16th Int. Conf. Eur. Energy Market (EEM)*, 2019, pp. 1–5.

[41] M. R. Sandgani and S. Sirouspour, "Coordinated optimal dispatch of energy storage in a network of grid-connected microgrids," *IEEE Trans. Sustain. Energy*, vol. 8, no. 3, pp. 1166–1176, Jul. 2017.

[42] A.-L. Klingler and L. Teichtmann, "Impacts of a forecast-based operation strategy for grid-connected PV storage systems on profitability and the energy system," *Sol. Energy*, vol. 158, pp. 861–868, Dec. 2017.

[43] H. Chitsaz, P. Zamani-Dehkordi, H. Zareipour, and P. P. Parikh, "Electricity price forecasting for operational scheduling of behind-the-meter storage systems," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6612–6622, Nov. 2018.

[44] B. P. Bhattarai, K. S. Myers, and J. W. Bush, "Reducing demand charges and onsite generation variability using behind-the-meter energy storage," in *Proc. IEEE Conf. Technol. Sustainability (SusTech)*, Oct. 2016, pp. 140–146.

[45] K. Abdulla, K. Steer, A. Wirth, and S. Halgamuge, "Improving the on-line control of energy storage via forecast error metric customization," *J. Energy Storage*, vol. 8, pp. 51–59, Nov. 2016.

[46] H. Cui, F. Li, X. Fang, H. Chen, and H. Wang, "Bilevel arbitrage potential evaluation for grid-scale energy storage considering wind power and LMP smoothing effect," *IEEE Trans. Sustain. Energy*, vol. 9, no. 2, pp. 707–718, Apr. 2018.

[47] Y. Levron and D. Shmilovitz, "Power systems' optimal peak-shaving applying secondary storage," *Electr. Power Syst. Res.*, vol. 89, pp. 80–84, Aug. 2012.

[48] Y. Xu and C. Singh, "Adequacy and economy analysis of distribution systems integrated with electric energy storage and renewable energy resources," *IEEE Trans. Power Syst.*, vol. 27, no. 4, pp. 2332–2341, Nov. 2012.

[49] Y. Xu, L. Xie, and C. Singh, "Optimal scheduling and operation of load aggregators with electric energy storage facing price and demand uncertainties," in *Proc. North Amer. Power Symp.*, Aug. 2011, pp. 1–7.

[50] A. Barré, B. Deguilhem, S. Grolleau, M. Gérard, F. Suard, and D. Riu, "A review on lithium-ion battery ageing mechanisms and estimations for automotive applications," *J. Power Sources*, vol. 241, pp. 680–689, Nov. 2013.

[51] S. Pelletier, O. Jabali, G. Laporte, and M. Veneroni, "Battery degradation and behaviour for electric vehicles: Review and numerical analyses of several models," *Transp. Res. B, Methodol.*, vol. 103, pp. 158–187, Sep. 2017.

[52] C. Ju, P. Wang, L. Goel, and Y. Xu, "A two-layer energy management system for microgrids with hybrid energy storage considering degradation costs," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6047–6057, Nov. 2018.

[53] S. X. Chen, H. B. Gooi, and M. Q. Wang, "Sizing of energy storage for microgrids," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 142–151, Mar. 2012.
[54] A. Oudalov, R. Cherkaoui, and A. Beguin, "Sizing and optimal operation of battery energy storage system for peak shaving application," in *Proc. IEEE Lausanne Power Tech*, Jul. 2007, pp. 621–625.
[55] K. Baker, G. Hug, and X. Li, "Energy storage sizing taking into account forecast uncertainties and receding horizon operation," *IEEE Trans. Sustain. Energy*, vol. 8, no. 1, pp. 331–340, Jan. 2017.
[56] M. Cao, Q. Xu, J. Cai, and B. Yang, "Optimal sizing strategy for energy storage system considering correlated forecast uncertainties of dispatchable resources," *Int. J. Elect. Power Energy Syst.*, vol. 108, pp. 336–346, Jun. 2019.
[57] Z. Deng, X. Hu, X. Lin, Y. Che, L. Xu, and W. Guo, "Data-driven state of charge estimation for lithium-ion battery packs based on Gaussian process regression," *Energy*, vol. 205, Aug. 2020, Art. no. 118000.
[58] X. Hu, X. Yang, F. Feng, K. Liu, and X. Lin, "A particle filter and long short-term memory fusion technique for lithium-ion battery remaining useful life prediction," *J. Dyn. Syst., Meas., Control*, vol. 143, no. 6, Jun. 2021.

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