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Distributed State Estimation Using RSC Coded Smart Grid Communications

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ABSTRACT Recently, the renewable distributed energy resources (DERs) have become more and more popular due to carbon-free energy sources and environment-friendly electricity generation. Unfortunately, these power generation patterns are mostly intermittent in nature and distributed over the electrical grid, which creates challenging problems in the reliability of the smart grid. Thus, the smart grid has a strong requisite for an efficient communication infrastructure to facilitate estimating the DER states. In contrast to the traditional methods of centralized state estimation (SE), we propose a distributed approach to microgrid SE based on the concatenated coding structure. In this framework, the DER state is treated as a dynamic outer code, and the recursive systematic convolutional (RSC) code is seen as a concatenated inner code for protection and redundancy in the system states. Furthermore, in order to properly monitor the intermittent energy source from any place, this paper proposes a distributed SE method. Particularly, the outputs of the local SE are treated as measurements, which are fed into the master fusion station. At the end, the global SE can be obtained by combining local SEs with corresponding weighting factors. The weighting factors can be calculated by inspiring the covariance intersection method. The simulation results show that the proposed method is able to estimate the system state properly.

INDEX TERMS Distributed energy resource, Kalman filter, recursive systematic convolutional code, smart grid, state estimation.

I. INTRODUCTION

The traditional electrical grid with one way flow of power and passive networks has been undergoing profound changes to an intelligent smart grid because of increasing complexity in managing the bulk power generation, growing concerns for the environment, energy sustainability and wide-area monitoring [1], [2]. To achieve these goals, distributed energy resources (DERs) such as solar cells and photovoltaic systems have drawn a significant interest in the world. They are typically available in a decentralized way [3]. From this technical point of view, customers are not only participating in the eco-aware global community to sustain the ozone layer after minimizing the global warming but also trying to minimise the distribution losses in the electricity network [4], [5]. Despite these desirable benefits, the renewable DER model shows a totally random power generation pattern because its instantaneous availability of energy depends on the wind, sunlight and other similar intermittent energy sources. Therefore, an effective supervision of appliances is required from the perspective of energy saving and power efficiency in distributed generation, utility, industry and homes. Based on the information and communication infrastructure, the smart grid can spread the intelligence of the energy distribution system from the central unit to long-distance remote areas, thus enabling accurate state estimation (SE) and wide-area real-time monitoring of these intermittent energy sources [6], [7].

A. RELATED WORK

Power system SE frequently uses the weighted least squares (WLS) method that minimizes the sum square of the weighted residuals [8]. The main problem of the WLS method is that the gain matrix may be ill-conditioned. Thereby, the solution may fail to converge, and system states cannot be obtained accurately [9], [10]. The numerically ill-conditioned problem is successfully solved by the trust region method with quadratic regulation factorization, but the convergence problem still exists [11]. Recently, a belief propagation (BP)-based static state estimator for the IEEE 4-bus distribution system is proposed in [12]. However, the system states continuously change over time. In fact, a BP algorithm for unregulated dynamic SE for a single microgrid is proposed in [13]. Unfortunately, the computational complexity of the BP method is very high, even though the performance is almost the same at a high signal-to-noise ratio. Furthermore, the smart grid is to integrate the multiple DERs into the main grid, which needs to be controlled properly, as it is distributed in remote areas. A comparison between the extended Kalman filter (EKF) and nonparametric BP (NBP) has been investigated for distributed dynamic state estimation [14]. A sum-product message-passing algorithm to compute the system state is developed, showing that the performance of the NBP is better than EKF algorithm. In [15] and [16], a factor graph based message-passing algorithm for power system state estimation is presented. Note that the factor graph consists of variable and factor nodes. The factor nodes are the logical representation of the sensor observation information, whereas the variable nodes do not exists physically [15]. The message can be processed and passed between the variable and factor nodes with certain sum product rules [15], [16]. The BP algorithm has interesting structural properties corresponding to nonlinear feedback dynamical systems in the context of decoding the received signal [17]. Overall, the BP-based statistical estimation techniques can provide a better performance if there is no loop in the graph [18]. In other words, this algorithm can converge to the true system states in the Bayesian-tree-like structure. When loops are present in the graph, the algorithm may cause oscillation and the estimated state may diverge from the true state [18], [19].

In order to estimate the system states, various distribution system and distributed state estimation algorithms have been proposed in the literature. To begin with, a dynamic distribution system state estimation using the EKF and unscented KF (UKF) algorithms is proposed in [20]. In this framework, the state transition matrix is obtained using the least squares approach. With the state transition matrices, the forecasted state vector and covariance matrix are continuously updated. Moreover, a comprehensive literature survey on state estimation in electric power grids is given in [21]. The state transition matrix is obtained using the classic Holt-Winters method. Then, WLS and EKF algorithm is applied for state estimation using the phaser measurement data. Furthermore, a new approach for three-phase distribution system state estimation is presented in [22] where WLS is used as a state estimation technique. The main concept is based on the network reduction, so the algorithm is very fast and provides feasible results. Moreover, a robust data-driven state estimation for AC power system is explored in [23]. Precisely, the kernel ridge regression is suggested in a Bayesian framework based on the robust nearest neighbors search algorithm.

Interestingly, in order to reduce the communication cost specifically in the island wind farms and grid across mountain areas, a distributed state estimation in smart grids with communication constraints is recommended in [24]. In this work, the communication capability is defined as the number of observation information (that is proportional to the necessary bandwidth of transmission) to be transmitted at the energy management systems over one time slot. Based on the measurements a minimum mean square error estimator is proposed in a distributed way. Furthermore, in order to reduce the communication expenses and save transmission bandwidth, a cognitive radio as the communication link between the sensor and the control center of the smart grid is proposed in [25]. This infrastructure saves money and bandwidth by sensing the available spectrum for unlicensed customers. At the end, the KF algorithm is applied for state estimation over the cognitive radio system.

The distributed KF (DKF) has received great attentions in the smart grid research community. In [26], a distributed hierarchical structure is provided in which local state estimation is computed independently by the local KF at each sensor node. In [27], the distributed extended information filter and unscented information filter are considered for condition monitoring of power transmission and distribution systems. Here, the local estimated states and covariance matrices are fed to an aggregator filter. Generally, the performance of the method depends upon the covariance matrices with the assumption that each measurement is similar. But in practice, the measurement for each local KF is different and these big covariance matrices lead to a large communication burden. After that, a decentralized UKF algorithm for the real-time power system state estimation is proposed in [28]. Here, it is assumed that the state estimation for one local substation is completely independent from the other substation. As a result, the transmission of remote signals to a central estimator is not required and thus the estimation process is very fast [28]. Next, the DKF with a weighted averaging method is proposed in [29], which requires the global information of the state covariance matrix.

Recently, consensus-based DKF methods have been proposed for sensor networks, where local observations are exchanged among neighbors in order to get the global state estimation [30], [31]. The DKF algorithm in [31] consists of micro-KFs and each embedded with a low-pass and a band-pass consensus filter, while in [30] a micro-filter architecture with identical high-pass consensus filters is proposed for the sensors with different observation matrices. It is assumed that each sensor node can communicate its measurement, covariance information and output matrix with its neighbours [30], [31]. Then, a trust based DKF approach to state estimation in power systems is proposed in [32]. This method uses an accuracy dependent consensus step in the standard KF steps. Different from the consensus approaches, now the diffusion strategy is widely used in the literature, where the estimates are linearly combined using a set of weights [33], [34]. This method is more practical when dealing with dynamic systems where new measurements must be processed in a timely manner instead of running consensus [35], [36]. However, finding the optimal combination weights is one of the important problems for enhancing the estimation performance. To do so, the Metropolis optimal weights are generally chosen to yield fast consensus and it is a strong candidate for distributed consensus.

Therefore, it requires only knowledge of the local topology to get a faster mixing with the guaranteed convergence of average consensus [37].

Generally speaking, the local state estimators are interconnected with each other, so there is cross-covariance between them. Considering this factor in an aggregator filter, it can play an important role in improving the estimation performance. To achieve a better performance, a diffusion KF based covariance intersection is investigated in the literature [38]–[40]. Finally, a diffusion least mean square based distributed static state estimation is proposed in [41] and [42]. However, the system states continuously change over time, so static estimation may not be suitable. Moreover, in the aforementioned methods, it is assumed that communication is perfect and it is not considered to apply the estimation method for DERs state estimation in the context of smart grids. The central estimator with the power line communication can be used if there is limitation-free channel bandwidth and enough processing power in the measurement devices [43]. As a result, such an arrangement is not suitable for the large area monitoring of these intermittent energy sources. In addition, a real-time central estimator in large scale power systems with thousand of sensors is almost impossible due to the processing power limitations, network congestion and security issues [44]. Therefore, an alternative approach is required to monitor such foreseeable resources.

B. CONTRIBUTIONS AND ORGANISATION

Based on the aforementioned motivations, this paper proposes a KF based microgrid distributed state estimation using recursive systematic convolutional (RSC) coded smart grid communications. Our preliminary work [4], [45] is based on the centralized SE while this paper focuses on the distributed SE. The centralized SE means a huge amount of state information is collected and processed at the central state estimation unit. This not only causes communication and computational burdens but also creates a possibility for central point failure [27], [46]. For this reason, the distributed estimation approaches are an striking alternate as they may need less communication bandwidth and allow parallel processing [44]. Note that the RSC-based distributed state estimation of smart grids is not available in the literature. In short, the main contributions of this paper are therefore fourfold. First of all, the modelling of a microgrid with four renewable micro sources is presented. After that the combined micro sources are represented by a state-space model. The microgrid model is linearized around the operating point so that the proposed KF based distributed SE using smart grid communications can be applied. Secondly, we propose a wireless sensor network (WSN) based communication network to sense and estimate the microgrid states. Thirdly, the state is considered as a dynamic outer code and the RSC code is treated as an inner code to protect the DER messages and add more redundancy in the system states. Furthermore, in order to properly monitor these intermittent energy sources from any place, this paper proposes a novel distributed state estimation method. Specifically, the outputs of the local state estimation are treated as measurements which are fed into the master fusion station. At the end, the global state estimation can be obtained by combining local state estimations with corresponding weighting factors. The weighting factors can be calculated by inspiring the covariance intersection method. The simulation is performed to illustrate that the proposed algorithm could be used to obtain the state estimation at an acceptable precision in the context of smart grid communications.

The rest of this paper is organized as follows. A microgrid incorporating multiple DERs models is presented in Section II. The network architecture for sensing the DER states is described in Section III. In addition, the proposed KF-based distributed dynamic SE scheme is described in Section IV, followed by the simulation results and discussions in Section V. Finally, the paper is wrapped up with conclusions and future work in Section VI.

Notation: Bold face lower and upper case letters are used to represent vectors and matrices, respectively; superscripts $\mathbf{x}^*$ and $\mathbf{x}^T$ denote the conjugate and transpose of $\mathbf{x}$, respectively; $\mathbf{I}$ is the identity matrix.

II. DISTRIBUTED MICROGRID

A microgrid is a cluster of micro energy sources, storage systems and loads which presents itself to the smart grid as a single entity that can respond to central or distributed control signals [47]. The core of the microgrid is the notion of a flexible, economically yet controllable interface between the microgrid and the wider power networks. From this point of view, renewable DERs such as micro-turbines, wind turbines, diesel generators and solar cells are important components of a microgrid in smart grids [48]. In order to connect the DER to the main grid, the electronics interface such as voltage source converter is also essential [47]. Unfortunately, the inherent intermittency and variability of such DERs complicates microgrid operations. In order to optimize the economic and environmental benefits, the DER will need to operate at their maximum power point and produce as much power as possible. Thus, it requires wide-area real-time state estimation and stability control for these intermittent energy sources. In this section a typical distributed microgrid structure is described. These micro sources are connected to the main grid through the IEEE-4 bus distribution line as shown in Fig. 1.

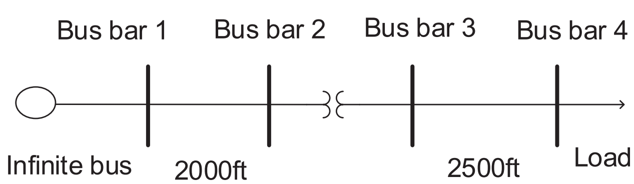

FIGURE 1. An illustration of the IEEE 4-bus distribution system [49].

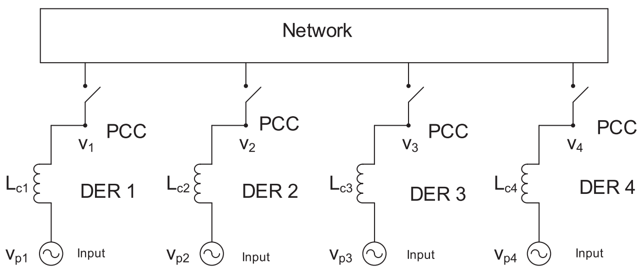

FIGURE 2. Four DERs are connected to the power network [49].

A. MATHEMATICAL DYNAMIC MODEL OF A MICROGRID INTEGRATING DERs

We adopt the model of interconnected DERs from [49], [50], as shown in Fig. 2. It is assumed that four DERs are modelled as voltage sources whose input voltages are denoted by $\mathbf{v}_p = (v_{p1}\ v_{p2}\ v_{p3}\ v_{p4})^T$, where v_{pi} is the i-th DER input voltage. The four DERs are connected to the main power network at the corresponding Point of Common Coupling (PCCs) whose voltages are denoted by $\mathbf{v}_s = (v_1\ v_2\ v_3\ v_4)^T$, where v_i is the i-th PCC voltage. In order to maintain the proper operation of DERs, these PCC voltages need to be kept at their reference values. A coupling inductor exists between each DER and the rest of the electricity network. Now applying the Laplace transformation in this microgrid to obtain the nodal voltage equations. The nodal voltage equation is given by:

$$\mathbf{Y}(s)\mathbf{v}_s(s) = \frac{1}{s}\mathbf{L}_c^{-1}\mathbf{v}_p(s), \tag{1}$$

where $\mathbf{L}_c = diag(L_{c_1},\ L_{c_2},\ L_{c_3},\ L_{c_4})$ and $\mathbf{Y}(s)$ is the admittance matrix of the power network. Based on the typical specifications of the IEEE 4-bus distribution feeder [49], the admittance matrix is given in (2), as shown at the bottom of this page. Now we can convert the Laplacian form into the linear state-space dynamic model. The detailed conversion can be found in [49]. Generally, the dynamic of the physical subsystem is given by:

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{n}(t), \tag{3}$$

where $\mathbf{x}(t) = \mathbf{v}_s - \mathbf{v}_{ref}$ is the PCC state voltage deviation, $\mathbf{v}_{ref}$ is the PCC reference voltage, $\mathbf{u}(t) = \mathbf{v}_p - \mathbf{v}_{pref}$ is the DER control input deviation, $\mathbf{v}_{pref}$ is the reference control effort, $\mathbf{n}(t)$ is the zero mean process noise whose covariance matrix is $\mathbf{Q}_n$, the state matrix $\mathbf{A}$ and input matrix $\mathbf{B}$ are given by:

$$\mathbf{A} = \begin{bmatrix} 175.9 & 176.8 & 511 & 103.6 \\ -350 & 0 & 0 & 0 \\ -544.2 & -474.8 & -408.8 & -828.8 \\ -119.7 & -554.6 & -968.8 & -1077.5 \end{bmatrix}, \tag{4}$$

$$\mathbf{B} = \begin{bmatrix} 0.8 & 334.2 & 525.1 & -103.6 \\ -350 & 0 & 0 & 0 \\ -69.3 & -66.1 & -420.1 & -828.8 \\ -434.9 & -414.2 & -108.7 & -1077.5 \end{bmatrix}. \tag{5}$$

In order to apply the discrete version of KF for DER SE, the discretisation of the state-space model is described in the next sub-section.

B. DISCRETISATION OF THE DER STATE-SPACE MODEL

By applying the Euler formula, equation (3) can be transformed into the following discrete form:

$$\mathbf{x}(k+1) = \mathbf{A}_d\mathbf{x}(k) + \mathbf{B}_d\mathbf{u}(k) + \mathbf{n}_d(k), \tag{6}$$

where $\mathbf{A}_d = exp(\mathbf{A}\Delta t) \approx \mathbf{I} + \mathbf{A}\Delta t$, $\mathbf{B}_d = \int_0^{\Delta t} exp(\mathbf{A}\xi)\, \mathbf{B}d\xi \approx \mathbf{B}\Delta t$, $\mathbf{n}_d(k) = \Delta t\mathbf{n}(k)$ with the variance $\mathbf{Q}_{nd}$, Δt is the discretization step size parameter, and $exp(.)$ is the exponential function [51], [52]. The communication architecture for sensing the DER states is described in the next section.

III. PROPOSED COMMUNICATION SYSTEMS

Smart gird is one of the most important applications of the communication network for environmental sustainability and energy efficiency issues in recent years. Therefore, the smart grid has been recognized as one of the vital applications of the communication network which makes the power sector to have a bidirectional communication with consumers and utility companies [1], [53]. The communication network brings about new perspectives to energy management systems and covers a diverse range of communication technologies, including sensing, communications, networking, computing, information processing and intelligent control technologies [2], [6]. In case the PCC voltages increase dramatically in the smart grid, it is necessary to apply a proper control method so that the PCC voltage deviations are driven to zero. Otherwise, it is very dangerous in terms of network stability and operation of the DERs [45]. To achieve the goal, the utility company deployed a lot of sensors in the electricity network for monitoring system states. Mathematically, the observations of the multiple DER states information are obtained by a set of sensors as follows:

$$\mathbf{y}(k) = \mathbf{C}\mathbf{x}(k) + \mathbf{w}(k), \tag{7}$$

where $\mathbf{y}(k)$ is the observation information, $\mathbf{C}$ is the observation matrix which maps the true state space to the observation space, and $\mathbf{w}(K)$ is the zero mean observation noise whose covariance matrix is $\mathbf{Q}_{wd}$. The observation information by the WSN is transmitted to the nearby relay node. The main reason

$$\mathbf{Y}(s) = (\mathbf{L}_c s)^{-1} + \begin{bmatrix} \frac{1}{0.1750+0.0005s} & \frac{-1}{0.1750+0.0005s} & 0 & 0 \\ \frac{-1}{0.1750+0.0005s} & \frac{1}{0.1750+0.0005s} + \frac{1}{0.1667+0.0004s} & \frac{-1}{0.1667+0.0004s} & 0 \\ 0 & \frac{-1}{0.1667+0.0004s} & \frac{1}{0.1667+0.0004s} + \frac{1}{0.2187+0.0006s} & \frac{-1}{0.2187+0.0006s} \\ 0 & 0 & \frac{-1}{0.2187+0.0006s} & \frac{1}{0.2187+0.0006s} + \frac{1}{12.3413+0.0148s} \end{bmatrix} \tag{2}$$

of using the relay node is that the distance between the DER and the destination is greater than the transmission range of sensors which have generally less processing capability [54]–[56]. In order for protection and redundancy in the DER states, the signal processing research community is trying to use channel code in the SE of smart grids.

A. RSC ENCODING

The channel code is used to protect the sent data over it for storage or retrieval even in the presence of noises (errors). Inspired by the convolutional coding concept (current output state depends on the previous state and input), the outer coding is considered similar to the DER state-space and observation models. After that, the uniform quantizer of this node maps each observation signal to a sequence of bits. The bit sequence is encoded by recursive systematic convolutional (RSC) channel code which is considered as an inner code for the concatenated coding structure [13]. The RSC is used to protect the DER messages sent over the networks in the presence of noises and interferences. As a result, it improves the system performance significantly due to the redundancy in the DER states. Figure 3 shows this encoding process in detail.

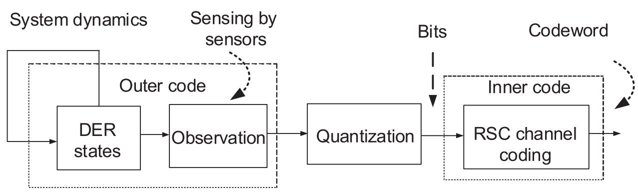

FIGURE 3. A concatenated coding structure of a dynamic power system [13].

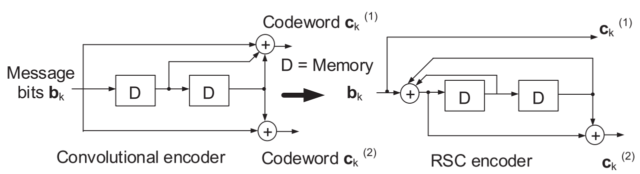

FIGURE 4. A (1, 5/7) convolutional encoder and RSC encoder [57].

Generally, the code rate k/n determines the amount of redundancy in the system state where k is the DERs message length and n is the codeword length [57]. Figure 4 shows the equivalent RSC code (rate 1/2) of the (1, 5/7) convolutional encoder [57]. The state transition and trellis diagrams of the (1, 5/7) RSC code are illustrated in Figs. 5 and 6.

The coded bit sequence is passed through the binary phase shift keying (BPSK), and the modulated signal $\mathbf{s}(k)$ is obtained. The modulated signal goes through the additive white Gaussian noisy (AWGN) channel with some noise. To illustrate, Fig. 7 shows the proposed communication procedure and dynamic SE. At the end, the received signal is given by:

$$\mathbf{r}(k) = \mathbf{s}(k) + \mathbf{e}(k), \tag{8}$$

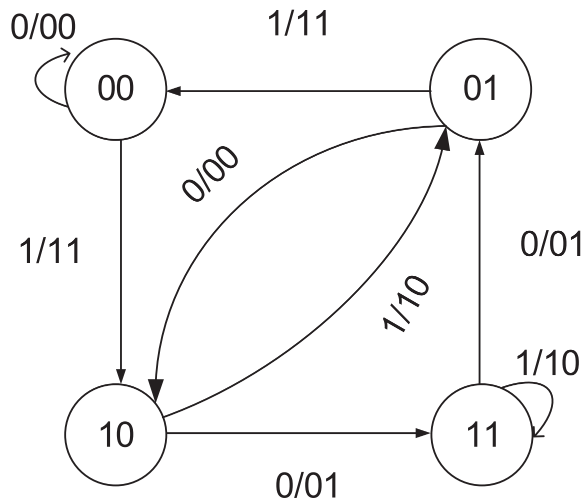

FIGURE 5. State transition diagram for the (1, 5/7) RSC code [57].

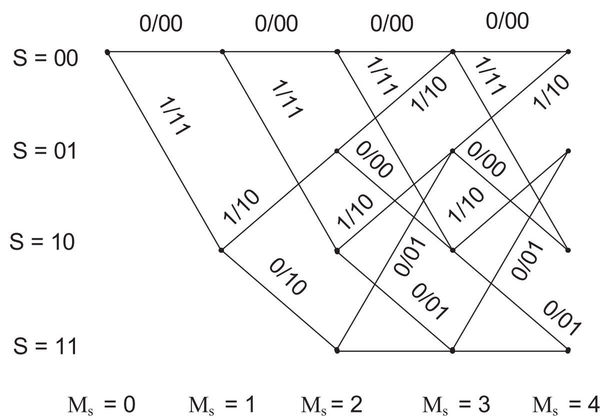

FIGURE 6. Trellis diagram for the (1, 5/7) RSC code [57].

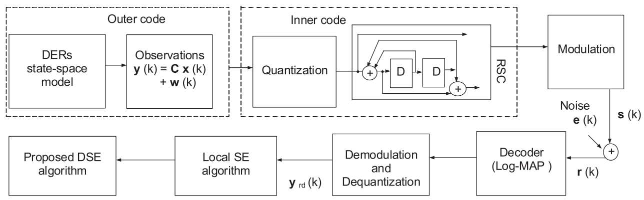

FIGURE 7. An illustration of the coded communication and dynamic systems.

where $\mathbf{e}(k)$ is the AWGN noise. The received signal is followed by the log-maximum A posteriori (Log-MAP) decoding for this dynamic systems [57].

B. LOG-MAP DECODING

The Log-MAP decoding is widely used for the decoding of RSC codes. For each transmitted symbol it generates its hard estimate and soft output in the form of a posteriori probability on the basis of received sequences [57], [58]. A Log-MAP consists of four processing units as follows:

i). Calculate the branch matrix Γ for $k = 1, 2, \cdots, L_r$ and $l = 0, 1, \cdots, M_s - 1$ as follows:

$$\Gamma_k^i(l', l) = log[p^i(k)exp\{-d^2[\mathbf{r}(k), \mathbf{s}(k)]/2\sigma^2\}], \quad i = 0, 1 \tag{9}$$

where L_r is the received sequence length, M_s is the number of states in the trellis diagram, $\mathbf{r}(k)$ is the received sequence, $\mathbf{s}(k)$ is the transmitted sequence, σ^2 is the noise variance, $d^2[\mathbf{r}(k), \mathbf{s}(k)]$ is the squared Euclidean distance between $\mathbf{r}(k)$ and $\mathbf{s}(k)$, $p^i(k)$ is the priori probability of each information bit, l is the state at time k and l' is the state at time $k-1$.

ii). Compute the forward recursion α from the beginning of the trellis to the end for $k = 1, 2, \cdots, L_r$ and $l = 0, 1, \cdots, M_s - 1$ as follows:

$$\alpha_k(l) = log[\sum_{l'=0}^{M_s-1} \sum_{i\epsilon(0,1)} \alpha_{k-1}(l')\Gamma_k^i(l', l)], \tag{10}$$

where α_{k-1} is the previous value with $\alpha_0(0) = 1$ and $\alpha_0(l) = 0$ for all $l \neq 0$.

iii). Compute the backward recursion β from the end of the trellis to the beginning for $k = L_r - 1, \cdots, 1, 0$ and $l = 0, 1, \cdots, L_r - 1$ as follows:

$$\beta_k(l) = log[\sum_{l'=0}^{M_s-1} \sum_{i\epsilon(0,1)} \beta_{k+1}(l')\Gamma_{k+1}^i(l, l')], \tag{11}$$

where β_{k+1} is the next value with $\beta_{L_r}(0) = 1$, $\beta_{L_r}(l) = 0$ for all $1 \neq 0$ and $\Gamma_{k+1}^i(l, l')$ is computed from the forward recursion step.

iv). Finally, the log likelihood is calculated as follows:

$$L(k) = log[\sum_{l=0}^{M_s-1} \{\alpha_{k-1}(l')\Gamma_k^1(l', l)\beta_k(l)\}/ \sum_{l=0}^{M_s-1} \{\alpha_{k-1}(l')\Gamma_k^0(l', l)\beta_k(l)\}]. \tag{12}$$

The decoded output is sent to demodulation and de-quantization and then finally used by the SE method for this dynamic systems.

IV. PROPOSED DISTRIBUTED STATE ESTIMATION

The KF algorithm is a set of mathematical equations that provide an efficient recursive means to estimate the state of a process in a way that minimizes the mean square error over time. Moreover, the KF algorithm can use the complete DER information including the statistical information of process noise, observation noise, process value and measurement value to obtain the optimal estimation of the DER states. This estimation technique works in two steps: time prediction step and measurement update step. In the prediction stage, the KF estimates the current state variables along with their uncertainties [59]. In the correction phase, the predicted estimation is further updated based on the measurement to get the desired state estimation. In other words, KF is required to save the DER state values and covariances at the previous step in each estimation process. The predicted state estimate for each local KF is given by:

$$\hat{\mathbf{x}}^-(k) = \mathbf{A}_d\hat{\mathbf{x}}(k-1) + \mathbf{B}_d\hat{\mathbf{u}}(k-1), \tag{13}$$

where $\hat{\mathbf{x}}(k-1)$ is the estimate states of the previous step. The predicted estimate covariance matrix is given by:

$$\mathbf{P}^-(k) = \mathbf{A}_d\mathbf{P}(k-1)\mathbf{A}_d^T + \mathbf{Q}_{nd}(k-1), \tag{14}$$

where $\mathbf{P}(k-1)$ is the estimate covariance matrix of the previous step. The measurement residual $\mathbf{d}(k)$ is given by:

$$\mathbf{d}(k) = \mathbf{y}_{rd}(k) - \mathbf{C}\hat{\mathbf{x}}^-(k), \tag{15}$$

where $\mathbf{y}_{rd}(k)$ is the dequantized and demodulated output bit sequences that can be seen in Fig. 7. The Kalman gain is given by:

$$\mathbf{K}(k) = \mathbf{P}^-(k)\mathbf{C}^T[\mathbf{C}\mathbf{P}^-(k)\mathbf{C}^T + \mathbf{Q}_{wd}(k)]^{-1}. \tag{16}$$

The updated state estimation is given by:

$$\hat{\mathbf{x}}(k) = \hat{\mathbf{x}}^-(k) + \mathbf{K}(k)\mathbf{d}(k). \tag{17}$$

The updated estimate covariance matrix $\mathbf{P}(k)$ for each local KF is given by:

$$\mathbf{P}(k) = \mathbf{P}^-(k) - \mathbf{K}(k)\mathbf{C}\mathbf{P}^-(k). \tag{18}$$

The equations infer that the amount of output correction is determined by $\mathbf{K}(k)$ which is dependent on the predicted covariance matrix $\mathbf{P}^-(k)$ over time. Specifically, from (16) it can be seen that the output correction will be less when the observation uncertainty covariance matrix $\mathbf{Q}_{wd}(k)$ is increased. As a result, the DER state estimate will be slowly adapted over time. Technically, if the projected covariance matrix $\mathbf{P}^-(k)$ increases, i.e., the predicted DER state $\hat{\mathbf{x}}^-(k)$ becomes inferior, it will change the KF gain accordingly. Thus, the outcome in an estimated DER state relies more on the observation than the predicted state. However, if the observation covariance matrix $\mathbf{Q}_{wd}(k)$ surges, i.e., the observation $\mathbf{y}(k)$ becomes worse, it will change the KF gain accordingly. Therefore, the result in an estimated DER state relies less on the observation result than the predicted DER states. The flow chart for each local KF is depicted in Fig. 8.

At each relay node, a local KF based state estimation runs. The outputs of the local estimated states are treated as measurements which are fed into the master fusion station. In other words, the global estimate can be obtained in terms of the local computed state estimates, covariance matrices and corresponding weighting factors. Specifically, we consider four local KFs and an aggregator filter for estimating the global DER states. Figure 9 demonstrates the structure of the proposed distributed SE using smart grid communications. For this case, the proposed distributed state estimation is described by the following equation:

$$\hat{\mathbf{x}}_g(k) = w_1\hat{\mathbf{x}}_1(k) + w_2\hat{\mathbf{x}}_2(k) + w_3\hat{\mathbf{x}}_3(k) + w_4\hat{\mathbf{x}}_4(k), \tag{19}$$

where $w_i > 0$ $(i \in 1, 2, 3, 4)$ is the weighting factor and $\hat{\mathbf{x}}_i(k)$ is the i-th local estimation. Inspired by the covariance intersection method [60], [61], the weighting factors in the

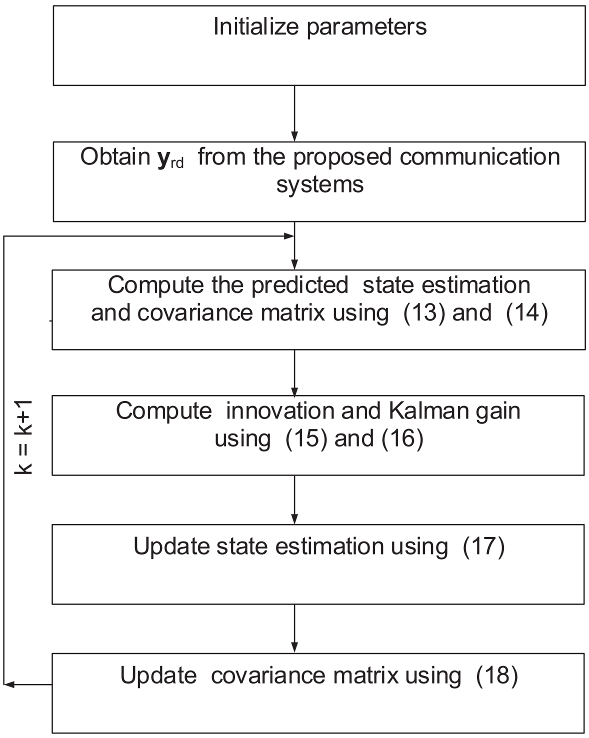

FIGURE 8. The flow chart for each local KF algorithm.

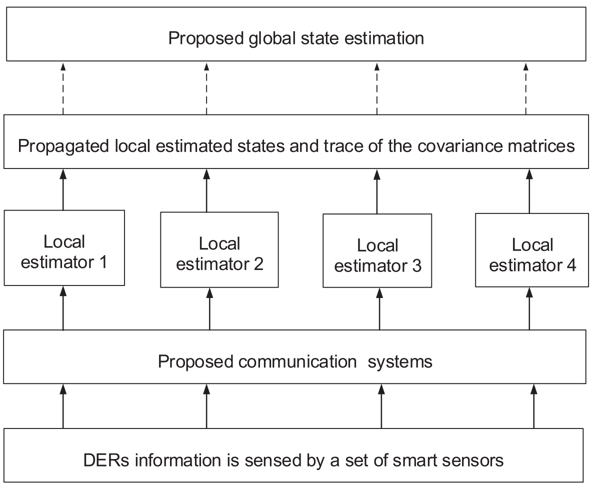

FIGURE 9. An illustration of the proposed method.

case of four subsystems can be approximately determined by the following equations:

$$trace(\mathbf{P}_1(k))\, w_1 - trace(\mathbf{P}_2(k))\, w_2 = 0, \tag{20}$$
$$trace(\mathbf{P}_2(k))\, w_2 - trace(\mathbf{P}_3(k))\, w_3 = 0, \tag{21}$$
$$trace(\mathbf{P}_3(k))\, w_3 - trace(\mathbf{P}_4(k))\, w_4 = 0, \tag{22}$$
$$w_1 + w_2 + w_3 + w_4 = 1, \tag{23}$$

where $\mathbf{P}_i(k)$ is the i-th covariance matrix from the i-th local estimator. For simplicity, define $d_i = trace(\mathbf{P}_i(k))$ as a scalar quantity. Based on (20)-(23), we have

$$w_1 = (1/d_1)/(1/d_1 + 1/d_2 + 1/d_3 + 1/d_4), \tag{24}$$
$$w_2 = (1/d_2)/(1/d_1 + 1/d_2 + 1/d_3 + 1/d_4), \tag{25}$$
$$w_3 = (1/d_3)/(1/d_1 + 1/d_2 + 1/d_3 + 1/d_4), \tag{26}$$
$$w_4 = (1/d_4)/(1/d_1 + 1/d_2 + 1/d_3 + 1/d_4). \tag{27}$$

The main advantage of this proposed estimation is the reduction of communication burdens as seen in Fig. 9. For testing the performance of the proposed distributed microgrid state estimation approach, the simulation results are presented in the next section.

TABLE 1. The parameters for the simulation using Matlab.

Parameters	Values	Parameters	Values
Δt	0.0001	RSC codes generator	5/7
Decoding	Log-MAP	Quantization	Uniform 16 bits
Code rate	1/2	Channel	AWGN
$\mathbf{Q}_{nd}$	0.005*$\mathbf{I}$	$\mathbf{Q}_{wd}$	0.05*$\mathbf{I}$

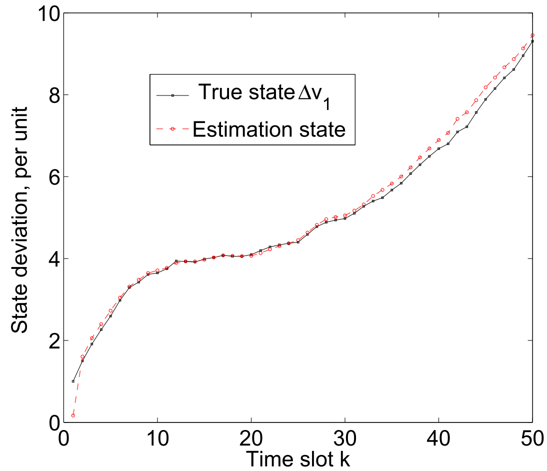

FIGURE 10. Δv_1 comparison between the true and estimated state.

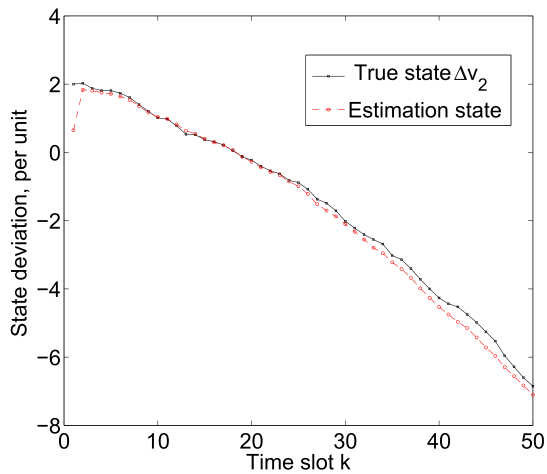

FIGURE 11. Δv_2 comparison between the true and estimated state.

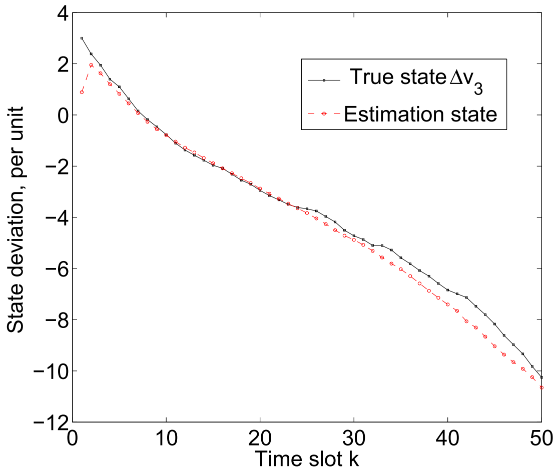

FIGURE 12. Δv_3 **comparison between the true and estimated state.**

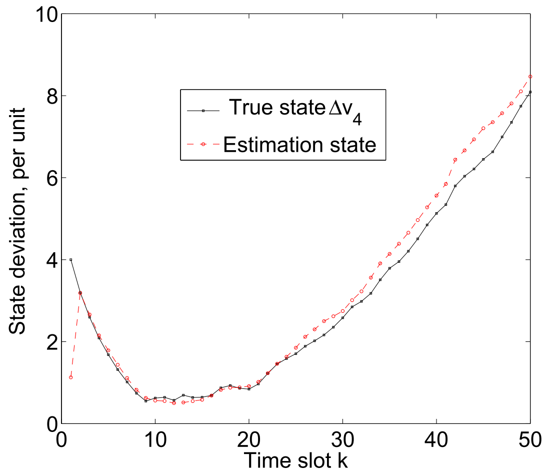

FIGURE 13. Δv_4 **comparison between the true and estimated state.**

V. SIMULATION RESULTS

In this section, we evaluate the performance of the proposed distributed state estimation using the RSC coded smart grid communications. We consider an interconnected unregulated microgrid model incorporating four DERs, which are sensed by a set of sensors. It is assumed that the complete state of microgrid could not be measured directly. The simulation parameters are summarized in Table 1.

Considering the above parameters, the simulation results are presented in Figs. 10–13. From the results, it is observed that the proposed method is able to estimate the system state properly.

VI. CONCLUSION

This paper explores the problem of distributed microgrid SE using RSC coded smart grid communications. The proposed global state estimation can be obtained in terms of the locally computed state estimates, covariance matrices and corresponding weighting factors. To reduce the computing complexity for finding the weighting factors, we derive an algorithm based on the trace of the estimated local covariance matrices. The effectiveness of the proposed method is demonstrated with a microgrid incorporating multiple DERs. In the future work, we will investigate how channel fading affects the system performance [62]. Furthermore, in order to improve the system performance, the low density parity check codes can be adopted as a channel code in the SE of smart grids [63].

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