IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 18 August 2023, accepted 8 September 2023, date of publication 14 September 2023,
date of current version 27 September 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3315591

RESEARCH ARTICLE

Short-Term Load Forecasting in Active Distribution Networks Using Forgetting Factor Adaptive Extended Kalman Filter

MENA S. ELMENSHAWY AND AHMED M. MASSOUD, (Senior Member, IEEE)
Department of Electrical Engineering, Qatar University, Doha, Qatar

Corresponding author: Mena S. ElMenshawy (me1203675@qu.edu.qa)

This work was supported in part by the Graduate Student Research Award (GSRA) through the Qatar National Research Fund (QNRF) under Grant GSRA9-L-1-0514-22014G, and in part by the Qatar National Library (Open Access Funding).

ABSTRACT The intermittent non-dispatchable power produced by Renewable Energy Sources (RESs) in distribution networks caused additional challenges in load forecasting due to the introduced uncertainties. Therefore, high-quality load forecasting is essential for distribution network planning and operation. Most of the work presented in literature focusing on Short-Term Load Forecasting (STLF) has paid little consideration to the intrinsic uncertainty associated with the load dataset. A few research studies focused on developing data filtering algorithm for the load forecasting process using approaches such as Kalman filter, which has good tracking capability in the presence of noise in the data collection process. To avoid the divergence of conventional Kalman filter and improve the system stability, Adaptive Extended Kalman Filter (AEKF) is introduced through incorporating a moving-window method with the Extended Kalman Filter (EKF). Nonetheless, the moving window adds an extra computational burden. In this regard, this paper employs the concept of Forgetting Factor AEKF (FFAEKF) for STLF in distribution networks to avoid the computational burden introduced by the AEKF. The forgetting factor improves the estimation accuracy and increases the system convergence when compared with the AEKF. In this paper, the AEKF and FFAEKF are compared in terms of their performance using Maximum Absolute Error (MaxAE) and Root Mean Square Error (RMSE). Matlab/Simulink platform is used to apply the AEKF and FFAEKF algorithms on the load dataset. Results have demonstrated that the FFAEKF improves the forecasting performance through providing less MaxAE and less RMSE. In which, the FFAEKF MaxAE and RMSE are reduced by two and three times, respectively, compared to the AEKF MaxAE and RMSE.

INDEX TERMS Adaptive extended Kalman filter, forgetting factor adaptive extended Kalman filter, maximum absolute error, root mean square error, and short-term load forecasting.

I. INTRODUCTION

The high electricity demand, distribution networks have witnessed high penetration of Renewable Energy Sources (RESs), including PV, wind turbines, and fuel cells. PV systems contribute to the highest share of this trend. However, due to the dependence of RESs sources on natural and meteorological conditions, the generated power tends to be non-dispatchable and uncontrollable [1]. In addition, the intermittency of the generated power leads to serious technical challenges in terms of load forecasting, such as uncertainty. Load forecasting refers to the power demand prediction after taking into account the electric power generated by the intermittent RESs. Therefore, accurate load forecasting is necessary to ensure that the power generated meets the customer's demand.

To address this problem, load forecasting models incorporate the data from conventional energy sources and RESs to provide accurate power supply and demand. This accordingly assists utility grid operators with well-informed energy

The associate editor coordinating the review of this manuscript and approving it for publication was Qiang Li.

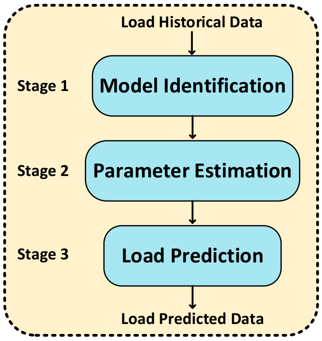

FIGURE 1. Load forecasting stages.

production and distribution decisions [2]. Although load forecasting is considered a challenging task for system operators, utilizing advanced modeling techniques can improve load forecasting accuracy. Short-Term Load Forecasting (STLF) in distribution networks predicts the load demand with a typical forecasting horizon that ranges from 30 minutes to one week of power demand forecasting [2].

Load forecasting involves mainly three stages which are: model identification, parameter estimation, and load prediction [3]. The load forecasting stages are presented in Figure 1. In the first stage, the model structure and order are identified where the historical load and weather data are used. In the second stage, the past load and weather data are used to estimate the model parameters through an estimation technique that provides the best estimate for the load and weather data at time k to the previous load and weather data at $k-1$. The third and last stage is load prediction where the estimated parameters at time k are used to predict the future load demand for the next hours [3].

Most of the work presented in literature focusing on Short-Term Load Forecasting (STLF) has paid little consideration to the intrinsic uncertainty associated with the load dataset. A few research studies focused on developing data filtering algorithm for the load forecasting process using approaches such as Kalman filter, which has good tracking capability in the presence of noise in the data collection process. To avoid the divergence of the conventional Kalman filter and improve the system stability, Adaptive Extended Kalman Filter (AEKF) is introduced through incorporating a moving-window method with the Extended Kalman Filter (EKF) for updating the covariance matrices. Nonetheless, the moving window adds an extra computational burden. In this regard, this paper employs the concept of Forgetting Factor AEKF (FFAEKF) presented in [4] for STLF in distribution networks to avoid the computational burden introduced by the AEKF.

The main contribution of this paper can be summarized in the following bullet points:

- Introducing the concept of FFAEKF for STLF in distribution networks to avoid the computational burden introduced by the AEKF. The process noise and measurement noise covariance matrices are updated to obtain better accuracy through adopting a forgetting factor to introduce adaptive estimation. The forgetting factor improves the estimation accuracy and increases the system convergence when compared to the AEKF.
- Comparing the AEKF and FFAEKF in terms of their performance using the performance indicators; Maximum Absolute Error (MaxAE) and Root Mean Square Error (RMSE). Matlab/ Simulink platform is used to apply the AEKF and FFAEKF algorithms on the load dataset.

The paper is structured as follows: Section II presents the literature review. Section III presents the algorithm for the FFAEKF. Section IV presents the simulation results using Matlab/ Simulink along with the performance assessment. Section V is the conclusion where the key outcomes are summarized.

II. LITERATURE REVIEW

High-quality load forecasting is essential for distribution network planning and operation. To clarify, accurate load forecasting informs the utilities of overloading situations and enables the utilities to schedule and dispatch energy storage devices for load peak shaving [5]. In this regard, during the last decades, STLF has gained researchers' attention and several research studies have been published [2], [3], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38]. A tree diagram, presenting the load forecasting classification and STLF Methods, is presented in Figure 2.

There are mainly two classes adopted for STLF which are: time series models and causal models, where time series models describe the load based on its historical data while causal models describe the load based on external factors such as weather and social behavior [2]. Time series models include estimation methods that are based on Kalman filters. Load forecasting methods can be classified into two main approaches: classical-based and artificial intelligence-based approaches. The classical-based method models the load using statistical modeling methods while the artificial intelligence-based methods utilize Artificial Neural Networks (ANN) and Fuzzy Neural Networks (FNN) to model the load [2]. To further illustrate, in classical approaches, statistical modeling and mathematical functions are used to forecast the future values of the load. This approach includes Auto-Regressive Moving Average (ARMA), multiple linear regression, regression exponential smoothing, and Kalman filters. In Kalman filters, state space equations are used to model the load. To clarify, load forecasting is based on a time-varying state space model to model the load demand. Due to the recursive feature and the standard deviations acquired through byproducts, Kalman filters are considered an attractive forecasting/estimation approach and have strong tracking capability [22]. The main challenge faced in this approach is selecting the states and identifying the model [5].

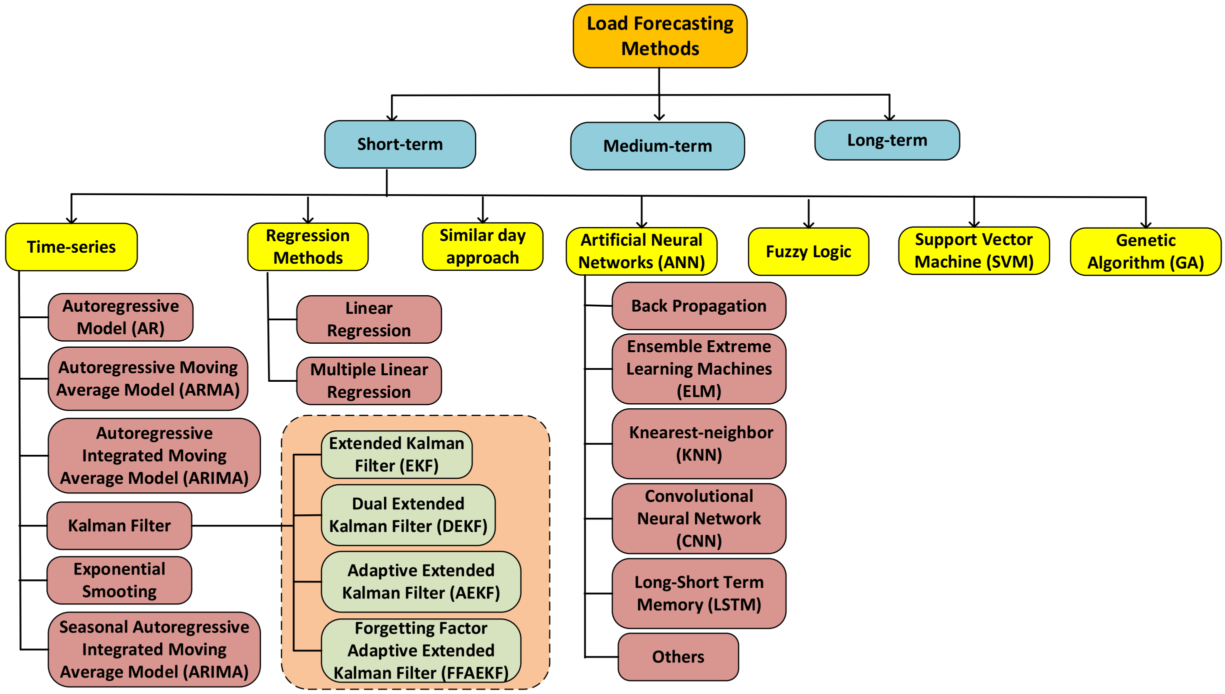

FIGURE 2. Load forecasting classification and STLF methods.

TABLE 1. Comparison between different load forecasting techniques [2], [3], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38].

Forecasting Methods	Advantages	Disadvantages
Time-series	✓ Can accommodate seasonal parameter variations. ✓ High tracking capability in the presence of noise.	× Suffers from numerical instability.
Regression	✓ Effective and efficient regardless the size of the dataset. ✓ Formulates the relation between historical load forecast data and weather conditions in terms of mathematical functions.	× Lacks accuracy where overfitting can occur. × Not efficient to handle load consumption non-linearity. × Instability when further parameters are added.
Similar day (SD) approach	✓ The pre-knowledge of the system is not required. ✓ Adaptable to unexpected and random events	× The time horizon of the load forecasting is limited only to few days (not applicable for medium term and long term forecasting). × The search space is limited.
Artificial Neural Networks (ANN)	✓ Handles sophisticated non-linear systems in an efficient way through weight adjustment in the training process.	× Requires large amount of data for training. × Training process is complex and requires more time. × Conventional ANN methods need to be combined with other methods to improve its performance. × Sensitive to data noise. If the data used for training is noisy, the unseen data will not be generalized by the network which may cause overfitting.
Fuzzy Logic	✓ Provides fast and accurate performance. ✓ Simplifies the load formulation.	× Rule formulation is based on trial and error.
Support Vector Machine (SVM)	✓ Reduces the model complexity. ✓ Improves the dimensionality of the feature space.	× Difficulties in choosing the appropriate kernel solution function. × The training process duration requires more time especially when the data sets are large × Complications in its interpretation because of the variables weights that are not constant.
Genetic Algorithm (GA)	✓ Provides fast convergence speed and flexibility. ✓ Offers strong versatility.	× Suffers from computational complexity. × Premature convergence may occur. × Dependent on the initial state.

With the progress witnessed recently in AI applications, load forecasting is carried out using ANN and FNN with backpropagation due to its simplicity and high adaptability since the network pre-knowledge is not required. Although ANN and FNN have the capability to approximate the nonlinear system through historical data, backpropagation remains to encounter some drawbacks such as poor convergence and speed [2]. To improve the accuracy of the forecasting process, ANNs are combined with other methods. For instance, in [23], radial basis function neural networks are combined with adaptive fuzzy neural inference to predict the load demand. In [24], ANNs with a backpropagation method are

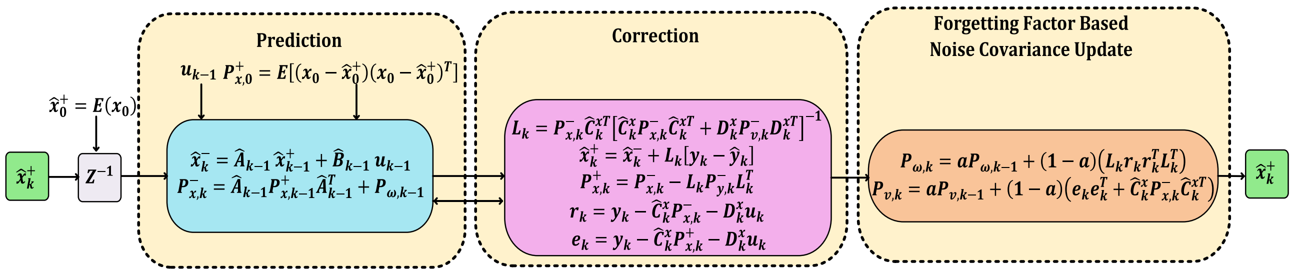

FIGURE 3. FFAEKF Algorithm.

proposed in [24] to forecast the load demand in the next day, in which, it has been found that the backpropagation method is not efficient since it takes time to converge to the actual values.

Deep Learning (DL) approaches are sensitive to the time series load data noise specifically with small load data. Therefore, data filtering methods are essential to improve the prediction process before applying DL methods [5]. In [25], the EKF is combined with neural networks where the states of the nonlinear dynamic system are the network weights to improve the convergence as well as the tracking capability of the conventional ANN method. However, the employment of EKF with ANNs adds extra computational effort. To solve this problem and reduce the computational efforts, decoupled EKF is established in [26] and [27] to improve the prediction performance and reduce the computational time. In [28], a statistical data filtering approach is introduced for STLF. The presented method in [28] combines the conventional ANN method with the time series Auto-Regressive Integrated Moving Average (ARIMA). In [29] and [30], time series ARIMA is combined with ANN for STLF. In [31] and [32], an STLF in distribution networks is presented using a radial basis function neural network. In [33], [34], and [35], deep learning methods are applied to perform STLF using Ensemble Extreme Learning Machines (ELM) and Knearest-neighbor (KNN). In [8] and [36], powerful ANNs including Convolutional Neural Network (CNN) and Long-Short Term Memory (LSTM) are presented for load forecasting. The CNN is used to identify the overall pattern, and the LSTM is utilized to find out the relation between the time steps. In [36], machine learning is combined with Boltzmann machine for residential load forecasting. A comparison between the main forecasting methods is carried out in Table 1.

Most of the reviewed research papers focusing on STLF in distribution networks do not consider the noise incorporated with the load dataset. Few research work focused on developing data filtering algorithm for the load forecasting process. In other words, the majority of the work presented in this area is on the load forecasting model without considering the noise in STLF and the uncertainties introduced by the RESs. The commonly used data filtering approaches for STLF include Kalman filter, discrete wavelet transform filter, and single spectrum analysis [28].

Single spectrum analysis is considered a non-parametric data filtering method. In which, Kalman filters are combined with single spectrum analysis to improve the performance, especially in forecasting through providing noise elimination and time series smoothing by using the Kalman filter state space equations [39]. The discrete wavelet transform is another method used for data filtering. However, Kalman filter is more effective as a noise-suppressing tool [40]. In addition, the wavelet transform filter requires intensive computation. To provide better performance for single spectrum analysis and wavelet transform filter, hybrid techniques using single spectrum analysis with Kalman filters and wavelet transform filter with Kalman filters are presented in [39] and [40], respectively.

Kalman filter is considered an effective technique for predicting the required load demand in distribution networks. It works as a real-time signal corrector approach, where its coefficients are formulated and adapted to the variations taking place in the key signal in the presence of the data collection noise. Consequently, the Kalman filter in STLF is applied as an estimator rather than utilizing it as a conventional filter to eliminate/suppress the noise during the data collection process [28]. Kalman filter in STLF can be applied as a standalone predicting approach or can be combined with other methods as a hybrid predictor [28]. EKF is introduced through modifying the error correction term to accept the system's non-linearity. Although Kalman filter has a good tracking capability in the presence of noise in the data collection process, it requires state space model formulation for the system parameters. In [25], Kalman filter-based smoothing method is combined with ANN for load forecasting. Results have demonstrated that in the existence of load variations and uncertainties, the presented approach can achieve competitive performance. In [38], a hybrid STLF method is presented using Support Vector Machine (SVM) optimized via BAT algorithm (BA) and Kalman filter. It has been found that the load forecasting accuracy is improved through correcting the SVM output using the Kalman filter.

The accuracy of the EKF algorithm depends on how accurately the load model parameters are identified and the pre-knowledge of the noise variable [4]. Incorrect noise variable causes divergence. To avoid divergence and improve stability, this issue is solved through the AEKF by incorporating

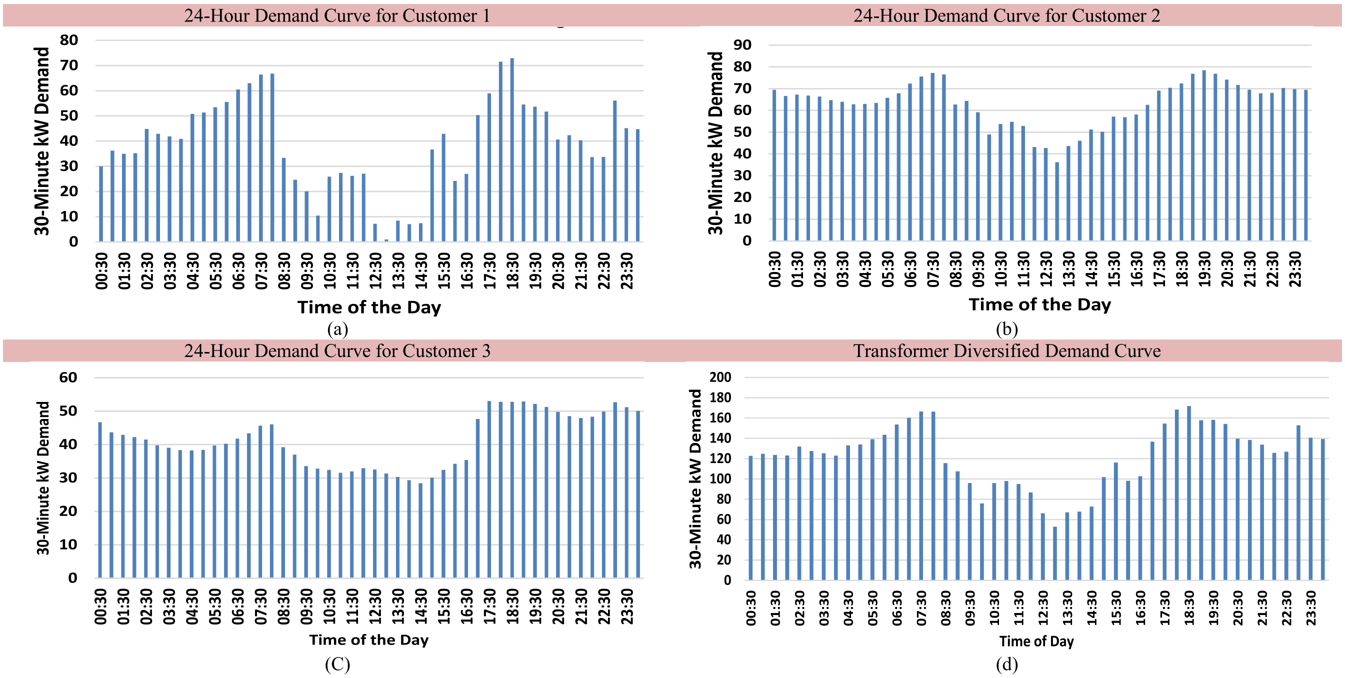

FIGURE 4. **24-Hour demand curve; (a) Load curve for customer 1, (b) Load curve for customer 2, (c) Load curve for customer 3, (d) Transformer diversified demand curve.**

a moving window method with the EKF for updating the covariance matrices. Nonetheless, the moving window adds an extra computational burden [4]. This is solved using an FFAEKF, which provides more variations throughout the prediction process considering the recent data samples. Therefore, this paper presents the concept of FFAEKF for STLF in distribution networks where the process noise and measurement noise covariance matrices are updated to obtain better accuracy through adopting a forgetting factor to introduce adaptive estimation. The forgetting factor improves the estimation accuracy and increases the system convergence when compared to the AEKF. The AEKF and FFAEKF are compared in terms of their performance using the performance indicators MaxAE and RMSE. An STLF using both filters is presented for a distribution transformer that serves three individual customers. The 24-hour demand curve for each customer is considered after adding the PV system as a renewable energy source. The power consumption data of the loads are rescaled data obtained from [41] and the PV data is rescaled data obtained from the IEEE data set portal presented in [42].

III. ADAPTIVE EXTENDED KALMAN FILTER (AEKF)

A typical representation of a non-linear system using discrete-time state space equations is as follows [4]:

$$\begin{cases} X_k = A_{k-1}X_{k-1} + B_{k-1}u_{k-1} + \omega_{k-1} \\ Y_k = C_k X_k + D_k u_k + \upsilon_k \\ \omega_k \approx N\left(0, P_{\omega,k}\right) \\ \upsilon_k \approx N\left(0, P_{v,k}\right) \end{cases} \tag{1}$$

where, X_k is the system's state, Y_k is the system's output vector, ω_k and υ_k are the zero mean small white noise signals with the covariance matrices $P_{\omega,k}$, and $P_{v,k}$, respectively and u_k is the control variable matrix. A_k, B_k, C_k and D_k are matrices that depend on the system dynamics, and k denotes the system vector time step.

To avoid divergence resulting in the AEKF estimation method employed in non-linear systems, an additional stage that updates the noise covariance matrix is used. The FFAEKF steps are presented in Figure 3 and can be summarized as follows:

•Initialization: the mean and the covariance are initialized at step $k = 0$

$$\begin{cases} \hat{x}_0^+ = E\left(x_0\right) \\ P_{x,0}^+ = E\left[\left(x_0 - \hat{x}_0^+\right)\left(x_0 - \hat{x}_0^+\right)^T\right] \end{cases} \tag{2}$$

where, $\hat{x}_0^+$ and $P_{x,0}^+$ represents the estimated initial state and covariance matrix error, respectively. The superscript represents the posterior values (+), the estimated value is represented by the circumflex ($\wedge$), the predicted value is represented by the tilde ($\sim$), and the matrix transportation is indicated by (T).

•Prediction: The prior state and its covariance matrix are obtained from the projection of step $k-1$ to step k. The predicted state estimation and priori covariance matrix can be expressed in (3) and (4), respectively:

$$\hat{x}_k^- = \hat{A}_{k-1}\hat{x}_{k-1}^+ + \hat{B}_{k-1}u_{k-1} \tag{3}$$

$$P_{x,k}^- = \hat{A}_{k-1}P_{x,k-1}^+\hat{A}_{k-1}^T + P_{\omega,k-1} \tag{4}$$

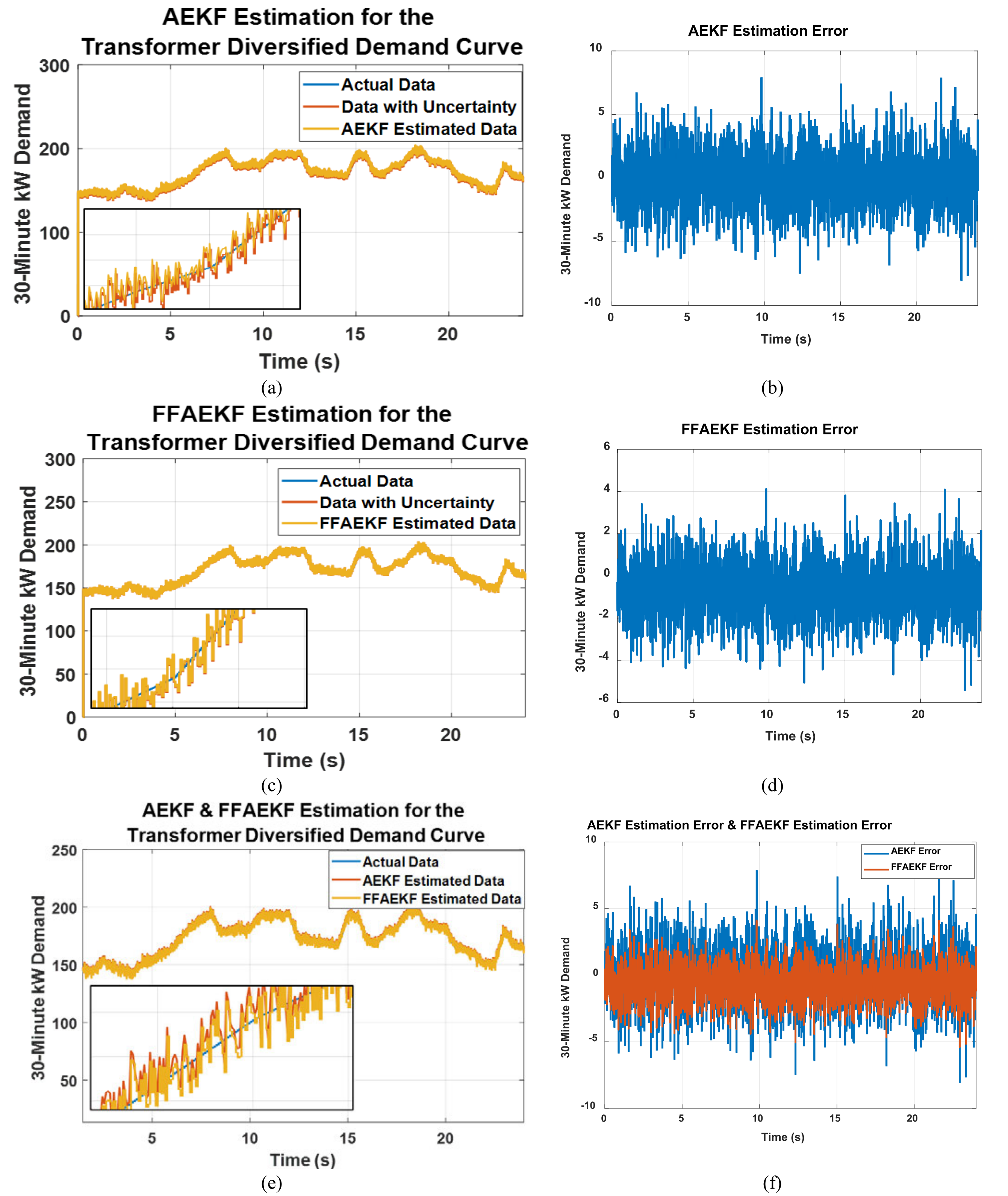

FIGURE 5. Simulation Results; (a) STLF using AEKF, (b) AEKF estimation error, (c) STLF using FFAEKF, (d) FFAEKF estimation error, (e) STLF using AEKF and FFAEKF, (f) AEKF and FFAEKF estimation error.

where, $\hat{A}_k = \left.\frac{\partial F(x_k,\theta_k,I_k)}{\partial x_k}\right|_{x_k=\hat{x}_k^-}$, $\hat{B}_{k-1} = \left.\frac{\partial F(x_k,\theta_k,I_k)}{\partial \omega_k}\right|_{\omega_k=\hat{\omega}_k^-}$, and $P_{\omega,k}$ is the covariance matrix of the process.

•Correction: In this stage, the difference between the actual and predicted measurements is calculated from the prior estimation and utilized to obtain an enhanced posterior estimation. The Kalman gain matrix, posteriori state estimation, and posteriori covariance matrix can be expressed as in (5), (6), and (7), respectively:

$$L_k = P^-_{x,k}\hat{C}^{xT}_k\left[\hat{C}^x_k P^-_{x,k}\hat{C}^{xT}_k + D^x_k P^-_{v,k} D^{xT}_k\right]^{-1} \tag{5}$$

$$\hat{x}^+_k = \hat{x}^-_k + L_k\left[y_k - \hat{y}_k\right] \tag{6}$$

$$P^+_{x,k} = P^-_{x,k} - L_k P^-_{y,k} L^T_k \tag{7}$$

where, $\hat{C}^x_k = \frac{\partial F(x_k,\theta_k,I_k)}{\partial x_k}\Big|_{x_k=\hat{x}^+_k}$, $D^x_k = \frac{\partial F(x_k,\theta_k,I_k)}{\partial v_k}\Big|_{v_k=\hat{v}^-_k}$, and $P_{v,k}$ is the covariance of the noise v_k.

In the FFAEKF, the process noise covariance matrix and the measurement noise covariance matrix are updated as expressed in (8) and (9), respectively, by applying more weight on the current values through the forgetting factor a which can vary from 0 to 1.

$$P_{\omega,k} = aP_{\omega,k-1} + (1-a)\left(L_k r_k r^T_k L^T_k\right) \tag{8}$$

$$P_{v,k} = aP_{v,k-1} + (1-a)\left(e_k e^T_k + \hat{C}^x_k P^-_{x,k}\hat{C}^{xT}_k\right) \tag{9}$$

where, $r_k = y_k - \hat{C}^x_k P^-_{x,k} - D^x_k u_k$ denoted as the innovation measurement and $e_k = y_k - \hat{C}^x_k P^+_{x,k} - D^x_k u_k$ denoted as the residual.

In this paper, the process noise and measurement noise covariance matrices are updated to obtain better accuracy through adopting a forgetting factor to introduce adaptive estimation. The forgetting factor improves the estimation accuracy and increases the system convergence when compared to the conventional EKF. Several types of performance evaluation are introduced to evaluate and assess the results obtained from load forecasting using the two filters. The evaluation matrices are used to compare the AEKF with the FFAEKF. In this work, the Maximum Absolute Error (MaxAE) and the Root Mean Square Error (RMSE) are obtained to evaluate the performance of the two filters. The MaxAE and the RMSE can be expressed as follows:

$$MaxAE = max\left[(Estimated)_k - (Measured)_k\right] \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}((Estimated)_k - (Measured)_k)} \tag{11}$$

where N is the number of sample points.

IV. PERFORMANCE ASSESSMENT

In this section, the 24-hour demand curve for each customer is considered after adding the PV system as a renewable energy source. The power consumption data of the loads are rescaled data obtained from [41], and the PV data is rescaled data obtained from the IEEE data set portal presented in [42]. Matlab/Simulink software is used to validate the performance of the FFAEKF using the algorithm presented in section III. In addition, the forecasted load results are compared using the AEKF and the FFAEKF in terms of their accuracy. The MaxAE and the RMSE are used as performance indicators. Time-varying state space model is used to model the load demand in order to forecast the load every 30 minutes. In other words, the STLF is carried out every half an hour.

TABLE 2. Performance indicators for the STLF using AEKF and FFAEKF.

	AEKF	FFAEKF
MaxAE	8.1 kW	4.7 kW
RMSE	1.05 kW	0.32 kW

The individual load demand curve for each customer is illustrated in Figure 4(a)-(c). The load curves for the three customers are presented considering the addition of the PV. The addition of the PV introduces more fluctuations to the load demand curve. The transformer diversified demand which represents the aggregated load demand curves for the three customers is presented in Figure 4(d).

Figure 5 presents the STLF using the AEKF and the FFAEKF with their error. As can be seen from Figure 5 the forecasted data converges to the actual data using both filters. In other words, Kalman filters can be used to accurately forecast/ estimate the load demand curve every 30 minutes. However, as can be seen from Figure 5(a)-(e), the FFAEKF algorithm provides better accuracy when compared to the AEKF algorithm. A zoomed-in illustration of all the results is presented to show the effectiveness of the FFAEKF in terms of accuracy when compared to the AEKF. The error resulting from both algorithms is presented in Figure 5(f). It can be observed that the FFAEKF algorithm results in less error when compared to the AEKF algorithm. As discussed in Section II, the MaxAE and the RMSE are calculated and presented in Table 2 to evaluate and assess the results obtained from the load forecasting using the two filters. As can be seen from Table 2, the MaxAE and the RMSE obtained using the FFAEKF are less than that obtained results using the AEKF.

V. CONCLUSION

In this paper, the concept of FFAEKF for STLF in distribution networks is introduced to obtain better accuracy and improve the performance of the forecasting through considering the uncertainties introduced by the RESs. This is achieved through the forgetting factor that focuses on updating both the measurement and process noise every time step which will improve the overall performance of the filter and achieve better accuracy. An STLF using both filters is presented for a distribution transformer that serves three individual customers. Matlab/ Simulink software is used to validate the concept of the FFAEKF and compare the performance of the AEKF and the FFAEKF considering the load dataset of the transformer diversified demand curve. Results have demonstrated that both filters have a good tracking capability and that the forecasted data converges to the actual data using the two algorithms. However, the FFAEKF algorithm provides better accuracy when compared to the AEKF algorithm and provides less error. In addition, performance indicators, which are the MaxAE and the RMSE, are calculated from the forecasted data for the AEKF and the FFAEKF. It has been found that the MaxAE and RMSE for the AEKF are 8.1 kW and 1.05 kW, respectively, while the MaxAE and RMSE for the FFAEKF are 4.7 kW and 0.32 kW, respectively. The presented FFAEKF in this work can be combined with other forecasting techniques including ANN and SVM or fuzzy inference systems to form a hybrid STLF technique. This can be done to merge the advantages of both techniques, the ANN in handling the high non-linearity of the system and the FFAEKF in data noise filtering.

REFERENCES

[1] H. Lee, N.-W. Kim, J.-G. Lee, and B.-T. Lee, "Kalman filter-based adaptive forecasting of PV power output," in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, Jeju, South Korea, Oct. 2020, pp. 1342–1347.

[2] M. M. Dixit and P. R. Chavan, "Short-term load forecasting using Kalman filter," *Int. Res. J. Eng. Technol.*, vol. 4, no. 5, pp. 3458–3461, May 2017.

[3] H. M. Al-Hamadi and S. A. Soliman, "Short-term electric load forecasting based on Kalman filtering algorithm with moving window weather and load model," *Electr. Power Syst. Res.*, vol. 68, no. 1, pp. 47–59, Jan. 2004.

[4] P. Shrivastava, T. K. Soon, M. Y. I. B. Idris, S. Mekhilef, and S. B. R. S. Adnan, "Combined state of charge and state of energy estimation of lithium-ion battery using dual forgetting factor-based adaptive extended Kalman filter for electric vehicle applications," *IEEE Trans. Veh. Technol.*, vol. 70, no. 2, pp. 1200–1215, Feb. 2021.

[5] X. Sun, P. B. Luh, K. W. Cheung, W. Guan, L. D. Michel, S. S. Venkata, and M. T. Miller, "An efficient approach to short-term load forecasting at the distribution level," *IEEE Trans. Power Syst.*, vol. 31, no. 4, pp. 2526–2537, Jul. 2016.

[6] H. Xu, G. Fan, G. Kuang, and Y. Song, "Construction and application of short-term and mid-term power system load forecasting model based on hybrid deep learning," *IEEE Access*, vol. 11, pp. 37494–37507, 2023.

[7] W. Kong, Z. Y. Dong, D. J. Hill, F. Luo, and Y. Xu, "Short-term residential load forecasting based on resident behaviour learning," *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 1087–1088, Jan. 2018.

[8] S. H. Rafi, Nahid-Al-Masood, S. R. Deeba, and E. Hossain, "A short-term load forecasting method using integrated CNN and LSTM network," *IEEE Access*, vol. 9, pp. 32436–32448, 2021.

[9] A. A. Muzumdar, C. N. Modi, and C. Vyjayanthi, "Designing a robust and accurate model for consumer-centric short-term load forecasting in microgrid environment," *IEEE Syst. J.*, vol. 16, no. 2, pp. 2448–2459, Jun. 2022.

[10] L. Jiang, X. Wang, W. Li, L. Wang, X. Yin, and L. Jia, "Hybrid multitask multi-information fusion deep learning for household short-term load forecasting," *IEEE Trans. Smart Grid*, vol. 12, no. 6, pp. 5362–5372, Nov. 2021.

[11] Y. Hong, Y. Zhou, Q. Li, W. Xu, and X. Zheng, "A deep learning method for short-term residential load forecasting in smart grid," *IEEE Access*, vol. 8, pp. 55785–55797, 2020.

[12] J. Gunawan and C.-Y. Huang, "An extensible framework for short-term holiday load forecasting combining dynamic time warping and LSTM network," *IEEE Access*, vol. 9, pp. 106885–106894, 2021.

[13] X. Chen, W. Chen, V. Dinavahi, Y. Liu, and J. Feng, "Short-term load forecasting and associated weather variables prediction using ResNet-LSTM based deep learning," *IEEE Access*, vol. 11, pp. 5393–5405, 2023.

[14] M. Tan, S. Yuan, S. Li, Y. Su, H. Li, and F. He, "Ultra-short-term industrial power demand forecasting using LSTM based hybrid ensemble learning," *IEEE Trans. Power Syst.*, vol. 35, no. 4, pp. 2937–2948, Jul. 2020.

[15] K. Chen, K. Chen, Q. Wang, Z. He, J. Hu, and J. He, "Short-term load forecasting with deep residual networks," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 3943–3952, Jul. 2019.

[16] J. Son, J. Cha, H. Kim, and Y.-M. Wi, "Day-ahead short-term load forecasting for holidays based on modification of similar days' load profiles," *IEEE Access*, vol. 10, pp. 17864–17880, 2022.

[17] Md. R. Haq and Z. Ni, "A new hybrid model for short-term electricity load forecasting," *IEEE Access*, vol. 7, pp. 125413–125423, 2019.

[18] S. Sharma, A. Majumdar, V. Elvira, and É. Chouzenoux, "Blind Kalman filtering for short-term load forecasting," *IEEE Trans. Power Syst.*, vol. 35, no. 6, pp. 4916–4919, Nov. 2020.

[19] B. Farsi, M. Amayri, N. Bouguila, and U. Eicker, "On short-term load forecasting using machine learning techniques and a novel parallel deep LSTM-CNN approach," *IEEE Access*, vol. 9, pp. 31191–31212, 2021.

[20] M. Madhukumar, A. Sebastian, X. Liang, M. Jamil, and M. N. S. K. Shabbir, "Regression model-based short-term load forecasting for university campus load," *IEEE Access*, vol. 10, pp. 8891–8905, 2022.

[21] C.-N. Ko and C.-M. Lee, "Short-term load forecasting using SVR (support vector regression)-based radial basis function neural network with dual extended Kalman filter," *Energy*, vol. 49, pp. 413–422, Jan. 2013.

[22] C. Guan, P. B. Luh, L. D. Michel, and Z. Chi, "Hybrid Kalman filters for very short-term load forecasting and prediction interval estimation," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 3806–3817, Nov. 2013.

[23] Z. Yun, Z. Quan, S. Caixin, L. Shaolan, L. Yuming, and S. Yang, "RBF neural network and ANFIS-based short-term load forecasting approach in real-time price environment," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 853–858, Aug. 2008.

[24] Y. Chen, P. B. Luh, C. Guan, Y. Zhao, L. D. Michel, M. A. Coolbeth, P. B. Friedland, and S. J. Rourke, "Short-term load forecasting: Similar day-based wavelet neural networks," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 322–330, Feb. 2010.

[25] S.-H. Hur, "Estimation of useful variables in wind turbines and farms using neural networks and extended Kalman filter," *IEEE Access*, vol. 7, pp. 24017–24028, 2019.

[26] X. Sun, P. B. Luh, L. D. Michel, S. Corbo, K. W. Cheung, W. Guan, and K. Chung, "An efficient approach for short-term substation load forecasting," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Vancouver, BC, Canada, Jul. 2013, pp. 1–5.

[27] X. Sun and C. Jin, "Impacts of solar penetration on short-term net load forecasting at the distribution level," in *Proc. IEEE 4th Int. Electr. Energy Conf. (CIEEC)*, Wuhan, China, May 2021, pp. 1–6.

[28] M. T. Cao, T. T. Pham, T. C. Kuo, D. M. Bui, H. V. Nguyen, and T. H. Nguyen, "Short-term load forecasting enhanced with statistical data-filtering method," in *Proc. IEEE Int. Conf. Power Electron., Smart Grid Renew. Energy (PESGRE)*, Cochin, India, Jan. 2020, pp. 1–8.

[29] R. K. Jagait, M. N. Fekri, K. Grolinger, and S. Mir, "Load forecasting under concept drift: Online ensemble learning with recurrent neural network and ARIMA," *IEEE Access*, vol. 9, pp. 98992–99008, 2021.

[30] F. Wu, R. Jing, X.-P. Zhang, F. Wang, and Y. Bao, "A combined method of improved grey BP neural network and MEEMD-ARIMA for day-ahead wave energy forecast," *IEEE Trans. Sustain. Energy*, vol. 12, no. 4, pp. 2404–2412, Oct. 2021.

[31] C. Cecati, J. Kolbusz, P. Różycki, P. Siano, and B. M. Wilamowski, "A novel RBF training algorithm for short-term electric load forecasting and comparative studies," *IEEE Trans. Ind. Electron.*, vol. 62, no. 10, pp. 6519–6529, Oct. 2015.

[32] J. Faraji, A. Ketabi, H. Hashemi-Dezaki, M. Shafie-Khah, and J. P. S. Catalão, "Optimal day-ahead self-scheduling and operation of prosumer microgrids using hybrid machine learning-based weather and load forecasting," *IEEE Access*, vol. 8, pp. 157284–157305, 2020.

[33] Z. Wang, L. Wang, C. Huang, and X. Luo, "A hybrid ensemble learning model for short-term solar irradiance forecasting using historical observations and sky images," *IEEE Trans. Ind. Appl.*, vol. 59, no. 2, pp. 2041–2049, Mar. 2023.

[34] M. Ali, Z. A. Khan, S. Mujeeb, S. Abbas, and N. Javaid, "Short-term electricity price and load forecasting using enhanced support vector machine and K-nearest neighbor," in *Proc. 6th HCT Inf. Technol. Trends (ITT)*, Ras Al Khaimah, United Arab Emirates, Nov. 2019, pp. 79–83.

[35] S. Khan, Z. A. Khan, Z. Noshad, S. Javaid, and N. Javaid, "Short term load and price forecasting using tuned parameters for K-nearest neighbors," in *Proc. 6th HCT Inf. Technol. Trends (ITT)*, Ras Al Khaimah, United Arab Emirates, Nov. 2019, pp. 89–93.

[36] H. Shi, L. Wang, R. Scherer, M. Wozniak, P. Zhang, and W. Wei, "Short-term load forecasting based on adabelief optimized temporal convolutional network and gated recurrent unit hybrid neural network," *IEEE Access*, vol. 9, pp. 66965–66981, 2021.

[37] C. Tian, J. Ma, C. Zhang, and P. Zhan, "A deep neural network model for short-term load forecast based on long short-term memory network and convolutional neural network," *Energies*, vol. 11, no. 12, p. 3493, Dec. 2018.

[38] Q. Liu, Y. Shen, L. Wu, J. Li, L. Zhuang, and S. Wang, "A hybrid FCW-EMD and KF-BA-SVM based model for short-term load forecasting," *CSEE J. Power Energy Syst.*, vol. 4, no. 2, pp. 226–237, Jun. 2018.

[39] M. Yarmohammadi, R. Z. Moghadam, and H. Hassani, "Improving recurrent forecasting in singular spectrum analysis using Kalman filter algorithm," *J. Stat. Model., Theory Appl.*, vol. 3, no. 1, pp. 135–146, Mar. 2023.

[40] Y. Patel and D. Deb, "Machine intelligent hybrid methods based on Kalman filter and wavelet transform for short-term wind speed prediction," *Wind*, vol. 2, no. 1, pp. 37–50, Jan. 2022.

[41] *Record of Power Consumption*, RTE Customer's Area—Rec. Power Consumption. Accessed: Mar. 3, 2023. [Online]. Available: http://clients.rte-france.com/lang/an/visiteurs/vie/vie_stats_conso_inst.jsp

[42] IEEE PES Intelligent Systems Subcommittee. *Open Data Sets*. [Online]. Available: Accessed: Mar. 1, 2023. [Online]. Available: https://site.ieee.org/pes-iss/data-sets/#pvge

MENA S. ELMENSHAWY received the B.Sc. and M.Sc. degrees in electrical engineering from Qatar University, Qatar, in 2016 and 2019, respectively, where she is currently pursuing the Ph.D. degree in electrical engineering. She was a Graduate Assistant with Qatar University, from 2016 to 2018, where she is currently a Research Assistant. Her current research interests include power electronics, renewable energy, energy management, and power systems.

AHMED M. MASSOUD (Senior Member, IEEE) received the B.Sc. (Hons.) and M.Sc. degrees in electrical engineering from Alexandria University, Egypt, in 1997 and 2000, respectively, and the Ph.D. degree in electrical engineering from Heriot-Watt University, Edinburgh, U.K., in 2004. He is currently a Full Professor with the Department of Electrical Engineering, College of Engineering, Qatar University. He holds five U.S. patents. He has published more than 100 journal articles in the fields of power electronics, energy conversion, and power quality. His current research interests include power electronics, energy conversion, renewable energy, and power quality.