Fault Tolerant Consensus with Multiagent Systems for Distributed Coordinated Control Algorithm in the Energy Internet Network

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Abstract. The future power system can be considered as an aggregation of controllable distributed systems devices that coordinate with each other through the Internet of Things (IoT), energy internet (EI) new paradigms arise. In EI environments, agreement among multiple computers is essential for power generation, transmission, distribution, and consumption etc. applications. Coordinated control and security protection play important roles in the application of a distributed computing environment. A consensus approach can provide fault tolerance and prevent system errors and attacks, thereby providing the system with strong security in distributed computing environment. In this paper, a distributed Kalman filter with consensus coordinated control algorithm for multiagent systems (MAS) was proposed to investigate the energy internet with links failure by cyber attack. The proposed algorithm is evaluated in the energy internet through a MAS model using MATLAB software.

Keywords—multiagent systems, consensus, energy internet

1. Introduction
The growing synergy between Internet of Things (IoT) and energy internet (EI) brings the potential of integrating more distributed generation and renewables in a cost effective way, enabling peer to peer trading of energy, e.g. electricity and heat. As part of the IoT, EI keeps the grid stable by balancing the power generated from renewables with the electricity that is consumed — by electric vehicles, for example. EI is, therefore, defined as an integrated dynamic network infrastructure based on standard and interoperable communication protocols that interconnect the energy network with the Internet allowing units of energy (locally generated, stored, and forwarded) to be dispatched when and where it is needed. With the significant increasing amount of distributed energy resources in the EI, researchers are interested in applying consensus based distributed control in EI related problems[1], such as economic dispatch [2], demand response [3], and plug-in electric vehicles charging coordination [4] etc. In those distributed applications, controllers (usually low-cost single-board microcontrollers) coordinate with neighboring peers and make decisions for local controllable devices [5]. In many realistic EI networks, due to the complexity of systems and undesirable cyber attacks or disturbance, the occurrence of sensors controllers (generically referred to as ‘nodes’) or communication link failure is inevitable[6]. There exists a cyber attack on sensors or a network exchanging data between sensors and controllers, which may be subject to maliciously destroy in common communication setting or wireless communication one[7]. This kind of phenomena is usually implemented by cyber attackers
with the aim of the enormous economy benefits. For real world energy internet network, representative examples of cyber attacks include an attack on Slammer worm on Davis Besse power plant in Ohio, U.S. [8], and recent Stuxnet worm targeted many industrial control systems[9].

As is well known, the main purpose of consensus based distributed control is to design a suitable control protocol such that the states of a team of agents can reach some common features. Obviously, the consensus issues with cyber attacks deserve adequate research attention simply because of the high requirements of security and reliability in EI environments, and this gives rise to the main motivation for our current research. For multiagent systems (MAS) under cyber attacks, a typical phenomenon is that the communication link among agents could be destroyed or compromised by adversaries in a random manner from the defenders’ perspective. When an attack occurs, the connectivity of network topology cannot be guaranteed and the resulting varying topology issue poses essential difficulties for the consensus control. Motivated by the above discussion, this paper is concerned with aim to design a distributed Kalman filter with consensus concept update approach to compensate for the undesirable effects of the failure links or nodes and the consensus property is retained after the recovery process in energy internet consensus control of networked multiagent systems for distributed coordination.

The organization of the remaining part is presented as follows. In Section II, distributed Kalman filter and consensus coordinated control approach are introduced. In Section III, a distributed Kalman filter with consensus coordinated control algorithm for multi-agent networks are presented and numerical simulations are given to show the effectiveness of the approach results in Section IV. In the final section, concluding remarks are drawn.

2. DISTRIBUTED KALMAN FILTER

In this section, we discuss the distributed Kalman filter. The distributed Kalman filtering that relies on communicating state estimates between neighboring nodes and refer to it as local node using Kalman filter.

2.1. Local Kalman Filtering

Assume that node $i$ only receives information from its neighbors. In each local node Kalman filtering, let be the set of neighbours of node on graph $G$. Each node of the EI network communicates its measurement, covariance information, and observation matrix with its neighbours. For node, we assume that the information flow from neighbouring nodes to node is prohibited if there is no nodes except for its neighbours exist. Therefore, node can use a Kalman filter that only utilizes the observation vectors and observation matrices of the nodes in. Then, we have the iterations of node $i$ in local node Kalman filtering as

$$ y^i = \sum_{j \in J_i} H_j^T R_j^{-1} Z_j = \sum_{j \in J_i} y_j $$

$$ S^i = \sum_{j \in J_i} H_j^T R_j^{-1} H_j = \sum_{j \in J_i} S_j $$

$$ \hat{x}_i = \bar{x}_i + M_i \left( y^i - S^i \bar{x} \right) $$

$$ M_i = \left( P_i^{-1} + S^i \right)^{-1} $$

$$ P_i^+ = A M_i A^T + B Q B^T $$

$$ \bar{x}_i^+ = A \hat{x}_i $$
Where \( y^i \) and \( S^i \) are local aggregate information vector and matrix, respectively and node \( i \) locally computes both \( y^i \) and \( S^i \). \{. +\} is the update operation.

2.2. Consensus Coordinated Control Approach

Consider a team of \( n \) agents to agree on specific consensus states, and at any discrete-time instant, the communication EI topology between agents can be described by the graph, the graph \( G \) is undirected, is the vertex set, and is the edge set. In the consensus coordinated control approach, each agent in the network maintains a local node copy of the consensus state and updates this value using its neighbours’ consensus states according to the consensus coordinated control rule:

\[
\zeta_i^{[\tau+1]} = \zeta_i^{[\tau]} + \sum_{j=1}^{n} \beta_{ij}^{[\tau]} (\zeta_j^{[\tau]} - \zeta_i^{[\tau]})
\]

(7)

where \( \tau \) indicates the consensus filter iteration step. To choose the weights \( \beta_{ij}^{[\tau]} \). We can use the Metropolis weights which preserves the averaging in consensus filters and can be computed by

\[
\beta_{ij}^{[\tau]} = \begin{cases} 
1 & \text{if } \frac{d_i}{d_j} > \frac{d_j}{d_i} \\
1 - \sum_{(i,j) \in E(\tau)} \beta_{ij}^{[\tau]} & \text{if } d_i = d_j \\
0 & \text{otherwise}
\end{cases}
\]

(8)

where \( d_i^{[\tau]} \) is the degree of agent \( i \) in the graph \( G^{[\tau]} \). Arrange the local consensus states into the vector \( \zeta^{[\tau]} = [\zeta_1^{[\tau]} \ldots \zeta_n^{[\tau]}]^T \) and define the matrix \( (B^{[\tau]})_{ij} = \beta_{ij}^{[\tau]} \) for \( i \neq j \); otherwise \( (B^{[\tau]})_{ii} = 1 - \sum_{(i,j) \in E(\tau)} \beta_{ij}^{[\tau]} \), and we can rewrite the update in (7) as

\[
\zeta^{[\tau+1]} = (B^{[\tau]} \otimes I) \zeta^{[\tau]}
\]

(9)

where \( I \) is the appropriate size identity matrix and \( \otimes \) denotes the matrix Kronecker product.

The \( ij \) th element of \( B^{[\tau]} \) in (9) satisfies the following four conditions:

1. \( (B^{[\tau]})_{ij} \geq 0 \)
2. \( \sum_i (B^{[\tau]})_{ij} = 1 \)
3. \( \sum_j (B^{[\tau]})_{ij} = 1 \)
4. each nonzero entry is both uniformly upper and lower bounded.

3. Distributed Kalman Filter with Consensus Coordinated Control Algorithm

We now present the distributed Kalman filter with consensus coordinated control algorithm in this section. The Kalman filter uses consensus coordinated control (7) on the state estimate in a distributed Kalman filter, where each node maintains a local node Kalman filter. Corresponding to (7), let \( \zeta_i^{[\tau]} = \bar{x}_i \) be the prior estimate at time \( \tau \) and \( \zeta_i^{[\tau+1]} = \bar{x}_i^c \) be fused prior estimate; each node fuses the prior estimates from its neighbours according to the rule:

\[
\bar{x}_i^c = \bar{x}_i + \sum_{j \in N_i} \beta_{ij}^{[\tau]} (\bar{x}_j - \bar{x}_i)
\]

(10)

Using the fused prior estimate \( \bar{x}_i^c \), the filter estimate at node \( i \) could be implemented by
The distributed Kalman filter with consensus coordinated control algorithm is summarized in the following as

**Initialization** (for agent (i.e. node) $i$):

$$\hat{x}_i = x(0) \quad P_i = P_0$$
$$\tau = 1 \quad \tau_p = \tau + T_p$$

**Loop** (Local iteration on node $i$)

1. Consensus coordinated control approach

   $$\hat{x}_i^\tau = \hat{x}_i + \sum_{j \in N_i} \beta_{ij} \left( \hat{x}_j - \hat{x}_i \right)$$

   $$y' = \sum_{j \in N_i} H_j^T R_j^{-1} z_j$$

   $$S' = \sum_{j \in N_i} H_j^T R_j^{-1} H_j$$

   $$\tau \leftarrow \tau + 1$$

2. If new observations are taken then the distributed Kalman consensus state estimate are updated

   $$\hat{x}_i = \hat{x}_i^\tau + M_i \left( y' - S' \hat{x}_i \right) = \hat{x}_i + M_i \left( y' - S' \hat{x}_i \right) + \left( I - M_i S' \right) \sum_{j \in N_i} \beta_{ij} \left( \hat{x}_j - \hat{x}_i \right)$$

   $$M_i = \left( P_i^{-1} + S' \right)^{-1}$$

3. If time for a predication step (i.e., $\tau = \tau_p$) then prediction step

   $$P_i = AM_i A^T + BQB^T$$

   $$\hat{x}_i^+ = A\hat{x}_i$$

   $$\tau_p = \tau + T_p$$

End loop

where $\tau$ is the time index for the consensus coordinated control approach and $T_p \in \mathbb{Z}^+$ is the time interval between prediction updates. One-time step $k-1 \rightarrow k$ is equivalent to $T_p$ time steps of the consensus time index $\tau \rightarrow \tau + 1$; that is, for each node, the information exchanges between neighboring nodes occurred faster than the prediction update step. The three steps in distributed Kalman filter prediction, local filter estimate, and consensus coordinated control update sequential.

4. **Numerical Simulations**

   By utilizing these generalized agents in combination, an effective MAS model can be created. A simple example is shown in Figure 1. In this energy internet, there are six generation sources (e.g. wind turbine, photovoltaics, or diesel generator etc.). The Energy Internet bus is connected to both the local generations and prosumers. The MAS is comprised of generation/prosumer agents assigned to each generator; in the interconnected state, each agent manages its assigned asset according to assigned objectives.
The distributed Kalman filter with consensus coordinated control algorithm

**Figure 1.** Example energy internet with assigned MAS agents. Dashed lines show communication; solid lines power flow.

In this EI network example, under a communication protocol and link connected network nodes, the distributed Kalman filter with consensus coordinated control algorithm can be achieved for multi-agent networks with quantization. The characteristics of the generators are modelled using the simplified synchronous generator from Matlab in the following two case studies which carried out to evaluate the performance of the proposed algorithm. It’s noted that it takes a longer time for the generators to reach a consensus due to the inertia of the generators. After about 2 sec, the generators reach the same consensus as shown in Figure 2. In the second case study of the simulations, we focus on the performance of fault tolerance for investigation the EI with links failure by cyber attack. For cyber attacks conduction, proposed algorithm is used to find EI generated power. Suppose some links fail at time $t = 28$ and the other agents had to compensate the shortage in the generated power after 32 sec (see Figure 3). The recovery process can be estimated to be able to converge after 40 sec (see Figure 4). Thus, the algorithm can be applied to large scale EI network.

**Figure 2.** The state estimation iterations of time instant for EI network.

**Figure 3.** Generation power compensation subject to link failure caused cyber attack.

**Figure 4.** The scenario of the EI network from links failure to recovery.
5. Conclusions
In this paper, detection of cyber attack or fault has been considered on a network of Energy Internet. The proposed algorithm not only able to detect a fault/cyber attack but also successfully tolerance and recovery nodes after failure in the EI network. Furthermore, the proposed algorithm has been proposed to safely and automatically recovery the faulty node under cyber attack. Finally, a numerical simulation cases study have been given with a typical example of six nodes in a hexagon EI network with a possible node and communication cyber attacks. Finally, a numerical case study has demonstrated that the residual generated at the monitoring node able to successfully detect and isolate the cyber attack. Also, the faulty node recovery has been shown effectively to maintain the quality of service accordingly. Future work includes extension of the proposed algorithm to handle more complex attack patterns and applying the approach for other types of EI network coordination missions.

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