

Bayesian Network and Semidefinite Programming Based Wireless Power Transfer Manufacturing System State Estimation and Regulation

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Abstract—In order to supply energy to the smart objects such as electric vehicles and smart phones using wireless power transfer (WPT) framework, the internet of things (IoT) embedded sensors and actuators can play critical roles for sensing, monitoring and regulating the WPT system states. Specifically, the smart sensors are used to transmit sensing state information to the control center, where the state estimation program runs to know the operating and health conditions of WPT system. This study proposes a Bayesian network based WPT system state estimation algorithm. This scheme can estimate the WPT system states in a distributed way using the Bayesian tree structure. Afterwards, the semidefinite programming based optimal feedback control scheme is proposed to regulate the system states. Simulations results show that the proposed approach provides significant performance improvement compared with the existing scheme.

Keywords—Bayesian network, controller, internet of things, sensors, semidefinite programming, system state estimation, wireless power transfer systems.

I. INTRODUCTION

In order to monitor and control the physical systems such as water distribution networks and traffic systems, the supervisory control and data acquisition (SCADA) is widely used over the world. The SCADA cyber system is far away from the physical location or network. This can form the cyber-physical systems for properly monitoring, planning, and controlling the system behaviour [1], [2], [3]. Generally speaking, the renewable microgrids and wireless power transfer systems can be connected to the grid [4]. From the remote control center, it will need to properly monitor and estimate the state operating conditions. When the renewable energy resources such as solar panels and wind turbines are integrated into the main grid, it is a challenging task for properly maintaining supply chain relationship [5]. Interesting, these can provide clean and green energy to customers and community. Therefore, the carbon dioxide emissions from the transportation and electricity generating units are significantly reduced [6]. The transportation and electricity generation sectors are the vital contributor for CO₂ emissions. Using these emerging renewable resources, we can try to mitigate the global warming at an acceptable level. Furthermore, the electricity clients and community can get green energy, reduce tariff, cost, and power loss.

When the smart transportation and road systems are based on cutting-edge technology and demand, energy can be wire-

less transferred to the smart devices such as cars or phones. Fig. 1 demonstrates energy supply and SCADA monitoring system. Observed that energy supply units such as solar panels

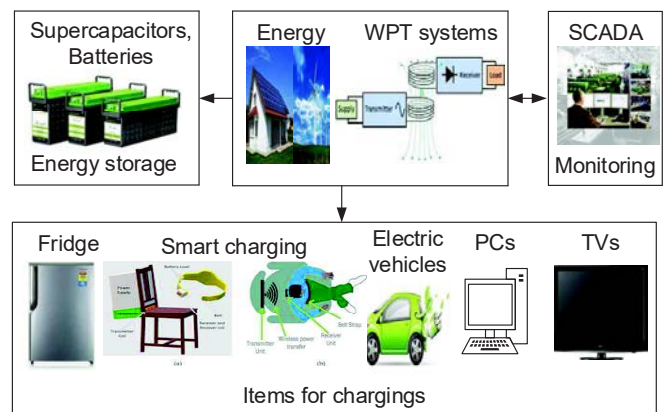


Fig. 1: Energy supply and SCADA monitoring system.

and WPT systems can be integrated into main network, and it can be monitored from the smart control center. In order to transfer information from the remote location, the internet of things (IoT) can be the potential network.

A neural network is adopted for estimating coupling coefficient between energy coils [7]. Using the trial and error approach, the state feedback controller is proposed in [8]. For primary-side of a two-transmitter inductive wireless energy transfer system, an effective method to estimate the output current and voltage is developed in [9]. It assumes that there is no direct measurement on the receiver side coil and load conditions. A distributed power allocation framework considering noise and interference for wireless networks is explored in [10]. Furthermore, the Kalman filter based WPT system state estimation method is presented in [11], [12]. It is a traditional and widely used method since 1960 and cannot provide high estimation accuracy. Differentiate from the aforementioned methods, the problem of effective wireless power transfer system and its state estimation is studied with the Bayesian network and semidefinite programming perspective by taking into account uncertainty in the communication channel and system framework.

II. WIRELESS POWER TRANSFER SYSTEMS MODEL

Energy in our smart device is the most important part for communication, information transmission and action. Sometimes charge in these devices are finished, and it creates many problems in real-time. When the transportation systems and devices are adopted the cutting-edge technology for charging, it is very helpful to get connection, transmission, sustainable and smart city. Fig. 2 shows the high-level block diagram of a modern charging system where energy can transfer through induction. When the smart cars or devices are required energy,

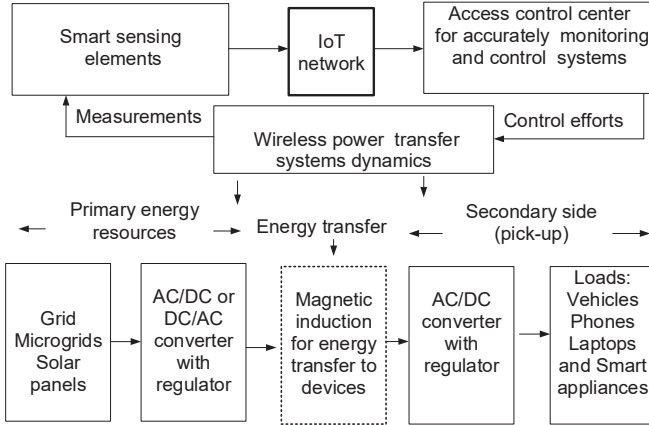


Fig. 2: A high-level block diagram of a modern charging system where energy can transfer through induction.

it can be transferred through induction within range. Specifically, the system-level block diagram of a WPT system is illustrated in Fig. 3 [13], [14] [15]. When the primary side and secondary unit are in transferring mode then the devices get charge for an example. The primary energy source can be renewable microgrid, solar panels, power grid and turbines. The secondary unit can be hybrid electric vehicles, phones and appliances. The whole transfer systems can be represented by dynamics with physical laws and circuit theory [16].

After apply physical laws and simplification, the WPT system can be represented as continuous-time state-space framework:

$$\dot{\mathbf{s}} = \mathbf{A}_c \mathbf{s} + \mathbf{B}_c \mathbf{u}. \quad (1)$$

Here, $\mathbf{s} = [i_{pi} \ v_{cpi} \ v_{pt} \ i_T \ i_{so} \ v_{cso} \ v_{st} \ i_{si}]^T$ is the energy transfer system state, v and i are the current and voltage in primary and secondary sides, $\mathbf{A}_c$ and $\mathbf{B}_c$ are the WPT state and input matrices, and $\mathbf{u} = [v_{pi} \ v_{so}]^T$ is the control effort. The WPT states can be locally linearized around the operating points $\mathbf{s}^*$, leading to $\Delta \mathbf{s} = \mathbf{s} - \mathbf{s}^*$ [17] i.e., $\mathbf{s} = [\Delta i_{pi} \ \Delta v_{cpi} \ \Delta v_{pt} \ \Delta i_T \ \Delta i_{so} \ \Delta v_{cso} \ \Delta v_{st} \ \Delta i_{si}]^T$ and $\mathbf{u} = [\Delta v_{pi} \ \Delta v_{so}]^T$. The values of $\mathbf{B}_c$ matrix are: $B_{1,1} = 1/L_{pi}$, $B_{5,1} = -1/L_{so}$, and $\mathbf{A}_c$ is given in the Appendix.

Now, (1) is written as a discrete-time state-space form as:

$$\mathbf{s}(k+1) = \mathbf{A} \mathbf{s}(k) + \mathbf{B} \mathbf{u}(k) + \mathbf{n}(k), \quad (2)$$

where $\mathbf{A} = \mathbf{I} + \mathbf{A}_c \Delta t$, $\mathbf{I}$ is the identity matrix, Δt is the sampling time, k is the time instance, $\mathbf{B} = \mathbf{B}_c \Delta t$, and $\mathbf{n}$ is

the exogenous disturbance with zero mean and $\mathbf{Q}$ covariance [17].

Using current and voltage sensors, the system measurements are described by:

$$\mathbf{z}(k) = \mathbf{C} \mathbf{s}(k) + \mathbf{v}(k), \quad (3)$$

where $\mathbf{z}$ is the observation vector, $\mathbf{C}$ is the sensing matrix and $\mathbf{v}$ is the observation noise with zero mean and $\mathbf{R}$ covariance [17]. From (2) and (3), it can be observed that WPT states are compromised by process and observation noise. From these compromised measurements, the system state process can try to recovery the original states after rectifying these uncertainties. In this way, charging, billing and information processing can be smartly completed at the control center.

III. PROPOSED BAYSEIAN NETWORK BASED STATE ESTIMATION AND CONTROLLER

From (2) and (3), it can be seen that the present WPT system state and observation depends on the previous state and measurement. They are interconnected to form the Bayesian tree network as shown in Fig. 4. In this considered network, the WPT states and measurements are travel between them. In each step, the WPT state and its error covariance is computed and upgraded. Afterwards, these information are forward to the observation node. With these given values, the observation system mean and error covariance are determined and updated. The updated information is backward to the root node. The forward and backward information process continues until N number of iterations. Finally, the state estimations and error covariances are gathered at the root node [for example $\mathbf{s}(k)$] to obtain reliable estimation results. These information aggregation and updated are completed using the Gaussian property of missing two variables [18], [19], [20], [21], [22]. Each iteration, the estimation error between original and estimated states are reduced leads to an perfect state prediction over time. When the system states are available by this process, the controller is adopted to regulate the WPT state trajectory.

With the given feedback gain $\mathbf{D}$ and after estimating the WPT system states over time, the control effort $\mathbf{u}(k)$ is give by:

$$\mathbf{u}(k) = \mathbf{D} \mathbf{s}(k). \quad (4)$$

The proposed controller gain is obtained by:

$$\mathbf{D} = \mathbf{G} \tilde{\mathbf{P}}, \quad (5)$$

where $\mathbf{G}$ and $\tilde{\mathbf{P}}$ are computed after solving the following inequality:

$$\begin{bmatrix} -\tilde{\mathbf{P}} & (\tilde{\mathbf{P}} \mathbf{A}' + \mathbf{G}' \mathbf{B}') & \tilde{\mathbf{P}} \mathbf{C}' \\ (\tilde{\mathbf{P}} \mathbf{A}' + \mathbf{G}' \mathbf{B}') & -\tilde{\mathbf{P}} & \mathbf{0} \\ \mathbf{C} \tilde{\mathbf{P}} & \mathbf{0} & -(\beta \mathbf{I}) \end{bmatrix} < \mathbf{0}. \quad (6)$$

Here, $\tilde{\mathbf{P}} = \tilde{\mathbf{P}}' > \mathbf{0}$ is the positive definite matrix and $\beta > 0$. With the given all initial variables as semidefinite programming, the proposed inequality can be solved using the YALMIP tool [23].

Proof: Inspired by [24], [25], [26] and given $\beta > 0$, the system is stable if following inequality holds:

$$(\mathbf{A} + \mathbf{B} \mathbf{D})' \mathbf{P} (\mathbf{A} + \mathbf{B} \mathbf{D}) + \beta^{-1} \mathbf{C}' \mathbf{C} - \mathbf{P} < \mathbf{0}. \quad (7)$$

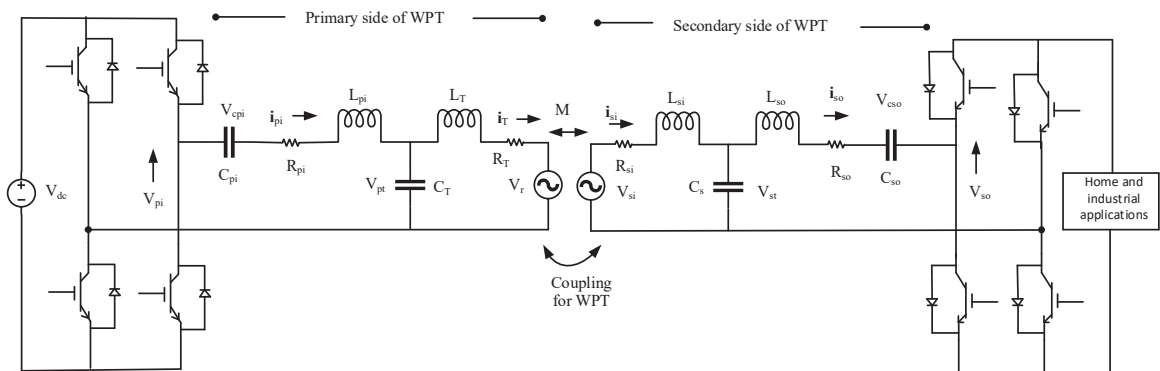


Fig. 3: System-level block diagram of a typical energy transfer system.

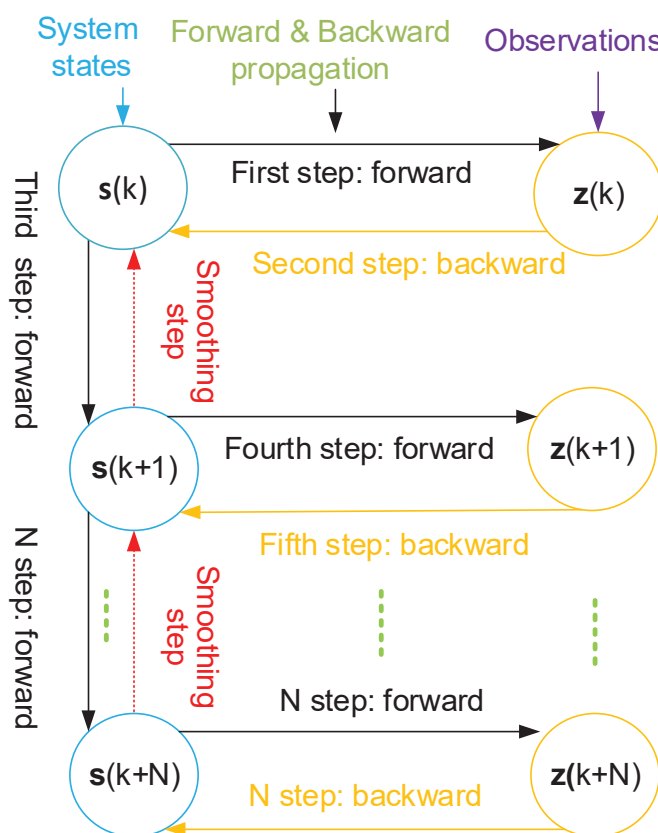


Fig. 4: Forward and backward Bayesian network for WPT state estimation.

Assume that $\tilde{\mathbf{P}} = \mathbf{P}^{-1}$, we have:

$$\begin{aligned} & (\mathbf{A} + \mathbf{B}\mathbf{D})'\tilde{\mathbf{P}}^{-1}(\mathbf{A} + \mathbf{G}\mathbf{D}) + \beta^{-1}\mathbf{C}'\mathbf{C} - \tilde{\mathbf{P}}^{-1} < \mathbf{0}, \\ & \tilde{\mathbf{P}}(\mathbf{A} + \mathbf{B}\mathbf{D})'\tilde{\mathbf{P}}^{-1}(\mathbf{A} + \mathbf{B}\mathbf{D})\tilde{\mathbf{P}} + \beta^{-1}\tilde{\mathbf{P}}\mathbf{C}'\mathbf{C}\tilde{\mathbf{P}} - \tilde{\mathbf{P}} < \mathbf{0}. \end{aligned} \quad (8)$$

After assuming $\mathbf{G} = \mathbf{D}\tilde{\mathbf{P}}$, we have:

$$\begin{bmatrix} -\tilde{\mathbf{P}} + \beta^{-1}\tilde{\mathbf{P}}\mathbf{C}'\mathbf{C}\tilde{\mathbf{P}} & \tilde{\mathbf{P}}\mathbf{A}' + \mathbf{G}'\mathbf{B}' \\ (\tilde{\mathbf{P}}\mathbf{A}' + \mathbf{G}'\mathbf{B}')' & -\tilde{\mathbf{P}} \end{bmatrix} < \mathbf{0}. \quad (9)$$

According to the Schur's complement, (9) leads to the (6). The effectiveness of the proposed method is verified in the following section.

IV. SIMULATION RESULTS AND DISCUSSIONS

This article studies a real-time smart monitoring system in which the destination devices are supposed to energise by induction. First of all, the mathematical framework of the WPT is established. Then the Bayesian network and semidefinite programming based wireless energy transfer system state estimation and control algorithm is proposed. The state estimation policy iteration and covariance is computed and updated in the Bayesian tree network. The controller is designed using semidefinite programming approach. For simulation, the wireless energy transfer parameter values are illustrated in Table I [13], [15]. The Matlab and YALMIP are used for simulations.

TABLE I: Considered WPT parameter values.

Symbols	Values	Symbols	Values
R_{pi}	0.0152 Ω	R_T	0.0158 Ω
R_{si}	0.0179 Ω	R_{so}	0.0122 Ω
C_{so}	2.5329×10^{-3} F	C_s	2.47×10^{-3} F
C_{pi}	2.5307×10^{-3} F	L_{so}	46.28×10^{-3} H
L_{si}	23.48×10^{-3} H	L_T	22.84×10^{-3} H
L_{pi}	46.51×10^{-3} H	C_T	2.49×10^{-3} F
M	8×10^{-3} H	Q	0.01*I
R	0.1*I	Δt	0.001

In order to see the state responses versus the time step, the simulation results are presented in Fig. 5. It can be seen that the proposed estimation algorithm requires 0.01 seconds ($k * \Delta t$) to estimate the systems states, while the existing method needs more than 0.05 seconds [27], [28]. Technically, it also means that the proposed algorithm requires much less time compared with the standard estimation time frame of 1 second [29]. This is due to the fact that the developed scheme can able to effectively reject the estimation errors to extract the system states.

In order to regulate the system states, the proposed feedback approach is applied. From Fig. 6, it can be clearly seen that the proposed approach is able to regulate the system states within 0.1 second which is much lower than the standard regulating time frame 1-5 seconds [29]. This is due to the

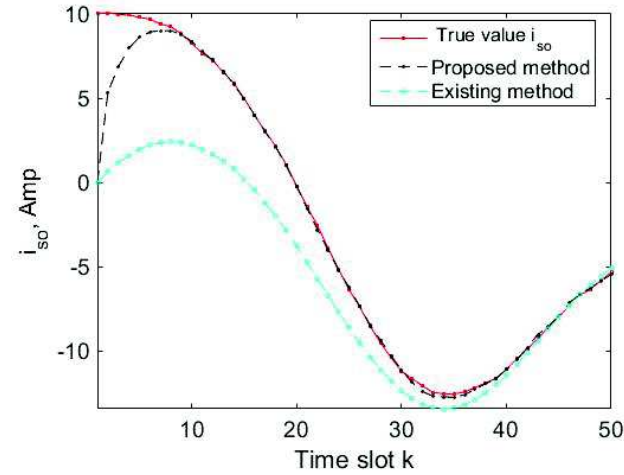


Fig. 5: Current Δi_{so} through inductor L_{so} and its estimation.

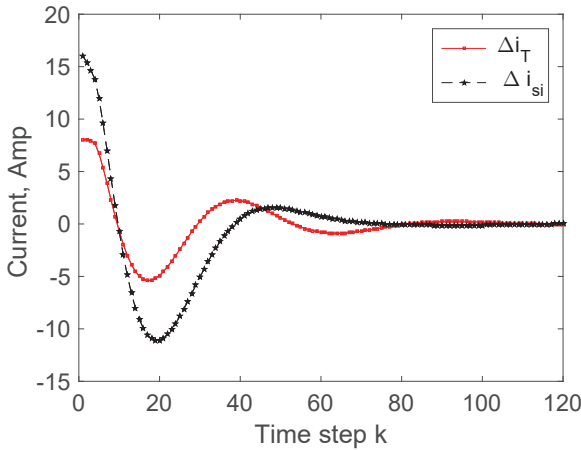


Fig. 6: Regulating the WPT currents Δi_T and Δi_{si} .

fact that the proposed approach can able to find the optimal gain to stabilise the systems states. deployed to self-sustain the IoT network.

V. CONCLUSION

This paper proposes the Bayesian network based state estimation algorithm for monitoring the wireless power transfer system states. Simulation results depict that the proposed method improves the estimation accuracy compared with the existing method. In order to regulate the system states, the feedback controller is proposed. The simulation result illustrates that the developed scheme can properly regulate the system states.

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Appendix: System State Matrix A_c

The WPT system state matrix A_c is given by:

$$\begin{bmatrix} -\frac{R_{pi}}{L_{pi}} & -\frac{1}{L_{pi}} & -\frac{1}{L_{pi}} & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{C_{pi}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{C_T} & 0 & 0 & -\frac{1}{C_T} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{\gamma}{L_T} & -R_T \frac{\gamma}{L_T} & 0 & 0 & -\gamma\beta & -\gamma\beta R_{si} \\ 0 & 0 & 0 & 0 & -\frac{R_{so}}{L_{so}} & -\frac{1}{L_{so}} & \frac{1}{L_{so}} & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{C_{sp}} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{C_s} & 0 & 0 & 1/C_s \\ 0 & 0 & \gamma\beta & -\gamma\beta R_T & 0 & 0 & -\frac{\gamma}{L_{si}} & -\frac{\gamma R_{si}}{L_{si}} \end{bmatrix}$$



Prof. Narendra B. Dahotre Of materials science and engineering, established the Laboratory of Laser Aided Additive and Subtractive Manufacturing (LAASM) at the University of North Texas (Denton, Texas). The state-of-the-art research facility houses multiple high-power infrared laser systems. These lasers are specifically designed and configured for efficient, reliable, cost-effective, precise, and efficient additive and subtractive manufacturing processes for advanced materials, including metals, ceramics, and composites.