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# Optimal state estimation techniques for accurate measurements in internet of things enabled microgrids using deep neural networks

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**ABSTRACT**

The employment of microgrids in smart cities is not only changing the landscape of power generation, transmission, and distribution but it helps in green alleviation by converting passive consumers into active produces (using renewable energy sources). Real-time monitoring is a crucial factor in the successful adoption of microgrids. Real-time state estimation of a microgrid is possible through internet-of-things (IoT). State estimation can provide the necessary monitoring of grid for many system optimization applications. We will use raw and missing data before we learn from data, the processing must be done. This paper describes various Kalman variants use for preprocessing. In this paper a formulated approach along with algorithms are described for optimal state estimation and forecasting, with weights update using deep neural networks (DNN) is presented to enable accurate measurements at component and system level model analysis in an IoT enabled microgrid. The real load data experiments are carried out on the IEEE 118-bus benchmark system for the power system state estimation and forecasting. This research paves a way for developing a novel DNN based algorithms for a power system under dynamically varying conditions and corresponding time dependencies.



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## 1. INTRODUCTION

The centralized power distribution has dominated the energy sector in the last century; but the exponential growth of load, need of power quality, environmental issues and shortage of fossil fuels have challenged the conventional methods [1]. As a consequence, many researchers started investigation on adoption of small-scale distributed generation by distributed energy resources (DERs). Recently, microgrid has received huge momentum due to its economic merit and environment friendly nature. With small, distributed grids consisting of sophisticated devices for power distribution, energy conversion and storage, microgrid has become a game changer in the energy sector [2]. This new trend has shifted the paradigm from centralized energy generation and distribution to local energy conversion, energy storage, power quality and optimization to enable the citizen of smart city to actively participate in production and distribution via smart grids [3]. The ever-increasing demand and usage of power have triggered investigations in the way that electricity is generated, distributed, managed, and consumed. In the field of power distribution, hitherto unprecedented requirements are expected to be satisfied [4]. Though microgrid has many advantages such as lower cost, high reliability, reduced carbon footprint, improved power quality, and asset security, its ability to convert passive consumers into active suppliers by enabling them to harvest renewable sources of energy is the key reason for the massive adoption of it [5].

Despite the fact that microgrid has increased our optimism about renewable sources, it comes with certain limitations such as frequent maintenance of equipment and need for load selection, power factor correction and new schemes of revenue collection. Microgrids are designed to enable two-way power flow and two-way data flow that require pervasive (and ubiquitous) instrumentation and connectivity on just about to every device within it [6]. Highly instrumented microgrids can strengthen grid resilience and help minimize outages in the larger utility grid. The ability of microgrid to operate autonomously from larger grids could prove to be a major driver of internet of things (IoT) adoption in smart cities of the future. IoT comes into picture when massive connectivity of sensors is required for analytics through machine learning for optimization [7]. As presented in Figure 1, the IoT ensures smooth functioning of a microgrid by enabling remote monitoring and control via web applications thereby conveying real-time info on hand-held multimedia devices. The data stored in smart meters will enable the electricity board to fix the tariff, create policies, and analyze the trends in electricity usage [8]. Fog computing can be used for analysis of voltage, current, and power locally while the data is stored at the cloud, centrally. The research gaps are identified on the research challenges, and these are presented in Table 1 of literature review conducted in brief.

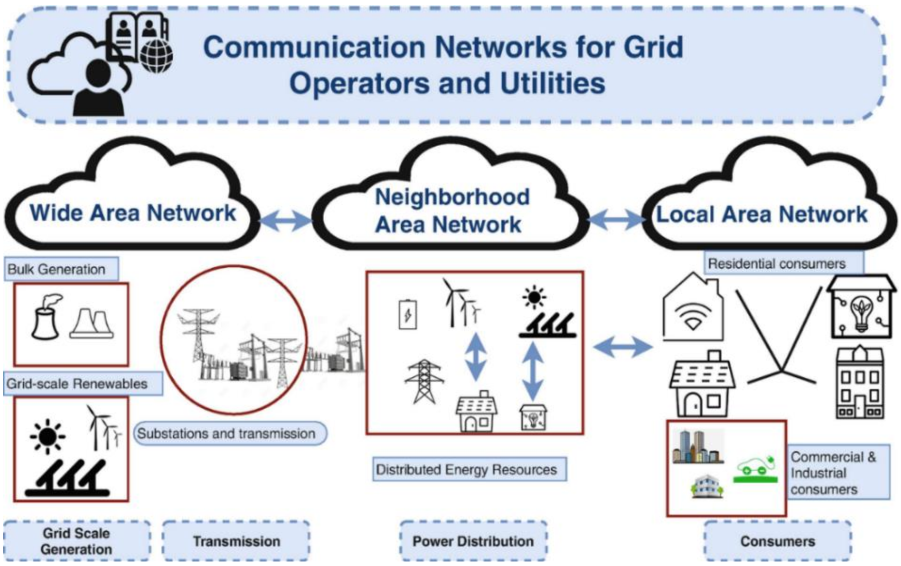



Figure 1. IoT communication network and microgrid dynamic state estimation process

Table 1. Summary of literature review conducted

| References | Variable parameter | Methodology adopted | Research gap |
|---|---|---|---|
| [9] | Efficiency of microgrid system | Control of energy storage under price fluctuation. | Problem of optimality in the battery |
| [10] | Optimality of micro-grid system | Manage the microgrid under load shifting approach | Optimal charging and discharging of battery cycles. |
| [11] | Minimized energy cost | Battery charge from utility of grid only | Optimal exploitation of renewable energy. |
| [12] | Power flow from battery to grid | A model free reinforcement learning. | Cost minimizing storage policy. |
| [13] | Electrical storage shifting | Load shifting approach | Usage of heterogeneous approaches. |

The convergence of technological, economic, and environmental forces, are driving the IoT and microgrids simultaneously, then each drives the other forward. Be it the IoT driving microgrids or vice-versa, the continued expansion of each is good for the other. The current trends we see in the microgrids and IoT, as well as energy generation and storage technologies, evoke visions of a vast network of microgrids balancing and optimizing energy use in a deeply connected world. The proliferation of IoT enabled microgrids will open up new frontiers of services and applications for next-generation power and energy systems. Although many communication infrastructures are proposed, a systematic study of a suitable two-way communication infrastructure for sensing, estimating, and controlling the microgrid incorporating multiple distributed energy sources is yet to be carried out. The problem statement is narrowed down as to develop a novel deep learning (DL) algorithm for power systems under dynamically varying conditions and corresponding time dependencies. Based on the problem statement the key contributions of this research are: i) a formulated approach to enable accurate measurements at component and system level model analysis using a deep neural network (DNN) architecture in an IoT enabled microgrid, ii) to describe several Kalman variants used for pre-processor of raw, redundant data and produce a reliable state estimate and forecasting using a DNN, and iii) to investigate the various ways of distributed system state estimation via Kalman filters and its variants with a DNN.

## 2. RESEARCH METHOD

In the mathematical foundations of Kalman filter, a recursive algorithm is that works on dynamic systems and uses measurement, estimation, prediction, and updating is presented in (1).

$$x_k = A_k x_k + B_k u_k + w_k \tag{1}$$

With $x_k \in R_n$, $A_k$, $w_k$, $B_k$ representing transition matrix, process noise, and control input model respectively, and measurement (or observation) of $z_k$ is depicted in (2).

$$z_k = H_k x_k + v_k \tag{2}$$

With $z_k \in R_m$, and $H_k$ being observation model if process noise wk and the measurement noise $v_k$ are assumed to be an independent random variable with Gaussian probability density functions and zero mean value. Let us go about to understand the model with equations, first of which is the state update (3).

$$x_k = x_{k-1} + z_k - H_{k-1} x_{k-1} \tag{3}$$

Here $x_{k-1}$ represents the previous estimate for the $k^{th}$ instant. The difference between the latest measurement and the previous estimate gives the measurement residual called innovation represented by $y_k$. The weight of innovation decreases with a greater number of iterations as the Kalman gain decreases.

This state update equation gives the present estimate at the $k^{th}$ instant. State extrapolation equation is the immediate shift from the state update equation after an instant. In (4) extrapolates the current state to the next state.

$$x_{k-1} = x_{|k-1|} + K_k y_k \tag{4}$$

Hence giving the prediction of the next state. From (4), the factor that is responsible for the addition of the difference between the present measurement and the previous estimate to the previous estimate is called Kalman gain [14]. This is defined by the third Kalman Filter equation, Kalman gain is presented in (5),

$$\mathrm{K_k} = \mathrm{P_{k-1}} H_K^T \left(\mathrm{H_k P_k} - 1 H_K^T + \mathrm{R_k}\right) \tag{5}$$

This is the ratio of the in estimate to the sum of the uncertainty in estimate with the uncertainty in the measurement.

$$[0 \le K_n \le 1]$$

From (3)

$$x_k = x_{k-1}(1 - H_k \,.\, K_k + Z_k \; K_k) \tag{6}$$

Hence, the weight is given to the measurement and 1-$H_k$ is given to the estimate, as the number of iterations increases the significance of the measurements decreases and the new value comes closer to the previous estimate value [15]. The uncertainty in the estimate needs to be updated with the updating of the state of the dynamic system, for finding the present uncertainty in the estimate using the previous uncertainty, estimate uncertainty update equation or covariance update (7):

$$P_k = (1 - H_k \,.\, K_k) \, P_{k-1} \tag{7}$$

where $(1 - K_k \leq 1)$ as the number of iterations increases, uncertainty in the present estimate decreases. Estimate uncertainty extrapolation equation as presented in (8) is applied to realize the present uncertainty using the previous uncertainty.

$$P_{k-1} = (A_k \, . P_{k-1})T_k + Q \tag{8}$$

So, (4) and (8) is categorized in priori, and represents the prediction of co-variance and state of the system [16], [17]. The equation (3) and (6) is categorized in posteriori and represents the correction of covariance and state of the system with the block diagram as depicted in Figure 2 which describes the workflow of categorized priori along with prediction of co-variance and state of system.

The Table 2 describes the summary of all Kalman filter variants based on state estimators. The different state estimators are extended, unscented, ensembled, and particle Kalman filters [18], [19]. They present a system model (linear, locally linear, non-linear) description for each variant of thee Kalman filter state estimator. Further the arranged distributions (Gaussian, non-Gaussian) along with a computational cost (low, medium, and high) is presented for each of the Kalman filter state estimator variants [20], [21].

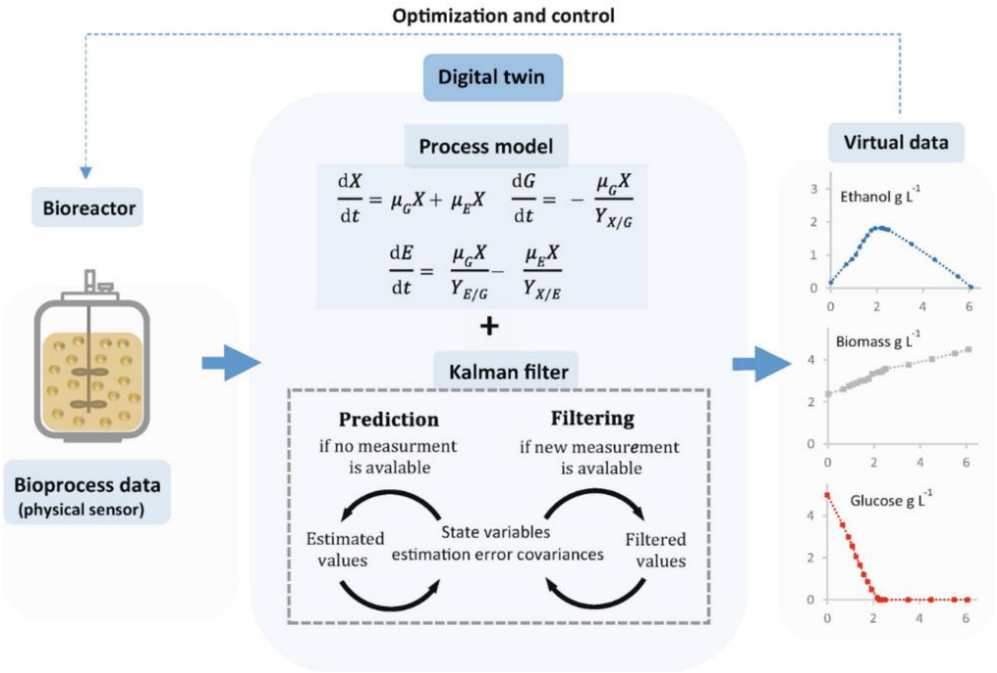



Figure 2. Workflow of categorized priori along with prediction of co-variance and state of system

Table 2. Summary of all Kalman based state estimators

| State estimator | System model | Assumed distribution | Computational cost |
|---|---|---|---|
| Kalman Filter (KF) | Linear | Gaussian | Low |
| Extended KF (EKF) | Locally linear | Gaussian | Low |
| Unscented KF (UKF) | Non-linear | Gaussian | Medium |
| Ensembled KF (EnKF) | Non-linear | Non-gaussian | High |
| Particle KF (PKF) | Non-linear | Non-gaussian | High |

The Figure 3 illustrates the IoT based smart grid network here in several instances of IoT based system, it has a tiny-computing device for monitoring, controlling, which often very limited in terms of resources and capacities, energy usage and also are constrained to communication bandwidth and network efficiency. Message queuing telemetry transport (MQTT) is a publishing/subscribing messaging protocol, it is designed to be open, simple, lightweight. In MQTT as a client, subscriber and publisher exist, communications are managed by a broker. Subscribers are linked to a broker and subscribe to interesting topics. The publisher also communicates and publishes issues with the broker. The publishing message will soon be sent to the subscriber who has subscribed to the message via the broker. In this case, its message is published with a topic, a smart meter in the distribution board measures how much power is consumed.

IoT-gateway: the IoT-gateway is a linking bridge between the sensor network and the MQTT network. This system is constructed of two components; it is responsible for the communication of devices and the collection of data. The contact of the device is, any request arrives via MQTT at the IoT-gateway, then an IoT gateway operates a device via the network of the target device and responds via MQTT to the requestor.

As depicted in Figure 4(a) a real time power system state estimation and forecasting of the historical voltage data is presented. The Figure 4(b) represents deep neural network model unfolded without the outputs, and Figure 4(c) presents deep neural network based real time monitoring of the power system. For tracking, automatic control and two-way communication functions, intelligent sensors and actuators are deployed. In other words, the voltage fluctuation is observed by several smart sensors, which will relay the information to the local intelligent control unit. The control unit calculates the deviation of the device state from a pre-defined reference value based on the received signal. In order to monitor the state variations, the predicted states are then used by voltage regulators.

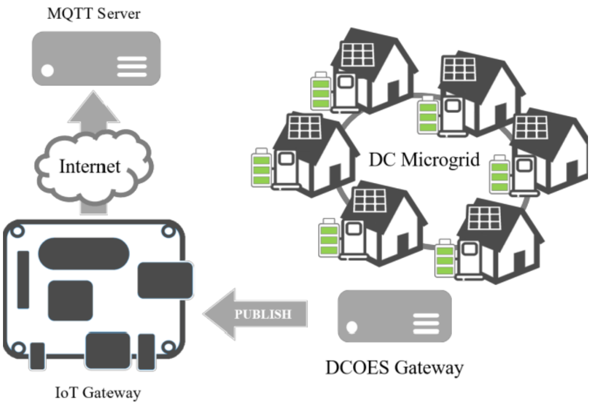



Figure 3. IoT based smart grid network

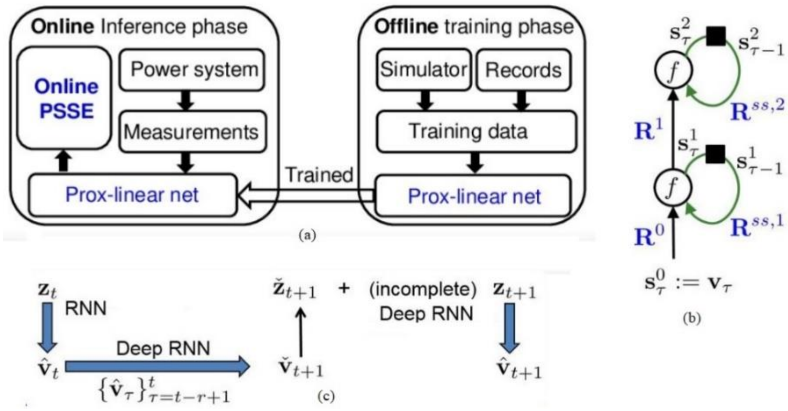



Figure 4. Real time power system state estimation and forecasting (a) deep recurrent neural network (RNN) based real time power system state estimation, (b) a deep RNN architecture model, and (c) DNN based real time monitoring of power system

## 3. ALGORITHM DESIGN

In the algorithm the weights are taken by using importance sampling. The samplings (support points) are taken sequentially as measurements and in this algorithm 1. The weights are updated to approach the true posterior density. The algorithm 1 discretizes the system state into a collection of state vectors analyzed. By integrating the ensemble of the state model, the mean and error covariance can be found [22], [23]. As the number of ensembles increases the probability density function can be approximated more accurately [24].

The algorithm 2 reduces the computational work, as it is sufficient to use a limited number of model states for reasonable statistical convergence. $X_2[x_1, ..., x_n]=[x_i]$, is n×N matrix, prior ensemble matrix, $D =[d_1,...., d_n]$, is m×N matrix, where d is the data column and has random vector from n-dimensional normal distribution N (0, R). The research further steps into algorithm 3 using the steps illustrated in the algorithm 2. In algorithm 3 the deep recurrent neural networks (Deep RNN's) are introduced for state estimation and forecasting using the historical data of the estimated voltages measured from sigma points in state space and measurements voltage data obtained from the sensors as illustrated in algorithm 2. The algorithm 3 is framed taking the Figure 4(a) to Figure 4(c) into the consideration [25].

Algorithm 1. Algorithm for optimal state estimation and accuracy measurements
```
Start
Input: sigma points: system dimensions (2N+1)
N=Dimensionality of System;
        while (N)
        Calculate:
                X: sigma point matrix;
                μ: mean of Gaussian;
                λ: scaling factor;
                ψ: distance of sigma point from mean point;
        if (ψ>=λ)
P:find covariance matrix weights;
        else if (sum of all weights=1)
                μ`: predicted mean;
                ξ': predicted co-variance;
                w: weights of sigma point;
                g: non-linear function;
end if()
end if()
Obtain the measurements from sensors;
Compute the update step;
end while()
Perform optimal state estimation;
Obtain accuracy;
Stop
```

Algorithm 2. Algorithm for weight update
```
Start
Input: Sigma Points: System Dimensions (2N +1)
N=Dimensionality of System;
        while (N)
        Calculate:
Z: transformed sigma points in measurements space;
z: mean in measurement space;
S: co-variance in measurement space;
Q: noise;
H: function that maps sigma points to measurement;
        end while ()
        if (Sigma points in state space and measurement)
        Obtain the measurements from sensors;
Compute the weight update step;
end if ()
Stop
```

The RNN power system state estimation solver with minimized complexity is presented in algorithm 3. Using the appropriate step sizes {μi} and η, the sequence {vi} generated and converges to a sigma point illustrated in algorithm 2. A large number of inner loop iterations (K) are required to approximate the solution. The quasi-reverse Bi has to be computed per outer loop iteration [26]. The next outer loop iterates $v_{i+1}$ can be obtained, once the inner optimum variable $u_i^*$ is found with (9).

$$v_{i+1} = [B_i(u_i^* + z) + v_i]/2 \tag{9}$$

The equation (8) follows the definition of $u_i^*$ and with respect to initialization, the $u_0^{\ 0}$ can be initialized as 0 without generality loss and $u_i^{\ 0}=u_{i-1}^{\ *}$ for i>1.

Algorithm 3. Minimized complexity recurrent NN
```
Start
Obtain the matrices (Hm)of the physical microgrid (zm)
zm=v^T > Hmv+ ϵm,∀m=1,...,M
Input: Data {(zm , Hm) ^M }m=1 , step size {μi }, ηi and initialization v0 = 1and u0^0 =0;
```

```
for i=0,1……..,I do
Initialize u_i^0 ;
for k = 0,1,……., K do
update u_i^(k+1) ;
end for
update v_(i+1)
end for
Stop
```

## 4. RESULTS OBTAINED

Microgrids, stand-alone distributed systems are required to shift the present power system towards renewable sources of energy. IoT is used to communicate the information retrieved from sensors and is used in smart grids for smart connectivity. Its use in smart grids for energy management systems extends the benefits of a smart grid beyond automation, distribution, and monitoring [27].

The Figures 5 and 6 illustrate plot results of EKF, UKF and modified UKF for smart grids that require state estimation for real-time supervisory control and monitoring. There are various techniques to perform state estimation, some of which are discussed in this paper. The recursive systematic convolution code is adopted from the communication point of view to introduce redundancy throughout the framework. In the end, the Viterbi soft output decoder is used to retrieve device information from noisy measurements and fluctuations of transmission. The Kalman filter is then used to estimate machine states, which serves as a reference for the control algorithm to be implemented [28], [29].

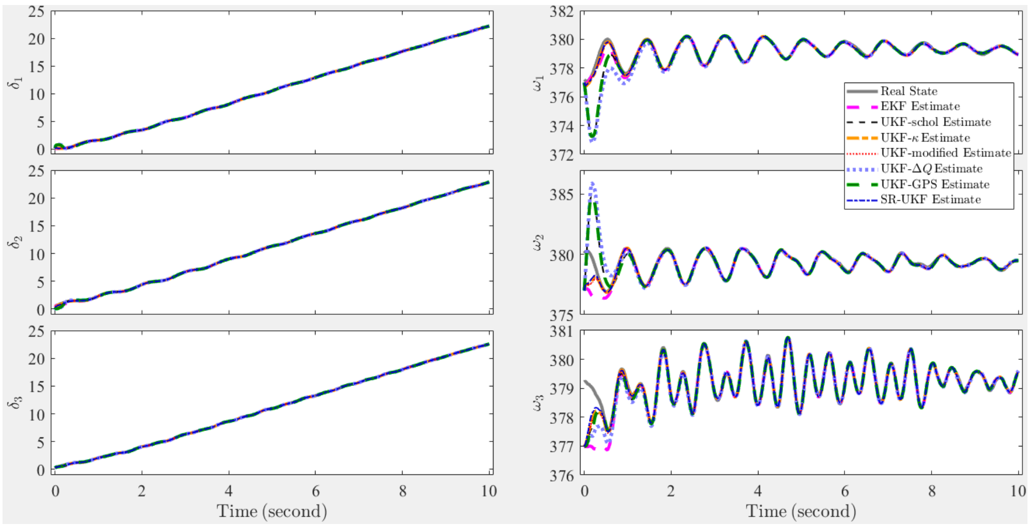



Figure 5. Plot results of EKF and UKF

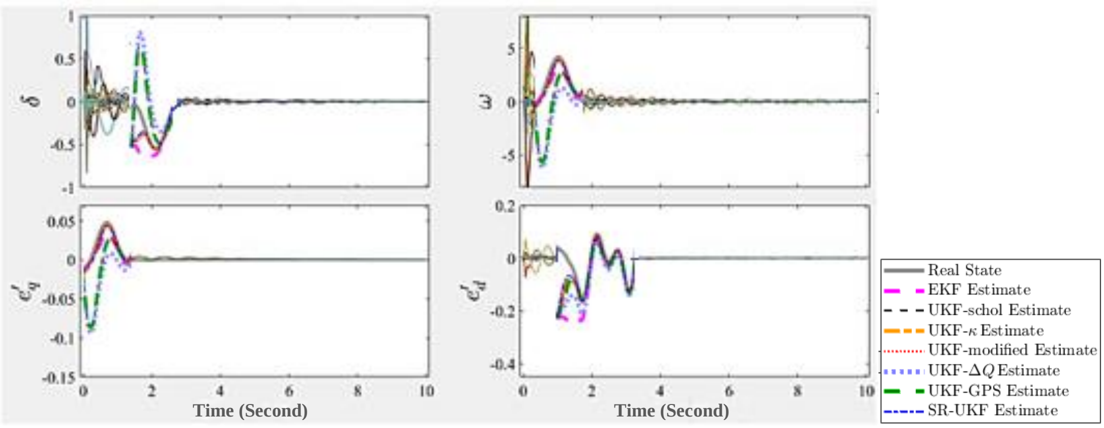



Figure 6. Plot results of UKF and modified UKF

We generate real states and measurements for this model as depicted in Figure 7 which presents of estimation error and 3σ interval for UKF, EKF and BS error. The first 100 values of the filtering results with UKF, EKF and bootstrap filter (BS) are calculated and obtained filtering results for UKF are as depicted in Figure 8. It is observed that BS gives clearly better performance than UKF and EKF. The comparison of estimation error and 3σ interval for UKF, extended UKF, modified EKF and BS error are as illustrated in Figures 9 and 10 respectively. Since no source is ideal, with the increase in the number of generators i.e., by decentralization the maintenance of constant voltage and frequency is a challenge.

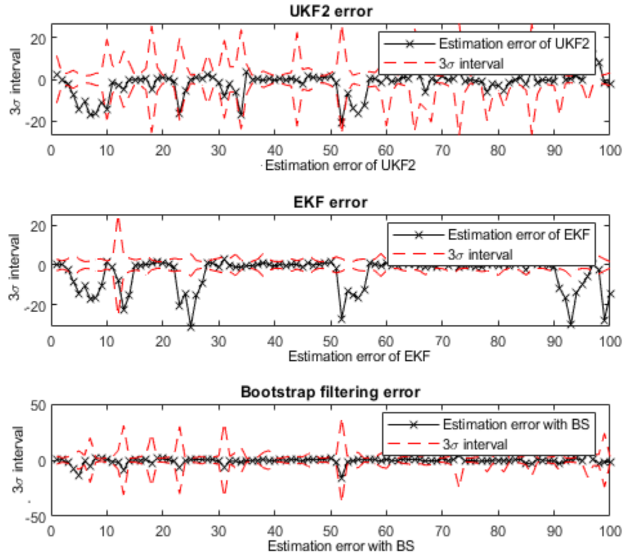



Figure 7. Comparison of estimation error and 3σ interval for UKF, EKF, and BS error

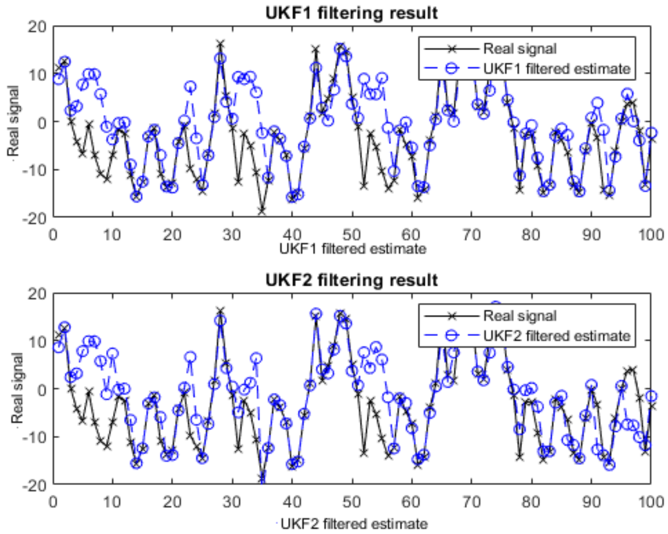



Figure 8. Comparison of real signal and UKF model filtered estimate

Power quality is mainly affected by the existence of transient voltages, irregular changes in load, harmonics, voltage sag, and swells. Maintaining the sinusoidal waveform could also be a challenge due to the same reasons. In simple words, power quality is the ability of the system (grid) to supply constant voltage and frequency with sinusoidal waveform, although it is impossible to eliminate the variations in power grids, they can, however, be maintained under tolerance limits.

A discrete-time state space equation models the microgrid. Then, in order to obtain the appropriate system details, cost-effective smart sensors are deployed. The recursive systematic convolution code is adopted from the communication point of view to introduce redundancy throughout the framework. The Table 3 illustrates mean square error obtained for several variants of Kalman filter. It is noteworthy that extended Kalman filter has got a high mean square error and bootstrap Kalman Filter has got a least mean square error. Derived from Table 2, Figures 11(a) and 11(b) depicts the estimation error estimation and angles in the microgrid sensor voltage magnitudes from test instances 1000-1050 for IEEE-118 bus 50 and bus 80 respectively.

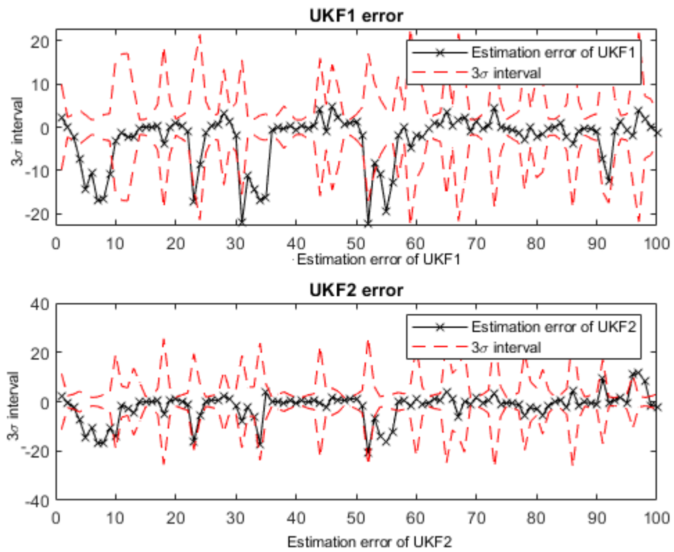



Figure 9. Comparison of estimation error and 3σ interval for UKF 1 and extended UKF 2 error

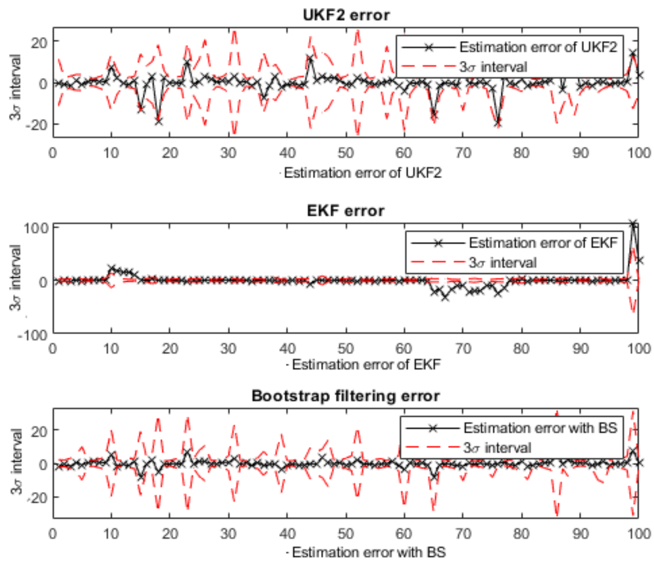
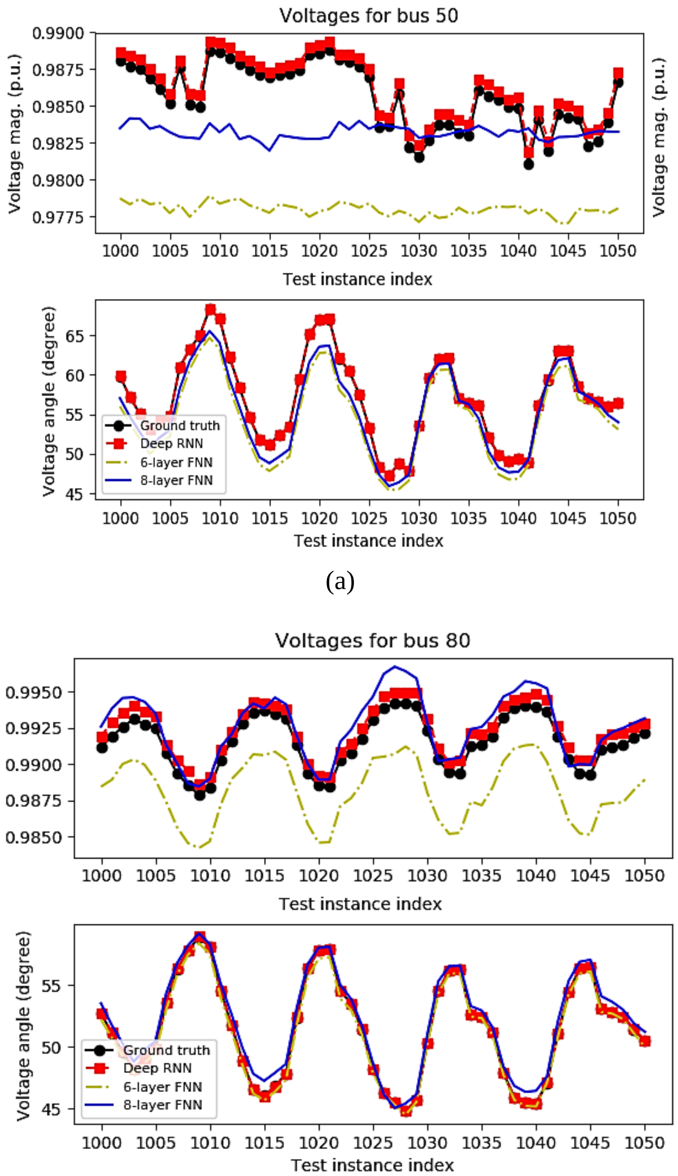



Figure 10. Comparison of estimation error and 3σ interval for UKF, modified EKF and BS error

The Table 4 as depicted compares the existing results in terms of computational efficiency, energy consumption, switching probability, misclassification error, and the throughput in the previous works carried out with our proposed work and also the % improvement or the % enhancement in the obtained results are as described in tabular column. Constant monitoring and prediction of states in grids will be a boon to maintaining good power quality. Power quality can also be improved using PWM active filters, power conditioning equipment like passive shunt L-C Filters, and by correcting power factor.

Table 3. Tabular column of mean square error (MSE) obtained

| Kalman filter variant | Mean square error |
|---|---|
| UKF1-MSE | 36.8932 |
| UKF2-MSE | 28.6441 |
| Extended KF-MSE | 75.1919 |
| PKF-MSE | 67.9096 |
| BS-MSE | 8.1377 |
| CKF-MSE | 60.6998 |
| Ensembled KF-MSE | 63.760 |




(a)

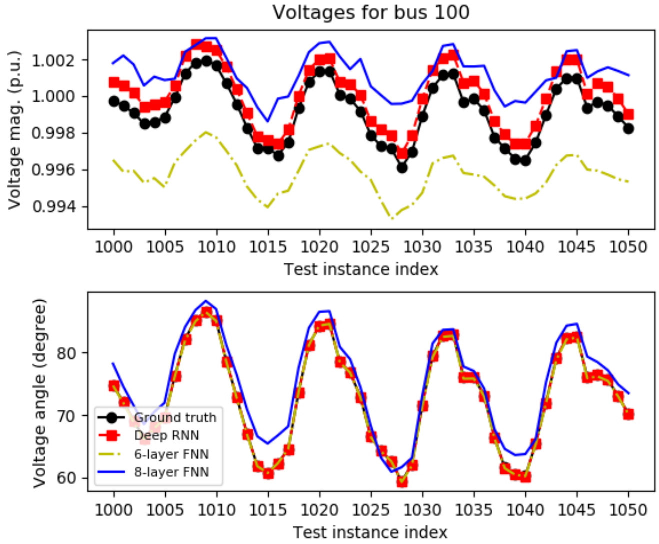
(b)

Figure 11. Microgrid sensor voltage magnitudes in angles and estimation error of IEEE-118 bus system from test instances 1000 to 1050 for (a) bus 50 and (b) bus 80

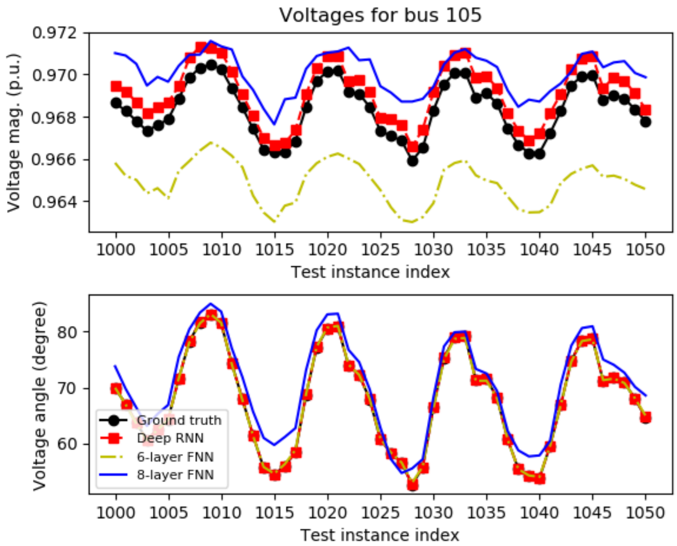
Further using Table 3, Figures 12(a) and 12(b) are obtained and presents the estimation error estimation and angles in the microgrid sensor voltage magnitudes from test instances 1,000-1,050 for IEEE-118 bus 100 and bus 105 respectively. The forecasting performance was evaluated with RNN based power system state forecasting scheme in terms of normalized root mean square error (RMSE) as described in Table 2 with $|v'-v|_2 /N$ of the forecast v' related to v (ground truth) [29]. The deep RNN and the activation functions were trained and tested on ground truth voltage time series. Here as illuminated in Figure 13 the microgrid sensor voltage magnitudes in angles and estimation error of IEEE-118 Bus system is calculated for the bus index at time 200. Further the Figure 14 represents microgrid sensor voltage magnitudes in angles and estimation error of IEEE-118 Bus system is calculated for the bus number at test instance of 1,000. Further the Table 5 illuminates the parameters of the simulation in terms of utility energy ($P_U$), battery parameters (maximum charging rate, depth of the discharge, stored energy ($P_B$) and the algorithm parameters such as convergence condition and efficiency of the algorithm is presented.

Table 4. Comparison of existing results with proposed work with % improvement

| Parameter | Previous Research | | | | Proposed Research | % Enhancement |
|---|---|---|---|---|---|---|
| | [30] | [31] | [32] | [33] | | |
| Computational Efficiency | 0.96 | 0.92 | 0.86 | 0.82 | 0.8 | 0.6% |
| Energy consumption | 12 J | 15 J | 13.2 J | 12.4 J | 14.7 J | 11.5% |
| Switching probability | 0.20 | - | - | 0.21 | 0.27 | 0.2% |
| Misclassification error (%) | 2.3 | 2.33 | 2.27 | 2.2 | 2.4 | 0.5% |
| Throughput (Mp/s) | 124.3 | 10 | - | 100 | 112.5 | 5.6% |




(a)




(b)

Figure 12. Microgrid sensor voltage magnitudes in angles and estimation error of IEEE-118 bus system from test instances 1,000-1,050 for (a) bus 100 and (b) bus 105

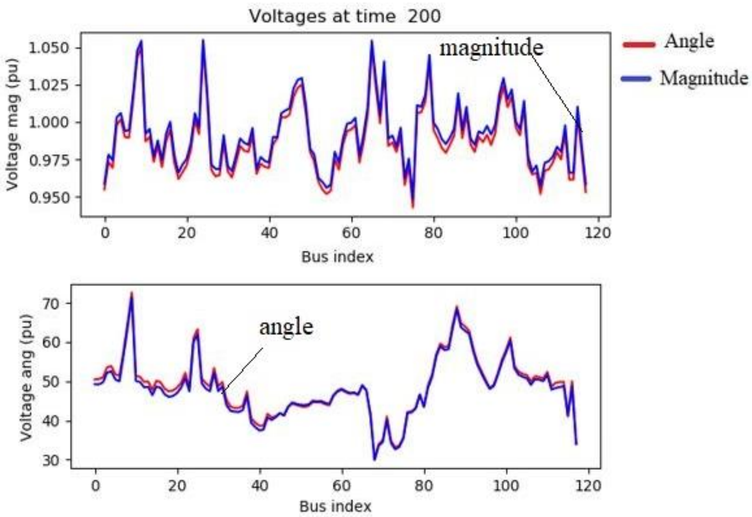



Figure 13. Microgrid sensor voltage magnitudes in angles and estimation error of IEEE-118 bus system for the bus index at time 200

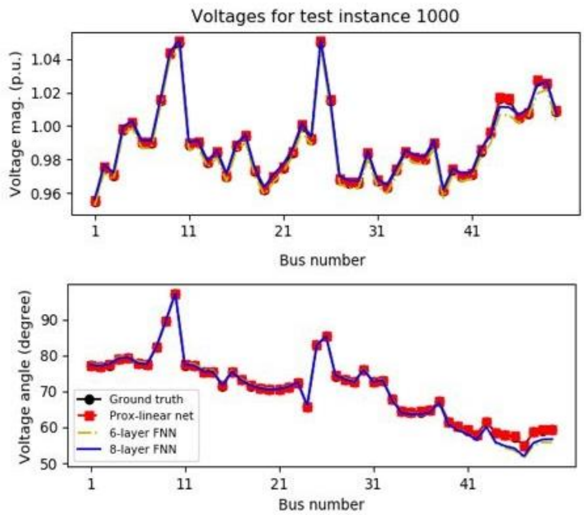



Figure 14. microgrid sensor voltage magnitudes in angles and estimation error of IEEE-118 Bus system for the bus number at test instance of 1,000

Table 5. Simulation parameters

| Serial Number | Parameters | | |
|---|---|---|---|
| I | $P_U$ (Utility Energy) | $P_U{}^1$ | 8.9 J |
| | | $P_U{}^2$ | 13.2 J |
| | | $P_U{}^3$ | 15 J |
| II | BATTERY | Maximum charging rate/maximum discharging rate | 5.28 kW h |
| | | Maximum charging rate | 0.526 |
| | | Depth of Discharge | 36% |
| | | $P_B$ (stored energy) | 12 J |
| III | Algorithm Parameters | γ | 0.96 |
| | | Convergence condition (μ) | 0.002 |

## 5. CONCLUSION

This paper investigates the various ways of distributed system state estimation via Kalman filters and its variants. The work focuses on detailing the working of Kalman filter with different works related to it discussed briefly. Comparisons on the variants of Kalman filter have been carried out and optimal filters for various settings are being advised based on their discussed mathematical modelling. With more optimization of the performing index, and appreciable flexibility factor by variants, Kalman filter are hence recommended to improve the state estimation of the distributed microgrids. This paper presented a formulated approach is presented to enable accurate measurements at component and system level model analysis in an IoT enabled microgrid. This paper described several Kalman variants used for pre-processor of raw, redundant data and produces a reliable state estimate and further investigates the various approaches of distributed system state estimation via Kalman filters and its variants. In this research a formulated approach along with algorithms is presented for optimal state estimation and forecasting, with weights update using DNN. The real load data experiments are carried out on the IEEE 118-bus benchmark system for the power system state estimation and forecasting and to enable calculations at component and system level model analysis in an IoT enabled microgrid. The future scope of this research is to develop a novel DNN based algorithms for a power system under dynamically varying conditions and corresponding time dependencies.

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