Optimal Control of Energy Storage in a Microgrid by Minimizing Conditional Value-at-Risk

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***Abstract*—This paper presents two methods for online rolling horizon optimal control of an energy storage unit in a grid-connected microgrid, subject to uncertainty in demand and electricity pricing. The proposed methods are based on the concept of rolling horizon control, where battery charge/discharge activities are determined by repeatedly solving a linear optimization problem over a moving control window. The predicted values of the microgrid net electricity demand and electricity prices over the control horizon are assumed to be uncertain. The first formulation of the control is based on the scenario-based stochastic conditional value at risk (CVaR) optimization, where the cost function includes electricity usage cost, battery operation costs, and grid signal smoothing objectives. Multivariate Gaussian distribution is used to model the variations of electricity prices and net demand power around their predicted nominal values. The second formulation of the control reduces the computations by taking a worst-case CVaR stochastic optimization approach. In this case, the uncertainty in demand is still stochastic but the problem constraints are made robust with respect to price variations in a range. Simulation results under different scenarios are presented to demonstrate the effectiveness of the proposed methods.**

***Index Terms*—Energy Management, Microgrid, Energy Storage, Rolling Horizon, Linear Program Optimization, Conditional Value at Risk, Worst-Case CVaR.**

I. Introduction

THE CONVENTIONAL power grid only permits a one-way flow of power from major electricity generators to consumers. However in recent years, a gradual transition to a smart grid environment has begun to allow for bi-directional flow of power between the grid and end-users for better integration of clean sources of energy and storage capacity in the power system. Potential economic and environmental benefits arising for such model of grid operation are enormous, ranging from lesser dependency on fossil fuels, improved efficiency, to greater reliability, and eventually reduced cost of electricity. Researchers have been studying a wide variety of options and opportunities that the smart grid paradigm can enable, including emission control [1]–[3], optimal integration of the electric vehicles [4]–[7], and optimal power planning [8].

This paper focuses on the specific problem of optimal energy storage management/scheduling in a grid-connected microgrid, as a core problem in operation of interactive smart grids. Prior literature exists on scheduling of loads [4]–[7] and distributed energy sources [9]–[11] in microgrids. The current work, however, addresses the central problem of battery storage control in the presence of uncertainty in the predicted demand and renewable energy. Battery storage systems will be common in future microgrids and their optimal control can yield potentially substantial economic gains. Storage devices can be effectively utilized to shift and flatten the power demand curve and increase the reliability of the clean but intermittent solar and wind power. Control of storage devices in microgrids has been subject of significant research in recent years. In [12], a method is proposed for optimal power flow in microgrids with energy storage, considering constraints on power, voltage, and current. In [1] and [13], a multi-objective optimization approach is developed for energy management in microgrids with batteries that aims at reducing the emissions and operating cost of the microgrids. In [14], an algorithm is introduced for the control of a hybrid ultacapacitor-battery as storage device. It is argued that this combination could yield a high-power and high-energy storage system that can improve microgrid efficiency and reduce its net energy cost.

Off-line control approaches have been extensively studied in energy management systems (EMS) [12], [15] and [16]. A common problem with these methods is their sensitivity to uncertainty, since control decisions are made ahead of time based on a model of the system and predicted demand and prices. Although there have been efforts to account for uncertainties and disturbances using off-line robust and stochastic optimization techniques, e.g., see [15], [17] and [18], lack of feedback from the actual system can substantially limit the performance of such techniques.

Online model predictive control (MPC) or rolling horizon control-based methods repeatedly solve the control optimization problem over a moving window, and hence are more robust to uncertainty than off-line approaches. There are examples of EMS with MPC in the literature, e.g., see [19]–[24]. Most online optimization-based MPC techniques rely on solving a real-time optimization problem using a nominal model of the system. Although the feedback mechanism inherent in MPC to some extent improves its robustness, large modeling errors and disturbances can still degrade the performance of such controllers. In EMS, significant uncertainty can arise from variations in the microgrid energy demand, output of renewable sources, and market price of electricity. Disregarding these uncertainties may cause the problem to become infeasible or the solution to be sub-optimal [25].

There have been attempts to increase robustness of EMS in the presence of demand and renewable generation uncertainty. Our group recently introduced a robust optimization-based

Manuscript received September 14, 2015; revised December 23, 2015 and February 17, 2016; accepted March 11, 2016. Date of publication March 21, 2016; date of current version June 16, 2016. Paper no. TSTE-00771-2015.

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Digital Object Identifier 10.1109/TSTE.2016.2543024

MPC to handle uncertainty in the prediction of the net demand in a microgrid with energy storage and renewable energy in [26]. In that work, the problem is posed as a worst-case robust optimization where the actual net demand is subject to box uncertainty around the predicted nominal demand. The work in [27] also considers worst-case transaction cost in energy management of a grid-connected microgrid to account for the variations in the output of renewable energy sources.

Although worst-case robust optimization provides a simple framework to deal with uncertainty, it can be overly conservative and risk averse, making it less attractive in some applications [28]. The adjustable robust optimization proposed in [29] is more flexible and reduces the over-conservatism associated with standard robust optimization. In particular, the adjustable robust optimization framework deals with two types of variables, namely, non-adjustable or "here and now", and adjustable or "wait and see" variables. In general, the adjustable robust counterpart (ARC) is NP-hard and hence intractable in practical applications. Nonetheless, it has been demonstrated in [29] that tractability is achievable for a family of problems where adjustable variables are restricted to be affine functions of uncertain data. The applications of this concept in optimal power flow control has also been highlighted in [30] and [31]. However, in practice, it is often not possible to express the adjustable variables as an affine function of the uncertain data.

Risk-based optimization presents an alternative philosophy for solving such problems. Probabilistic risk measures including variance and value at risk (VaR) have been a subject of research in portfolio management. One of the drawbacks associated with variance as a risk measure is its symmetric nature which weighs over- and under-performance equally [32]. VaR is also a non-coherent risk measure that suffers from undesirable mathematical properties including lack of convexity and subadditivity making it unattractive in practical optimization problems [33]. On the other hand, Conditional value at risk (CVaR), introduced by Rockafellar and Uryasev [34], is a coherent risk measure focusing on the expectation of β-percentile of cost distribution. Moreover, for linear cost functions, minimizing CVaR can be formulated as a simple linear programming problem, making it particularly attractive for practical optimization problems requiring real-time solution.

CVaR has been recently applied to the microgrid energy management problem as a risk-aware stochastic approach to account for uncertainties [9]–[11], [35]. In [10] and [11], CVaR has been used as a regularizer to achieve a trade-off between the operating cost of the system and the risk of uncertainties. In [11], demand response optimization subject to inaccurate predicted data including electricity price, outdoor temperature, and PV generation is considered. However, the resulting optimization problem is not actually directly solved since the formulated problem is not computationally tractable. Instead, a fuzzy logic controller is used to determine battery charge/discharge activities, which cannot guarantee an optimal solution. References [9] and [10] focus on robust scheduling of distributed energy sources under uncertainty, which is a different problem from what is studied in the current work. The work in [35] is also concerned with optimal management of distributed energy resources with demand response optimization under uncertainty of electricity and fuel price.

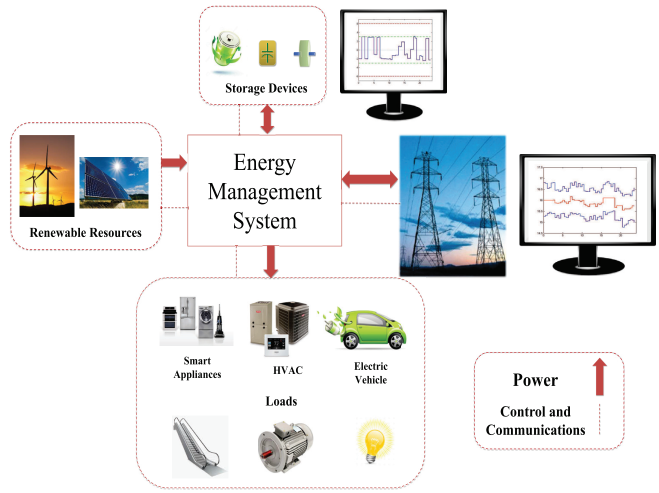

Fig. 1. Schematic of a grid-connected microgrid with storage devices and Energy Management System.

This paper proposes two methods for online optimal rolling horizon-based control of an energy storage device in a grid-connected microgrid with explicit consideration of uncertainty in the formulation of the optimization problem at each time-step. A block diagram of the control system is presented in Figure 1. Although this work assumes battery for energy storage, its results could be extended to the control of other types of storage such as thermal storage. Controllable loads such as electric vehicles and HVAC systems may also be included in the problem formulation. However, binary variables may be needed in the optimizations resulting in mixed-integer programming problems. The controller essentially determines the rates by which the battery should be charged or discharged. The goal is to minimize the cost of electricity, ensure smoothness of the power profile at the point of common coupling to the grid, reduce battery operating cost, while supplying the user power demand. It is worth noting that unlike the previous work in [10] and [11] that use CVaR as a regularizer to retain a balance between expected cost and risk, the objective in this work is to minimize the CVaR of system operating cost; this would also reduce the expectation of the cost. The microgrid can include renewable energy, e.g., wind or solar energy, a battery for energy storage, conventional loads, and a common AC bus which connects the battery and wind/solar power converters to the utility grid. The solar and wind power converters are assumed to be controlled for maximum power output, hence their control is excluded from the optimization framework, but their predicted outputs with their associated uncertainty are considered in the problem formulation. Note that although dispatchable units such as micro-turbines are not considered in the current formulation of this work, their operation can easily be captured by adding extra decision variables representing their generated power as well as the relevant constraints to the optimization framework.

The microgrid net predicted demand power, i.e., the difference between the user demand and power from renewable sources, as well as the market price of electricity are assumed to be uncertain. The first proposed method employs scenario-based minimization of CVaR of the cost considering joint uncertainty in the electricity demand and prices around their predicted nominal values. The resulting optimization problem in each step of the rolling horizon is of a linear program (LP) form.

The required number of sample scenarios to efficiently approximate the CVaR minimization problem grows exponentially in proportion to the number of uncertain parameters. In order to speed up the optimization, a second method is proposed in which scenario-based minimization only takes samples from net demand with Gaussian uncertainty. Electricity prices are assumed to vary within known bounds and this uncertainty is handled by worst-case robust approach. In particular, a reformulation of a constraint in CVaR minimization ensures that the worst-case cost with respect to price variations is considered in the optimization. This elimination of price uncertainty from sampling space significantly reduces computations of the sample-based CVaR minimization, but obviously compromises the performance because of conservatism associated with worst-case methods. It is important to note that the robust energy management method in [26] only addressed uncertainty in demand but not price. While fixed known prices are commonplace for small consumers of electricity today, in the future smart grid environment, these prices will most likely be set by market forces and, hence, would be subject to uncertainty. Moreover, the proposed formulations in this work eliminate the need for introducing binary variables and the resulting optimization problems are of LP forms. Such convex optimization problems can be solved much more effectively than the non-convex mixed-integer-linear programs proposed for energy management in prior work. This is in contrast with prior formulations in the literature that have used binary/integer variables to deal with different buy/sell prices and different charge/discharge efficiencies for battery/storage devices. The rest of this paper is organized as follows. In Section II, the method for sample-based minimization of CVaR is briefly reviewed. Section III is concerned with rolling horizon CVaR-based optimization for microgrid energy management with joint uncertainty in the net demand and electricity price. Section IV presents a worst-case CVaR approach to model the variations of electricity prices by an uncertainty set, while the stochastic assumption on demand variations is maintained. Simulation results are presented in Section V to compare the performance of proposed methods to a rolling horizon controller based on nominal demand and price predictions. The paper is concluded in Section VI.

II. Preliminaries

Let $f(x,y)$ be the loss associated with a set of decision variables denoted by x and random model parameters y. The objective is to obtain optimal value of the decision variable x which would minimize the loss subject to uncertainty in parameter y. One possible approach is to find the set of decision variables that would minimize the worst-case cost for all possible realizations of y, i.e.,

$$\min_{x} \quad \max_{y} \quad f(x,y). \tag{1}$$

Alternatively, using a probabilistic framework where the probability density function of y, denoted by $\mathcal{P}_y$, is known may yield less conservative solutions to this problem. One possible solution can be obtained by minimizing the β-percentile of the distribution associated with $f(x,y)$ induced by $\mathcal{P}_y$, $\beta\text{-}VaR$, defined as

$$\beta\text{-}VaR \triangleq min\{\alpha \in \mathbb{R} : \ P\{f(x,y) \leq \alpha\} \geq \beta\} \quad \text{for } 0 \leq \beta < 1. \tag{2}$$

In other words, for a given confidence level β, $\beta\text{-}VaR$ is defined as the smallest cost α, such that, probability of losses above that level is at most $1-\beta$. This has been a very popular risk measure in finance and portfolio optimization [36]. However, VaR is a non-coherent risk measure that suffers from undesirable mathematical properties including lack of convexity and subadditivity making it unattractive in practical optimization problems [33]. To avoid these problems, an alternative risk measure, CVaR, for a given confidence level β, is defined as

$$\beta\text{-}CVaR \triangleq \mathbb{E}_y(f(x,y) | f(x,y) \geq \beta\text{-}VaR)), \tag{3}$$

which is the conditional expected value of the cost, conditioned on its value exceeding the β-percentile.

In contrast to conventional robust optimization approaches, minimization of CVaR offers more flexibility in selection of the objective and can potentially improve performance by using distributional information on the uncertain parameter y. In fact, minimizing CVaR of the cost minimizes the risk of system being exposed to high losses rather than minimizing the worst-case cost. Moreover, for linear cost functions, minimizing CVaR can be formulated as a simple linear programming problem which makes it attractive in practical applications.

CVaR of the cost can be approximated using samples generated from distribution of the uncertain parameter y as demonstrated in [34].

$$\beta\text{-}CVaR \approx \min_{\alpha} (\alpha + \frac{1}{N(1-\beta)} \sum_{i=1}^{N} [f(x,y_i) - \alpha]^+), \tag{4}$$

where $[x]^+$ refers to the positive component of x, α is the $\beta\text{-}VaR$, N is the number of samples generated to approximate the cost distribution, and y_i denotes the i^{th} generated sample of the uncertain parameters vector.

The auxiliary variables $z_i|_{i=1}^{N}$ are defined to replace $[.]^+$.

$$z_i \triangleq [(f(x,y_i) - \alpha]^+ = \max(0, f(x,y_i) - \alpha). \tag{5}$$

Using these new variables, the equivalent optimization problem for minimizing $\beta\text{-}CVaR$ is formulated as following [34]

$$\begin{aligned} &\min_{\alpha,x,z} \quad \left(\alpha + \frac{1}{N(1-\beta)} \sum_{i=1}^{N} z_i\right) \\ &\text{subject to:} \quad z_i \geq 0, \\ &\qquad\qquad\quad\ \ z_i \geq f(x,y_i) - \alpha. \end{aligned} \tag{6}$$

III. CVaR Optimization-Based Rolling Horizon Energy Management

The proposed rolling horizon controller employs a 24-hour ahead prediction window of net demand power vector and electricity prices to make optimal battery charge/discharge decisions at each time-step. This work is not concerned with the prediction algorithm and assumes the predicted demand and prices are available as inputs to the optimal energy storage controller. In this section, a CVaR optimization-based problem is formulated and solved to obtain the control decision in the presence of probabilistic uncertainty in the net demand vector denoted by p_d as well as electricity market prices.

In this work, the control values are optimized considering the following cost function associated with the decisions and system parameters,

$$\begin{aligned} J \triangleq\ & c_c p^+ - c_d p^- + c_e \max(E_p - E_{bat}, 0) \quad (a) \\ & + c_{smg}^T u_g \quad (b) \\ & + c_{peak} p_g^{ob} + c_{flat}(p_g^{max} - p_g^{min}) \quad (c) \\ & + c_u \quad (d). \end{aligned} \tag{7}$$

The sum of the terms in (a) represents the cost associated with operating the batteries. Here, p^+ and p^- are power rates for charging and discharging the batteries and c_c and c_d are the associated costs. The last term in (a) penalizes the battery energy, i.e., E_{bat}, below a certain level E_p. This is mainly because any reduction of residual capacity of battery below a certain limit (e.g. 50% of the nominal capacity for lead-acid batteries) degrades the battery performance and reduces its lifetime. The term in (b) penalizes the grid signal non-smoothness, where u_g represents the magnitude of the variations in grid power rates in consecutive horizon time-steps and c_{smg} is the associated cost. The first term in (c) reduces the peak in demand at point of common coupling by penalizing excess demand denoted by p_g^{ob} over a baseline power rate p_g^{base}, set by the user (see [26] for details). The second term flattens the grid power signal p_g, by penalizing the difference between its maximum and minimum values. The last term in (d), which is uncertain, represents the actual cost of electricity bought/sold from/to the utility grid and is defined as follows

$$c_u \triangleq c_{buy}^T p_b + c_{sell}^T p_s, \tag{8}$$

where c_{buy} and c_{sell} represent the electricity buying and selling prices, and p_b and p_s are time-averaged energy bought or sold, respectively. They are defined as

$$p_b \triangleq \max\left(p_d + p_{bat}, 0\right), \tag{9}$$

$$\begin{aligned} p_s &\triangleq \min\left(p_d + p_{bat}, 0\right) \\ &= p_d + p_{bat} - p_b, \end{aligned} \tag{10}$$

where p_{bat} represents total power of batteries and is related to individual charging/discharging powers as following

$$\begin{aligned} p^+ &= \max(p_{bat}, 0), \\ p_{bat} &= p^+ + p^-. \end{aligned} \tag{11}$$

Substituting (10) in (8) yields

$$\begin{aligned} c_u = & (c_{buy}^T - c_{sell}^T) p_b \\ & + c_{sell}^T (p_d + p_{bat}). \end{aligned} \tag{12}$$

Assuming $c_{buy} \geq c_{sel}$ and $c_c > 0$, which is reasonable, the nonlinearity introduced in the cost by the max function in (9) and (11) can be eliminated using the following constraints

$$\begin{aligned} & p_b \geq p_d + p_{bat}, \\ & p_b \geq 0, \\ & p^+ \geq p_{bat}, \\ & p^+ \geq 0. \end{aligned} \tag{13}$$

Similarly, for $c_e > 0$ we have

$$\begin{aligned} & E \triangleq \max(E_p - E_{bat}, 0), \\ & E \geq E_p - E_{bat}, \\ & E \geq 0. \end{aligned} \tag{14}$$

Incorporating the loss function J in (7) into the CVaR optimization framework in (6) yields a linear problem as follows

$$\min_{\alpha, x, z_i} \left(\alpha + \frac{1}{N(1-\beta)} \sum_{i=1}^{N} z_i \right)$$

subject to:

$$\begin{aligned} & c_c^T p^+ + c_d^T (p^+ - p_{bat}) + c_e^T E + c_{smg}^T u g^i \\ & + c_{peak} p_g^{ob,i} + c_{flat}(p_g^{max,i} - p_g^{min,i}) \\ & + (c_{buy,i}^T - c_{sell,i}^T) p_b^i + c_{sell,i}^T (p_d^i + p_{bat}) \leq z_i + \alpha, \\ & z_i \geq 0, \end{aligned} \tag{15}$$

$$\begin{aligned} & p_b^i \geq p_d^i + p_{bat}, \\ & p_b^i \geq 0 \qquad \forall i \in \{1, \ldots, N\}, \\ & p^+ \geq p_{bat}, \\ & p^+ \geq 0, \\ & E \geq E_p - E_{bat}, \\ & E \geq 0, \end{aligned} \tag{16}$$

$$E_{bat}^{min} \leq E_{bat,k} \leq E_{bat}^{max} \quad \text{for} \quad k \in [1, Nh], \tag{17}$$

$$\begin{aligned} E_{bat,k} = & \eta_c \sum_{i=1}^{k} h_i p^+ - p_{bat}^{loss} \sum_{i=1}^{k} h_i \\ & + \eta_d^{-1} \sum_{i=1}^{k} h_i (p_{bat} - p^+) + E_{bat}^0 \quad \text{for} \quad k \in [1, Nh], \end{aligned} \tag{18}$$

$$\begin{aligned} & 0 \leq p_{bat} \leq p_{bat}^{max} \\ & 0 \leq p^+ \leq p^{max}, \end{aligned} \tag{19}$$

$$\eta_c h^T p^+ + \eta_d^{-1} h^T (p_{bat} - p^+) - P_{bat}^{loss} h^T 1 = E_{bat}^{final} - E_{bat}^0, \tag{20}$$

$$-\Delta p_{bat} h \leq p_{bat_k} - p_{bat_{k-1}} \leq \Delta p_{bat} h, \tag{21}$$

$$-u^i_{g_k} \leq p_{bat_k} + p^i_{d_k} - p_{bat_{k-1}} - p^i_{d_{k-1}} \leq u^i_{g_k} \quad \forall i = 1, \ldots, N, k \in [1, N_h], \tag{22}$$

$$p_g^{min,i}1 \leq p_{bat} + p^i_d \leq p_g^{max,i} \quad \forall i = 1, \ldots., N, \tag{23}$$

$$p_{bat} + p^i_d \leq p_g^{base}1 + p_g^{ob,i}1 \quad \forall i = 1, \ldots., N, \tag{24}$$

where variables with index i are optimization variables corresponding to the i^{th} generated sample vector which is drawn from a certain measure $\mathcal{P}_y$.

In this work, a discrete-time model for battery storage devices is employed as follows

$$E_{bat,k+1} = E_{bat,k} + \eta_c h_k p^+_k + \eta_d^{-1} h_k p^-_k - P^{loss}_{bat} h_k, \tag{25}$$

where $E_{bat,k}$ represents the energy of battery at time step k in kWh, h_k is the length of the time step measured in hours, P^{loss}_{bat} is the self discharging power of the battery in kW per hour, p^+ and p^-, η_c and η_d represent battery charging and discharging power and efficiency, respectively. The inequality constraint in (17) ensures that the battery energy level remains within safe limits at each time-step; here E^0_{bat} is battery energy level at the beginning of the control horizon, and E^{min}_{bat} and E^{max}_{bat} denote minimum and maximum allowable battery energy levels.

The battery charge/discharge costs c_c/c_d in (7) can easily be determined based on the rated lifetime of battery and its initial capital cost as

$$c_c = c_d = C.\frac{T}{E_t} \text{in \$h/kWh}, \tag{26}$$

Here C is the initial capital cost of the battery and E_t is the total charged/discharged energy over the entire life cycle of the battery; T is the length of the control step in hours. The value of E_t can be estimated as follows

$$E_t = \sum_{k=0}^{N_{cd}-1} (1-\delta)^k E^{max}_{bat} = \frac{1-(1-\delta)^{N_{cd}}}{\delta} E^{max}_{bat}, \tag{27}$$

where N_{cd} is the rated lifetime of the battery in number of charge cycles, and δ is the rate of decline in battery capacity per charge cycle.

Battery powers are also constrained through (19), where the scalar constants p^{max}_{bat}, p^{max} represent the maximum battery rates. The assumption here is that the battery charge/discharge commands are sent to a battery management system (BMS) that operates at a much higher control update rate. The BMS, which monitors the battery health, its state of charge and its voltage, ensures that the required power is delivered to the microgrid bus, e.g. by controlling the current injected to the bus. This low-level controller can also handle voltage and frequency regulation objectives, if required. The BMS provides the battery state of charge and power and energy limits to the optimization-based scheduler at each time-step of optimization.; these limits can be adjusted on the fly, e.g. based on the battery voltage, to avoid unrealistic charge/discharge commands.

The equality constraint (20) simply relates the battery initial energy level E^0_{bat} to its final energy level E^{final}_{bat}, and is based on the battery model in (25). The inequality constraint in (21) limits the amount of change in the battery power over consecutive sample times. Large fluctuations in the microgrid power at the point of common coupling over consecutive sample times are penalized via (22) and the associated term in the cost; here u^i_g is an auxiliary variable corresponding to the i^{th} generated sample vector of net demand. The constraint in (23) in conjunction with a term in the cost reduces the difference between the microgrid minimum and maximum powers at the point of coupling to the grid. The inequality in (24) is also added to reduce the peak usage over some baseline denoted by p^{base}_g. It should be noted that the grid power profile related objectives and constraints are introduced to allow for smoothing of the demand profile. They can be easily relaxed to enable greater fluctuations in the microgrid power profile, e.g. to compensate for peak load generated from conventional loads in the grid, if needed. It is worth mentioning that the cost associated with grid losses is taken into consideration by the utility operator in determining the electricity buy/sell prices. Furthermore, the cost function defined in (7) can be modified to capture the grid power loss by adding a term proportional to the square of grid power, i.e., p_g, since the power loss is proportional to the square of the line current. This would turn the problem into a convex quadratic optimization. The reader is referred to [26] for further information on the cost objective and constraints.

At each time-step, the LP problem defined in (15)–(24) is solved to find optimal values for the following decision variables

$$\begin{aligned} & p_{bat}, p^+, E \in \mathbb{R}^{N_h}, \\ & u^i_g, p^i_b \quad \in \mathbb{R}^{N_h} (\text{for} \quad i = 1, \ldots, N), \\ & p_g^{ob,i}, p_g^{max,i}, p_g^{min,i}, z_i, \alpha \quad \in \mathbb{R} (\text{for} \quad i = 1, \ldots, N). \end{aligned} \tag{28}$$

In the rolling horizon control framework, the battery charge/discharge command is simply computed from the first sample of the optimal decision vectors p^+ and $p_{bat} - p^+$.

IV. Energy Management Based on Worst-Case Conditional Value at Risk

In this section, the joint uncertainty problem is formulated and solved based on a combination of a worst-case robust and CVaR approaches. Particularly, variations of net demand is modeled by a Gaussian distribution while electricity prices are assumed to vary within an uncertainty set around their nominal values. A similar LP problem as the previous section is formulated and solved except that the constraints including electricity prices are made robust with respect to their worst case values. In other words, the constraints are ensured to remain feasible under all the realizations of electricity prices within the uncertainty set. The optimization problem to solve is given by

$$\begin{aligned} \min_{\alpha, x, z_i} \quad & \left(\alpha + \frac{1}{N(1-\beta)} \sum_{i=1}^{N} z_i\right) \\ \text{subject to:} \quad & z_i \geq 0, \\ & z_i \geq \tilde{f}(x, y_i, \tilde{c}) - \alpha \\ & + \text{the constraints in} (16)-(24), \end{aligned} \tag{29}$$

where $\tilde{f}(x, y_i, \tilde{c})$ represents true value of the loss associated with a certain strategy x, true value of electricity prices $\tilde{c}$, and a set of demand samples generated from a Gaussian distribution denoted by y_i, and is defined as follows

$$\begin{aligned}\tilde{f}(x, y_i, \tilde{c}) = {} & c_c^T p^+ + c_d^T(p^+ - p_{bat}) + c_e^T E \\ & + c_{smg}^T u_g^i \\ & + c_{peak} p_g^{ob,i} + c_{flat}(p_g^{max,i} - p_g^{min,i}) \\ & + (\tilde{c}_{buy}^T - \tilde{c}_{sell}^T) p_b^i \\ & + \tilde{c}_{sell}^T (p_d^i + p_{bat}) \quad \text{for} \quad i = 1, \dots, N. \end{aligned} \tag{30}$$

The key point here is that samples only need to be generated for the net demand values with smaller sample space dimensions, yielding considerable reduction in computations. Let us assume that electricity prices can be modeled as

$$\tilde{c}_{buy} = c_{buy} + \zeta_1 \hat{c}_{buy}, \tag{31}$$

$$\tilde{c}_{sell} = c_{sell} + \zeta_2 \hat{c}_{sell}, \tag{32}$$

where c_{buy} and c_{sell} represent nominal prices, $\hat{c}_{buy}$ and $\hat{c}_{sell}$ are constant positive perturbations, and ζ_1 and ζ_2 are random variables which are subject to uncertainty. A comprehensive literature on different uncertainty sets and their corresponding robust counterpart can be found in [37]. In this work, a combined box and polyhedral uncertainty set is employed for modeling the variations of electricity prices around their predicted nominal values. The main idea of robust counterpart optimization is to transform the above uncertain problem to a deterministic LP, which attempts to find a feasible solution under all realizations of uncertain parameters within the uncertainty set [37].

The only set of constraints including the electricity prices in (29) are $z_i \geq \tilde{f}(x, y_i, \tilde{c}) - \alpha \quad \forall i = 1, \dots, N$. Their robust counterpart become

$$\begin{aligned} & c_c^T p^+ + c_d^T(p^+ - p_{bat}) + c_e^T E + c_{smg}^T u_g^i + c_{peak} p_g^{ob,i} \\ & + c_{flat}(p_g^{max,i} - p_g^{min,i}) + c_{buy}^T p_b^i + c_{sell}^T(p_d^i + p_{bat} - p_b^i) \\ & + \Psi^T w_1^i + \Psi^T w_2^i + \Gamma w_3^i \leq z_i + \alpha \quad \text{for} \quad i = 1, \dots, N, \end{aligned} \tag{33}$$

where $w_1, w_2 \in \mathbb{R}^{N_h}$ and $w_3 \in \mathbb{R}$ are additional auxiliary variables needed for the worst-case robust optimization [37]. It is also necessary to add the following extra robust counterpart constraints to the optimization formulation.

$$w_{1j}^i + w_{3j}^i \geq \hat{c}_{buy}^T p_b^i \quad \text{for} \quad j \in [1, N_h], i = 1, \dots, N, \tag{34}$$

$$\begin{aligned} & w_{2j}^i + w_{3j}^i \geq \hat{c}_{sell}^T |p_d^i + p_{bat} - p_b^i| \\ & \qquad \text{for } j \in [1, N_h], i = 1, \dots, N. \end{aligned} \tag{35}$$

Note that constraint (35) contains absolute value function. In order to remove this non-linearity, an equivalent robust formulation can be obtained as follows

$$\begin{aligned} & w_{2j}^i + w_{3j}^i \geq \hat{c}_{sell}^T u^i, \\ & - u^i \leq p_d^i + p_{bat} - p_b^i \leq u^i, \\ & \text{for} \quad j \in [1, N_h], i = 1, \dots, N, \end{aligned} \tag{36}$$

TABLE I
THE EFFECT OF THE NUMBER OF SAMPLES ON COST AND COMPUTATION TIME PER CONTROL TIME STEP

Cost Improvement over non-robust controller	CVaR	Worst-case CVaR
up to 20%	$N = 300, T = 10s$	$N = 50, T = 1.3s$
$20 - 25\%$	$N = 400, T = 17s$	Not Possible

where the term x_j is substituted with auxiliary variable u_j and the constraints $-u_j \leq x_j \leq u_j$. At each time-step, the following LP optimization problem is solved

$$\begin{aligned} \min_{\alpha, x, z_i} \quad & \left(\alpha + \frac{1}{N(1-\beta)} \sum_{i=1}^{N} z_i \right) \\ \text{subject to:} \quad & z_i \geq 0 \\ & + \text{the constraints in}(16) - (24) \\ & + (33), (34) \text{and} (36), \end{aligned} \tag{37}$$

where x refers to the optimization variables consisting of the following elements

$$\begin{aligned} & p_{bat}, p^+, E, w_1, w_2 \in \mathbb{R}^{N_h} \\ & u_g^i, p_b^i, u^i \in \mathbb{R}^{N_h} \quad \text{for} \quad i = 1, \dots, N, \\ & p_g^{ob,i}, p_g^{max,i}, p_g^{min,i}, z_i, \alpha, w_3 \in \mathbb{R} \quad \text{for} \quad i = 1, \dots, N. \end{aligned} \tag{38}$$

V. SIMULATION RESULTS

Simulations are performed on a commercial/residential setting data (with peak usage less than 24 kW) provided by Burlington Hydro Inc. Nominal electricity prices are chosen based on the winter time of use electricity pricing in the province of Ontario, Canada, i.e., 6.2 ¢/kWh 7pm-7am, 9.2 ¢/kWh 11am-5pm, 10.8 ¢/kWh 7am-11am and 5pm-7pm. All other costs including the flattening cost, grid and battery signal smoothing costs, and battery energy penalizing cost are set to small non-zero values. The battery characteristics are $E_{bat}^{min} = 0kWh$, $E_{bat}^{max} = 50kWh$, $E_p = 25kWh$, $p_{bat}^{max} = 10kW$, $P_{bat}^{loss} = 0$, $\eta_c = 0.95$, and $\eta_d = 0.9$. The time horizon used is 24 h with variable time-step vector h=[0.5 0.5 0.5 0.5 1 1 2 2 2 2 3 3 3 3], therefore $N_h = 14$ and the rolling horizon controller updates the decisions every half an hour. The nominal hourly electricity buy cost, i.e., c_{buy} is determined by the time of day, hourly buy price, and employed rolling horizon vector h. For example at midnight c_{buy}=[3.1 3.1 3.1 3.1 6.2 6.2 12.4 17 21.6 20 27.6 29.2 23.2 18.6]^T. Here we assume $c_{sell} = 0$, i.e., there is no revenue generated from selling energy back to the grid.

The energy management problem is formulated and solved under joint uncertainty of electricity demand and prices. Two different approaches are proposed to model the variations of these uncertain parameters. The first one models the uncertainty in net demand and electricity prices by a multivariate Gaussian distribution around their predicted nominal values, while the second one models the uncertainty in electricity prices by a "Box+Polyhedral" uncertainty set. The simulations are performed over one winter month under different magnitudes of actual uncertainty in the demand as well as electricity costs.

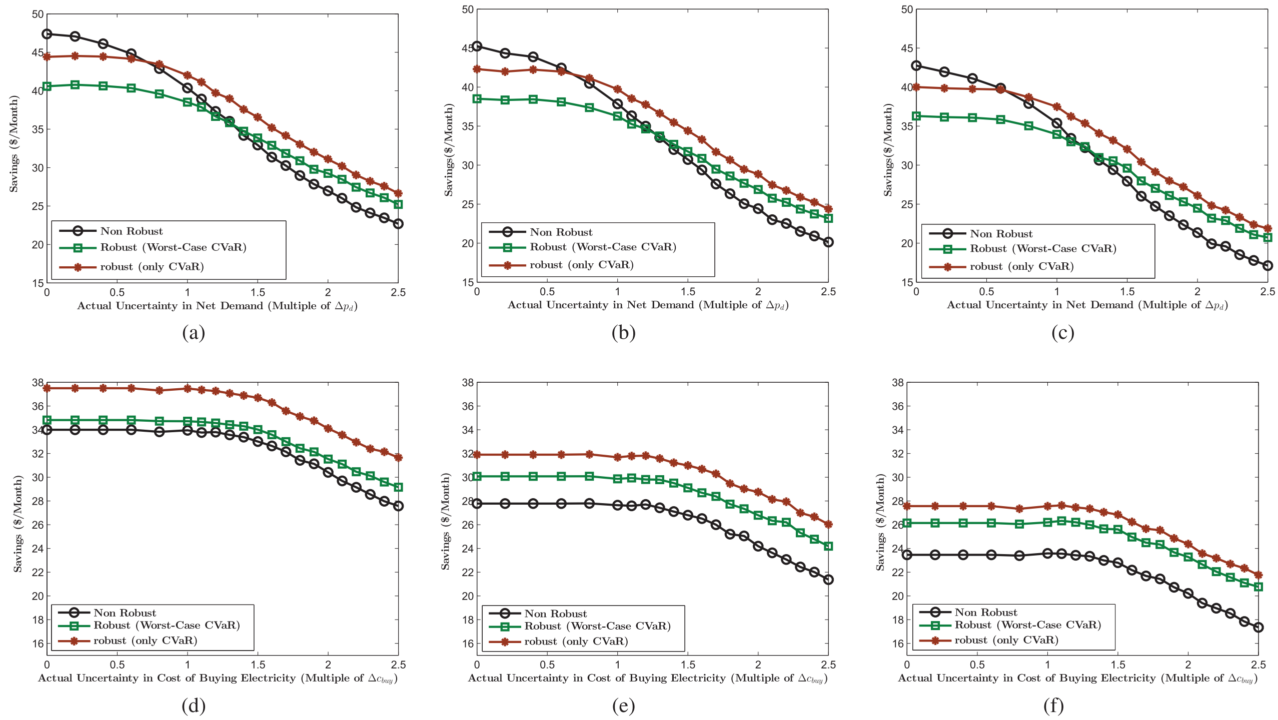

Fig. 2. Comparison of the robust controllers to their non-robust counterparts in the presence of uncertainty in both electricity prices and demand signal. Performance of the controllers is plotted as a function of actual uncertainty in demand in (a),(b) and (c) and actual uncertainty in buying price in (d), (e) and (f).

Performance of the proposed approaches are compared to their non-robust counterpart through a series of Monte-Carlo simulations in which the nominal data is perturbed by Gaussian noise and standard deviation of up to 2.5 times square root of the nominal values. It should be noted that the non-robust controller is the nominal MPC which makes decisions only based on the nominal values of electricity prices and demand. Matlab is used with IBM ILOG CPLEX MILP as optimization solver using an Intel(R) Core(TM) i7-3770 CPU and 32 GB RAM to solve the optimization problem.

A. Comparing the Performance of the Proposed Robust Approaches to Their Nonrobust Counterpart

The CVaR-based approach in (15) is employed in a rolling-horizon control framework to obtain optimal storage charge/discharge decisions when the net demand and electricity prices have joint Gaussian distribution around their predicted nominal values. The covariance matrix of multivariate normal distribution used to model the uncertainty in electricity prices and demand is given as

$$\Sigma \triangleq \begin{bmatrix} \Delta p_d^2 & \rho \Delta p_d \Delta c_{buy} \\ \rho \Delta p_d \Delta c_{buy} & \Delta c_{buy}^2 \end{bmatrix} \tag{39}$$

where $\Delta p_d, \Delta c_{buy}$ are defined as the square root of the nominal values of electricity demand and buy prices; ρ is the correlation ratio between the two uncertain parameters and is set to 0.5 in the simulations. In all simulations, CVaR parameter is $\beta = 0.9$. The worst-case CVaR method obtains the robust counterpart formulation of the problem by tuning the parameters of "Box+Polyhedral" uncertainty set, Ψ, and Γ to 1 and two times square root of N_h, respectively. The constant positive perturbations in modeling electricity buying price, i.e., $\hat{c}_{buy}$ is also set to square root of the nominal electricity buy price.

In the CVaR-based method, the sampling space consists of both electricity prices and net demand and sufficiently large number of samples must be generated to achieve a good approximation of the cost distribution. Note that the number of constraints in (15) is proportional to the number of generated samples, so the computational load of the algorithm is affected by this number. The data in Table (I) shows the impact of the number of samples on the optimization computation time per time-step as well as monthly cost reduction over the non-robust controller, for both CVaR-based and worst-case CVaR-based optimizers.

The average monthly savings obtained from $M = 1000$ Monte Carlo simulations are plotted as a function of different magnitudes of actual uncertainty in demand in Figure 2 (a,b,c) and actual uncertainty in costs in Figure 2 (d,e,f). Figures 2 (a,b,c) depict the monthly saving of the controllers at three different levels of uncertainty in cost of buying electricity, i.e., $1.5\Delta c_{buy}$, $2\Delta c_{buy}$, and $2.5\Delta c_{buy}$, respectively. The uncertainty levels are controlled by covariance matrix of the multivariate Gaussian noise generated to evaluate performance of the controllers. From these plots it is clear that, for the most part, the CVaR-based has the best performance followed by the worst-case CVaR controller, and the standard non-robust controller. A notable exception is in the case of small uncertainties in the net demand, where the non-robust controller outperforms the robust controllers. This anomaly is due to the fact that the average values of cost savings are plotted as opposed to the CVaR for the chosen β percentile, which is minimized in CVaR

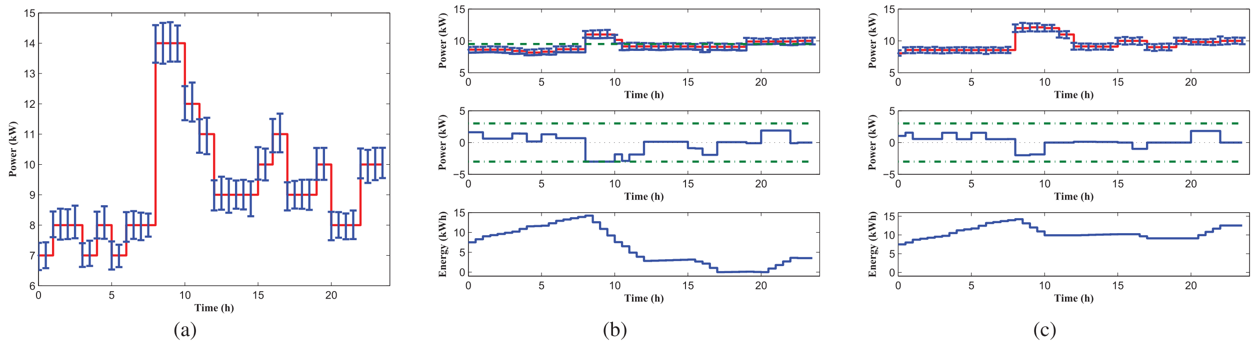

Fig. 3. Grid and battery signals with different sub-objectives (CVaR approach): a) net demand profile; grid power profile when battery charge/discharge commands are set to zero b) grid power profile with peak penalizing and smoothing sub objectives (top figure); battery power profile (middle figure); battery energy profile (bottom figure) c) grid power profile with grid flattening, smoothing, and battery usage sub objectives (top figure); battery power profile (middle figure); battery energy profile (bottom figure).

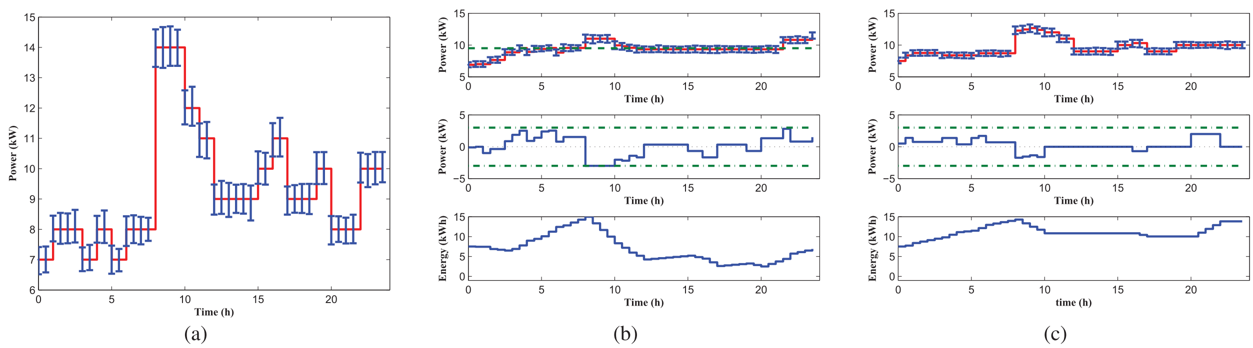

Fig. 4. Grid and battery signals with different sub-objectives (WCVaR approach): a) net demand profile; grid power profile when battery charge/discharge commands are set to zero b) grid power profile with peak penalizing and smoothing sub objectives (top figure); battery power profile (middle figure); battery energy profile (bottom figure) c) grid power profile with grid flattening, smoothing, and battery usage sub objectives (top figure); battery power profile (middle figure); battery energy profile (bottom figure).

optimization. Figures 2 (d,e,f) presents average monthly saving of the controllers at three different levels of uncertainty in net demand, i.e. $1.5\Delta p_d$, $2\Delta p_d$, and $2.5\Delta p_d$ in (d), (e), and (f), respectively. As expected, the CVaR-based controller and the non-robust controller have the best and worst performance, respectively.

B. *Grid and Battery Signals*

Figures 3 and 4 depict the grid and battery power signals associated with the proposed robust controllers under joint uncertainty of demand and electricity buy prices. The simulations are performed using the same commercial/residential setting as in the previous section but with different battery specifications, i.e., as following: $E_{bat}^{min} = 0kWh$, $E_{bat}^{max} = 15kWh$, $E_p = 7.5kWh$, $p_{bat}^{max} = 5kW$, $P_{bat}^{loss} = 0$, $\eta_c = 0.95$, and $\eta_d = 0.9$. The horizon vector employed, as well as electricity buy/sell prices are similar to those in the previous section. Figures 3 and 4 (a) represent the grid power profile without active presence of batteries. Then, the grid signal is smoothened with $c_{smg} = 0.1h$ along with penalizing peak demand with $c_{peak} = 1$ \$/kWh over a power baseline set to $p_g^{base} = 9.5kW$ and the controller attempts to keep the peak usage below that level. The grid signals associated with first and second proposed robust approaches are presented in Figures 3 and 4(b), respectively. Figures 3 and 4 (c) also demonstrate the flattening and smoothing of the grid signal with $c_{flat} = 0.1$ \$/kW and $c_{smg} = 0.1h$ \$/kW, respectively along with sub-objective of battery usage with $c_c = c_d = c_e = 0.1h$ \$/kW. Note that in all the plots uncertainty in electricity buy price is set to a certain level, i.e., $0.5\Delta c_{buy}$, and the blue lines in grid power profiles indicate upper and lower envelopes of the grid power with $N = 1000$ different realizations of demand signal within an uncertainty interval around the nominal values. It can be seen that penalizing batteries in both approaches lead to less battery activity and consequently to non-smoothness of the grid signal.

VI. Conclusion

A CVaR-based optimization algorithm for energy management problem of microgrids in the presence of uncertainty in electricity demand and prices was proposed in the paper. The uncertainties in these parameters are modeled with a multivariate Gaussian distribution around their predicted nominal values. The proposed method outperforms its non-robust counterpart by up to 25% in the monthly electricity savings. Furthermore, in order to reduce the computations of the proposed scenario-based approach, a worst-case CVaR formulation of the problem is developed. The latter speeds the optimization process up considerably, however compromises the performance because of conservatism associated with worst-case methods. Our simulation results indicate that not only the proposed methods improve the utilization of renewable energy production, but they also reduce the electricity cost by a considerable amount. Moreover, this is accompanied with achievement of utility-oriented goals including battery/grid signal shaping.

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