Optimal Operation of Climate Control Systems of Produce Storage Facilities in Smart Grids

Mohammad Chehreghani Bozchalui, *Member, IEEE,* Claudio A. Cañizares, *Fellow, IEEE,*
and Kankar Bhattacharya, *Senior Member, IEEE*

***Abstract*—This paper presents mathematical optimization models of produce storage facilities to optimize the operation of their energy systems in the context of Smart Grids. In the storage facilities, climate control of the storage rooms consumes considerable energy; thus, in this paper, a mathematical model of storage facilities appropriate for their optimal operation is developed, so that it can be implemented as a supervisory control in existing climate controllers. The proposed model incorporates weather forecasts, electricity price information, and the end-user preferences to optimally operate existing climate control systems in storage facilities. The objective is to minimize total energy costs and demand charges while considering important parameters of storage facilities, i.e., inside temperature and humidity should be kept within acceptable ranges. The performance of the proposed model for various electricity price and weather conditions and their variations are studied via Monte Carlo Simulations (MCS). The presented simulation results show the effectiveness of the proposed model to reduce total energy costs while maintaining required operational constraints.**

***Index Terms*—Smart grids, energy systems, optimization, climate control systems, mathematical modeling.**

I. NOMENCLATURE

Indices

dh	Dehumidifier
f	Fan
h	Humidifier
ht	Heating system
mx	Mixer
pr	Produce
r	Refrigeration system
t	Index of time intervals
z	Index of zones
i	Index of devices

Sets

A	Set of devices: $A = \{dh, f, h, ht, mx, r\}$
T	Set of scheduling time intervals: $T = \{1 \ldots N_T\}$
Z	Set of zones: $Z = \{1 \ldots N_Z\}$

Functions

J	Objective function of the optimization model

Variables

$\hat{p}$	Peak demand [kW]
$\phi_z(t)$	Relative humidity of zone z at time t [%]
p_a	Actual water vapour pressure at temperature θ [Pa]
$p_{par,z}(t)$	Partial pressure [Pa]
$p_{sat,z}(t)$	Saturated water vapour pressure at temperature θ [Pa]
$p_{tot}(t)$	Total electricity demand at time t
$q_{ev,z}(t)$	Evaporation heat at zone z [kJ/h]
$q_{re,z}(t)$	Respiration heat at zone z [kJ/h]
$q_{f,z}(t)$	Heating effect of circulated air flow through fans at zone z [kJ/h]
$s_{i,z}(t)$	Operation state of device i of zone z at time t
$\theta_z(t)$	Temperature of zone z at time t [$^\circ$C]
$w_z(t)$	Water content of air in zone z at time t [$\mathrm{kg_{H_2O}/kg_{air}}$]
$\widehat{w}_z(t)$	Saturated vapour concentration in zone z at time t [$\mathrm{kg_{H_2O}/kg_{air}}$]

Parameters

A_{sp}	Specific surface area of produce [$\mathrm{m^2_{pr}/m^3_{bulk}}$]
α_z	Thermal leakage of zone z [kJ $\mathrm{h^{-1}}$ $\mathrm{K^{-1}}$]
β_z	Cooling effect of fan operation [kJ $\mathrm{h^{-1}}$ $\mathrm{K^{-1}}$]
C_1	Constant: 100
C_2	Constant: 1.7001 Pa
C_3	Constant: 7.7835 Pa
C_4	Constant: 1/17.0789 $\mathrm{K^{-1}}$
C_5	Constant: 0.6228 $\mathrm{kg_{H_2O}/kg_{air}}$
C_a	Specific heat of air: 1.006 kJ/(kg K)
C_{dc}	Demand charge [$/kW]
C_{ec}	Energy cost [$/kWh]
C_z	Total heat capacity of zone z [kJ/K]
ε	Porosity: 0.34 $\mathrm{m^2_{pr}/m^3_{bulk}}$
η_r	Performance coefficient of the refrigeration system: 1
η_{ht}	Efficiency of the heating system: 1
$\Phi^u_z(t)$	Upper limit of relative humidity in zone z at time t
$\Phi^l_z(t)$	Lower limit of relative humidity in zone z at time t
Γ_z	Cooling rate of the refrigeration system in zone z [kJ/h]
H_{ev}	Evaporation heat of water: 2270 $\mathrm{kJ/kg_{H_2O}}$
H_{re}	Respiration heat rate: 38.7×10^{-3} $\mathrm{kJ/(kg_{pr}\ h)}$
K_{ev}	Evaporation coefficient: 0.14 $\mathrm{kg_{air}/(m^2_{pr}\ h)}$
$M_{pr,z}$	Total weight of produce in zone z [kg]
M_w	Molar mass of water: 18.0153×10^{-3} kg/mol
μ_z	Effect of operation of humidifier on water content of air in zone z [$\mathrm{kg_{H_2O}/\ (kg_{air}\ h)}$]
n_v	Number of moles in the ideal gas law
ν_z	Effect of operation of dehumidifier on water content of air in zone z [$\mathrm{kg_{H_2O}/\ (kg_{air}\ h)}$]
N_T	Total number of intervals in the scheduling horizon T
N_Z	Number of zones
$P_{atm,z}(t)$	Atmospheric air pressure [Pa]
P_i	Rated power of device i [W]

This work was supported by the Ontario Centres of Excellence (OCE), Hydro One Networks Inc., Milton Hydro Distribution Inc., Energent Inc., and the Ontario Power Authority (OPA). An international patent associated with this work has been filed.

The authors are with the Department of Electrical and Computer Engineering, University of Waterloo, Ontario, Canada, N2L 5E3; (e-mail: {mchehreg, ccanizar, kankar}@uwaterloo.ca).

Ψ_z	Heat rate of the heating system in zone z [kJ/h]
$Q_{m,z}(t)$	Miscellaneous heat loads like lights, fans, other devices at zone z [kJ/h]
Q_z^{leak}	Air leakage from zone z: 290 m^3/h
Q_z^{max}	Maximum volumetric air flow rate of fans in zone z: 29000 [m^3/h]
R	Ideal gas constant: 8.314472 J/(mol K)
ρ_a	Density of air: 1.27 kg/m^3
ρ_b	Density of bulk: 670 kg/m^3
Θ_0	Absolute temperature at $0°\mathrm{C}$: 273.15 K
$\Theta_{out}(t)$	Outdoor temperature at time t $[°\mathrm{C}]$
Θ_{out}^{min}	Minimum acceptable outdoor temperature: $-3°\mathrm{C}$
$\Theta_z^{set}(t)$	Temperature set point in zone z at time t $[°\mathrm{C}]$
$\Theta_z^{l}(t)$	Lower limit of temperature in zone z at time t $[°\mathrm{C}]$
$\Theta_z^{u}(t)$	Upper limit of temperature in zone z at time t $[°\mathrm{C}]$
τ	Length of one time interval: $1[h]$
U_z	Area integrated thermal resistance for heat transfer between ambient and inside air: 3836 kJ/(h K)]
V_z	Volume of zone z [m^3]
V_a	Air volume per volume zone z [pu]
V_p	Produce volume per volume zone z [pu]
$W_{out}(t)$	Water content of outside air at time t [$\mathrm{kg}_{\mathrm{H_2O}}/\mathrm{kg}_{\mathrm{air}}$]
W_h^{max}	Maximum water rate of humidifier [$\mathrm{kg}_{\mathrm{H_2O}}$/h]
W_{dh}^{max}	Maximum rate of dehumidifier [$\mathrm{kg}_{\mathrm{H_2O}}$/h]
ξ_z	Effect of fans' operation on water content of air in zone z [h^{-1}]
ζ_z	Effect of air leakage on water content of air in zone z [h^{-1}]

II. INTRODUCTION

THE RAPID growth of energy demand and supply, increasing energy costs, and environmental concerns are motivating the development of new technologies to make better use of existing energy systems and resources and slow demand growth to achieve sustainable energy systems. Deregulation of the power sector, increased competition, new energy pricing schemes, and the advent of "Smart Grid" technologies is making Energy Management Systems (EMSs) feasible and attractive. All of these facts are leading to the proposal of novel approaches to optimize the use of energy in different sectors to reduce the customer's total energy costs, demand and greenhouse gas (GHG) emissions while taking into account the end-user preferences.

Utilities have implemented Demand Side Management (DSM) and Demand Response (DR) programs to better manage their network, offer better services to their customers, handle the increase in electricity demand, and at the same time manage security issues and reduce environmental impacts [1]. DR programs induce customers to reduce loads during periods of critical grid conditions or periods of high energy costs; in return, customers pay less [2]. It is envisioned that Smart Grids will support large penetrations of distributed demand-side resources coupled with system-wide DR driven by economic and reliability signals [3]. Information technology and smart meters improve the effectiveness and capability of EMSs and facilitate the development of automated operational decision-making structures for energy systems. In this context, mathematical modeling of energy systems for EMSs, which is the main concern of the present work, plays a critical role.

Energy systems of commercial and agricultural facilities usually comprise multi-carrier energy systems such as electricity, natural gas, gasoline, and thermal energy. Lighting, heating, cooling, milking, processing foods and feeding animals, and storing produce in a storage facility are some examples of energy consuming activities within commercial and agricultural facilities [4]. Some of these activities are required to be carried out at a specific time regardless of other factors such as energy price. However, energy consumption can be optimized to reduce the total energy costs while taking into account the operational constraints of associated devices and processes. For example, large quantities of harvested products need to be stored for a long time in storage facilities where climate control systems are employed to keep the products at a steady temperature to prevent spoilage; these facilities consume considerable energy and can be scheduled to reduce energy consumption and costs.

Prediction of indoor climate conditions in produce storage facilities has been studied and reported in the literature, for example in [5]–[7]. Detailed physical models of storage facilities on the other hand are presented in [5], [6], [8], [9]. Various methods have been reported in the literature for the purpose of climate control in produce storage facilities. The potentials of Receding Horizon Optimal Control (RHOC) for climate control in storage facilities for agricultural products are demonstrated in [10] and [8]. A method based on Model Predictive Control (MPC) is proposed in [11] for temperature and humidity control of storage rooms. In [12], a fuzzy controller for fruit storage using neural networks and genetic algorithms is developed, and in [13] the application of fuzzy logic in automated control of climate is studied and implemented. Since the implementation of fuzzy logic based controllers implies tuning of many parameters for each case, which normally is a heuristic and burdensome task, it is not practically feasible. The computational burden of optimal controls is mentioned as a barrier in [10] for direct real-time implementation of optimal control methods in climate control applications.

Most of the existing works in the literature focus on controlling the indoor climate without considering the effects of its operation on energy costs. Hence, this paper proposes a supervisory MPC-based operation scheduling approach for produce storage facilities, incorporating a comprehensive modeling of indoor climate systems and operational requirements of existing climate control devices, and considering energy and demand charged to reduce total operating costs, while meeting all the indoor climate control requirements of such facilities. Thus, a mathematical model of storage facilities appropriate for optimal operation purposes is developed based on approximate physical models of produce storage facilities and climate conditions predictions, so that it can be implemented as a supervisory control in existing climate control systems. The proposed supervisory control in conjunction with current existing climate controllers would allow coordinated optimal operation of multiple produce storage facilities in a single site, while considering the user-defined preferences,

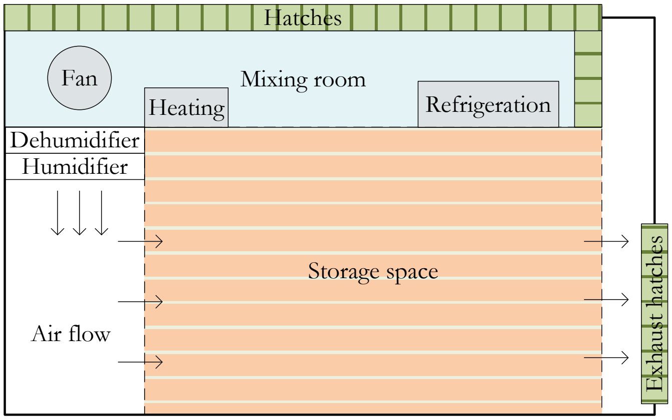


Fig. 1. Layout of a storage facility

thus facilitating the integration of agricultural and commercial customers into Smart Grids.

The remainder of the paper is organized as follows: In Section III required background topics in climate control systems and energy pricing are presented. In Section IV the proposed control strategy is described. The proposed mathematical model for the supervisory controller is presented in Section V, discussing the objective functions and constraints. In Section VI the results of various simulation case studies are presented and discussed. The main conclusions and contributions of the presented work are highlighted in Section VII.

III. BACKGROUND

A. Climate Control Systems of Storage Facilities

The objective in the indoor climate control of storage facilities is to keep the internal parameters (e.g., inside temperature and humidity) within pre-defined ranges, which are affected by parameters such as the stored produce and outdoor weather conditions. Most storage facilities take advantage of natural and forced air flows, in addition to mechanical heating and cooling systems, to control the inside climate. Although the former consumes less energy, in some weather conditions it might be essential to utilize more the expensive heating or cooling systems to maintain the internal parameters within the desired ranges. Figure 1 depicts the layout of a climate control system for storage facilities; mixture of outdoor and inside air is circulated through the fans, the air flow is controlled by the fans' capacity and the position of hatches in the air mixer, and humidifiers and dehumidifiers are used to control the humidity of the storage space.

A proportional-integral-derivative (PID) feedback controller dedicated to control inside temperature and relative humidity using direct measurements is the common existing climate control system in storage facilities [14]. The main features of such feedback controllers are boolean logics to determine the use of ventilation and mechanical heating and cooling systems, and PID controllers to control the hatch positions. In these systems the objective is to decrease/increase the inside temperature to its set point value and avoid dropping below a lower limit or exceeding an upper limit by activating either cooling or heating devices in response to temperature variations. Usually, the feedback controllers use constant temperature set points for different times. These set points depend on the type of crop and are usually in the range of 4-8 °C, but in practice the actual inside temperature varies over a wider range.

B. Electricity Pricing

Fixed-Rate Plan (FRP), Time-of-Use (TOU), and Real-Time Pricing (RTP) are three pricing schemes currently available to electricity customers in various utilities. TOU pricing is the simplest form of dynamic pricing, in which the electricity price per kWh varies for different times of the day. For example, in Ontario-Canada, TOU pricing is currently based on three periods of On-peak, Mid-peak, and Off-peak use of energy and the classification of these periods varies by season and day of the week. In RTP tariff, the price varies continuously and is posted hourly and/or day-ahead for pre-planning; it provides a direct link between the wholesale and retail energy markets and reflects the changing supply/demand balance of the system.

For example, in Ontario-Canada the Hourly Ontario Electricity Price (HOEP) is the RTP that applies to large customers who participate in the wholesale electricity market [15]. In addition to energy consumption costs, large electricity customers pay peak demand charges based on the maximum amount of power withdrawn by the customer during the billing period, usually averaged over 15-minute time periods and measured in kilowatts (kW); for example, demand charges during winter and summer in Ontario-Canada are currently \$7/month-kW and \$8/month-kW, respectively [16].

IV. PROPOSED SUPERVISORY OPERATION STRATEGY

Nowadays, day-ahead forecasts for real-time electricity prices, and accurate weather forecasts for the next few days, updated every few hours, are available. These forecasts can be employed to improve the operation of climate control systems. Hence, a hierarchical operation strategy incorporating electricity price and weather forecasts is proposed here for optimal operation of climate control systems. The architecture of the proposed scheme for the climate control systems of produce storage facilities is presented in Fig. 2. The existing control system is shown in the lower part of the figure, and the proposed supervisory control is depicted above the existing local controllers. The proposed supervisory control uses an MPC approach that incorporates energy prices, demand charges, and weather forecasts to optimally schedule and coordinate the operations of multiple local controllers in existing climate control systems. Notice that the proposed supervisory controller provides optimal settings to multiple existing local controllers (such as PID controllers), which operate unaware of energy prices, demand charges, and the status of other local controllers.

The supervisory control would use the mathematical model of each component in the system, parameter settings, external information, and user preferences to optimize the operation of existing climate control systems in the storage facility. Thus, the outputs of the optimization model would be used as set points of the existing, real-time feedback control systems,

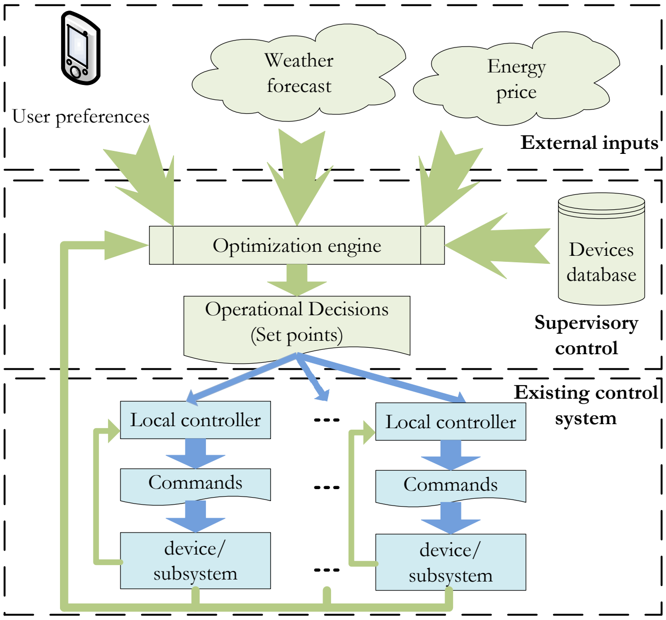


Fig. 2. The supervisory and feedback controllers architecture.

assuming that the existing local controllers remain in the system to perform the actual control actions such as turning on/off devices. The supervisory control would update the outputs every hour, while the local controllers continuously monitor the parameters under control and follow the target set points in real time, and would also monitor the system and re-run the model in case of large discrepancies between the calculated and measured parameters, based on an MPC approach.

The scheduling horizon in the optimization model can vary from a few hours to days, with the selection depending on the types of activities which take place within the storage facility and the accuracy of weather and energy price forecasts. For example, the scheduling horizon could be set to one week, with 1 hour to a few hours time intervals. One-week scheduling horizons with time intervals of one hour have been used in this work to carry out the simulations.

V. MATHEMATICAL MODEL

In a typical storage facility, three categories of components can be identified: heating/refrigeration systems, fans, and hatches. Each of these components has its own specific behaviour, operational constraints, and settings required to operate appropriately. The mathematical models that represent the components of the system considering their operational constraints are described next.

A. Objective Function

Depending on the end-user's choice, different objective functions can be adopted to solve the optimization problem. Thus, minimization of the customer's total energy costs, total energy consumption, peak load, and temperature deviations over the scheduling horizon are considered here as possible objective functions for the optimization model.

1) Minimization of temperature deviations: To follow the temperature settings closely, minimizing the sum of squares of the temperature variations from the given set points is considered as a nonlinear objective function as follows:

$$J_1 = \sum_{t \in T} \left(\theta_z(t) - \Theta_z^{set}(t)\right)^2 \tag{1}$$

All indices, variables, and parameters in this and the following equations are defined in Section I.

2) Minimization of energy costs: The following objective function corresponds to the minimization of the customer's total energy costs over the scheduling horizon:

$$J_2 = \sum_{t \in T} \sum_{i \in A} \sum_{z \in Z} C_{ec}(t)\, P_i\, s_{i,z}(t) \tag{2}$$

3) Minimization of peak demand charges: This objective can be adopted to reduce the demand costs as follows:

$$J_3 = C_{dc} \times \hat{p} \tag{3}$$

where $\hat{p}$ is a non-negative variable used along with the following constraint to represent the peak demand during the scheduling horizon:

$$\hat{p} \geq p_{tot}(t) \qquad \forall t \in T \tag{4}$$

4) Minimization of total energy costs: The objective function for minimization of total energy costs over the scheduling horizon can be represented as follows:

$$J_4 = J_2 + J_3 \tag{5}$$

B. Model Constraints

Heat transfer through walls, solar radiation, and ventilation with outdoor air are some examples of the ways that outdoor weather conditions can affect indoor climate. The products also produce heat due to respiration, with the product temperature determining the reaction rates, which affect the quality and weight loss of the product. Furthermore, inside humidity drives evaporation or condensation [11]. Thus, the developed model should be able to represent the storage facility temperature and humidity, and maintain these within a specified range, while taking into account technical aspects of the heating and cooling systems operation.

1) Inside humidity: Relative humidity of the storage facility, which needs to be kept within specific ranges, is defined as:

$$\phi_z(t) = \frac{p_{par,z}(t)}{p_{sat,z}(t)} 100\% \tag{6}$$

where, the saturated vapor pressure and the partial pressure can be approximated by the following nonlinear and linear equations, respectively [17]:

$$p_{sat,z}(t) = C_1 \left(-C_2 + C_3 e^{C_4 \theta_z(t)}\right) \tag{7}$$

$$p_{par,z}(t) = \frac{w_z(t) P_{atm,z}(t)}{C_5} \tag{8}$$

To model the humidity inside the storage facilities, the water content of air inside the storage facility needs to be modeled; this can be represented by the following nonlinear constraint:

$$\begin{aligned} w_z(t) = w_z(t-1) + \tau\, [&\mu_z s_{f,z}(t) s_{h,z}(t) \\ &+\zeta_z (W_{out}(t) - w_z(t)) \\ &-\nu_z s_{dh,z}(t) + w_{ev,z}(t) \\ &+\xi_z s_{f,z}(t) s_{mx,z}(t)\,(W_{out}(t) - w_z(t))] \quad \forall t \in T \quad (9) \end{aligned}$$

where the parameters μ_z, ζ_z, ν_z, and ξ_z can be calculated based on measurements or estimations from simple performance tests using the following formulas:

$$\zeta_z = Q_z^{leak}/(V_a V_z) \quad (10a)$$

$$\xi_z = Q_z^{max}/(V_a V_z) \quad (10b)$$

$$\mu_z = W_h^{max}/(\rho_a V_a V_z) \quad (10c)$$

$$\nu_z = W_{dh}^{max}/(\rho_a V_a V_z). \quad (10d)$$

This constraint represents the water content in air inside the storage facility at time t as a function of its water content at time $t-1$; water produced because of evaporation; moisture loss through air leakage; and the operation of fans, mixers, humidifiers, and dehumidifiers. The effect of evaporation on the water content of air can be calculated using [5]:

$$w_{ev,z}(t) = \frac{K_{ev} A_{sp}}{\varepsilon \rho_a} (\widehat{w}_z(t) - w_z(t)) \quad (11)$$

where $\widehat{w}_z(t)$ is the saturated vapour concentration that can be calculated from approximate conversion from $[Pa]$ to $[g/kg]$ derived from the nonlinear ideal gas law:

$$\begin{aligned} p_{a,z}(t) &= \frac{n_v}{V_z} R\,(\theta_z(t) + \Theta_0) \\ &= \frac{w_z(t)\rho_a}{M_w} R\,(\theta_z(t) + \Theta_0) \quad (12) \end{aligned}$$

Thus, $\widehat{w}_z(t)$ is obtained from (12) yielding the following nonlinear equation:

$$\begin{aligned} \widehat{w}_z(t) &= \frac{p_{sat}}{\frac{R\rho_a}{M_w}(\theta_z(t) + \Theta_0)} \\ &= \frac{C_1 \left(-C_2 + C_3 e^{C_4 \theta_z(t)}\right)}{\frac{R\rho_a}{M_w}(\theta_z(t) + \Theta_0)} \quad (13) \end{aligned}$$

The following nonlinear constraints ensure that relative humidity of inside air is kept within the range defined by a minimum and a maximum relative humidity:

$$w_z(t) \le \Phi_z^u \frac{C_1 C_5}{P_{atm,z}(t)} \left(-C_2 + C_3 e^{C_4 \theta_z(t)}\right) \quad \forall t \in T \quad (14a)$$

$$w_z(t) \ge \Phi_z^l \frac{C_1 C_5}{P_{atm,z}(t)} \left(-C_2 + C_3 e^{C_4 \theta_z(t)}\right) \quad \forall t \in T \quad (14b)$$

2) Inside temperature: Since the focus of this work is on operation of the climate control system in the context of smart grids, steady-state temperatures of the storage rooms are of interest. Hence, thermal dynamics of the storage facility are modeled using the following constraints:

$$\begin{aligned} \theta_z(t) = \theta_z(t-1) + \frac{\tau}{C_z}\, [&\kappa_z s_{ht,z}(t) + Q_{mx,z}(t) \\ &-\gamma_z s_{r,z}(t) + \alpha_z\,(\Theta_{out}(t) - \theta_z(t)) \\ &+q_{f,z}(t) + Q_{re,z}(t) - q_{ev,z}(t)] \quad \forall t \in T \quad (15) \end{aligned}$$

where the parameters α_z, β_z, γ_z, and κ_z can be calculated based on measurements or estimations from simple performance tests using the following formulas:

$$\alpha_z = U_z + \rho_a C_a Q_z^{leak} \quad (16a)$$

$$\beta_z = \rho_a C_a Q_z^{max} \quad (16b)$$

$$\gamma_z = P_r^{max} \eta_r \times 3600/1000 \quad (16c)$$

$$\kappa_z = P_{ht}^{max} \eta_{ht} \times 3600/1000 \quad (16d)$$

where P_r^{max} and P_{ht}^{max} represent rated power of the refrigeration and heating systems, respectively. Constraint (15) states that the temperature of the storage space at time t is a function of its temperature at time $t-1$; miscellaneous heat of mechanical devices within the storage facility; heat loss through walls and air leakage; respiration and evaporation heats of the produce; and operations of fans, mixers, refrigeration and heating systems. Respiration and evaporation heats of the produce can be approximated at certain air temperature and pressure for various products. For example, the following can be used to represent the evaporation and respiration heats of potatoes [5]:

$$q_{ev,z}(t) = \frac{K_{ev} A_{sp} M_{pr} H_{ev}}{\rho_b} (\widehat{w}_z(t) - w_z(t)) \quad (17)$$

$$Q_{re,z}(t) = H_{re} M_{pr,z}] \quad (18)$$

Exhaust hatches on the rear end of the storage facilities operate according to the opening position of the mixer hatches and the operations of the fans to keep the inside air pressure constant. This can expressed as exhausting the same volume of air circulated into the storage facility through fans and mixer hatches via exhaust hatches. Therefore, the effect of circulated air flow through fans can be obtained from the following nonlinear equation:

$$\begin{aligned} q_{f,z}(t) =\, &\beta_z s_{f,z}(t)\,(s_{mx,z}(t)\Theta_{out}(t) - (1 - s_{mx,z}(t))\theta_z(t)) \\ &- \beta_z s_{f,t}(t)\,(s_{mx,z}(t)\theta_z(t)) \quad (19) \end{aligned}$$

Here, the first and second terms represent the effects of the air entering into the storage facility and exhausting air from the storage facility, respectively. This can be simplified to the following nonlinear equation:

$$q_{f,z}(t) = \beta_z s_{f,z}(t) s_{mx,z}(t)\,(\Theta_{out}(t) - \theta_z(t)) \quad (20)$$

Inside temperature of the storage facility must be kept within a range specified by a minimum and a maximum temperature, and average inside temperature over the scheduling horizon must be within a tighter pre-defined temperature range. These requirements are represented by the following constraints:

$$\Theta_z^l \le \theta_z(t) \le \Theta_z^u \qquad \forall t \in T \quad (21)$$

$$\Theta_z^{l_0} \le \sum_{t \in T} \theta_z(t)/N_T \le \Theta_z^{u_0} \quad (22)$$

where $\Theta_z^{l_0}$ and $\Theta_z^{u_0}$ represent the lower and upper limits of the average inside temperature, respectively.

3) Operational constraints: The operational constraints of the cooling system in the optimization model are as follows:

$$0 \leq s_{i,z}(t) \leq 1, \quad \forall i \in A \qquad \forall t \in T \qquad (23)$$

$$0 \leq s_{r,z}(t) \perp s_{ht,z}(t) \geq 0 \qquad \forall t \in T \qquad (24)$$

$$0 \leq s_{h,z}(t) \perp s_{dh,z}(t) \geq 0 \qquad \forall t \in T \qquad (25)$$

$$\left(\Theta_{out}(t) - \Theta_{out}^{min}\right) s_{f,z}(t) \geq 0 \qquad \forall t \in T \qquad (26)$$

$$s_{f,z}(t) \leq s_{mx,z}(t) \qquad \forall t \in T \qquad (27)$$

Constraint (23) states that the mechanical refrigeration and heating system, fans, mixer, humidifier, and dehumidifier can be controlled continuously. The nonlinear constraints (24) and (25) ensure that the refrigeration and heating system, and humidifier and dehumidifier, respectively, do not operate at the same time. The nonlinear constraint (26) states that when outdoor temperature is less than a pre-specified value, Θ_{out}^{min}, fans do not circulate very cold air into the storage room, and (27) forces the fan to be off when the mixer hatches are closed, because the fan must not operate when the hatches are closed, since this may damage the fans due to lack of air circulation. However, this equation also imposes an additional constraint in the fan operation with respect to the mixer, forcing it to be smaller, which is not necessary in principle. Nevertheless, since the power consumption of the fan is much greater than the mixer and the objective is to minimize overall power/energy consumption, a feasible and optimal solution will have to meet this constraint anyway, and hence this constraint will not change the outcome of the optimization model. In the implementation of the model, each complementarity constraint is reformulated as a set of constraints enforcing the product of the complement terms to be equal to zero, while each term is forced to be greater than or equal to zero.

VI. NUMERICAL RESULTS

Several case studies have been conducted to examine the performance of the developed mathematical model for storage facilities with single and multiple storage spaces, of which the most relevant ones are presented in this section. In these case studies, the mathematical model is run for a typical storage facility, where parameters and device ratings are suitably chosen and realistic data inputs for outside temperatures, illumination levels, electricity price and demand charges have been used. Current FRP, TOU and RTP tarrifs for electricity and demand charges in Ontario-Canada are used to calculate total electricity costs. AMPL [18], a modeling language for mathematical programming, has been used to implement the developed mathematical models of the storage facility, and IPOPT [19], a popular solver based on interior point methods, has been used to solve the developed Non-Linear Programming (NLP) problem. The solutions reported for all case studies are obtained using the IPOPT solver, which yields local optimal solutions of the optimization model in less than 5 seconds on an Intel 1.8 GHz, 8 GB RAM computer. It should be mentioned that since this is a non-convex NLP problem, one can only guarantee the solution to be a local minimum, which for practical applications, as demonstrated by the results reported in this section, yields reasonable savings. Furthermore, since the proposed supervisory controller is not expected to perform real-time control actions, providing only optimal settings (trajectories) to the existing local climate controls, and considering that most climate control equipment in modern storage facilities can be continuously controlled, the proposed mathematical optimization model assumes continuous control settings of devices. Nevertheless, since the model is not intended for real-time but supervisory control, even in the case of some equipment requiring discrete controls, the outputs of the proposed supervisory control could be rounded-off to the nearest available discrete control setting for the real-time controls, thus yielding at least sub-optimal operating conditions.

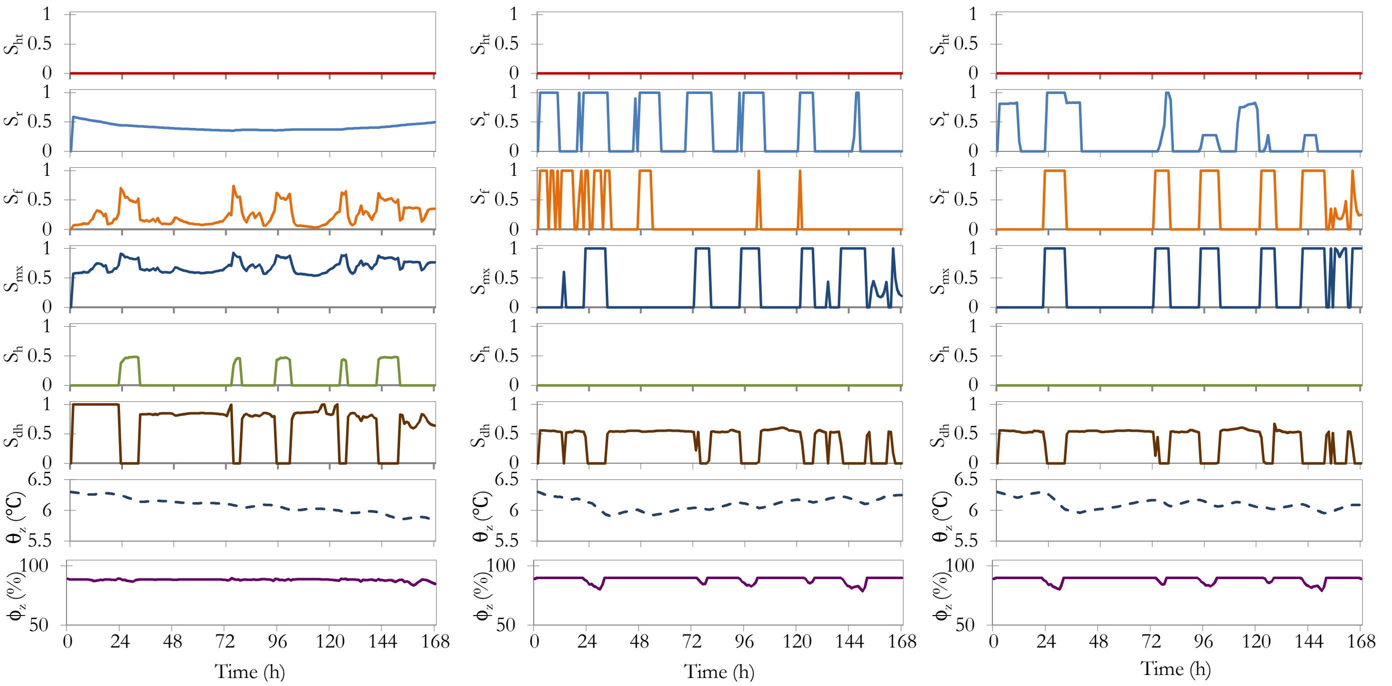
A. Case Study

Information of an actual storage facility is taken from [20] and modified to carry out the case study simulations. The storage facility has a total capacity of 5000 metric tonnes, composed of six large storage bins, which can operate independently in pairs, thus resulting in three separate climate control zones. The temperature set points for Zone 1, 2, and 3 are assumed to be 5 °C, 6 °C, and 7 °C, respectively, and the maximum allowed temperature deviation is set to ±0.5 °C. The total volume of the storage facility and of each bin are 15510 m^3, and 1255 m^3, respectively. The rest of the storage facility's space is comprised of the loading areas and ventilation canals. Temperature and humidity of each pair of bins are controlled simultaneously through a distribution canal providing ventilation air for both bins. Three 3.7 kW fans provide 87,000 m^3/h, and a humidifier system with a total capacity of 9.5 l/h. Mixing chambers are equipped with air intake louvers to adjust the ratio of fresh incoming air and circulated air. Two 20 kW electrical heaters are installed to supplement heat or for drying fresh incoming air when dehumidification is required. The cooling capacity of the refrigeration system is assumed to be 209 kW.

B. Simulation Scenarios

The following four simulation case studies that illustrate the capabilities and performance of the developed model are presented in this section. In Case 0, the objective is to find a feasible solution for the model while all constraints on operation of the devices, inside temperature, and humidity are met, which is considered here to be a realistic "base case" to establish a reference for comparison purposes. In Case 1 and Case 2, the models minimize total costs of energy consumption and demand charges of all devices, respectively, while the inside temperatures can vary within the same ranges defined in Case 0. Case 3 is Case 1 and Case 2 combined, where total costs including energy and demand charges are minimized.

Optimal solutions generated by the model for Zone 2 in multi-zone operation (all zones are optimized simultaneously) of the storage facility in summer are presented in Fig. 3. In these figures, decision variables for all devices and the resulting inside temperatures and relative humidities are presented.



(a) Base case (Case 0) (b) Minimize energy costs (Case 1) (c) Minimize total costs (Case 3)

Fig. 3. Optimal solution generated by the model for Zone 2 in multi-zone operation of the storage facility for RTP in a summer week.

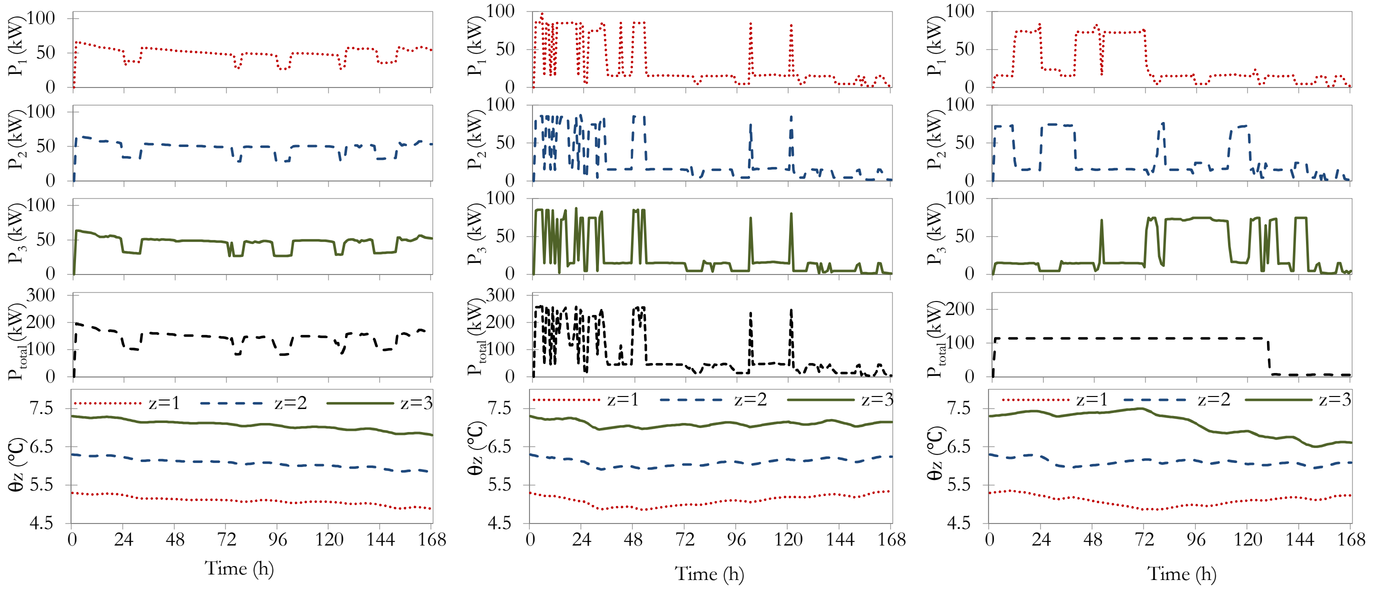
Figure 3a depicts the optimal solution obtained from minimizing temperature deviations from their set points; observe that the model keeps the inside temperature very close to the set point and maintains the inside humidity within the defined ranges by utilizing the refrigeration system, dehumidifier, and fans. Figure 3b depicts the optimal solution obtained from minimizing energy costs; in this case, while the inside temperature and relative humidity vary within the predefined ranges, the model reduces costs by operating the refrigeration system, dehumidifier, and fans during lower energy price periods. The optimal solution obtained from minimizing total costs, i.e., energy and demand charges, are presented in Fig. 3c; in this case, while the inside temperature and relative humidity vary within the predefined ranges, the model reduces total costs by operating the devices during lower energy price periods and by lowering the peak demand of the facility.

The power consumption of each zone and corresponding inside temperatures for multi-zone operation of the storage facility in summer are shown in Fig. 4. Observe that the model minimizes temperature deviations from the set points in Fig. 4a, while all the three zones' peak powers occur at the same time, resulting in high peak demand for the facility. In the minimization of energy costs, depicted in Fig. 4b, the model operates the devices in each zone during low energy prices and keeps the inside temperatures and humidities within the predefined ranges; observe that although the model operates the devices of each zone during low energy price periods, the total cost is the highest because of high demand charges. By minimizing total costs, depicted in Fig. 4c, the model allows temperature variations within the pre-defined limits while changing the operation of devices for each zone to reduce both total peak demand and energy charges; thus, peak demand of the storage facility is reduced from 294 kW in Case 0 to 114 kW, yielding significant reductions in demand charges.

A comparison of energy charges, demand charges, and total costs in multi-zone operation of the storage facility in summer for different pricing schemes is presented in Table I. FRP, TOU, and RTP tariffs in Ontario-Canada have been used to carry out these simulations. It can be observed that energy charges using FRP are higher than those obtained with TOU and RTP tariffs for all cases. By minimizing energy charges, the energy costs are reduced significantly for all three pricing schemes, whereas the demand charges increase as compared to the base case. In Case 2, demand charges are the least among all cases and energy costs are reduced compared to Case 0; however, total costs are higher as compared to Case 3. Total charges are the least in the minimization of total costs case for all pricing schemes, obtaining more than 44% reductions in total costs as compared to the base case.

C. Monte Carlo Simulations

MCS are run to further validate and test the proposed approach, as well as get a better sense of the performance of the proposed supervisory controller in achieving costs savings considering weather and energy price uncertainties. Thus, multiple open-loop simulations were run over different sets of input data to calculate expected savings for typical weeks in summer and winter. The sets of input data were generated randomly based on actual data of outdoor temperature, humidity, and HOEP. Random values of energy prices for each hour are generated using a uniform distribution with



(a) Base case (Case 0)   (b) Minimize energy costs (Case 1)   (c) Minimize total costs (Case 3)

Fig. 4. Simulation results for multi-zone operation of the storage facility for RTP in a summer week.

TABLE I
COMPARISON OF ENERGY CHARGES, DEMAND CHARGES, AND TOTAL COSTS FOR MULTI-ZONE OPERATION OF THE STORAGE FACILITY FOR DIFFERENT PRICING SCHEMES IN SUMMER.

Item	Pricing scheme	Energy charges ($)	Demand charges ($)	Total charges ($)	Savings w.r.t. Case 0 (%)
Case 0	FR	1810.40	1564.97	3375.38	
	TOU	1532.73	1564.97	3097.71	
	RT	847.532	1564.97	2412.51	
Case 1	FR	875.84	2049.85	2925.69	13.3
	TOU	702.90	2049.85	2752.75	11.1
	RT	379.01	2145.27	2524.28	-4.6
Case 2	FR	1260.09	800.06	2060.15	38.9
	TOU	1043.28	800.06	1843.34	40.4
	RT	584.88	800.06	1384.94	42.5
Case 3	FR	1029.88	862.47	1892.36	43.9
	TOU	913.95	850.54	1764.49	43.0
	RT	502.86	821.13	1323.98	45.1

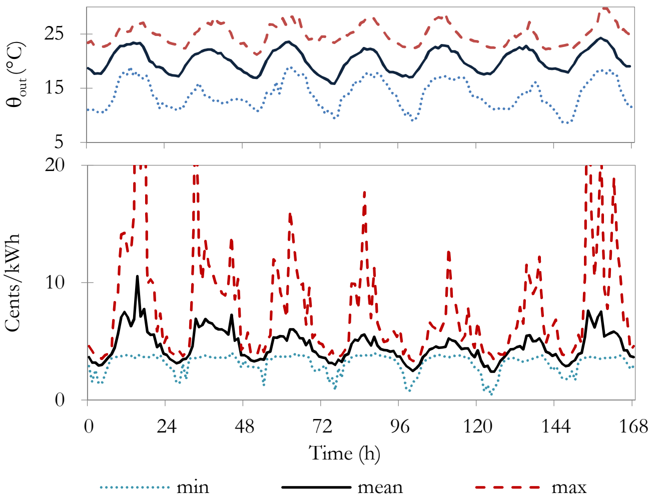


Fig. 5. Minimum, maximum, and mean values of outdoor temperature and real rime prices in summer used in the MCS.

associated lower and upper limits for each hour obtained from actual data over each season; this models highly volatile prices, and hence represents a worst case scenario. Also, for temperature and humidity, random values are generated using normal distributions with mean values and standard deviations obtained from actual data for each hour over each season. Minimum, maximum and mean values of outdoor temperature and real time prices for summer used in these simulations are shown in Fig. 5.

For each MCS, the same sets of input data are used to run Case 0 (base case) and Case 3, with the only difference being the selected objective functions; thus, Case 0 represents a non-optimized operation strategy, i.e., the PID controllers are assumed to follow the set points generated using a min. set-point deviation objective function, and Case 3 is the optimized operation strategy obtained with the objective of minimizing total costs. Since both cases use the same perfect-forecast data as inputs, the results of the MCS should provide a reasonable basis to demonstrate the value of using the proposed optimal supervisory control approach versus non-optimal operation.

The MCS results are shown in Fig. 6 for summer. This figure depicts the total costs of the storage facility in multi-zone operation mode for each MCS iteration, and the average of the total costs at each MCS iteration for Cases 0 and

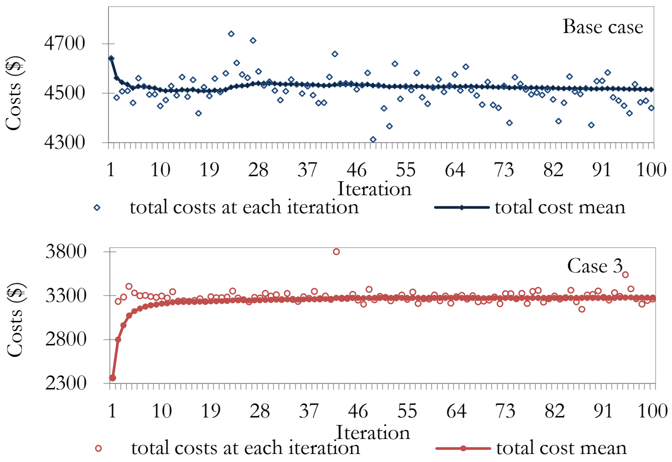


Fig. 6. Total costs at each iteration and mean total costs from MCS for multi-zone operation in summer.

3. It can be observed in these plots that the total costs' average value converges to within a 5% tolerance in about 50 MCS iterations. It can also be observed that even when considering large variations in weather and energy price inputs, the model yields significant costs savings (27% expected total cost savings). The total costs best fit a Log-Logistic (3P) probability density function (pdf) for the base case with a wide profile corresponding to $\alpha = 56.584$, $\beta = 1953.1$, and $\gamma = 2560.3$ [21], and a much narrower Chi-Squared pdf with a $\nu = 3278$ for the proposed optimal supervisory control.

VII. CONCLUSIONS

Mathematical models for optimal operation of climate control systems of storage facilities in the context of smart grids were presented. The developed models incorporate weather forecasts, electricity price information, and the end-user preferences to optimally operate existing climate control systems of produce storage facilities. The model considers important characteristics of these storage facilities such as inside temperature and humidity, which are kept within user-defined ranges, to schedule the operation of various devices to minimize total energy costs and demand charges. The simulations results obtained show that significant cost savings can be achieved using the proposed model for various weather conditions and energy price variations.

REFERENCES

[1] F. Rahimi and A. Ipakchi, "Demand response as a market resource under the smart grid paradigm," *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 82 –88, 2010.

[2] M. Albadi and E. El-Saadany, "Demand response in electricity markets: An overview," in *Proc. IEEE PES GM*, 2007, pp. 1 –5.

[3] A. Ipakchi and F. Albuyeh, "Grid of the future," *IEEE Power Energy Mag.*, vol. 7, no. 2, pp. 52–62, 2009.

[4] K. Refsgaard, N. Halberg, and E. S. Kristensen, "Energy utilization in crop and dairy production in organic and conventional livestock production systems," *Agricultural Systems*, vol. 57, no. 4, pp. 599–630, 1998.

[5] L. Lukasse, J. de Kramer-Cuppen, and A. van der Voort, "A physical model to predict climate dynamics in ventilated bulk-storage of agricultural produce," *Int. J. Refrigeration*, vol. 30, no. 1, pp. 195–204, 2007.

[6] K. Gottschalk, "Mathematical modelling of the thermal behaviour of stored potatoes & developing of fuzzy control algorithms to optimise the climate in storehouses," in *Proc. Acta Hort. 406*. ISHS, 1994, pp. 331–340.

[7] Y. Xu and D. Burfoot, "Predicting condensation in bulks of foodstuffs," *J. Food Engineering*, vol. 40, no. 1-2, pp. 121–127, 1999.

[8] K. Keesman, D. Peters, and L. Lukasse, "Optimal climate control of a storage facility using local weather forecasts," *Control Engin. Pract.*, vol. 11, no. 5, pp. 505–516, 2003.

[9] S. van Mourik, H. Zwart, and K. Keesman, "Switching control for post-harvest food storage," 2007, pp. 189–194.

[10] L. Lukasse, J. van Maldegem, E. Dierkes, A. van der Voort, J. de Kramer-Cuppen, and G. van der Kolk, "Optimal control of indoor climate in agricultural storage facilities for potatoes and onions," *Control Engin. Pract.*, vol. 17, no. 9, pp. 1044–1052, 2009.

[11] G. Verdijck, "Product quality control," Ph.D. dissertation, University of Eindhoven, 2003.

[12] T. Morimoto, J. Suzuki, and Y. Hashimoto, "Optimization of a fuzzy controller for fruit storage using neural networks and genetic algorithms," *Engin. Appl. Artif. Intelli.*, vol. 10, no. 5, pp. 453–461, 1997.

[13] K. Gottschalk, L. Nagy, and I. Farkas, "Improved climate control for potato stores by fuzzy controllers," *Comp. Elect. Agri.*, vol. 40, no. 1-3, pp. 127–140, 2003.

[14] K. J. Keesman and T. Doeswijk, "Uncertainty analysis of weather controlled systems," in *Coping with Uncertainty*. Springer, 2010, vol. 633, pp. 247–258.

[15] "A guide to electricity charges - market participants." [Online]. Available: http://www.ieso.ca/imoweb/role/wholesaleCharges.asp

[16] "A guide to electricity charges for business." [Online]. Available: http://www.ieso.ca/imoweb/siteshared/electricity_charges.asp

[17] T. G. Doeswijk, "Reducing prediction uncertainty of weather controlled systems," Ph.D. dissertation, Wageningen University, 2007.

[18] R. Fourer, D. M. Gay, and B. W. Kernighan, *AMPL: A Modeling Language for Mathematical Programming*. Brooks/Cole, 2003.

[19] A. Wachter and L. Biegler, "On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming," *Mathematical Programming*, vol. 106, no. 1, pp. 25–57, 2006.

[20] J. Landry, "Computer software for the control of potato storage environment," Ph.D. dissertation, McGill University, 1994.

[21] J. F. Lawless, *Statistical models and methods for lifetime data*. John Wiley & Sons, 2011, vol. 362.

Mohammad Chehreghani Bozchalui (S'05, M'11) received his B.Sc. degree in Electrical Engineering from the Iran University of Science and Technology, Tehran, Iran, in 2004, and his M.Sc. degree, also in Electrical Engineering, from the University of Tehran, Iran, in 2007. He completed his PhD studies in Electrical Engineering with a major in Power and Energy Systems at the University of Waterloo, Canada, in 2011. Mohammad is currently a Research Staff Member in the Energy Management Department, at NEC Laboratories America, Inc., Cupertino, USA. His areas of interest cover applications of optimization techniques in power and energy systems, power system operation and control, and power system stability analysis.

Claudio A. Cañizares (S'85, M'91, SM'00, F'07) received in April 1984 the Electrical Engineer Diploma from the Escuela Politécnica Nacional (EPN), Quito-Ecuador, where he held different teaching and administrative positions from 1983 to 1993. His MS (1988) and PhD (1991) degrees in Electrical Engineering are from the University of Wisconsin-Madison. Dr. Cañizares has held various academic and administrative positions at the E&CE Department of the University of Waterloo since 1993, where he is currently a full Professor, the Hydro One Endowed Chair and the Associate Director of the Waterloo Institute for Sustainable Energy (WISE). His research activities concentrate on the study of modeling, simulation, control, stability, computational and dispatch issues in sustainable power and energy systems in the context of competitive markets and Smart Grids.

Kankar Bhattacharya (M'95, SM'01) received the Ph.D. degree in Electrical Engineering from the Indian Institute of Technology, New Delhi, India in 1993. He was in the faculty of Indira Gandhi Institute of Development Research, Mumbai, India, during 1993-1998, and then the Department of Electric Power Engineering, Chalmers University of Technology, Gothenburg, Sweden, during 1998-2002. He joined the E&CE Department of the University of Waterloo, Canada, in 2003 where he is currently a full Professor. His research interests are in power system economics and operational aspects.