

# Supervisory Predictive Control of an Integrated Wind/Solar Energy Generation and Water Desalination System

Wei Qi\* Jinfeng Liu\* Panagiotis D. Christofides<sup>\*,\*\*,1</sup>

\* *Department of Chemical and Biomolecular Engineering, University of California, Los Angeles, CA, 90095-1592, USA.*

\*\* *Department of Electrical Engineering, University of California, Los Angeles, CA, 90095-1592, USA.*

---

**Abstract:** This work focuses on the design of a supervisory predictive control system for the optimal management and operation of a stand-alone wind-solar energy generation system which provides power to a reverse-osmosis (RO) water desalination system. We design the supervisory control system via model predictive control which coordinates the wind and solar subsystems as well as a battery bank to best satisfy the power demand of the RO system. Simulations are carried out to illustrate the applicability and effectiveness of the proposed supervisory predictive control design.

*Keywords:* Wind energy; Solar energy; Water desalination; Supervisory predictive control.

---

## 1. INTRODUCTION

Alternative energy technologies, like wind/solar-based energy generation systems, are receiving national and worldwide attention owing to the rising rate of consumption of fossil fuels. In particular, drivers for solar/wind renewable energy generation systems are the environmental benefits, reduced investment risk, fuel diversification and energy autonomy, increased energy efficiency as well as potential increase of power quality and reliability and in certain cases, potential grid expansion deferral due to the possibility of generation close to demand.

On the other hand, reverse osmosis (RO) membrane desalination has emerged as one of the leading methods for water desalination due to the low cost and energy efficiency of the process (Zhu et al. (2010)). Lack of fresh water sources has necessitated further development of these desalination plants, especially in areas with dry climates. Even with advances in reverse osmosis membrane technology, maintaining the desired process conditions is essential to successfully operating a RO desalination system. Seasonal, monthly, or even daily changes in feed water quality can drastically alter the conditions in the reverse osmosis membrane modules, leading to variable water production and energy demand, sub-optimal system performance, or even permanent membrane damage.

Renewable energy sources, for example wind and solar energy, are attractive choices for providing energy to RO desalination systems for small communities in remote areas and isolated islands that have access to sea or brackish-water. Many studies have been done on the integration of renewable energy generation systems with RO desalination

systems including wind-powered and solar-powered desalination systems (Charcosset (2007); Heijman et al. (2009)).

However, the combination of renewable energy sources and water desalination systems requires addressing challenges in the operation of the integrated systems. Specifically, unexpected drops in energy production of a solar or wind energy system may require quick start units to cover the shortfall while unexpected increases require the ability to absorb the unscheduled generation. One way to deal with the variable output of wind and solar energy generation systems is through the use of integrated energy generation systems using both wind and photovoltaic energy, which are also tightly integrated with distributed energy storage systems (batteries) and controllable energy loads like; for example, a water desalination system that operates at controllable time intervals to meet specific demand.

With respect to previous results on control of wind and solar systems, most of the efforts have focused on stand-alone wind (Tan and Islam (2004); Chinchilla et al. (2006)) or solar systems (Hamrouni et al. (2008); Yoshida et al. (2007)). With respect to the control of RO water desalination systems, a nonlinear model-based control technique was recently proposed to deal with large set-point changes and variations in feed water salinity (Bartman et al. (2009)). In our previous work (Qi et al. (in press)), we proposed a supervisory predictive control method for stand-alone wind-solar energy generation systems in which the supervisory control system was designed via model predictive control (MPC) to take into account optimal allocation of generation assignment between the two subsystems. However, little attention has been given to the optimal operation and control of integrated wind-solar energy generation and RO water desalination systems.

In the present work, we re-design the supervisory MPC in Qi et al. (in press) to satisfy specific requirements for

---

<sup>1</sup> Corresponding author: Panagiotis D. Christofides. Tel.: +1 310 794 1015; fax: +1 310 206 4107; e-mail: pdc@seas.ucla.edu.

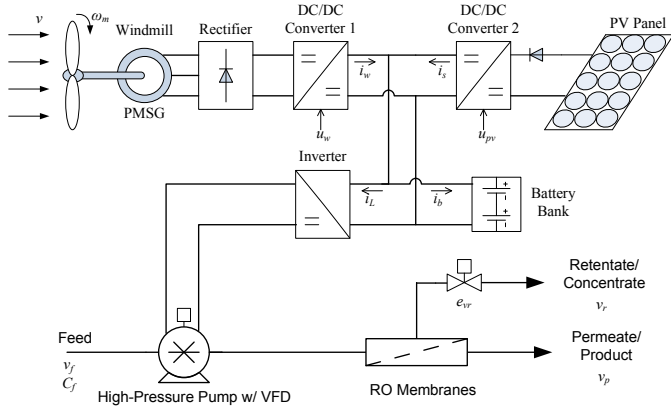


Fig. 1. Integrated energy generation and water desalination system.

the control of a stand-alone hybrid wind-solar energy generation system which provides power to a RO membrane water desalination system. The primary control objective is to coordinate the wind and solar subsystems as well as a battery bank to provide enough energy to the RO system to satisfy the power demand of the scheduled water production. In the supervisory MPC, a specific cost function is designed to take into account the desired control objective. Simulations are carried out to illustrate the applicability and effectiveness of the proposed design.

## 2. INTEGRATED SYSTEM DESCRIPTION

In this section, we introduce the modeling of the integrated energy generation and RO water desalination system. A schematic of the integrated system is shown in Fig. 1.

### 2.1 Energy generation system description

In the energy generation system, there are three subsystems: a wind generation subsystem, a solar generation subsystem and a lead-acid battery bank which is used to overcome periods of scarce generation.

In the wind generation subsystem, there is a windmill, a multipolar permanent-magnet synchronous generator (PMSG), a rectifier, and a DC/DC converter to interface the generator with a DC bus. The converter is used to control indirectly the operating point of the wind turbine (and consequently its power generation) by commanding the voltage on the PMSG terminals. The mathematic description of the wind subsystem written in a rotor reference frame is as follows:

$$\begin{aligned} \dot{i}_q &= -\frac{R_s}{L}i_q - \omega_e i_d + \frac{\omega_e \phi_m}{L} - \frac{\pi v_b i_q u_w}{3\sqrt{3}L\sqrt{i_q^2 + i_d^2}} \\ \dot{i}_d &= -\frac{R_s}{L}i_d - \omega_e i_q - \frac{\pi v_b i_d u_w}{3\sqrt{3}L\sqrt{i_q^2 + i_d^2}} \\ \dot{\omega}_e &= \frac{P}{2J}(T_t - \frac{3P}{2}\phi_m i_q) \end{aligned} \quad (1)$$

where  $i_q$  and  $i_d$  are the quadrature current and the direct current in the rotor reference frame, respectively;  $R_s$  and  $L$  are the per phase resistance and inductance of the stator windings, respectively;  $\omega_e$  is the electrical angular speed;  $\phi_m$  is the flux linked by the stator windings;  $v_b$  is the

voltage on the battery bank terminals;  $u_w$  is the control signal (duty cycle of DC/DC Converter 1 in Fig. 1),  $P$  is the PMSG number of poles,  $J$  is the inertial of the rotating parts and  $T_t$  is the wind turbine torque. The wind turbine torque can be written as:  $T_t = \frac{1}{2}C_t(\lambda)\rho A R v^2$  where  $\rho$  is the air density,  $A$  is the turbine-swept area,  $R$  is the turbine radius,  $v$  is the wind speed, and  $C_t(\lambda)$  is a nonlinear torque coefficient which depends on the tip speed ratio ( $\lambda = R\omega_m/v$  with  $\omega_m = 2\omega_e/P$  being the angular shaft speed).

Based on Eq. 1, we can express the power generated by the wind subsystem and injected into the DC bus as follows:

$$P_w = \frac{\pi v_b}{2\sqrt{3}}\sqrt{i_q^2 + i_d^2}u_w. \quad (2)$$

In the solar subsystem, there is a photo-voltaic (PV) panel array and a half-bridge buck DC/DC converter (DC/DC Converter 2 in Fig. 1). The solar subsystem is connected to the DC bus via the DC/DC converter. In this subsystem, similar to the wind subsystem, the converter is used to control the operating point of the PV panels. The description of the solar subsystem is as follows:

$$\begin{aligned} \dot{v}_{pv} &= \frac{i_{pv}}{C} - \frac{i_s}{C}u_{pv} \\ \dot{i}_s &= -\frac{v_b}{L_c} + \frac{v_{pv}}{L_c}u_{pv} \\ i_{pv} &= n_p I_{ph} - n_p I_{rs} \left( \exp\left(\frac{q(v_{pv} + i_{pv}R_s)}{n_s A_c K T}\right) - 1 \right) \end{aligned} \quad (3)$$

where  $v_{pv}$  is the voltage level on the PV panel array terminals,  $i_s$  is the current injected on the DC bus,  $C$  and  $L_c$  are electrical parameters of the buck DC/DC converter,  $u_{pv}$  is the control signal (duty cycle),  $i_{pv}$  is the current generated by the PV array,  $n_s$  is the number of PV cells connected in series,  $n_p$  is the number of series strings in parallel,  $K$  is the Boltzman constant,  $A_c$  is the cell deviation from the ideal  $p-n$  junction characteristic,  $I_{ph}$  is the photocurrent which has dependence on insolation  $\lambda_l$ , and  $I_{rs}$  is the reverse saturation current. The power injected by the PV solar module into the DC bus is:

$$P_s = i_s v_b. \quad (4)$$

Note that this power indirectly depends on the control signal  $u_{pv}$ .

The lead-acid battery bank may be modeled as a voltage source  $E_b$  connected in series with a resistance  $R_b$  and a capacitance  $C_b$ . Based on this simple model and Eq. 7, the DC bus voltage expression can be written as follows:

$$v_b = E_b + v_c + i_b R_b, \quad (5)$$

where  $i_b$  is the current across the battery bank,  $v_c$  is the voltage in capacitor  $C_b$  and its dynamics is as follows:

$$\dot{v}_c = \frac{1}{C_b}i_b. \quad (6)$$

The DC bus collects the energy generated by both wind and solar subsystems and delivers it to the water desalination system and, if necessary, to the battery bank. The voltage of the DC bus is determined by the battery bank which comprises of lead-acid batteries.

Because all subsystems are linked to the DC bus, their concurrent effects can be easily analyzed by considering their currents in the common DC side. In this way, assuming an ideal voltage inverter and denoting the total

power demand from the water desalination system as  $P_T$ , the current can be referred to the DC side as an output variable current  $i_L = \frac{P_T}{v_b}$ . Therefore, the current across the battery bank can be written as:

$$i_b = \frac{\pi}{2\sqrt{3}} \sqrt{i_q^2 + i_d^2} u_w + i_s - i_L. \quad (7)$$

The calculation of  $P_T$  will be discussed in Section 2.2.

Note that the maximum power that can be drawn from the wind and solar subsystems is determined by the maximum power that can be generated by the two subsystems. When the two subsystems are not sufficient to complement the generation to satisfy the water production power requirements, the battery bank should discharge to provide extra power to satisfy the power requirements. However, when the power limit that can be provided by the battery bank is surpassed, the load must be disconnected to recharge the battery bank and avoid damages.

## 2.2 Water desalination system description

In the RO system, water enters the feed pump, which is equipped with a variable frequency drive (VFD), and is pressurized to the feed pressure  $P_{sys}$ . The pressurized stream enters the membrane module where it is separated into a low-salinity product (or permeate) stream with velocity  $v_p$ , and a high-salinity brine (or retentate) stream with velocity  $v_r$ . The pressure downstream of the actuated valve and at the permeate outlet is assumed to be equal to atmospheric pressure. The model is based on a mass balance taken around the entire system and an energy balance taken around the actuated retentate valve as follows (Bartman et al. (2009)):

$$\frac{dv_r}{dt} = \frac{P_{sys} A_p}{\rho_w V} - \frac{1}{2} \frac{A_p e_{vr} v_r^2}{V} \quad (8)$$

where  $v_r$  is the retentate stream velocity,  $A_p$  is the pipe cross-sectional area,  $V$  is the system volume,  $\rho_w$  is the fluid density, and  $e_{vr}$  is the retentate valve resistance. The system pressure  $P_{sys}$  can be calculated as follows:

$$P_{sys} = \frac{\rho_w A_p}{A_m K_m} (v_f - v_r) + \Delta\pi. \quad (9)$$

where  $A_m$  is the membrane area,  $K_m$  is the membrane overall mass transfer coefficient,  $v_f$  is the feed stream velocity, and  $\Delta\pi$  is the difference in osmotic pressure between the feed side of the membrane and the permeate side. Note that the three velocities  $v_f$ ,  $v_r$  and  $v_p$  satisfy an overall steady-state mass balance as follows:

$$0 = v_f - v_r - v_p. \quad (10)$$

Using the above dynamic equation, various control techniques can be applied using the valve resistance value ( $e_{vr}$ ) as the manipulated input.

We operate the RO system at a fixed recovery rate,  $Y$ ; that is,  $\frac{v_p}{v_f}$  is a constant. We assume that the future total water production demand,  $F_d(t)$ , is known which implies that  $v_p(t) = \frac{F_d(t)}{A_p}$ . Based on Bernoulli equation and ignoring the water elevation change, we can obtain the power needed for the water desalination system as follows:

$$P_T = \eta \left( P_{sys} \frac{F_d}{Y} + \frac{1}{2} \frac{F_r^3}{Y^3 A_p^2} \rho_w \right) \quad (11)$$

where  $\eta$  is the overall power efficiency of the RO desalination system.

The dynamics of the integrated system can be written in the following compact form:

$$\begin{aligned} \dot{x} &= f(x) + g(x)u \\ h(x) &= 0 \end{aligned} \quad (12)$$

where  $x = [i_q \ i_d \ \omega_e \ v_{pv} \ i_s \ v_c \ v_r]^T$ ,  $u = [u_w \ u_{pv} \ e_{vr}]^T$ , and  $f, g, h$  are nonlinear vector functions whose explicit forms are omitted for brevity.

## 3. SUPERVISORY CONTROL SYSTEM DESIGN

In this section, we re-design the supervisory MPC in Qi et al. (in press) for the control of the integrated energy generation and water desalination system. In this proposed new design, the supervisory MPC still optimizes the power references  $P_{w,ref}$  and  $P_{s,ref}$  (operating points) of the wind and solar subsystems, respectively, but also takes into account the dynamics of the RO system. The primary control objective is to coordinate the wind and solar subsystems as well as the battery bank to provide enough energy to the RO system to satisfy the power demand of the scheduled water production. In addition, we try to reduce battery short-term charge-discharge cycles which can be caused by the variability of the renewable energy resources or the load demand. We operate the wind subsystem as the primary generation system and only activate the solar subsystem when the wind subsystem alone can not satisfy the power demand. Specifically, we first design the cost function used in the model predictive control to take into account the control objectives and then formulate the model predictive control based on the cost function.

In order to proceed, we first create an operating reference,  $P_{w,max}$ , for the wind subsystem which will be used in the design of the supervisory control system to estimate the maximum power that can be generated by the wind subsystem.  $P_{w,max}$  depends on a few turbine parameters and on a simple measurement of the angular shaft speed as follows:

$$P_{w,max} = P_{w,max}(x) = K_{opt} \omega_m^3 - \frac{3}{2} (i_q^2 + i_d^2) r_s \quad (13)$$

where  $K_{opt} = \frac{C_t(\lambda_{opt}) \rho A R^3}{2 \lambda_{opt}^2}$  and  $\lambda_{opt}$  is the tip speed ratio at which the coefficient  $C_p(\lambda) = C_t(\lambda) \lambda$  reaches its maximum (Valenciaga et al. (2000)), and  $C_t(\cdot)$  is the torque coefficient of the wind turbine.

We also introduce an operating reference for the solar subsystem,  $P_{pv,max}$ , which is the maximum power operating point (MPOP) of the solar subsystem. In principle, it can be calculated by the following expression:

$$\frac{\partial P_{pv}}{\partial v_{pv}} = \frac{\partial i_{pv}}{\partial v_{pv}} v_{pv} + i_{pv} = 0 \quad (14)$$

In the present work, the maximum solar power provided,  $P_{pv,max}$ , is computed numerically through direct evaluation of the following expression (Valenciaga et al. (2001)) in the region where Eq.14 is close to zero:

$$P_{pv,\max} = P_{pv,\max}(x) = -\frac{\partial i_{pv}}{\partial v_{pv}} v_{pv}^2 \cong -\frac{\Delta i_{pv}}{\Delta v_{pv}} v_{pv}^2. \quad (15)$$

Note that there are two local controllers for the wind and solar generation subsystems designed via sliding mode control as discussed in Valenciaga et al. (2004, 2001), and Qi et al. (in press), respectively. They can drive the wind and solar subsystems to track the power references  $P_{w,ref}$  and  $P_{s,ref}$ , respectively. Note also that there is a local control system for the RO system which is able to stabilize the system at different operating points (Bartman et al. (2009)). Detailed description of these controllers is omitted due to space limitations.

### 3.1 Supervisory controller design

We design the supervisory control system via MPC because it can take into account optimality considerations and handle state and input constraints. MPC is a popular control strategy based on using a model of the system to predict at each sampling time the future evolution of the system from the current state along a given prediction horizon. Using these predictions, the input/set-point trajectory that minimizes a given cost function over a finite-time horizon is computed solving a suitable optimization problem subject to constraints.

The operation strategy of the hybrid energy generation system is as follows: 1) when the wind subsystem can generate enough energy to satisfy the total power demand, only the wind subsystem is activated and operated to track the power demand; 2) when the wind subsystem alone can not generate enough energy to satisfy the total power demand, the solar subsystem is also activated to provide extra energy to satisfy the power demand; 3) when the two subsystems are not sufficient to complement the generation to satisfy the total power demand, the battery bank discharges to provide extra power to satisfy the load requirements. However, when the power limit that can be provided by the battery is surpassed, the load must be disconnected to recharge the battery and avoid damages.

We consider the case where the future water demand is known, that is  $F_d(t)$  is known. The main implementation element of supervisory predictive control is that the supervisory controller is evaluated at discrete time instants  $t_k = t_0 + k\Delta$ ,  $k = 0, 1, \dots$ , with  $t_0$  being the initial time and  $\Delta$  being the sampling time, and the optimal future power references,  $P_{w,ref}$  and  $P_{s,ref}$ , for a time period (prediction horizon) are obtained and only the first part of the references are sent to the local control systems and implemented on the two units. In order to design this controller, first, a proper number of prediction steps,  $N$ , and a sampling time,  $\Delta$ , are chosen. Before going to the formulation of the supervisory MPC, we design the cost function used in the MPC to take into account the control objectives. Specifically, the proposed design of the cost function is as follows:

$$J(t_k) = \sum_{t_k}^{t_k+N} \alpha (P_T - P_{w,ref}(t_{k+j}) - P_{s,ref}(t_{k+j}))^2 + \sum_{t_k}^{t_k+N} \beta P_{s,ref}^2(t_{k+j}) + \sum_{t_k}^{t_k+N} \zeta (P_b(t_{k+j}) - P_b(t_{k+j-1}))^2 \quad (16)$$

where  $\alpha$ ,  $\beta$  and  $\zeta$  are positive weighting factors on different terms and  $j = 0, \dots, N$ . The first term in the cost function

penalizes the difference between the power generated by the wind-solar system and the total power demand, which drives the wind and solar subsystems to satisfy the total demand to the maximum extent. Because there are infinite combinations of  $P_{w,ref}$  and  $P_{s,ref}$  that can minimize the first term, in order to allow only one solution to the optimization problem and to operate the wind subsystem as the primary generation system, we also put a small penalty on the reference power of the solar subsystem,  $P_{s,ref}$ . This term guarantees that the solar generation subsystem is only activated when the wind subsystem alone can not satisfy the power demand. The third term in the cost function penalizes the change of the power provided by the battery bank to the load to reduce battery short-term charge-discharge cycles. Note that, if one wants to operate the solar system as the primary generation subsystem, the second term in the cost function can be modified to penalize the power reference of the wind subsystem. Note also that, other considerations (for example, charge of the battery bank) can be also taken into account in the design of the cost function by adding additional terms or modifying existing terms.

The proposed MPC design for the supervisory control system is as follows:

$$\min_{P_{w,ref}, P_{s,ref} \in S(\Delta)} J(t_k) \quad (17a)$$

$$\text{s.t. } P_{w,ref}(\tau) \leq \min_{\tau} \{P_{w,\max}(\tau)\}, \tau \in [t_{k+j}, t_{k+j+1}] \quad (17b)$$

$$P_{s,ref}(\tau) \leq \min_{\tau} \{P_{pv,\max}(\tau)\}, \tau \in [t_{k+j}, t_{k+j+1}] \quad (17c)$$

$$P_{w,ref}(t_{k+j+1}) - P_{w,ref}(t_{k+j}) \leq dP_{w,\max} \quad (17d)$$

$$P_{s,ref}(t_{k+j+1}) - P_{s,ref}(t_{k+j}) \leq dP_{s,\max} \quad (17e)$$

$$\dot{\tilde{x}}(\tau) = f(\tilde{x}(\tau)) + g(\tilde{x}(\tau))u(\tau) \quad (17f)$$

$$h(\tilde{x}) = 0 \quad (17g)$$

$$\tilde{x}(0) = x(t_k) \quad (17h)$$

$$P_{w,\max}(\tau) = P_{w,\max}(\tilde{x}(\tau)) \quad (17i)$$

$$P_{pv,\max}(\tau) = P_{pv,\max}(\tilde{x}(\tau)) \quad (17j)$$

where  $J(t_k)$  is the cost function to be minimized at time  $t_k$ ,  $dP_{w,\max}$  and  $dP_{s,\max}$  are the maximum allowable increasing value of  $P_{w,ref}$  and  $P_{s,ref}$  in two consecutive power references,  $j = 0, \dots, N-1$ ,  $\tilde{x}$  is the predicted future state trajectory of the integrated system and  $x(t_k)$  is the state measurement obtained at time  $t_k$ . We denote the optimal solution to the optimization problem of Eq. 17 as  $P_{w,ref}^*(\tau|t_k)$  and  $P_{s,ref}^*(\tau|t_k)$ .

The power references of the wind and solar subsystems generated by the supervisory controller of Eq. 17 are defined as follows:

$$\begin{aligned} P_{w,ref}(t) &= P_{w,ref}^*(t|t_k), \forall t \in [t_k, t_{k+1}) \\ P_{s,ref}(t) &= P_{s,ref}^*(t|t_k), \forall t \in [t_k, t_{k+1}) \end{aligned} \quad (18)$$

In the optimization problem of Eq. 17, Eq. 17a defines the optimization cost that needs to be minimized. Because the MPC optimizes the two power references in a discrete time fashion and the references are constants within each sampling interval, the constraints of Eqs. 17b-17c require that the computed power references should be smaller than the minimum of the maximum available within each sampling interval, which means the power references should be achievable for the wind and solar subsystems. Constraints of Eqs. 17d-17e impose constraints on the increasing rate of the two power references. In order to estimate the

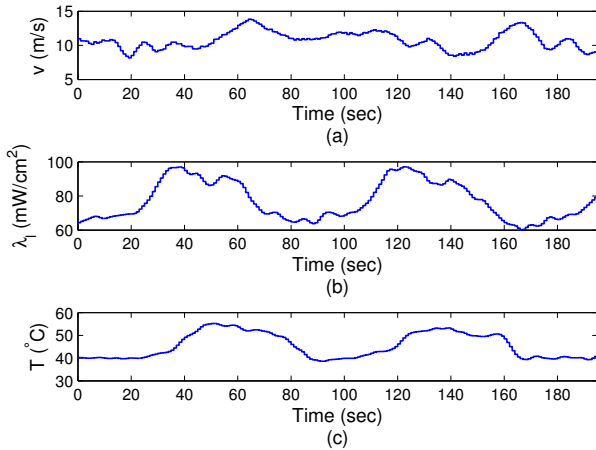


Fig. 2. Environmental conditions. (a) Wind speed  $v$ ; (b) insolation  $\lambda_i$ ; and (c) PV panel temperature  $T$ . maximum available power of the two subsystems along the prediction horizon as well as the power needed by the RO system, the model of the system (Eq. 17f), the current state (Eq. 17g) and the equations expressing the relation between the maximum available power and the state of each subsystem (Eq. 17i and Eq. 17j) are used. Note that in the MPC optimization problem, in order to estimate the future maximum available power of each subsystem, we assume that the environmental conditions such as wind speed, insolation and temperature remain constant. When the sampling time is small enough and the prediction horizon is short enough, along with high-frequency wind variations caused by gusts and turbulence being reasonably neglected, this assumption makes physical sense. The constraints of Eqs. 17b-17j are inspired by results on the design of Lyapunov-based model predictive control systems (please see Christofides and El-Farra (2005); Mhaskar et al. (2006)).

#### 4. SIMULATION RESULTS

In this section, we carry out simulations to demonstrate the effectiveness and applicability of the proposed supervisory MPC. The sampling time and the prediction horizon of the MPC are chosen to be  $\Delta = 1$  s and  $N = 2$ . Note that the choice of the prediction horizon is based on the fast dynamics of the wind-solar energy generation system and the RO system, the uncertainty associated with long-term wind speed and is also made to achieve a balance between the evaluation time of the optimization problem of the supervisory MPC and the desired closed-loop performance. The maximum increasing values of the two power references are chosen to be  $dP_{w,\max} = 1000$  W and  $dP_{s,\max} = 500$  W, respectively. The RO water desalination system is operated at a recovery rate  $Y = 0.8$  and the overall power efficiency is assumed to be  $\eta = 0.7$ . The weighting factors in the cost function are chosen to be  $\alpha = 1$ ,  $\beta = 0.01$  and  $\zeta = 0.4$ .

We first carry out simulations under varying environmental conditions without disturbances. The time evolution of wind speed, PV panel temperature and insolation are shown in Fig. 2(a)-(c).

We consider time-varying water demand  $F_d(t)$  with step changes as shown in Fig. 3(a) (dashed line). This water

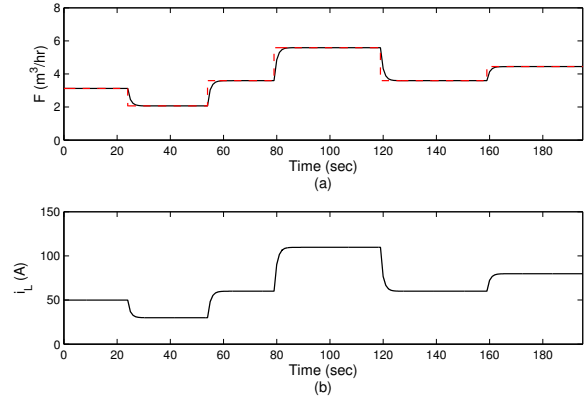


Fig. 3. (a) Time-varying water demand (dashed line) and actual water production (solid line) and (b) corresponding load current  $i_L$ .

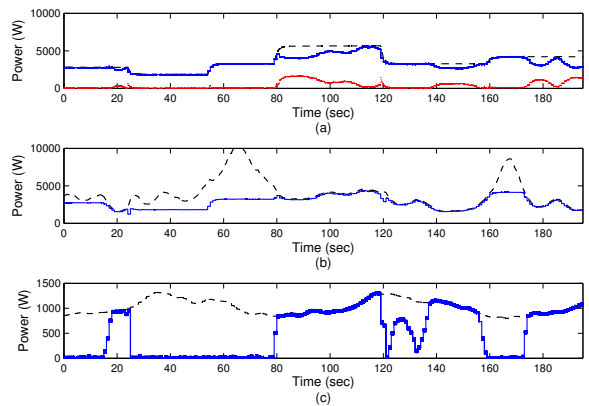


Fig. 4. (a) Generated power  $P_w + P_s$  (solid line), total power demand  $P_T$  (dashed line) and power provided by battery bank  $P_b$  (dotted line); (b) Power generated by wind subsystem  $P_w$  (solid line) and maximum wind generation  $P_{w,\max}$  (dashed line); and (c) Power generated by solar subsystem  $P_s$  (solid line) and maximum solar generation  $P_{s,\max}$  (dashed line).

demand is reflected as a load current  $i_L$  with transient processes on the side of the energy generation system as shown in Fig. 3(b), which are due to the dynamic properties of the RO system.

The simulation results are shown in Fig. 4. It can be seen from Fig. 4(a) that the wind/solar/battery powers coordinate their behavior to meet the power demand of the RO system. Time evolution of output power and maximum available power from the wind subsystem and the solar subsystem are plotted in Fig. 4(b)-(c). When sufficient energy supply can be extracted from the two subsystems such as during  $0 \sim 17$  s,  $25 \sim 78$  s,  $125 \sim 137$  and  $155 \sim 173$  s, the battery is being recharged. In other periods, load demand is relatively high and the weather condition, which determines the maximum available generation capacity of the two subsystems, cannot permit sufficient energy supply. Thus, the supervisory controller drives the wind/solar subsystems to their instant maximum capacity and calls the battery bank for shortage compensation. Note that because of the dynamics of the RO desalination system, when there is a step change in the water demand, the RO desalination system takes a short time to track the water demand (see Fig. 3(a) (solid line)).

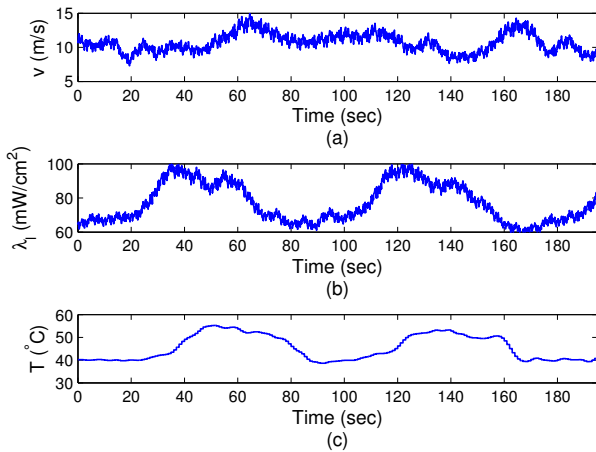


Fig. 5. Environmental conditions. (a) Wind speed  $v$ ; (b) insolation  $\lambda_i$ ; and (c) PV panel temperature  $T$ .

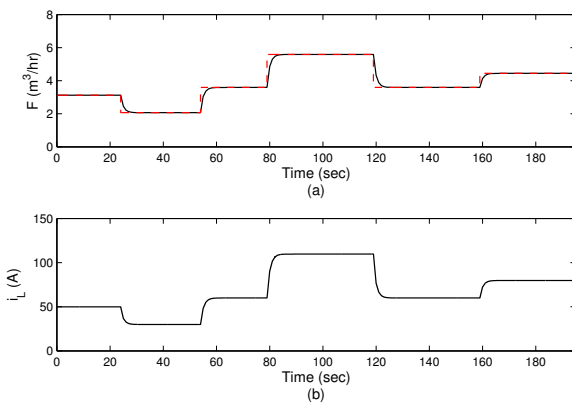


Fig. 6. Time-varying water demand  $F_d$  and corresponding load current  $i_L$ .

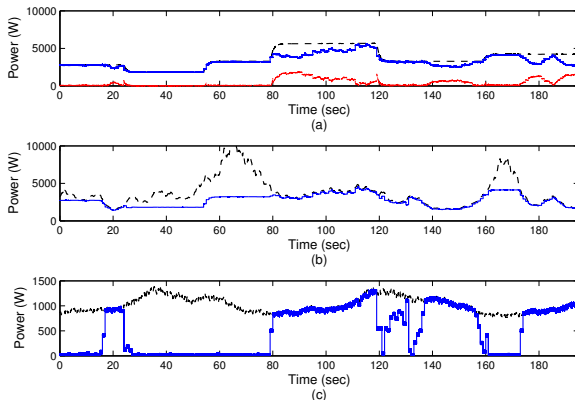


Fig. 7. (a) Generated power  $P_w + P_s$  (solid line), total power demand  $P_T$  (dashed line) and power provided by battery bank  $P_b$  (dotted line); (b) Power generated by wind subsystem  $P_w$  (solid line) and maximum wind generation  $P_{w,max}$  (dashed line); and (c) Power generated by solar subsystem  $P_s$  (solid line) and maximum solar generation  $P_{s,max}$  (dashed line).

We have also carried out simulations to evaluate the robustness of the proposed supervisory control system subject to disturbances in wind speed and insolation; specifically, 10% variation in the wind speed and 5% variation in the insolation. The profiles of the wind speed and insolation are shown in Figs. 5(a)-(b). The simulation

results are shown in Figs. 6-7. From these figures, we can see that the proposed supervisory control system operates in a robust fashion to coordinate the wind and solar subsystems as well as the battery bank to meet the total power demand of the desired water production.

## REFERENCES

- Bartman, A.R., Christofides, P.D., and Cohen, Y. (2009). Nonlinear model-based control of an experimental reverse-osmosis water desalination system. *Ind. Eng. Chem. Res.*, 48, 6126–6136.
- Charcosset, C. (2007). A review of membrane processes and renewable energies for desalination. *Desalination*, 245, 214–231.
- Chinchilla, M., Arnaltes, S., and Burgos, J.C. (2006). Control of permanent-magnet generators applied to variable-speed wind-energy systems connected to the grid. *IEEE Trans. Energy Conv.*, 21(1), 130–135.
- Christofides, P.D. and El-Farra, N.H. (2005). *Control of nonlinear and hybrid process systems: Designs for uncertainty, constraints and time-delays*. Springer-Verlag, Berlin, Germany.
- Hamrouni, N., Jraidi, M., and Cherif, A. (2008). New control strategy for 2-stage grid-connected photovoltaic power system. *Renewable Energy*, 33, 2212–2221.
- Heijman, S.G.J., Rabinovitch, E., Bos, F., Olthof, N., and van Dijk, J.C. (2009). Sustainable seawater desalination: Stand-alone small scale windmill and reverse osmosis system. *Desalination*, 248, 114–117.
- Mhaskar, P., El-Farra, N.H., and Christofides, P.D. (2006). Stabilization of nonlinear systems with state and control constraints using Lyapunov-based predictive control. *Systems and Control Letters*, 55, 650–659.
- Qi, W., Liu, J., Chen, X., and Christofides, P.D. (in press). Supervisor predictive control of stand-alone wind-solar energy generation systems. *IEEE Trans. Contr. Syst. Techn.*
- Tan, K. and Islam, S. (2004). Optimum control strategies in energy conversion of pmsg wind turbine system without mechanical sensors. *IEEE Trans. Energy Convers.*, 19(2), 392–399.
- Valenciaga, F., Puleston, P.F., and Battaiotto, P.E. (2001). Power control of a photovoltaic array in a hybrid electric generation system using sliding mode techniques. *IEE Proc. - Control Theory Appl.*, 148, 448–455.
- Valenciaga, F., Puleston, P.F., and Battaiotto, P.E. (2004). Variable structure system control design method based on a differential geometric approach: application to a wind energy conversion subsystem. *IEE Proc. - Control Theory Appl.*, 151, 6–12.
- Valenciaga, F., Puleston, P.F., Battaiotto, P.E., and Mantz, R.J. (2000). Passivity/sliding mode control of a stand-alone hybrid generation system. *IEE Proc. - Control Theory Appl.*, 147, 680–686.
- Yoshida, T., Ohniwa, K., and Miyashita, O. (2007). Simple control of photovoltaic generator systems with high-speed maximum power point tracking operation. *EPE Journal*, 17, 38–42.
- Zhu, A., Rahardianto, A., Christofides, P.D., and Cohen, Y. (2010). Reverse osmosis desalination with high permeability membranes - cost optimization and research needs. *Desalination and Water Treatment*, 15, 256–266.