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Networked Control of Distributed Energy Resources Using an Adaptive Communication Policy ⋆

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Abstract: This work presents a model-based networked control structure with an adaptive communication policy for managing Distributed Energy Resources (DERs) over a shared, resource-constrained communication network. The central objective is to find a state-dependent strategy for establishing and terminating communication between the supervisor and the DERs in a way that minimizes network resource utilization without jeopardizing the desired stability and performance properties. To this end, a bounded robust Lyapunov-based controller that enforces constrained closed-loop stability in the absence of communication suspension is initially designed for each DER. A dynamic model of each DER is then included within the supervisor to provide estimates of the states of the DER when measurements are not transmitted through the network. To determine when communication between a given DER and the supervisor must be re-established, the evolution of the Lyapunov function is monitored within the DER's stability region such that if it begins to breach a state-dependent stability or performance threshold at any time, the sensor suite is prompted to send its data over the network to update its corresponding model in the supervisor. Communication is then suspended for as long as the Lyapunov function satisfies the specified threshold. The underlying idea is to use the Lyapunov stability constraint for each DER as the basis for adaptively switching on or off the communication with the supervisor. Finally, the results are illustrated through an application to a solid oxide fuel cell example.

Keywords: Distributed energy resources, Model-based control, Communication networks, Adaptive communication logic, solid oxide fuel cells.

1. INTRODUCTION

Distributed Energy Resources (DERs) are a suite of on-site, grid-connected or stand-alone power generation systems that can be integrated into residential, commercial, or institutional buildings and/or industrial facilities. Examples include micro-turbines, fuel cells, and renewable systems such as photovoltaic arrays and wind turbines. Such distributed resources offer advantages over conventional grid electricity by offering end users a diversified fuel supply; higher power reliability, quality, and efficiency; lower emissions and greater flexibility to respond to changing energy needs (Borbely and Kreider (2001)).

With the increase in number and diversity of DERs in recent years, it has become evident that traditional supervisory control and data acquisition systems with centralized control rooms, dedicated phone lines, and specialized operators, are no longer cost effective to coordinate and timely dispatch a large number of DERs spread over the grid, and that advanced communication and control technologies are needed to enable the integration and interoperability functions of a broad range of DERs. While managing DERs over a communication network offers an appealing solution to the control of distributed power generation, it poses a number of challenges due to the inherent limitations on the information transmission and processing capabilities of communication networks, such as bandwidth limitations, network-induced delays, data losses, signal quantization and real-time scheduling constraints, which can interrupt the connection between the central control authority, the generation units and the loads, and consequently degrade the overall power quality supplied if not properly accounted for in the control system design (see, for example, Zhang et al. (2001); Walsh et al. (2002); Hespanha et al. (2007); Munoz de la Pena and Christofides (2008) for some results and references on control over communication networks). The fact that the distributed power market is primarily driven by the need for super-reliable, high-quality power implies that the impact of even a brief communication disruption (e.g., due to local network congestion or server outage) can be substantial, and provides a strong incentive for the development of robust control and communication strategies that ensure the desired levels of power supply and quality with minimal communication requirements between the supervisor and the DERs in order to minimize their susceptibility to communication losses.

Over the past decade, several efforts have been made towards the development and implementation of control strategies for DERs (e.g., Paradkar et al. (2004); Marwali

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and Keyhani (2004); Macken et al. (2004); Dimeas and Hatziargyriou (2005); Lasseter (2007)). While the focus of these studies has been mainly on demonstrating the feasibility of the developed control algorithms, the explicit characterization and management of communication constraints in the formulation and solution of the DER control problem have not been addressed. An effort to address this problem was initiated in Sun et al. (2009) where a model-based networked control approach was developed. The main idea was to reduce the rate at which the data are exchanged between the DER and the supervisor as much as possible (without sacrificing the desired stability and performance properties) to reduce network utilization. A dynamic model that supplies the supervisor with the needed DER state information when communication is suspended over the network was embedded in the supervisor. The state of the model was then updated using the actual state that is provided by the DER sensors at discrete time instances. A key feature of the communication logic used in this case is that it is static in the sense that the communication rate is constant and can be computed off-line prior to DER operation. An alternative approach is to design the networked control system in a way such that the necessary communication rate can be determined and adjusted on-line (i.e., during DER operation) based on the state of the DERs. An advantage of this dynamic (feedback-based) communication policy is that it is more robust to unpredictable disturbances and allows the supervisor to respond quickly in an adaptive fashion to a DER that requires immediate attention. Another advantage of this approach is that it ultimately leads to a more efficient utilization of network resources since the communication rate is increased only when necessary to maintain the desired closed-loop stability or performance level.

Motivated by these considerations, we present in this work a model-based networked control structure with a state-dependent communication policy for managing distributed energy resources over a shared, resource-constrained communication network. The rest of the paper is organized as follows. Following some preliminaries in Section 2, we initially synthesize in Section 3 for each DER a robust nonlinear controller that enforces the desired closed-loop stability and performance properties in the absence of communication outages. To reduce the necessary sensor-controller communication, we include within the supervisor a dynamic model of the DER to provide estimates of its states when communication is suspended and measurements are not transmitted through the network. An adaptive communication policy in which a Lyapunov stability constraint is used as the basis for switching on or off the communication between the sensors and the supervisor is then devised. The results are illustrated in Section 4 through a simulation example.

2. PRELIMINARIES AND PROBLEM FORMULATION

We consider an array of DERs managed by a higher-level supervisor over a communication network. Each DER is modeled by a continuous–time system with uncertain variables and input constraints with the following state–space description:

$$\begin{aligned} \dot{x}_i &= f_i(x_i) + G_i(x_i)u_i + W_i(x_i)\theta_i(t) \\ \|u_i\| &\leq u_i^{\max},\ \|\theta_i\| \leq \theta_i^{\max} \end{aligned} \quad (1)$$

where $x_i \in \mathbb{R}^{p_i}$ denotes the vector of state variables associated with the i–th DER (e.g., exhaust temperatures and rotation speed in turbines and internal combustion engines, operating temperature and pressure in fuel cells), $u_i \in \mathbb{R}^{q_i}$ denotes the vector of manipulated inputs associated with the i–th DER (e.g., inlet fuel and air flow rates in fuel cells, shaft speed in turbines), which is constrained by $\| u_i \| \leq u_i^{\max}$, where $\| \cdot \|$ denotes the standard Euclidean norm of a vector and $u_i^{\max}$ is a positive real number, $\theta_i \in \mathbb{R}^{r_i}$ denotes the vector of uncertain (possibly time-varying), but bounded, variables, and satisfies $\| \theta_i \| \leq \theta_i^{\max}$ where $\theta_i^{\max}$ is a positive real number. The uncertain variables may describe time-varying parametric uncertainty and/or exogenous disturbances. Without loss of generality, it is assumed that the origin is an equilibrium point of the nominal system (i.e., with $u_i \equiv 0$, $\theta_i \equiv 0$), the uncertain variables are non-vanishing (i.e., the nominal and uncertain systems do not share the same equilibrium point) and that the nonlinear functions $f_i(\cdot)$, $G_i(\cdot)$, and $W_i(\cdot)$, are sufficiently smooth.

Each DER has local (on-board) sensors and actuators with some limited built-in intelligence that gives the DER the ability to run autonomously for periods of time when no communication exists with the remote software controller (the supervisor). The local sensors in each DER transmit their data over a shared communication network to the supervisor where the necessary control calculations are carried out and the control commands are sent back to each DER. Based on load changes, changes in utility grid power prices and the state and capacity of each DER, the supervisor regulates and coordinates power generation among the DERs. Our objective is to devise a networked control strategy that robustly stabilizes the individual DERs at or near the desired set-points with minimal utilization of network resources. Specifically, we consider the configuration in which the network interrupts the sensor-controller communication links, while the controller and actuator are assumed to be co-located (i.e., the controller-actuator communication is continuous). Extensions to more general configurations in which the network also interrupts the controller-actuator are conceptually straightforward.

3. ROBUST MODEL-BASED NETWORKED CONTROL STRUCTURE

3.1 Bounded robust feedback controller synthesis

To realize the desired networked control structure, the first step is to synthesize for each DER a feedback controller that satisfies the control constraints and enforces robust closed-loop stability with an arbitrary degree of asymptotic attenuation of the effect of the uncertainty on the closed-loop system in the absence of communication suspension (i.e., when the sensors of each DER transmit their data continuously to the supervisor). As an example, we consider here bounded Lyapunov-based control techniques (Christofides and El-Farra (2005)) to synthesize the controller; in general, however, any other controller design method that achieves these objectives can be used. Using a robust control Lyapunov function $V_i(x_i)$ (Freeman and Kokotovic (1996)) for the i-th DER, the following bounded robust nonlinear controller can be designed:

$$u_i = p_i(x) = k_i(x_i, u_i^{\max}, \theta_i^{\max}, \rho_i, \chi_i, \phi_i)(L_{G_i} V_i)', \quad (2)$$

for $i = 1, 2, \cdots, n$, where:

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$$k_i(\cdot) = -\frac{L_{f_i}^* V_i + \sqrt{(L_{f_i}^{**} V_i)^2 + (u_i^{\max} \| (L_{G_i} V_i)' \|)^4}}{\| (L_{G_i} V_i)' \|^2 \left[1 + \sqrt{1 + (u_i^{\max} \| (L_{G_i} V_i)' \|)^2}\right]} \quad (3)$$

when $\| (L_{G_i} V_i)' \| \neq 0$, and $u_i = 0$ when $\| (L_{G_i} V_i)' \| = 0$, where

$$L_{f_i}^{**} V_i = L_{f_i} V_i + \rho_i \| x_i \| + \chi_i \| (L_{W_i} V_i)' \| \theta_{bi} \quad (4)$$

$$L_{f_i}^* V_i = L_{f_i} V_i + \left(L_{f_i}^{**} V_i - L_{f_i} V_i\right) \left(\frac{\| x_i \|}{\| x_i \| + \phi_i} \right) \quad (5)$$

and $L_{f_i} V_i = (\partial V_i / \partial x_i) f_i(x_i)$, $L_{G_i} V_i = [L_{g_{i,1}} V_i \ \cdots \ L_{g_{i,q_i}} V_i]$, $L_{g_{i,j}} V_i = (\partial V_i / \partial x_i) g_{i,j}(x_i)$, $g_{i,j}(x_i)$ is the j-th column of $G_i(x_i)$, $L_{W_i} V_i = [L_{w_{i,1}} V_i \ \cdots \ L_{w_{i,r_i}} V_i]$, $L_{w_{i,j}} V_i = (\partial V_i / \partial x_i) w_{i,j}(x_i)$, $w_{i,j}(x_i)$ is the j-th column of $W_i(x_i)$, and ρ_i, χ_i, ϕ_i are tunable parameters that satisfy $\rho_i > 0$, $\chi_i > 1$ and $\phi_i > 0$.

Let Π_i be the set defined by:

$$\Pi_i := \{x_i \in \mathbb{R}^{p_i} : L_{f_i}^{**} V_i \leq u_i^{\max} \| (L_{G_i} V_i)' \| \} \quad (6)$$

and consider the subset:

$$\Omega_i(u_i^{\max}, \theta_i^{\max}) := \{x_i \in \Pi_i : V_i(x_i) \leq c_i^{\max}\} \quad (7)$$

for some $c_i^{\max} > 0$. Then, it can be shown using standard Lyapunov arguments that if $x_i(0) \in \Omega_i(u_i^{\max}, \theta_i^{\max})$, there exists a positive real number $\tilde{\phi}_i$ such that if $\phi_i \leq \tilde{\phi}_i$, the time-derivative of V_i along the trajectories of the closed-loop system of (1)-(3) satisfies:

$$\begin{aligned} \dot{V}_i \leq & -\frac{\rho_i \frac{\| x_i \|^2}{\| x_i \| + \phi_i}}{\left[1 + \sqrt{1 + (u_i^{\max} \| (L_{G_i} V_i)' \|)^2}\right]} := -\beta_i(x_i) < 0 \\ & \forall \ \| x_i \| \geq \delta_i := \phi_i (\chi_i - 1)^{-1}, \ \ i = 1, 2, \cdots, n \end{aligned} \quad (8)$$

which implies that the closed-loop state of the i-th DER remains bounded and converges in finite-time to a terminal neighborhood of the origin whose size can be made arbitrarily small by appropriate selection of the controller tuning parameters ϕ_i and χ_i.

3.2 Model-based networked control of DERs

In order to reduce sensor-controller communication over the network, we embed a dynamic model of each DER in the supervisor to provide it with an estimate of the evolution of the states of the DER when measurements are not available. The use of a model at the controller/actuator side to recreate the dynamics of each DER allows the on-board sensors to transmit their data at discrete time instances and not continuously (since the model can provide an approximation of the DER dynamics) thus allowing conservation of network resources. The computational load associated with this step (e.g., model forecasting and control calculations) is justified by the capabilities of modern computing systems used by the central control authority. Feedback from the DER is then performed by updating the state of the model using the actual state that is provided by its sensors at discrete time instances.

Under this architecture, the networked control law for each DER is implemented as follows:

$$\begin{aligned} u_i(t) &= k_i(\widehat{x}_i, u_i^{\max}, \theta_i^{\max}, \rho_i, \chi_i, \phi_i)(L_{G_i} V_i(\widehat{x}_i))' \\ \dot{\widehat{x}}_i(t) &= \widehat{f}_i(\widehat{x}_i(t)) + \widehat{G}_i(\widehat{x}_i(t)) u_i(t), \ t \in (t_k^i, t_{k+1}^i) \\ \widehat{x}_i(t_k^i) &= x_i(t_k^i), \ k = 0, 1, 2, \cdots \end{aligned} \quad (9)$$

where $\widehat{x}_i$ is an estimate of x_i, $\widehat{f}_i(\cdot)$ and $\widehat{G}_i(\cdot)$ are nonlinear functions that model the dynamics of the i-th DER. Note that the models used by the supervisor to recreate the behavior of the DERs do not necessarily match those used for controller synthesis. Furthermore, a choice of $\widehat{f}_i = O$, $\widehat{G}_i = O$ corresponds to the special case where in between consecutive transmission times, the corresponding model acts as a zero-order hold by keeping the last available measurement from the sensor suites until the next one is available from the network. The notation t_k^i is used to indicate the k-th transmission time for the sensor suite of the i-th DER in the collection. The model state is used by the controller as long as no measurements are transmitted over the network, but is updated (or re-set) using the true measurement whenever it becomes available from the network.

3.3 A state-dependent communication policy

A key parameter in the analysis of the control and update laws in (9) is the update period for each DER, $h^i := t_{k+1}^i - t_k^i$, which determines the frequency at which the sensor suite of the i-th DER collects and sends measurements to the supervisor through the network to update the corresponding model state. The update period (the reciprocal of which is the communication rate) is an important measure of the extent of network resource utilization since a larger h_k^i indicates a larger reduction in sensor-controller communication. In Sun et al. (2009), we developed a static communication policy in which the update period was considered constant and the same for all the units (i.e., $t_{k+1}^i - t_k^i := h, \ i = 1, 2, \cdots, n$) and thus could be calculated off-line.

Our aim in this section is to devise a dynamic communication policy that allows the local sensor suite to determine and adjust the necessary communication rate on-line (i.e., during operation) based on the state of each DER. The main idea is to use the Lyapunov stability condition derived in Section 3.1 as a guide for establishing and suspending communication. Specifically, consider the i-th DER of (1) subject to the model-based networked controller of (9). Evaluating the time-derivative of the Lyapunov function, V_i, along the trajectories of the networked closed-loop system for $t \in (t_k^i, t_{k+1}^i)$ yields:

$$\begin{aligned} \dot{V}_i &= L_{f_i} V_i(x_i) + L_{G_i} V_i(x_i) p_i(\widehat{x}_i) + L_{W_i} V_i(x_i) \theta_i \\ &\leq -\beta_i(x_i) + L_{G_i} V_i(x_i) \left[p_i(\widehat{x}_i) - p_i(x_i)\right] \\ &\forall \ \| x_i \| \geq \delta_i, \ \ i = 1, 2, \cdots, n \end{aligned} \quad (10)$$

where we have used the bound in (8) to derive the above inequality. Examining this inequality and comparing it with the inequality of (8) obtained in the case of the non-networked DER (i.e., under continuous communication) reveals explicitly the perturbation effect of suspending communication between the DERs and the supervisor on stability. Specifically, the discrepancy between $p_i(\widehat{x}_i)$ and $p_i(x_i)$, which arises due to the reliance of the supervisor on the states of the uncertain model of the i-th DER during periods of communication suspension, alters the rate at

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which the Lyapunov function decays. As the model estimation error grows, the error in the implemented control action grows as well and may become large enough so as to dominate the stability margin (the negative term) thus causing growth of the Lyapunov function and rendering the closed-loop system potentially unstable. When this happens, communication with the local sensor suite of the i-th DER must be re-established to allow updating the states of the model embedded in the supervisor in a way such that the plant-model mismatch can be corrected in time to avert instability. This communication policy is formalized in the following theorem. The proof follows directly from (10).

Theorem 1. Consider the nonlinear DERs of (1), for which the Lyapunov functions V_i, $i = 1, \cdots, n$, satisfy (8) when state measurements are exchanged continuously between the DERs and the supervisor. Consider also the i-th DER subject to the model-based networked controller of (9). If at any time t_k^i such that $x_i(t_k^{i-}) \in \Omega_i(u_i^{\max}, \theta_i^{\max})$ and $\| x_i(t_k^{i-}) \| > \delta_i := \phi_i(\chi_i - 1)^{-1}$ the following condition holds:

$$\dot{V}_i(x_i(t_k^{i-})) \geq 0 \tag{11}$$

where $x_i(t_k^{i-}) = \lim_{t \to t_k^{i-}} x_i(t)$, then the update law given by $\widehat{x}_i(t_k^i) = x_i(t_k^i)$ ensures that $\dot{V}_i(x_i(t_k^i)) < 0$.

Remark 1: The implementation of the dynamic communication policy described in Theorem 1 requires that each DER monitor the evolution of the corresponding Lyapunov function within the constrained stability region to determine when the model's states must be updated and communication re-established. Specifically, if V_i begins to increase at any time while the state is inside the stability region and outside the terminal region, the sensor suite of the i-th DER is prompted to send its data over the network to update the corresponding model embedded in the supervisor. Communication from the sensor suite of the i-th DER to the supervisor is then suspended for as long as the Lyapunov function V_i continues to decay. In this way, only DERs that require attention (i.e., those on the verge of instability) transmit measurement updates over the network, while the other units sharing the network do not. This targeted update strategy helps reduce overall network utilization further.

Remark 2: The update law given in Theorem 1 applies when the monitored local state x_i is inside the stability region Ω_i but has not yet entered the terminal set. By ensuring that the time-derivative of V_i along the trajectories of the i-th networked closed-loop DER remains negative-definite for all times that x_i is outside the terminal set, this law acts to enforce stability and ultimate boundedness and guarantees that the state of this DER also converges in finite-time to the terminal set. Once the closed-loop state enters the terminal set, however, a different criterion for terminating and establishing communication need to be employed since the time-derivative of V_i (even for the non-networked system) is no longer expected to remain negative inside the terminal set. Specifically, the transmission of measurements from the i-th DER to the supervisor can be suspended for as long as x_i remains confined within the terminal set. As soon as x_i starts to escape this set, however, the local sensor suite of the i-th DER is prompted to send its measurements to update the corresponding model within the central controller and keep x_i confined within the terminal set.

Remark 3: In addition to stability considerations, performance specifications can also be incorporated into the proposed communication logic by appropriate modification of the update law. For example, if $x(t_k^{i-}) \in \Omega_i$, an update law of the form:

$$\begin{aligned} \widehat{x}_i(t_k^i) &= x_i(t_k^i), \text{ where} \\ \dot{V}_i(x_i(t_k^{i-})) &\geq -(1-\alpha)\beta_i(x_i), \ \| x_i(t_k^{i-}) \| > \delta_i \end{aligned} \tag{12}$$

where $\alpha \in (0, 1)$, ensures not only that V_i decays monotonically along the trajectories of the i-th networked closed-loop system, but also that it does so at a certain minimum rate (which is a fraction of the rate prescribed for the non-networked DER per (8)). By examining (10), it can be seen that an update law of the form of (12) with $\alpha \neq 1$ imposes a stronger restriction on the growth of the model estimation error than the stability-based logic of Theorem 1 in that it limits the extent to which model estimation errors (resulting from communication suspensions) can slow down the non-networked closed-loop response. This in turn implies that accommodating the additional performance requirements may come at the expense of an increase in the rate at which the sensor suite of the i-th DER needs to send measurement updates to the supervisor.

4. SIMULATION STUDY: APPLICATION TO A SOLID OXIDE FUEL CELL

Fuel cells are important distributed resources due to their high efficiency, low levels of noise and environmental pollution, and flexible modular designs that match versatile demands of customers. As an illustrative example, we consider in this work a stack of solid oxide fuel cells (SOFC) as a DER in a power distribution system (see Sun et al. (2009) for the process model and parameters). Following the methodology presented in Section 3, the plant is initially cast in the following form:

$$\dot{x} = f(x) + g(x)u + w(x)\theta(t)$$

where x and u are the (dimensionless) state and manipulated input vectors, respectively, defined by $x = [\frac{x_{H_2} - x_{H_2}^s}{x_{H_2}^s} \ \frac{x_{O_2} - x_{O_2}^s}{x_{O_2}^s} \ \frac{x_{H_2O} - x_{H_2O}^s}{x_{H_2O}^s} \ \frac{T_s - T_s^s}{T_s^s}]'$, $u = [\frac{q_{H_2}^{in} - q_{H_2}^{in,s}}{q_{H_2}^{in,s}} \ \frac{q_{O_2}^{in} - q_{O_2}^{in,s}}{q_{O_2}^{in,s}}]'$ where, $i : H_2, \ O_2, \ H_2O$, x_i and q_i^{in} are, respectively, the mole fraction and inlet molar flow rate of component i, the superscript s denotes the steady state values of the corresponding states and inputs, and $\theta(t)$ represents the vector of uncertain variables.

Using a quadratic Lyapunov function of the form $V = x'Px$, a controller of the form of (2)-(5) is initially designed for the SOFC plant to enforce robust stability and uncertainty attenuation in the presence of control constraints when state measurements are communicated continuously between the sensors and the supervisor. To illustrate the controller's robust stabilization capabilities in this case, we consider uncertainties in the form of a time-varying (sinusoidal) disturbance in the load current, as well as parametric uncertainties in the valve molar constants, and the specific heat of reaction, such that $\theta^{\max} = 0.35$, and choose the control constraints such that $u^{\max} = 1$. The controller tuning parameters are chosen as $\chi_i = 1.1$,

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$\rho_i = 0.0001$, $\phi_i = 0.1$, to ensure that the closed-loop state converges in finite time to a small neighborhood of the desired steady-state. The solid lines in Fig. 1 depict the SOFC temperature, power and manipulated input profiles when the controller is implemented under continuous sensor-controller communication. It can be seen from this figure that the controller satisfies the control constraints and successfully stabilizes the closed-loop state of the SOFC plant near the desired steady state. It can also be seen that, compared with the open-loop profiles shown by the dotted lines in Fig. 1, the controller enhances the speed at which the temperature and power reach their set-points.

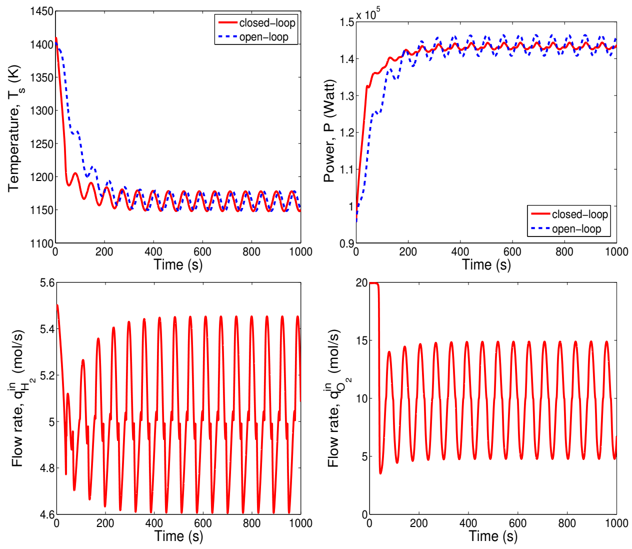

Fig. 1. Closed-loop temperature, power and manipulated input profiles under continuous communication between the controller and the sensors.

For the case when direct measurements from the sensors to the controller can be received only through the shared network, and in order to reduce the utilization of network resources, instead of the actual state, an estimate is provided to the supervisor by an embedded model (which for simplicity is chosen as the same model used for controller synthesis). Using the state estimates, the control law is implemented as in (9) where the estimates are used by the supervisor so long as no measurements from the local sensors are transmitted over the network, but are updated using the true measurements whenever they become available from the network. Panels (a), (c) and (e) in Fig. 2 depict the resulting evolution of the closed-loop power output profiles when the SOFC plant is operated using the dynamic communication policy presented in Section 3 under different model uncertainties. In this case, the evolution of the Lyapunov function is monitored within the stability region, and a measurement update is requested (and transmitted over the network) from the sensors only when either (1) the Lyapunov function is on the verge of increasing while the state is outside the terminal set, or (2) the state is on the verge of escaping the terminal set while inside. Fig. 2(a) corresponds to the case when the model embedded in the supervisor is an exact representation of the SOFC plant (i.e., no plant-model mismatch), while Fig. 2(c) corresponds to the case where the model contains parametric uncertainties of 10% in the valve molar constants and 5% in the heat of reaction. Fig. 2(e) reflects the case for which parametric uncertainties of 30% in the valve molar constants and 20% in the heat of reaction are present. It can be seen from the figures that the closed-loop power output can be successfully stabilized near the desired set-point with a closed-loop response similar to the one obtained under continuous communication.

Panels (b), (d) and (f) in Fig. 2 show the time instances at which the model embedded in the supervisor is updated when different model uncertainties are considered. The variable Update takes a value of 1 when the supervisor requires (and receives) a measurement from the sensors to reset the state of the model, and takes a value of zero when no updates are needed. It can be seen from Fig. 2(b) that no communication between the supervisor and the sensors is needed for the case when there is no plant-model mismatch, since the model can accurately reproduce the evolution of the fuel cell plant. Fig. 2(d) shows that communication is needed only initially and over a short period of time when an uncertain model of the SOFC plant is used, and as the closed-loop power settles close to the desired operating point (see Fig. 2(c)), no further communication between the supervisor and the sensor suite is required, which implies that network resources can be further saved during this time (relative to the case of a static communication logic). However, when the plant-model mismatch is increased further, the supervisor has to communicate more frequently (and even continuously) with the sensors in order to maintain the desired closed-loop stability and performance properties. This case is depicted in Fig. 2(f).

In addition to closed-loop performance and network utilization considerations, we have also investigated the disturbance-handling capabilities of the dynamic communication policy in order to assess its robustness with respect to disturbances during SOFC operation. To this end, a 30% step disturbance was introduced in the load current at time $t = 500$ s (i.e., after the SOFC plant has reached the desired set-point), and this disturbance lasts for 200 s. The solid lines in Panels (a), (c) and (d) in Fig. 3 depict the resulting closed-loop power output and manipulated input profiles subject to the external disturbance. For comparison, we also implemented a static communication policy based on the results presented in Sun et al. (2009). In this case, the supervisor communicates with the sensors over the network periodically, and the sensors transmit their measurements at a constant rate to update the model embedded in the supervisor (in this example we used a constant update period $h = 10$ s). It can be seen that while the control system under the dynamic communication policy can successfully suppress the effect of the disturbance and force the plant to return to its steady-state (see the solid profile), the closed-loop performance deteriorates under the static communication policy where the states move away from the desired steady-state significantly in the presence of the disturbance and also there exists a significant steady-state offset after the disturbance disappears (see the dashed profile). Fig. 3(b) shows the update times of the model embedded in the supervisor when the dynamic communication policy is implemented. This plot highlights the adaptive nature of the dynamic communication policy which is the reason for its ability to overcome the influence of the disturbance on

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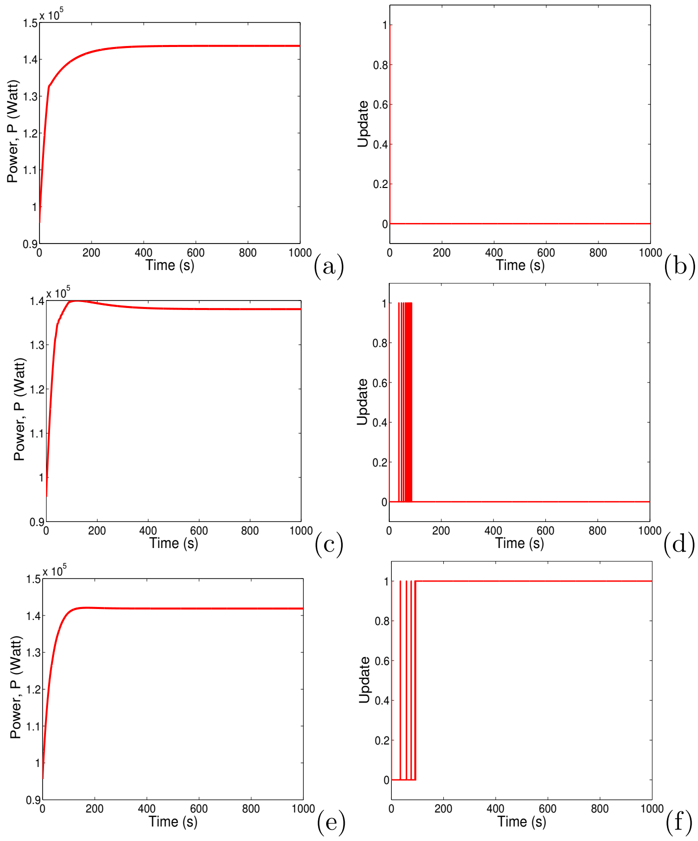

Fig. 2. Plots (a), (c), (e): Closed-loop power output profiles under dynamic communication between the supervisor and the local sensor suite when different models are used to provide the state estimate. Plots (b), (d), (f): Update times of the model embedded in the supervisor when a perfect model is used (b), a moderately accurate model is used (d), and a highly inaccurate model is used (f).

the closed-loop plant. Specifically, it can be seen that the dynamic policy responds to the external disturbance by increasing the frequency of communication between the supervisor and the local sensor suite following the onset of the disturbance. This in turn allows the plant states to remain close to the desired steady-state during (and after) the disturbance following which no further communication is needed to maintain the desired stability and performance level. By contrast, the static communication policy with a fixed update period cannot handle the effect of the disturbance as effectively.

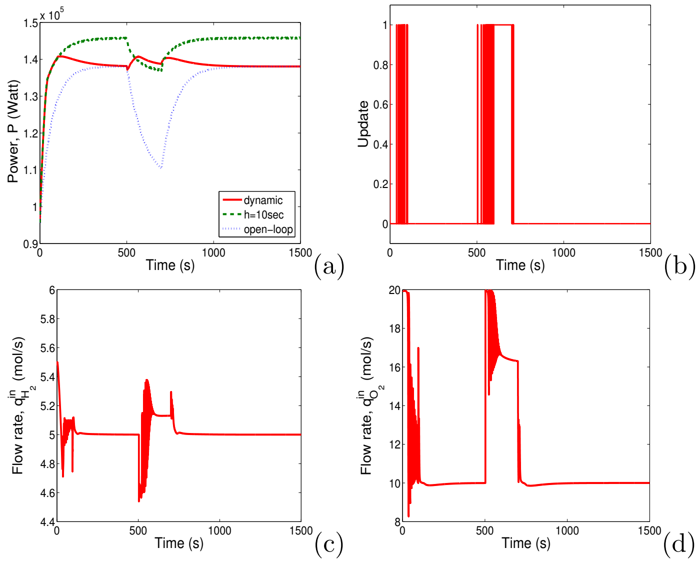

Fig. 3. Plot (a): Closed-loop power out profile under dynamic and static communication policies between the supervisor and the sensors when the closed-loop system is subject to external disturbances in the load current. Plot (b): Update times of the model embedded in the supervisor when the dynamic communication policy is used. Plots (c)-(d): Closed-loop manipulated input profiles under the dynamic communication policy.

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