Proceedings of the Sustainable Research and Innovation Conference
JKUAT Main Campus, Kenya
6 - 7 October, 2021

A Review of Wind Speed and Power Forecasting Techniques and Optimal Sizing of Battery Energy Storage Systems

Hampfrey Z. Odero[1], Cyrus W. Wekesa[2] and George K. Irungu[3]

Abstract - The incorporation of wind power into the electric power grid has seen tremendous growth in many countries across the globe. This is because of the many benefits wind energy possesses such as its environmental friendliness and declining cost. However, due to its intermittent and uncertain nature, its high penetration brings several hurdles in the operations and planning of power systems. For instance, maintaining balance between demanded power and supplied power, which is necessary for secure grid operation, becomes a challenge. To mitigate this challenge, several studies have proposed improved wind speed forecasting and the application of Battery Energy Storage Systems (BESS). Therefore, this paper provides a detailed review of various wind energy forecasting techniques, both Artificial Intelligence and traditional statistical techniques, and optimal BESS sizing considerations and approaches, highlighting their various competing advantages and disadvantages. Lastly, the paper identifies possible areas in wind forecasting techniques and optimal storage sizing that require further exploration.

Keywords - Artificial Intelligence, Battery Energy Storage System, Bio-inspired optimization, Wind forecasting techniques.

I. INTRODUCTION

WIND power constitutes the renewable generation technology which has experienced the fastest growth among all types of renewable generation technologies being currently investigated. It is considered to be the most mature in terms of commercial development in the world for meeting the energy demand from various perspectives such as environment, energy security and socioeconomic aspects without foregoing economic development and thus, a significant portion of electrical power can be generated from wind energy [1]. The development costs of wind power have decreased dramatically in recent years due to more competitive supply chains, increasing economies of scale and further technological improvements [2].

Electricity generated from wind power can be highly variable at several different timescales: hourly, daily, or seasonally. Though annual variation also exists, it is not so notable. Like other electricity sources, wind energy must be scheduled. Wind power forecasting methods are used, but predictability of wind plant output remains low for short-term operation. Because instantaneous electrical generation and consumption must remain in balance to maintain grid stability, this variability can present substantial challenges to the power system operators/planners, who have to ensure the reliable and secure grid operation when large amounts of wind power are incorporated into a grid system.

The forecast for wind-power generation is more challenging than that for solar photovoltaic. Large variations can occur within minutes. Moreover, previous studies [3],[4] have shown that the designing and training of wind forecasting (WF) models such as Artificial Neural Networks (ANNs), fuzzy and Autoregressive Moving Average (ARMA) are most challenging these days. This is because the WF model designed for one site is not suitable for another site due to change in terrain, distinct wind speed patterns, distinct atmospheric parameters such as pressure, temperature or humidity.

As power generation from wind energy is significantly increasing, it is of paramount importance to accurately predict the generation output of the wind energy resource as fast as possible [3]. This is for the purposes of ensuring better planning and reliable operation by the system planners and operators. To overcome the various challenges arising from the intermittency of wind resources, optimal storage is considered to be a very economical solution as depicted by many ongoing studies and projects around the globe. Various AI techniques have been found to be very efficient in both forecasting the generation output of WES [3] and optimizing their storage designs [5]–[7]. For this reason, this paper presents an updated review of various wind speed and power forecasting techniques with optimal BESS sizing considerations and approaches.

The paper is organized as follows. Section II highlights the classification of forecast time horizons depending on the requirements of the power systems operation. Next, in section III, several wind speed and power forecasting techniques are discussed in detail. Section IV deals with BESS sizing approaches and considerations. Finally, section V gives the conclusion.

[1] H. Z. Odero of Pan African University, Institute for Basic Sciences, Technology and Innovation. (Telephone contact: +254706503869; e-mail: hampfreyzurua@gmail.com)

[2] C. W. Wekesa of School of Engineering, University of Eldoret. (e-mail: cwekesa@uoeld.ac.ke)

[3] G. K. Irungu of Electrical and Electronic Engineering Department, JKUAT (e-mail: girungu@jkuat.ac.ke)

II. CLASSIFICATION OF FORECAST HORIZONS

The forecast can be classified into four different time horizons depending on the requirements of the power system operation, namely: long-term (more than a month ahead), medium-term (week, month ahead), short-term (day ahead) [8] and very short-term (few seconds to 30 min ahead) [9]. Table I highlights the time horizon classification of wind forecasting techniques. Different wind power and speed prediction approaches have different characteristics and yield better results for different forecast locations and time horizons in [9]. Fig. 1 shows the challenges of integrating Wind Energy Resource (WER) into the electrical grid.

III. WIND FORECASTING TECHNIQUES

A simple time-series based approach for wind power prediction was first developed in 1984 by Brown et al [10] by utilizing utility's power curve. Thereafter, numerous researches have been conducted in the field of predicting wind power or the speed produced by wind energy resources (WER) and this has led to the development of several different approaches as well as reliable and effective tools which have been used with different success rates in various wind Farms. The most widely used approaches are statistical approaches, AI-based approaches, physical approaches or combination approaches.

TABLE I
TIME HORIZON CLASSIFICATION OF FORECASTING TECHNIQUES.

Time-scale	Applications	Time plan
Very short-term [11] (from a few seconds to 30-minutes ahead)	- Grid stability operations, -load tracking -turbine control - Voltage regulation actions	10-seconds ahead
Short-term [11] (from 30 minutes to day-ahead)	-Economic load dispatch planning	1-hour ahead
	-Load increment or decrement decisions	3-hour ahead
	-Power reserve management	5-hour ahead
	-Operational security in day-ahead electricity market	6-hour ahead
	-Generator Online/Offline decisions	24-hour ahead
Medium-term (from day-ahead to month-ahead)	- Unit commitment decisions - Maintenance scheduling	72-hour ahead
Long-term (more than month-ahead)	- Wind farm optimal design - Restructured electricity	30-days ahead markets 1-year ahead 4-years ahead

A. *Statistical Forecasting Approaches*

Statistical forecasting approaches are data-driven models and uses large amounts of the recorded wind speed values of any site for prediction. They are mainly intended for very short-term and short-term forecasting. There are several time-series based approaches statistical models, namely; autoregressive model (AR), moving average model (MA), autoregressive moving average model (ARMA), and autoregressive integrated moving average model (ARIMA) which gives prediction value as a function of past wind speed or power.

In many instances such as short-term, medium-term, and long-term forecasting, the statistical approaches give good results. Nevertheless, in the very short-term and short-term horizon, the effect of atmospheric dynamics becomes more vital, thus the utilization of the physical approaches becomes essential [3]. They are also easy to model and inexpensive and are capable of providing timely forecasts. However, unlike the physical methods, they require huge sets of historical data to train the model. Fig. 2 shows the general statistical approach for wind power and speed forecast.

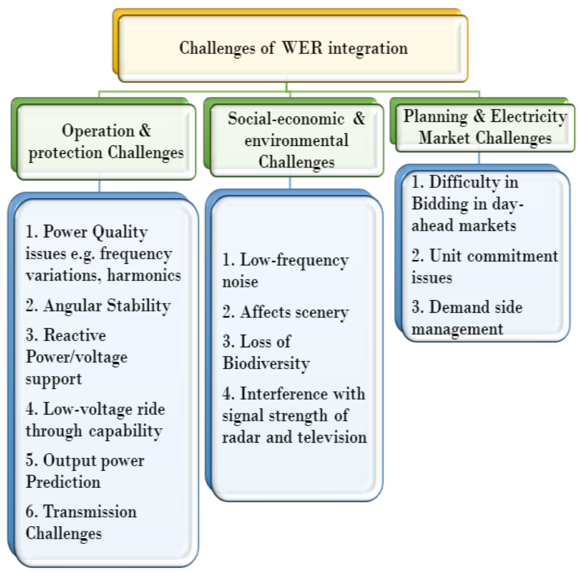

Fig. 1. Challenges of wind energy resource integration.

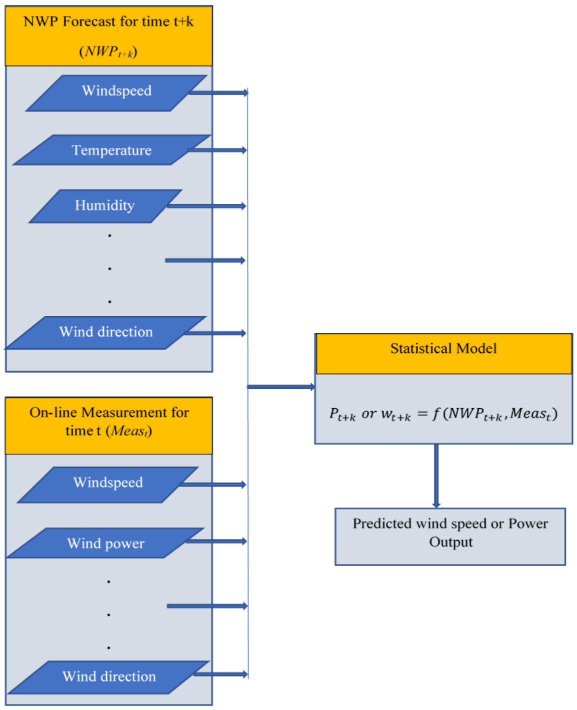

Fig. 2. The general form of statistical approach to forecast wind speed and power [3].

B. Physical Forecasting Approaches

These approaches utilize the detailed physical description from the meteorological data of wind farms such as humidity, atmospheric pressure, temperature, obstacles, and surface coarseness to model the onsite conditions and predict the wind speed. However, these physical approaches involve intense calculation hence requiring much time. Several physical approaches have been developed and used, namely; The Prediktor [12], The Previento [13], The LocalPred [14] and the eWind [15]. The general form of the model is shown in Fig. 3.

C. AI-Based forecasting Approaches

AI-based approaches are also data-driven models. Using the recorded historical data from any site and based on the various learning algorithms, the network can be trained. For instance, ANN can model complex non-linear relationships between the inputs and outputs and derive the dependence between the inputs and outputs via learning and training while Fuzzy logic performs better than others when handling reasoning problems, especially where learning and training abilities are not important. Unlike the statistical and physical approaches, this approach does not need explicit mathematical expressions. In addition, it has the ability of self-learning, self-organizing and self-adaption [3]. Other AI-based approaches used include ANN–Fuzzy approach. Fig. 4 shows the general ANN approach for wind power and speed forecast.

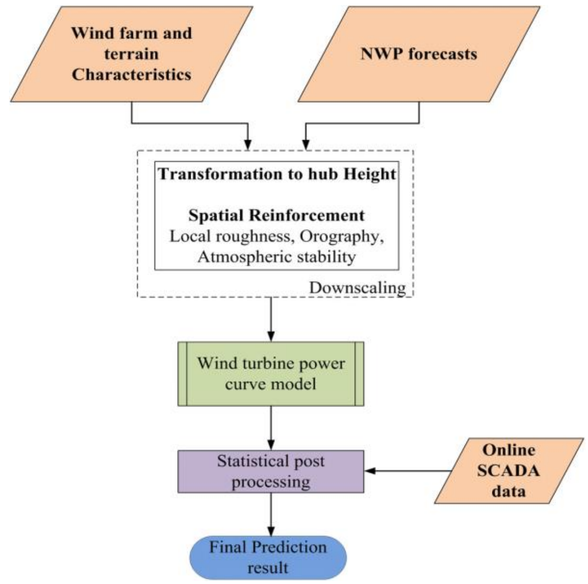

Fig. 3. Flow diagram of physical approaches of wind speed forecasting [16].

Due to its ability to model a complex non-linear relationship and extract the dependence between the input and output via the learning process, ANN has been found to be generally a good selection for wind speed and power forecasting. Furthermore, it is easy to construct and requires only short development periods, and it does not need explicit mathematical expressions. In most cases, no particular independent method is the best. However, most forecasting studies using ANN have offered the best performance as compared to other techniques [3].

Using historical data and ANN modelling the authors in [17] presented a tool that would be used by operators of RES system to achieve better monitoring and management of the whole system. The development of the prognostic tool was able to give adequate and sufficient forecast eight hours ahead of the absolute minimum, maximum and the mean hourly wind power at a specific location in Tilos Island, Greece. This was generated by an E-53 Enercon wind turbine using real-recorded wind speed data and the corresponding wind turbine power curve. In [18], wind farm prediction models both for short-term and long-term period are constructed using data mining approach. The model generated by an ANN outperformed all other models for both short-term and long-term forecast.

Using the input parameters— generation hours, relative humidity and mean wind speed, the neural network model developed in [19] offers a reliable indicator of the wind power output from wind farms. The authors in [20] used ANN approach to approximate the wind speed at a particular site utilizing the wind speed at a strong correlation site among neighboring sites.

A wide comparison based on time horizons, performance analysis and statistical distribution of normalized errors is carried out between the five kinds of ANN models, ARMA models, and ANFIS models in [21]. ANN models showed better performance.

An in-depth comparison study of three types of typical ANN approaches, namely; Adaptive Linear Element (ADALINE), Radial Basis Function (RBF) and Feed Forward Back Propagation (FFBP) approaches is conducted in [22]. Results indicated that different model structures, inputs and learning rates had a direct influence on the forecast accuracy. In addition, even for the same wind dataset, no individual approach outperformed others universally based on the evaluation criteria.

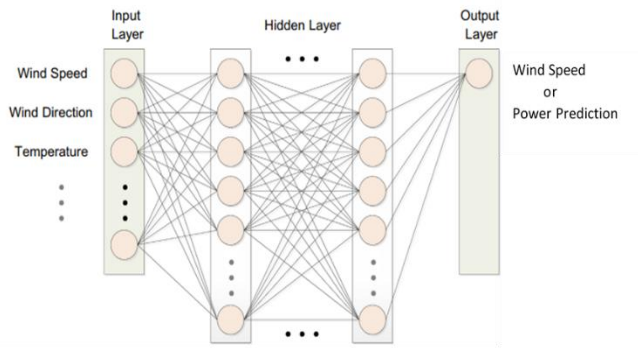

Fig. 4. ANN approach for wind speed and power forecast.

D. Combination Forecasting Approaches

The excellent qualities of the prediction approaches mentioned above have been merged to obtain hybrid models which have not only demonstrated improved accuracy of forecasting and wider prediction horizons as demonstrated by Feng *et al* [23], but also minimizes the risk from extreme events. For example, the combination of the Fuzzy logic with ANN approach produces the hybrid ANN–Fuzzy approach which yields excellent performance. However, this approach does not always perform better than the best individual forecasts [3]. Many combination approaches have been reviewed in [3] and [16].

The authors in [24] predict wind speed automatically employing a hybrid neural network approach, comprising a Self-Organizing Map (SOM) and a Radial Basis Function (RBF) neural network. The results indicated that the proposed method yielded better output of wind speed prediction with less error rates.

An advanced study was performed by the authors in [25] who proposed Bayesian Model Averaging (BMA) approach to combine the wind speed forecasts gotten from different ANN models, namely, Radial Basis Function (RBF) network, Back-Propagation (BP) network and Adaptive Linear Element (ADALINE) network. Based on their posterior model probabilities, the BMA approach weights individual forecast. The better performing predictions acquire higher weights than the worse. This approached proved to be effective as shown by the simulation results.

The mean of a sorted number of similar wind speed days from Similar Days (SD) approach is utilized for the input of different Soft Computing Models (SCMs) - Adaptive Neuro-Fuzzy Inference System (ANFIS), Back-Propagation Neural Network (BPNN) and Radial Basis Function Neural Network (RBFNN) in [26]. Combination of the SD model with SCMs showed some level of improved performance, with the SD–ANFIS model outperforming all other individual and combined models.

E. Other Approaches

Other approaches include *persistence approach*. This is the widely known benchmark approach. As mentioned by Nielsen et al [27], the accuracy of this method is very high for very short-term intraday predictions (a few seconds to 6-hour ahead).

At sites where inadequate information is not available, *spatial correlation forecasting* such as Measure-Correlate-Predict (MCP) method [28] can be used to estimate the characteristics of the WER. This is achieved by evaluating the sufficiency of the wind power of the adjacent regions. In comparison to the common time-ahead forecasting models, these models are more strenuous since they need measurements from several spatially correlated sites and the associated measurement delay times [3].

More approaches for wind power prediction such as r*egional forecasting* and *probabilistic forecasting* (e.g. the parametric approach, non-parametric approach, distribution-free approaches and ensemble forecast) are extensively discussed in [3] and g*aussian-Process-based method* in [29]. The *frequency domain approach* is introduced for characterizing the wind speed patterns in [30].

As a result, these prediction tools have been found to minimize the overall costs of operations and enhance reliability linked with the increased penetration of wind power into the existing electrical grids [31]–[33].

Other various promising approaches for enhancing the accuracy of the prediction models includes; Combining different forecasting or NWPs models as discussed in [34]–[38], filtering of systematic errors emanating from NWPs using Kalman filtering [39], proper selection of input parameters [40], or the combination of the any of the above mentioned promising approaches [16], [41]. However, the combined approaches do not always outperform the single method for all the forecasting time horizons investigated as shown by studies in [35]. Table II highlights the various advantages and disadvantages of different wind forecasting techniques.

IV. BESS OPTIMAL SIZING: CONSIDERATIONS AND APPROACHES

A. Brief Overview

According to [5], design and executions of most practical RES hybrid system often depend on continuous experience including trial and error. However, such methods always lead to unexpected problems such as premature battery degradation. This may be very expensive due to the required design corrections after installation.

B. *Techniques and Considerations in BESS Sizing*

TABLE II
ADVANTAGES AND DISADVANTAGES OF DIFFERENT WINDFORECASTING TECHNIQUE

Forecasting approach	**Advantages**	**Disadvantages**
Time-series based approaches/Statistical approaches (Example: AR, MA, ARMA, ARIMA, GARCH, and so on	- No need of expert skill. - Most reliable forecasting approach because it utilizes readily available meteorological data. - Determination of prediction intervals are very simple, accurate for short-term forecasts.	- Less accurate for long-term forecasts. - Intermittent behavior of prediction parameter (wind speed or wind power) cannot capture perfectly. - These approaches require large number of past input values.
Persistence method	-Highly accurate for very short-term forecasts which are ranging from few seconds to 6-hour ahead.	-Time horizon increases because of overcast and intermittent nature of wind speed, forecasting accuracy will be decreased for long-term forecasts.
NWP/Physical approaches	-Best suitable for long-term forecasting.	- Not applicable for short-term forecasting due to computational complexities. - Difficult to get physical input data. -Much time required due to intensity of calculations.
Support Vector Machine -based approaches	- Exhibits better generalization capabilities.	- Consists of complex optimization structure - Accuracy rely on genuine tuning of parameters. - Requires longer training time.
ANN-based approaches	- Adaptable to wide range of parameters. - Highly nonlinear models like wind speeds. - Knowledge-based systems and learns through the training process. - ANNs will react to even the smallest change in data.	- Need huge training dataset and optimal training algorithm. - difficult to design and needs large amount of computational resources.
Fuzzy-logic approaches	- Easy to implement and have the ability to deal with uncertainties and nonlinearities. - Comparatively less complex approach and acceptable for models that are tough to design precisely. - Improves the accuracy of forecasts by rule-based learning process.	- Model becomes complex and computational time also increases. - Exhibits weak learning ability.
Hybrid AI Approaches	- These approaches will use best features of the above single forecasting approaches in order to minimize the effect of drawbacks, computational complexity. - These methodologies are implemented for larger systems.	- Designing and training of these types of forecasting approaches are challenging. - The input data must be preprocessed for enhanced and obtain accurate forecasts generalization capability.

Various strategies have been suggested for obtaining the optimal size of BESS. For instance, many classical optimization algorithms and metaheuristic techniques such as GA, PSO, ABC or a hybrid combination of AI and evolutionary computation such as ANN-PSO have been used in the optimal design of storage system.

Classical optimization algorithms employ differential calculus to obtain optimum solutions for continuous and differentiable functions. These methods of optimization techniques have been widely utilized in optimal sizing of hybrids systems as reviewed in [5] and are generally categorized as: dynamic programming (DP), Linear programming model (LPM), and nonlinear programming (NLP). However, with the increased integration of intermittent Renewable Energy Sources (RES) into the existing grids, the optimization problem becomes more complex due to the non-linear and non-convex nature of the problem with multiple local optima. Fig. 5 shows the optimization techniques that have been applied in BESS optimal sizing.

As a result, although the above stated classical methods are effective, they are cumbersome and time-consuming rendering them inefficient and unsuitable in solving complex optimization problem [5].

For instance, a life cycle planning methodology of BESS in an off-grid was put forward in [42]. Using decomposition-coordination algorithm, the optimal allocation of DER capacity was carried out under multi-

stage decision framework to meet the demand growth while considering dynamic factors such as demand growth, battery capacity fading and components' contingencies.

Recently, several bio-inspired optimization techniques have gained popularity in solving the complex non-linear and non-convex optimization problems of sizing RES.

In [43], several evolutionary algorithms, namely, the genetic algorithm (GA), moth–flame optimization algorithm (MFO), artificial bee colony (ABC), grey wolf optimizer (GWO), differential evolution (DE), teaching–learning-based optimization (TLBO), particle swarm optimization (PSO) and gravitational search algorithm were used to optimize the characteristics of the proposed BESS model which was to be easily applied to a permanent magnet synchronous generator wind turbine in the grid-connected mode. SOC and REL. However, the two algorithms had some drawbacks, majorly due to the too much programming required, longer run-time and the difficulty of setting parameter.

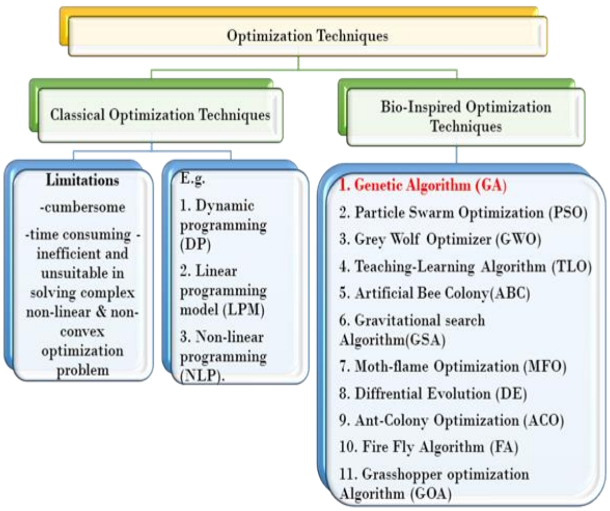

Fig. 5. Optimization approaches applied in BESS sizing.

The methods presented indicated the ability to increase the final State of Charge (SOC) of the batteries, increase the Remaining Expected Life (REL) of the batteries, and minimize the number of batteries, hence lowering the costs of the whole system. In addition, the results indicated that the GWO and TLBO algorithms were the best algorithms in terms of reducing the operation time of the standby battery and increasing the final

Authors in [44] uses an incremental cost approach to obtain the optimal values of BESS to achieve the minimum running cost for an islanded DC microgrid while in [45], the authors employ the grasshopper optimization algorithm to size the BESS while considering the efficiency of power supply probability end energy cost for an islanded operated microgrid penetrated with wind, solar PV and diesel generators. A unit commitment problem was minimized using a convex optimization technique in [46].

In [47], optimal sizing of BESS for a wind-penetrated, grid-connected microgrid and standalone microgrid were studied. The optimization was done within 24 hours in every month from January to December and the sizes of BESS energy and power capacities resulting from the minimum operational costs of the microgrid were computed. The study found out that the grid-connected BESS was cheaper to operate than the stand-alone one and it was worth to be considered for efficient dispatch of wind power since it was very economical.

To fully meet demand due to uncertainty of wind and solar PV, authors in [48] asserted that capacity sizing was vital. They formulated PSO algorithm to determine the optimal capacity for hybrid PV-wind with battery storage while considering uncertainty in generation of wind energy and solar energy. The objective was to minimize the system cost while constrained to having a given reliability for a given load.

The study in [49] used two constraint-based iterative search algorithms, namely, source-sizing and battery sizing algorithms to determine the optimal sizes of RES and BESS in hybrid wind and solar for a grid-connected microgrid system to maximize reliability and minimize cost. Besides, authors in [50] used the firefly algorithm and considered the BESS's depth of discharge when modeling the real-time battery operation cost. The results also showed that the operation cost was well minimized.

The GA is a heuristic evolutionary algorithm used for hybrid search and optimization problems. It mimics the Charles Darwin's theory of natural selection and was developed by John Holland in 1960–1970 [51]. Two of the most notable merits of GA over the traditional optimization algorithms are its ability to handle complex problems and parallelism. GA looks for solutions among populations of points, simultaneously works from a set of points and in parallel climbs many peaks, which leads to reduction in false peak finding probability [7]. It can effectively handle different types of optimizations, whether the fitness (objective) function is linear or non-linear, stationary or nonstationary (changes with time), continuous or discontinuous, or with random noise. Nevertheless, GA has few drawbacks. The fitness function formulation, the choice of critical parameters, namely, cross over and mutation rates and the selection criteria of new population must be done carefully, otherwise it will be difficult for the algorithm to converge. GA still remains one of the most widely used technique in modern non-linear optimization despite the above-mentioned disadvantages [52].

Many researches have employed GA to optimally design and size BESS. For instance, authors in [53] and [54] used multi-objective GA optimization method in hybrid system with battery storage to minimize the annualized cost of system (ACS), the Loss of Power Supply Probability (LPSP), the Levelized Cost of Energy (LCOE) as well as the CO_2 emissions. In [55], the optimization of an off-grid power system that consisted of the PV, WTG, diesel generator and ESS was investigated using GA. The proposed algorithm was found effective to aid the distribution network operators to minimize the total cost that was related to the operation of a microgrid system. Authors in [50], [56] considered the battery life of BESS in formulating an objective function in a wind-ESS penetrated microgrid. In [56], simulations performed by the rule-based and genetic algorithm indicated that the operation cost was well optimized.

The ANN is used to validate the forecasted load model with historical weather and holidays as input predictors while the uncertainties associated with RES are handled by a chance-constrained model, and solved by a genetic algorithm (GA) in [59][7]. The results indicated an increase in percentage of clean energy from 13 to 39%, and a sharp drop in CO_2 emissions, thereby reducing the devastating effect on the environment. The study revealed that for the betterment of the environment, the storage system plays a very important role to renewable energy integration.

V. CONCLUSION

Numerous researchers and utilities have been conducting systematic investigation on many wind forecasting approaches. It is worth noting that each approach used has unique techniques and has yielded the best test results based on forecast horizons and the size of the datasets. Different models perform differently under different situations. It is difficult to say which model is the best due to site dependence. The forecasting accuracy goes down with increasing forecast time horizon, unstable weather regimes and terrain complexity.

Though several optimal BESS sizing studies have been conducted previously, there is still a need to continue to investigate various methods or combinations of various methods, parameters and constraints that could aid in finding optimal BESS size.

REFERENCES

[1] S. Sawyer, S. Teske, L. Fried, and S. Shukla, *Global Wind Energy Outlook 2016*. 2016.

[2] IRENA, *Future of Wind: Deployment, investment, technology, grid integration and socio-economic aspects*. 2019.

[3] J. Jung and R. Broadwater, “Current status and future advances for wind speed and power forecasting,” *Renew. Sustain. Energy Rev.*, vol. 31, pp. 762–777, Mar. 2014, doi: 10.1016/j.rser.2013.12.054.

[4] D. Cinar and G. Kayakutlu, “Forecasting Production of Renewable Energy Using Cognitive Mapping and Artificial Neural Networks,” 2007.

[5] C. Mekontso, A. Abubakar, S. Madugu, O. Ibrahim, and Y. Adediran, “Review of Optimization Techniques for Sizing Renewable Energy Systems,” *Comput. Eng. Appl.*, vol. 8, pp. 13–30, 2019.

[6] R. Baños, F. Manzano-Agugliaro, F. G. Montoya, C. Gil, A. Alcayde, and J. Gómez, “Optimization methods applied to renewable and sustainable energy: A review,” *Renew. Sustain. Energy Rev.*, vol. 15, no. 4, pp. 1753–1766, 2011, doi: https://doi.org/10.1016/j.rser.2010.12.008.

[7] F. Abbas, S. Habib, D. Feng, and Z. Yan, “Optimizing Generation Capacities Incorporating Renewable Energy with Storage Systems Using Genetic Algorithms,” *Electron. MDPI*, Jul. 2018.

[8] J. Dobschinski *et al.*, “Uncertainty Forecasting in a Nutshell: Prediction Models Designed to Prevent Significant Errors,” *IEEE Power Energy Mag.*, vol. 15, no. 6, pp. 40–49, 2017, doi: 10.1109/MPE.2017.2729100.

[9] S. Soman, H. Zareipour, O. P. Malik, and P. Mandal, *A review of wind power and wind speed forecasting methods with different time horizons*. 2010.

[10] B. G. Brown, R. W. Katz, and A. H. Murphy, “Time Series Models to Simulate and Forecast Wind Speed and Wind Power,” *J. Clim. Appl. Meteorol.*, vol. 23, no. 8, pp. 1184–1195, Jul. 1984, [Online]. Available: http://www.jstor.org/stable/26181389.

[11] S. Fang and H. Chiang, “A High-Accuracy Wind Power Forecasting Model,” *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 1589–1590, 2017, doi: 10.1109/TPWRS.2016.2574700.

[12] L. Landberg, “Short-term prediction of local wind conditions,” *J. Wind Eng. Ind. Aerodyn.*, vol. 89, no. 3, pp. 235–245, 2001, doi: https://doi.org/10.1016/S0167-6105(00)00079-9.

[13] U. Focken, M. Lange, and H.-P. (Igor) Waldl, “Previento - A Wind Power Prediction System with an Innovative Upscaling Algorithm,” Jan. 2001.

[14] I. Martí *et al.*, “Wind power prediction in complex terrain: from the synoptic scale to the local scale,” Jan. 2004.

[15] C. McGowin, “California wind energy forecasting system development and testing. Phase 1: Initial testing,” 2003.

[16] M. Santhosh, C. Venkaiah, and D. M. Vinod Kumar, “Current advances and approaches in wind speed and wind power forecasting for improved renewable energy integration: A review,” *Eng. Reports*, vol. 2, no. 6, pp. 1–20, 2020, doi: 10.1002/eng2.12178.

[17] K. Moustris, D. Zafirakis, K. A. Kavvadias, and J. Kaldellis, “Wind power forecasting using historical data and artificial neural networks modeling,” in *Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MedPower 2016)*, Jan. 2016, pp. 105 (6 .)-105 (6 .), doi: 10.1049/cp.2016.1094.

[18] H. Zheng and Z. Song, “Wind Farm Power Prediction: A Data-Mining Approach,” *Wind Energy*, vol. 12, pp. 275–293, Apr. 2009, doi: 10.1002/we.295.

[19] M. Carolin Mabel and E. Fernandez, “Analysis of wind power generation and prediction using ANN: A case study,” *Renew. Energy*, vol. 33, no. 5, pp. 986–992, 2008, doi: https://doi.org/10.1016/j.renene.2007.06.013.

[20] D. Bechrakis and P. Sparis, “Correlation of Wind Speed Between Neighboring Measuring Stations,” *Energy Conversion, IEEE Trans.*, vol. 19, pp. 400–406, Jul. 2004, doi: 10.1109/TEC.2004.827040.

[21] M. G. De Giorgi, A. Ficarella, and M. Tarantino, “Error analysis of short term wind power prediction models,” *Appl. Energy*, vol. 88, no. 4, pp. 1298–1311, 2011, doi: https://doi.org/10.1016/j.apenergy.2010.10.035.

[22] G. Li and J. Shi, “On comparing three artificial neural networks for wind speed forecasting,” *Appl. Energy*, vol. 87, pp. 2313–2320, Jul. 2010, doi: 10.1016/j.apenergy.2009.12.013.

[23] X. Feng, Q. Li, Y. Zhu, J. Hou, L. Jin, and J. Wang, “Artificial neural networks forecasting of PM2.5 pollution using air mass trajectory based geographic model and wavelet transformation,” *Atmos. Environ.*, vol. 107, pp. 118–128, 2015, doi: https://doi.org/10.1016/j.atmosenv.2015.02.030.

[24] R. Velusamy and S. N. Deepa, “An Efficient Hybrid Neural Network Model for Wind Speed Prediction,” *Asian J. Res. Soc. Sci. Humanit.*, vol. 6, p. 1998, Jan. 2016, doi: 10.5958/2249-7315.2016.01148.5.

[25] G. Li, J. Shi, and J. Zhou, “Bayesian adaptive combination of short-term wind speed forecasts from neural network models,” *Renew. Energy*, vol. 36, no. 1, pp. 352–359, 2011, doi: https://doi.org/10.1016/j.renene.2010.06.049.

[26] A. U. Haque, P. Mandal, M. E. Kaye, J. Meng, L. Chang, and T. Senjyu, “A new strategy for predicting short-term wind speed using soft computing models,” *Renew. Sustain. Energy Rev.*, vol. 16, no. 7, pp. 4563–4573, 2012, doi: https://doi.org/10.1016/j.rser.2012.05.042.

[27] T. S. Nielsen, A. Joensen, H. Madsen, L. Landberg, and G. Giebel, “A new reference for wind power forecasting,” *Wind Energy*, vol. 1, no. 1, pp. 29–34, Sep. 1998, doi: https://doi.org/10.1002/(SICI)1099-1824(199809)1:1<29::AID-WE10>3.0.CO;2-B.

[28] M. Thøgersen, M. Motta, T. Sørensen, P. Nielsen, and N. Jernesvej, “Measure-Correlate-Predict Methods: Case Studies and Software Implementation,” 2007.

[29] H. Mori and E. Kurata, “Application of Gaussian Process to wind speed forecasting for wind power generation,” in *2008 IEEE International Conference on Sustainable Energy Technologies*, 2008, pp. 956–959, doi: 10.1109/ICSET.2008.4747145.

[30] J. Jung and K.-S. Tam, “A frequency domain approach to characterize and analyze wind speed patterns,” *Appl. Energy*, vol. 103, pp. 435–443, Mar. 2013, doi: 10.1016/j.apenergy.2012.10.006.

[31] J. Usaola, O. Ravelo, G. González, F. Soto, and B. Díaz-Guerra, “Benefits for Wind Energy in Electricity Markets from Using Short Term Wind Power Prediction Tools; A Simulation Study,” *Wind Eng.*, vol. 28, pp. 119–127, Jan. 2004, doi: 10.1260/0309524041210838.

[32] C. Lowery and M. O’Malley, “Impact of Wind Forecast Error Statistics Upon Unit Commitment,” *Sustain. Energy, IEEE Trans.*, vol. 3, pp. 760–768, Oct. 2012, doi: 10.1109/TSTE.2012.2210150.

[33] W. Mahoney *et al.*, “A Wind Power Forecasting System to Optimize Grid Integration,” *Sustain. Energy, IEEE Trans.*, vol. 3, pp. 670–682, Oct. 2012, doi: 10.1109/TSTE.2012.2201758.

[34] E. Cadenas and W. Rivera, “Wind speed forecasting in three different regions of Mexico, using a hybrid ARIMA–ANN model,” *Renew. Energy*, vol. 35, no. 12, pp. 2732–2738, 2010, doi: https://doi.org/10.1016/j.renene.2010.04.022.

[35] J. Shi, J. Guo, and S. Zheng, “Evaluation of hybrid forecasting approaches for wind speed and power generation time series,” *Renew. Sustain. Energy Rev.*, vol. 16, no. 5, pp. 3471–3480, 2012, doi: https://doi.org/10.1016/j.rser.2012.02.044.

[36] B. Kanna and S. Singh, “AWNN-Assisted Wind Power Forecasting Using Feed-Forward Neural Network,” *IEEE Trans. Sustain. Energy*, vol. 3, pp. 306–315, Apr. 2012, doi: 10.1109/TSTE.2011.2182215.

[37] Y.-Y. Hong, H.-L. Chang, and C.-S. Chiu, “Hour-ahead wind power

and speed forecasting using simultaneous perturbation stochastic approximation (SPSA) algorithm and neural network with fuzzy inputs," *Energy*, vol. 35, no. 9, pp. 3870–3876, 2010, doi: https://doi.org/10.1016/j.energy.2010.05.041.

[38] J. Catalão, H. M. I. Pousinho, and V. M. F. Mendes, "Hybrid wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal," *Sustain. Energy, IEEE Trans.*, vol. 2, pp. 50–59, Feb. 2011, doi: 10.1109/TSTE.2010.2076359.

[39] Z. Dongmei, Z. Yuchen, and Z. Xu, "Research on wind power forecasting in wind farms," in *2011 IEEE Power Engineering and Automation Conference*, 2011, vol. 1, pp. 175–178, doi: 10.1109/PEAM.2011.6134829.

[40] H. Liu, C. Chen, H. Tian, and Y. Li, "A hybrid model for wind speed prediction using empirical mode decomposition and artificial neural networks," *Renew. Energy*, vol. 48, pp. 545–556, Dec. 2012, doi: 10.1016/j.renene.2012.06.012.

[41] J. P. S. Catalão, H. M. I. Pousinho, and V. M. F. Mendes, "Short-term wind power forecasting in Portugal by neural networks and wavelet transform," *Renew. Energy*, vol. 36, no. 4, pp. 1245–1251, 2011, doi: https://doi.org/10.1016/j.renene.2010.09.016.

[42] W. Jianxue, Y. Zhang, A. Berizzi, and X. Cao, "Life Cycle Planning of Battery Energy Storage System in Off-grid Wind-Solar-Diesel Microgrid," *IET Gener. Transm. Distrib.*, vol. 12, Sep. 2018, doi: 10.1049/iet-gtd.2018.5521.

[43] R. Sakipour and H. Abdi, "Optimizing Battery Energy Storage System Data in the Presence of Wind Power Plants: A Comparative Study on Evolutionary Algorithms," *Sustainability*, vol. 12, p. 10257, Dec. 2020, doi: 10.3390/su122410257.

[44] K. Hesaroor and D. Das, "Optimal sizing of energy storage system in islanded microgrid using incremental cost approach," *J. Energy Storage*, vol. 24, p. 100768, 2019, doi: https://doi.org/10.1016/j.est.2019.100768.

[45] A. L. Bukar, C. W. Tan, and K. Y. Lau, "Optimal sizing of an autonomous photovoltaic/wind/battery/diesel generator microgrid using grasshopper optimization algorithm," *Sol. Energy*, vol. 188, pp. 685–696, 2019, doi: https://doi.org/10.1016/j.solener.2019.06.050.

[46] M. Zolfaghari, N. Ghaffarzadeh, and A. J. Ardakani, "Optimal sizing of battery energy storage systems in off-grid micro grids using convex optimization," *J. Energy Storage*, vol. 23, pp. 44–56, 2019, doi: https://doi.org/10.1016/j.est.2019.02.027.

[47] U. Salman, F. Al-Ismail, and M. Khalid, "Optimal Sizing of Battery Energy Storage for Grid-Connected and Isolated Wind-Penetrated Microgrid," *IEEE Access*, vol. PP, p. 1, Jan. 2020, doi: 10.1109/ACCESS.2020.2992654.

[48] A. Navaeefard, S. M. Moghaddas-Tafreshi, M. Barzegari, and A. Shahrood, "Optimal sizing of distributed energy resources in microgrid considering wind energy uncertainty with respect to reliability," Dec. 2010, doi: 10.1109/ENERGYCON.2010.5771795.

[49] U. Akram, M. Khalid, and S. Shafiq, "Optimal Sizing of a Wind/Solar/Battery Hybrid Grid-connected Microgrid System," *IET Renew. Power Gener.*, vol. 12, Oct. 2017, doi: 10.1049/iet-rpg.2017.0010.

[50] M. Sufyan, N. Abd Rahim, C. Tan, M. A. Muhammad, and S. R. Sheikh Raihan, "Optimal sizing and energy scheduling of isolated microgrid considering the battery lifetime degradation.," *PLoS One*, vol. 14, no. 2, p. e0211642, 2019, doi: 10.1371/journal.pone.0211642.

[51] J. H. Holland, "Genetic Algorithms," *Sci. Am.*, vol. 267, no. 1, pp. 66–73, Jul. 1992, [Online]. Available: http://www.jstor.org/stable/24939139.

[52] X.-S. Yang, "Chapter 6 - Genetic Algorithms," X.-S. B. T.-N.-I. O. A. (Second E. Yang, Ed. Academic Press, 2021, pp. 91–100.

[53] B. Bilal, V. Sambou, P. Ndiaye, C. Kébé, and M. Ndongo, "Multi-objective design of PV-wind-batteries hybrid systems by minimizing the annualized cost system and the loss of power supply probability (LPSP)," *2013 IEEE Int. Conf. Ind. Technol.*, pp. 861–868, 2013.

[54] B. O. Bilal, V. Sambou, C. M. F. Kébé, P. A. Ndiaye, and M. Ndongo, "Methodology to Size an Optimal Stand-Alone PV/wind/diesel/battery System Minimizing the Levelized cost of Energy and the CO2 Emissions," *Energy Procedia*, vol. 14, pp. 1636–1647, 2012, doi: https://doi.org/10.1016/j.egypro.2011.12.1145.

[55] T. Adefarati, S. Potgieter, R. Naidoo, R. Bansal, R. Rizzo, and P. Sanjeevikumar, "Optimization of PV-Wind-Battery Storage Microgrid System Using Genetic Algorithm," Jul. 2019, doi: 10.1109/ICCEP.2019.8890204.

[56] Y. Liu, X. Wu, J. Du, Z. Song, and G. Wu, "Optimal sizing of a wind-energy storage system considering battery life," *Renew. Energy*, vol. 147, pp. 2470–2483, 2020, doi: https://doi.org/10.1016/j.renene.2019.09.123.