SLAC-PUB-17103

Optimal Subhourly Electricity Resource Dispatch Under Multiple Price Signals With High Renewable Generation Availability

David P. Chassin[1,2], Sahand Behboodi[2] and Ned Djilali[2]
[1] *SLAC National Accelerator Laboratory, Menlo Park CA (USA)*
[2] *Inst. for Integrated Energy Systems, and Mechanical Engineering Dept, University of Victoria, Victoria BC (Canada)*

Abstract

This paper proposes a system-wide optimal resource dispatch strategy that enables a shift from a primarily energy cost-based approach, to a strategy using simultaneous price signals for energy, power and ramping behavior. A formal method to compute the optimal sub-hourly power trajectory is derived for a system when the price of energy and ramping are both significant. Optimal control functions are obtained in both time and frequency domains, and a discrete-time solution suitable for periodic feedback control systems is presented. The method is applied to North America Western Interconnection for the planning year 2024, and it is shown that an optimal dispatch strategy that simultaneously considers both the cost of energy and the cost of ramping leads to significant cost savings in systems with high levels of renewable generation: the savings exceed 25% of the total system operating cost for a 50% renewables scenario.

Keywords: Electricity pricing, bulk electric system, optimal energy dispatch, optimal ramping, renewable integration, resource allocation

Highlights

- A method to minimize the cost of subhourly dispatch of bulk electric power systems.
- Dispatch based on simultaneous use of energy and ramping costs yields significant savings
- Savings from optimal dispatch increase as transmission constraints increase.
- Savings from optimal dispatch increase as variable generation increases.

1. Introduction

The growth of renewable electricity generation resources is driven in part by climate-change mitigation policies that seek to reduce the long-term societal costs of continued dependence on fossil-based electricity generation and meet growing electric system load using lower cost resources. However, each class of renewable generation comes with one or more disadvantages that can limit the degree to which they may be effectively integrated into bulk system operations.

Hydro-electric generation has long been employed as a significant renewable electric energy and ramping resource. But climate change may jeopardize the magnitude and certainty with which the existing assets can meet demand [1, 2]. Concerns about population displacement, habitat loss and fishery sustainability often limit the growth of new hydro-electric generation assets, placing additional constraints on new ramping response resources, such as requiring the use of additional reserves and ramping resources. Shifts in both load and hydro-electric generation potentially increase uncertainty in long term planning and further enhance the need for technological configurations that support operational flexibility [3].

Wind power has seen rapid growth, but concern about system reliability has limited the amount of wind generation that can be supported without additional planning and operational measures, such as committing more carbon-intensive firming resources [4]. Solar resources are also becoming increasingly available but the intermittency challenges are similar to those of wind. In addition, residential rooftop solar resources are challenging the classical utility revenue model [5], can cause voltage control issues in distribution systems [6], and in extreme cases can result in overgeneration [7]. Taken together these considerations have given rise to questions about the reliable, robust control and optimal operation of an increasingly complex bulk electricity system [8].

The conventional utility approach to addressing renewable generation variability is to allocate additional firm generation resources to replace all potentially non-firm renewables resources. These firm resources are typically fast-responding thermal fossil resources or hydro resources when and where available. For new renewable resources the impact of this approach is quantified as an intermittency factor, which discounts for instance the contribution of wind in addition to its capacity factor and limits the de-

This material is based upon work supported by the U.S. Department of Energy,
Office of Science, under Contract No. DE-AC02-76SF00515.

gree to which renewables can contribute to meeting peak demand [9]. However, the intermittency factor does not account for the ramping requirements created by potentially fast-changing renewable resources [10]. The need for fast-ramping resources discourages the dispatch of high-efficiency fossil and nuclear generation assets and can encourage reliance on low-efficiency fossil-fuel resources for regulation services and reserves [11].

One solution to overcoming the renewable generation variability at the bulk electric level is to tie together a number of electric control areas into a super-grid so that they can share generation and reserve units through optimal scheduling of system interties [12]. In an interconnected system, the combined power fluctuations are smaller than the sum of the variations in individual control areas. Furthermore, fast-acting energy storage systems and demand response programs can provide required ancillary services such as real-time power balancing [13] and frequency regulation [14] if they are equipped with suitable control mechanisms. A competitive market framework in which energy resources participate to sell and buy ancillary service products can accelerate the transition to a high-renewable scenario by supporting the long-term economic sustainability of flexible resources.

Concerns about the financial sustainability of utilities under high level of renewables are also beginning to arise. The question is particularly challenging when one seeks solutions that explicitly maximize social welfare rather than simply minimizing production cost [15]. The growth of low-marginal cost renewable resources can lead one to expect utility revenues to decline to the point where they can no longer recover their long term average costs. But this conclusion may be erroneous if one fails to consider both the impact of demand own-price elasticity, as well as the impact of load control automation on substitution elasticity. The latter type of demand response can significantly increase the total ramping resource on peak and decrease ramping resource scarcity. One option for replacing energy resource scarcity rent is increasing fixed payments. But this may lead to economic inefficiencies as well as an unraveling of the market-based mechanisms built so far. Another option is to enable payments based on ramping resource scarcity rent through existing markets for ancillary services. At the present time, the majority of resources continue to be dispatched based on the energy marginal cost merit order. But it is not unreasonable to consider how one might operate a system in which the energy price is near zero and resources are dispatched instead according the ramping cost merit order.

In the presence of high levels of variable generation, the scheduling problem is a co-optimization for allocating energy and ramping resources [16]. Under existing energy deregulation policies, there is usually a market in which energy producers compete to sell energy, and a separate market in which they compete to sell power ramping resources for flexibility. Producers get paid for their energy deliveries in the energy market and for power ramping flexibility in the flexibility market. But today's dual-pricing mechanism is dominated by the energy markets, which drives generation resources to secure revenue primarily in the energy market, and only deliver residual ramping resources in the flexibility market. Meanwhile poor access to energy markets leads loads and storage to seek participation primarily in the flexibility market while only revealing their elasticities to the energy market. This relegates loads and storage to only a marginal role in the overall operation of the system, which is the motivation for seeking policy solutions to improving their access to wholesale energy markets, such as FERC Orders 745 and 755.

1.1. Recent Work

Work to address the problem of integrating ramping behavior into electricity pricing mechanisms originated with efforts to minimize total production cost by dispatching generators subject to ramping constraints in addition to system capacity reserve constraints, fuel and emission constraints, network line flow limits [17]. If all costs are revealed to the system operator, as in a fully regulated system, then the optimal power flow solution satisfies all the constraints under a fixed demand assumption [18]. To address the problem of elastic demand, the developers of transactive control have relied on the fact that a solution can be found in a deregulated environment where entire cost functions are not revealed [19], provided only generation capacity, demand response capacity and line flow constraints are considered. The solutions demonstrated to date have not addressed ramping constraints or the cost of dispatching both supply and demand ramping resources.

Studies of the strategic use of ramping rates beyond the limits of a generator's self-dispatch in a power market illustrate the use of a set of ramping processes based on ramping-cost versus ramping time. The approach includes ramping costs for various levels of ramping rates that exceed the performance limit of the generators and showed that the benefit from the strategic use of ramp rates limits the supply capacity available for dispatch based solely on ramping prices [20].

The problem becomes more difficult when integrating renewable energy resources into the bulk power grid. System reliability requires that supply and demand remain balanced at all times. However, some distributed energy resources are more flexible than generators and can provide lower cost dispatch opportunities both in the day-ahead scheduling and the real-time dispatch. In spite of the availability of ramping resources being uncertain over time, the two-level scheduling problem can be solved in closed form, and when the resources are persistent the problem reduces to a standard Markov decision process that can be solved using standard techniques without recourse to explicit use of ramping prices from bulk energy markets [21].

Growing recognition of the problem with discovering and responding to ramp prices emerged with new insights into classical real-time pricing (RTP). The concept of the real-time ramping costs was derived from an extended form of RTP that achieves the optimal rate of change in quantity demanded by explicitly taking the ramping costs into account [22]. Using this approach, the energy price is reduced during the onset of a high ramp, and then raised toward the end of th period. This results is a more controlled ramp rate with associated reliability benefits. The use of a single RTP energy price to capture the ramp costs also ensures that the optimal response is achieved by allocating both generation and demand response resources efficiently.

To address the problem of ramping resource shortages and associated ramping cost volatility. The current ISO practice is to pay for these resources as increased reserve margin, withholding supply capacity and/or offsetting the forecast load, scheduling additional fast-start supply units, scheduling must-run units, and sometimes using multi-interval dispatch in the real-time markets. But these can distort energy markets and may not fully remedy the problem. The solution appears to lie with a market model that discovers the ramp price independently of the energy and capacity prices [23]. The following key features of this market model have been identified:

- Ramping requirements are specified to meet forecasted and uncertain variability within a defined response time.
- Resource contributions to ramping include allowances for availability offers and contributions from offline units if desired.
- Ramp capability demand curves model the value of meeting the desired level variability coverage.
- Prices for up- and down-ramping products provide market transparency and market-based incentives.
- Simultaneous cooptimization of the ramp capability with energy and ancillary services.

The general conclusion from this is that ancillary markets must change to consider the scarcity rent on ramping resources [24]. The addition of an explicit and independent ramping resource scarcity price provides an opportunity to consider new resource dispatch strategies that can facilitate economically efficient tracking of hourly import/export energy schedules by individual control area within an ISO territory while continuing to maintain high system reliability and robust frequency regulation.

Most recently the use of local markets was proposed so distribution system operators can maintain the stability and security of the distribution network at minimum cost using the flexibility of customer resources such as on-site generation, storage devices, and electric vehicles. These local markets can act like transactive systems for ramping resources and clear the local flexibility bids in the wholesale market [25].

Moreover, the aggregation of demand-side flexibility services is regarded as necessary to allow small customers to deliver resources in both transmission and distribution networks. Aggregators need to obtain local flexibility services using local retail markets for distribution. This creates a potentially valuable opportunity to export excess resources to the wholesale market. However, technical and regulatory barriers to the development of such retail aggregators persist, including a lack of smart resource metering, unsuitable markets conditions such as minimum bidding volume and bid durations, market entry barriers, lack of resource performance criteria, and the absences of local flexibility markets [26].

Mixed integer linear programming problems for aggregators can be solved to manage and bid flexibility services from the point of view of an aggregator that control a portfolio of commercial and industrial flexilibity resources [27]. An effective method for generalized modeling and control of aggregated residential resources is also available using a Nash bargaining coordination strategy. This approach is based on the virtual battery model that can be used to aggregate thermostatic loads, energy storage, residential pool pumps, and electric vehicles [28]. Using these methods, aggregators can optimize any number of objectives such as start/stop times, expected revenues, duration, or peak power [29]. Voltage control, congestion management, network capacity, loss reduction, increased hosting capacity and reduced distributed/renewable generation curtailment have also been identified as important opportunities where joint flexibility from demand and generation can result in tangible benefits for distribution system operators [30].

1.2. Contribution

The existing literature reveals a wide range of outstanding problems and issues. The problem we are motivated to address in this paper focuses the detemination of what production or consumption profile operators, aggregators and resources should choose to maximize their own benefit given that ramping may be priced separately from energy and capacity in the near future, and that sometimes the ramping price may contribute more to the long-term average cost of electricity than energy or capacity. This question remains open and its answer seems likely to be relevant at every level of system operation below the ISO itself, i.e., where control area operator, aggregators and retailers have the ability to set dispatch levels in a profit/utility maximizing way.

Consequently, this paper presents a novel optimal resource dispatch strategy that enables a progressive shift from primarily energy cost-based approach to primarily ramping cost-based one. This optimal dispatch answers the question of what power schedule to follow during each hour as a function of the marginal prices of energy, power and ramping over the hour[1]. The main contributions of

[1] We define the marginal price of a product or service as the change in its price when the quantity produced or delivered is increased by one unit.

this paper are (1) the derivation of the formal method to compute the optimal sub-hourly power trajectory for a system when the cost of energy and ramping are both of the same order, (2) the development of an optimal resource allocation strategy based on this optimal trajectory, and (3) a simulation method to evaluate the cost savings of choosing the optimal trajectory over the conventional sub-hourly dispatch used in today's system operation.

In Section 2 we develop the optimal control function in both time and frequency domains. In the case of the frequency domain optimal control function the solution is presented as a continuous function. A discrete-time solution suitable for periodic feedback control systems is presented in Section 3. In Section 4 we examine the performance of this optimal dispatch solution in terms of varying prices for a given "typical" hour and in Section 5, we analyze the cost savings in an interconnection that models the Western Electric Coordinating Council (WECC) system for the year 2024 under both low (13%) and high (50%) renewable generation scenarios. Finally, in Section 6 we discuss some of the consequences that appear to arise from this new paradigm and our perspectives on possible future research on this topic.

2. Methodology

Consider a utility's cost minimization problem over a time interval T. The utility's customers purchase their net energy use $E(T)$ at a pre-determined retail price. So in today's systems, profit maximization and cost minimization are essentially the same problem. For each hour the utility pays for energy delivered at a real-time locationally-dependent wholesale price that is also dependent on demand under typical deregulated nodal pricing markets. The utility's scheduled energy use is forecast for each hour based on their customers' expected net energy use, which is then used to compute the utility's net load over that hour. We assume that over any interval T the utility may incur additional costs for any deviation in actual net load from the scheduled load.

The price function at the operating point is split up into the marginal price of energy $a = \frac{\partial P}{\partial Q}$ (measured in \$/MW^2·h), the marginal price of power $b = \frac{\partial R}{\partial Q}$ (measured in \$/MW^2), and the marginal price of ramping $c = \frac{\partial R}{\partial \dot{Q}}$ (measured in \$·h/MW^2). In order to reflect resource scarcity all cost functions are assumed to be quadratic so that the price function for each is linear as shown in Fig. 1. The marginal prices a and b determine prices as a function of the power demand Q, and the marginal price c determines prices based on the ramp rates $\dot{Q}$. The cost parameters arise from the schedule and may vary from hour to hour, but do not change within any given hour. Any of the marginal prices may be zero or positive depending on the market design and prevailing conditions in the system. For the purposes of this paper, we will assume that they cannot be negative.

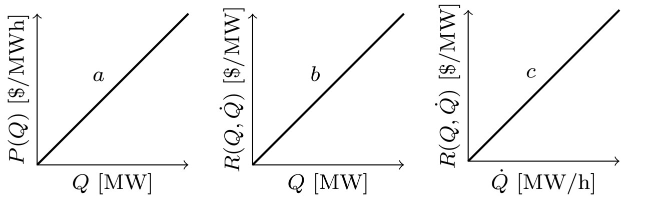

Fig. 1: Energy price (left) and ramp price (center and right) functions.

Over the time interval T the total cost of both the power trajectory $Q(t)$ and the ramping trajectory $\dot{Q}(t)$ given the power price $P(t) = aQ(t)$ and ramp price $R(t) = bQ(t) + c\dot{Q}(t)$, respectively, is given by

$$C(T) = \int_0^T P[Q(t)]Q(t) + R[Q(t), \dot{Q}(t)]\dot{Q}(t)dt. \tag{1}$$

Given the dispatch from $Q(0)$ to $Q(T)$ and the scheduled energy use $E(T) = \int_0^T Q(t)dt$ we augment the cost function with the Lagrange multiplier λ so that we have

$$\int_0^T a(Q - Q_z)Q + b(Q - Q_z)|\dot{Q}| + c\dot{Q}^2 + \lambda Q \; dt \tag{2}$$

$$= \int_0^T G(t, Q, \dot{Q})dt, \tag{3}$$

where the $|\dot{Q}|$ represents the magnitude of the ramp rate $\dot{Q}$, and Q_Z is the amount of must-take generation having zero or effectively zero marginal energy cost. Then the optimal dispatch trajectory $Q(t)$ is the critical function obtained by solving the Euler-Lagrange equation

$$\frac{\partial G}{\partial Q} - \frac{d}{dt}\frac{\partial G}{\partial \dot{Q}} = 0. \tag{4}$$

From this we form a second-order ordinary differential equation describing the critical load trajectory

$$\ddot{Q} - \frac{a}{c}Q = \frac{\mu}{2c}. \tag{5}$$

where $\mu = \lambda - aQ_Z$. Using the Laplace transform we find the critical system response in s-domain is

$$\hat{Q}(s) = \frac{Q_0 s^2 + \dot{Q}_0 s + \frac{\mu}{2c}}{s(s^2 - \omega^2)}, \tag{6}$$

where $\omega^2 = \frac{a}{c}$. The general time-domain solution for the critical function over the interval $0 \leq t < T$ is

$$Q(t) = \left(Q_0 + \frac{\mu}{2a}\right)\cosh \omega t + \frac{\dot{Q}_0}{\omega}\sinh \omega t - \frac{\mu}{2a}, \tag{7}$$

where Q_0 and $\dot{Q}_0$ are initial power and ramp values.

We can determine whether this solution is an extremum by computing the second variation

$$\frac{\partial^2 C}{\partial Q^2}(T) = \int_0^T [\alpha(v)^2 + 2\beta(vv') + \gamma(v')^2]dt \tag{8}$$

$$= \int_0^T H(t)dt, \tag{9}$$

with $H(t) > 0$ for all $v \neq 0$ subject to $v(0) = 0 = v(T)$. We then have

$$\alpha = \frac{\partial^2 G}{\partial Q^2} = 2a, \quad \beta = \frac{\partial^2 G}{\partial Q \partial \dot{Q}} = b, \quad \gamma = \frac{\partial^2 G}{\partial \dot{Q}^2} = 2c. \tag{10}$$

Thus for all $a, b, c > 0$, $H(t) > 0$ and $Q(t)$ is a minimizer. Since the only physical meaningful non-zero values of a and c are positive, this is satisfactory. We will examine cases when a and c are zero separately. Note that when $\dot{Q} < 0$, we have $b < 0$, so that the sign of b does not affect the general solution.

Given the constraints $\int_0^T Q(t)dt = E_T$ and $Q(T) = Q_T$, which come from the hour-ahead schedule, we obtain the solution for μ and $\dot{Q}_0$ for the case where $a, c > 0$:

$$\begin{bmatrix} \mu \\ \dot{Q}_0 \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} \begin{bmatrix} E_\Delta \\ Q_\Delta \end{bmatrix}, \tag{11}$$

where

$$A = \frac{\sinh \omega T - \omega T}{2a\omega} \qquad B = \frac{\cosh \omega T - 1}{\omega^2} \tag{12}$$

$$C = \frac{\cosh \omega T - 1}{2a} \qquad D = \frac{\sinh \omega T}{\omega} \tag{13}$$

$$E_\Delta = E_T - \frac{\sinh \omega T}{\omega} Q_0 \quad Q_\Delta = Q_T - Q_0 \cosh \omega T. \tag{14}$$

When $a = 0$, the cost of energy is zero and only the ramping cost is considered. Then the time-domain solution is

$$Q(t) = \frac{\mu}{4c} t^2 + \dot{Q}_0 t + Q_0, \tag{15}$$

with

$$A = \frac{T^3}{12c} \qquad B = \frac{T^2}{2} \tag{16}$$

$$C = \frac{T^2}{4c} \qquad D = T \tag{17}$$

$$E_\Delta = E_T - Q_0 T \qquad Q_\Delta = Q_T - Q_0, \tag{18}$$

which gives the critical response in s-domain

$$\hat{Q}(s) = \frac{\mu}{4cs^3} + \frac{\dot{Q}_0}{s^2} + \frac{Q_0}{s}. \tag{19}$$

When $c = 0$, there is no scarcity for ramping so that the ramping price is based only on the marginal energy cost of additional units that are dispatched. Then we have the time-domain solution

$$Q(t) = -\frac{\mu}{2a}, \tag{20}$$

with

$$\mu = -\frac{2aE_T}{T}. \tag{21}$$

This gives the critical response is s-domain

$$\hat{Q}(s) = -\frac{\mu}{2as}, \tag{22}$$

and the initial and final ramps from $Q(0)$ to $-\frac{\mu}{2a}$ and from $-\frac{\mu}{2a}$ to $Q(T)$ are limited by the ramping limits of the responding units.

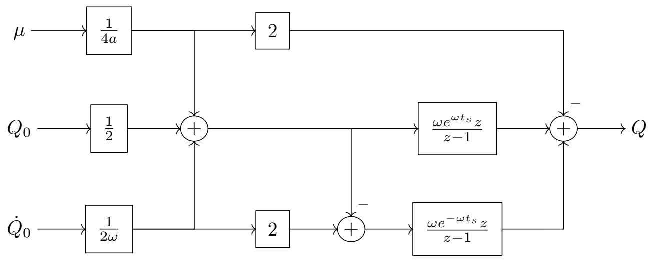

Fig. 2: Optimal dispatch controller with discrete update time t_s.

3. Optimal Dispatch Controller

The partial fraction expansion of Eq. 6 is

$$\frac{K_1}{s+\omega} + \frac{K_2}{s} + \frac{K_3}{s-\omega}, \tag{23}$$

where $K_1 = \frac{Q_0}{2} - \frac{\dot{Q}_0}{2\omega} + \frac{\mu}{4a}$, $K_2 = -\frac{\mu}{2a}$, and $K_3 = \frac{Q_0}{2} + \frac{\dot{Q}_0}{2\omega} + \frac{\mu}{4a}$, with the values of the parameters are computed from Eq. 11.

The initial response of the optimal controller is dominated by the forward-time solution

$$K_1 \, e^{-\omega t} = \mathcal{L}^{-1} \left[\frac{\frac{Q_0}{2} - \frac{\dot{Q}_0}{2\omega} + \frac{\mu}{4a}}{s+\omega} \right](s), \tag{24}$$

which handles the transition from the initial system load Q_0 to the scheduled load $Q_E = -\frac{\mu}{2as}$. The central response is dominated by the scheduled load solution

$$K_2 = \mathcal{L}^{-1} \left[-\frac{\mu}{2as} \right](s). \tag{25}$$

Finally, the terminal response is dominated by the reverse-time solution

$$K_3 \, e^{\omega t} = \mathcal{L}^{-1} \left[\frac{\frac{Q_0}{2} + \frac{\dot{Q}_0}{2\omega} + \frac{\mu}{4a}}{s-\omega} \right](s), \tag{26}$$

which handles the transition from the scheduled load to the terminal load Q_T. A discrete-time controller that implements the solution of Eq. 23 is shown in Figure 2. The controller implements the three main components to the optimal solution with step inputs μ, Q_0, and $\dot{Q}_0$. Note that the marginal prices a, b and c for the entire hour are constants in the controller blocks, which makes the controller design linear time-invariant within each hour, but time-variant over multiple hours. The discrete-time solution is then

$$Q^*(k) = \begin{cases} K_1 \tau^k + K_2 + K_3 \tau^{-k} & : a > 0, c > 0 \\ \frac{\mu}{4c} t_s^2 k^2 + \dot{Q}_0 t_s k + Q_0 & : a = 0, c > 0 \\ -\frac{\mu}{2a} & : a > 0, c = 0 \end{cases} \tag{27}$$

where $\tau = e^{\omega t_s}$.

The discrete-time dispatch control is illustrated in Figure 3 for various values of $\omega = \sqrt{a/c}$ with discrete sampling time $t_s = 5$ minutes. When the value of ω is large,

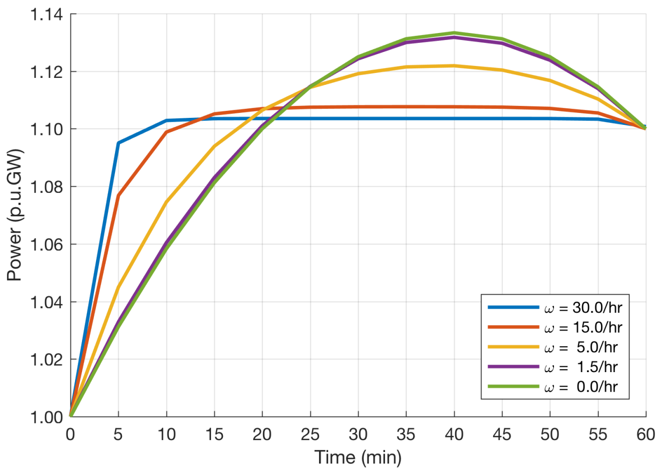

Fig. 3: Optimal discrete time control for various energy-to-ramp price ratios, ω.

the optimal dispatch is dominated by the energy cost and the cost of high ramp rates is negligible compared to the energy cost. The result is a dispatch that moves as quickly as possible to scheduled load Q_E. In the limit of zero ramping cost, the optimal response is a step function[2]. As the cost of ramping increases relative to the energy cost, the optimal dispatch begins to reduce the ramp rate while still following a trajectory that satisfies the hourly energy delivery requirement. In the limit of zero energy cost, the optimal dispatch trajectory is parabolic.

4. Performance Evaluation

In this section we develop the cost performance metric of the optimal dispatch control design. The optimal dispatch cost function is found by evaluating Equation 1 using Equations 7, 15 and 20. Thus when $a, b, c > 0$ we have[3]

$$
\begin{aligned}
C(T) = {} & \frac{\sinh 2\omega T}{2\omega}\left[a(A^2+B^2)+bAB\omega\right] && (28)\\
& + \frac{\sinh^2 \omega T}{2\omega}\left[b(A^2+B^2)\omega+4aAB\right] && (29)\\
& + \frac{\cosh \omega T - 1}{\omega}[(bA\omega+2aB)C-(aB+bA\omega)Q_z] && (30)\\
& + \frac{\sinh \omega T}{\omega}[(bB\omega+2aA)C-(aA+bB\omega)Q_z] && (31)\\
& + \left[aC^2 - aCQ_z\right]T. && (32)
\end{aligned}
$$

[2] Step responses are only possible by generation or load tripping, which is not considered as part of the conventional control strategy.

[3] Note that if the ramp rate $\dot{Q}$ changes sign at the time $t_c = \frac{1}{\omega}\tanh^{-1}(-\frac{B}{A})$ and $0 < t_c < T$, then we must divide the cost integral into two parts to account for the absolute value of $\dot{Q}$ on b terms.

where $A = Q_0 + \mu/2a$, $B = \dot{Q}_0/\omega$ and $C = -\mu/2a$. For the case when $a = 0$ we have

$$
\begin{aligned}
C(T) = {} & \tfrac{1}{2}bA^2T^4 + [bB + \tfrac{4}{3}cA]AT^3 && (33)\\
& + [\tfrac{1}{2}b(B^2+2AC) + 2cAB - bAQ_z]T^2 && (34)\\
& + [(bC+cB)B - bBQ_z]T, && (35)
\end{aligned}
$$

where $A = \mu/4c$, $B = \dot{Q}_0$, and $C = Q_0$. When $c = 0$ we have

$$
C(T) = aE_T\left(\frac{E_T}{T} - Q_z\right). \qquad (36)
$$

We use as the base case a conventional unit dispatch strategy that requires generators ramp to their new operating point during the 20 minutes spanning the top of the hour. Accordingly the generators begin ramping 10 minutes before the hour and end ramping 10 minutes after the hour. In the aggregate for a given hour this strategy is illustrated in Figure 4 where

$$
Q_E = \frac{6}{5}\left(E_T - \frac{Q_0+Q_T}{12}\right), \qquad (37)
$$

with the initial and terminal ramp rates

$$
\dot{Q}_0 = 6(Q_E - Q_0) \qquad \text{and} \qquad \dot{Q}_T = 6(Q_T - Q_E). \quad (38)
$$

Three cases are shown for production errors that can arise from renewable, load and demand response forecasting errors. Shown are the dispatch profiles needed to compensate for past under-production (red), no past production error (black), and past over-production error (blue) that must be compensated for in the current dispatch.

The cost of the base case is then

$$
\begin{aligned}
C_{base}(T) = {} & \tfrac{aT}{18}(Q_T^2 + Q_TQ_E + 14Q_E^2 + Q_EQ_0 + Q_0^2) && (39)\\
& - \tfrac{aT}{12}(Q_T + 10Q_E + Q_0)Q_z && (40)\\
& + |\tfrac{b}{2}(Q_E - Q_0)|(Q_E + Q_0 - 2Q_z) && (41)\\
& + |\tfrac{b}{2}(Q_T - Q_E)|(Q_T + Q_E - 2Q_z) && (42)\\
& + \tfrac{6c}{T}(Q_T^2 - 2Q_TQ_E + 2Q_E^2 - 2Q_0Q_E + Q_0^2). && (43)
\end{aligned}
$$

The zero-order hold ramp discrete form of Equation 1 gives us the cost of operating with a discrete control timestep t_s, i.e.,

$$
\begin{aligned}
C^*(T) = {} & \sum_{k=0}^{T/t_s}\left(P^*[Q^*(k)]Q^*(k) + R^*[Q^*(k),\dot{Q}^*(k)]\dot{Q}^*(k)\right)t_s && (44)\\
= {} & \sum_{k=0}^{T/t_s}\tfrac{at_s}{4}\Big[Q^*(k)^2 + 2Q^*(k)\dot{Q}^*(k) && (45)\\
& \qquad + \dot{Q}^*(k)^2 - 2Q_z[Q^*(k)+\dot{Q}^*(k)]\Big] && (46)\\
& + \tfrac{1}{2}\left[\left|b(\dot{Q}^*(k) - Q^*(k))\right|(\dot{Q}^*(k) + Q^*(k) - 2Q_z\right] && (47)\\
& + \tfrac{c}{t_s}\left[Q^*(k)^2 - 2Q^*(k)\dot{Q}^*(k) + \dot{Q}^*(k)^2\right] && (48)
\end{aligned}
$$

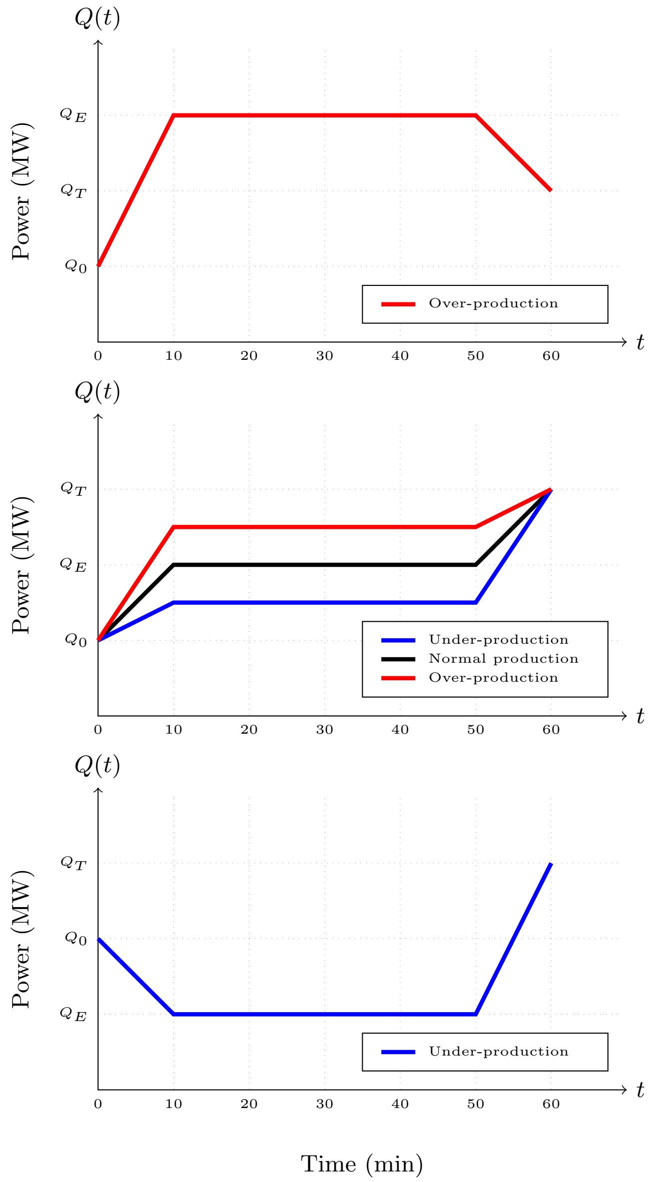

Fig. 4: Base-case dispatch for large under-production (top), small production (center), and large over-production (bottom) errors.

where $Q^*(k) = Q(kt_s)$ and $\dot{Q}^*(k) = Q^*(k+1)$. We evaluate the performance of the control strategy for different control update rates t_s using two future scenarios, one for low renewables where $\omega > 1$, and one for high renewables where $\omega < 1$ for both unconstrained and constrained transmission operating conditions.

5. Case Study: WECC 2024

In this section we examine the cost savings associated with using the optimal control solution on the WECC 2024 base case model introduced in [12]. The WECC 2024 model is a 20-area base case used by WECC for planning studies. The 20-area model combines a number of smaller control areas based on the anticipated intertie transfer limits reported in the WECC 2024 common case [31]. In this model constraints within control areas are ignored, while internal losses are approximated. The peak load, annual energy production and demand consumption are forecast, including intermittent wind, solar, and run-of-river hydro for the entire year.

The model also includes a hypothetical market for each consolidated control area, with a flat zero-cost supply curve for all renewable and must-take generation resources and a constant positive supply curve slope for all dispatchable units. The hourly generation of intermittent resources is provided by the base case model and incorporated into the supply curve so that there is effectively no marginal cost of production for renewable energy and must take generation. All generating units are paid the hourly clearing price, and when the marginal energy price in a control area is zero then renewable generation may be curtailed. As a result, under the high renewable scenario, zero energy prices are commonplace and renewable generation is curtailed more frequently. Demand response is similarly considered for each control area and the output of this scheduling model provides the hourly nodal prices required to satisfy the transmission constraints, if any.

The low renewables case is the WECC forecast for the year 2024, which correspond to 29.5 GW (16.1%) of renewable capacity and 117.8 GW (63.5%) of annual renewable generation. The high renewables case is given as 400% of capacity of the WECC forecast for the year 2024, which corresponds to 117.8 GW (63.5%) and 523.9 TWh (49.6%) respectively. The blended energy price of operations is \$130.6/MWh and \$50.2/MWh for the low and high renewables cases, respectively.

The ramping price was not considered in the WECC 2024 base case model. For this study we have assumed that the ramping energy cost is based on the marginal energy cost for the dispatchable generation and the demand response, as well as the cost of changing the dispatchable generation output, as shown in Table 1. In both cases, the marginal price of power b is the average marginal price of energy a over the hour. In the low renewables case the marginal price of ramping c is the marginal price of power b multiplied by 12 seconds. In the high renewables case, c is the marginal price of power b multiplied by 49 hours. The value of ω is approximately 121 times greater in the low renewable case than it is in the high renewable case. Note that a is zero when renewables are curtailed while b is assumed to also be zero because curtailed renewables and demand response are presumed to be dispatchable.

The values of the ramping response constant c were also selected such that the overall cost of operating the system remains more or less constant when going from the low to high renewables scenarios under the base case. This allows us to evaluate the impact of the optimal control strategy without involving the question of revenue adequacy under the high renewables scenario. Given that there are few markets from which to determine these values, we must

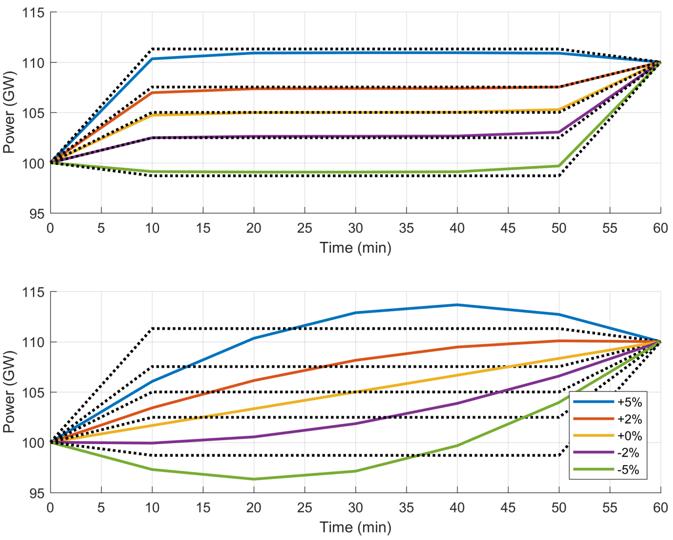

Fig. 5: Optimal dispatch for low (top) and high (bottom) renewable scenarios for various production errors.

be satisfied with this assumption for now.

The statistical nature of the intermittency and load forecast errors and their connection to load following and regulation was studied at length in [32]. The authors showed that consolidated control of WECC could yield both cost savings and performance improvements. In particular, the study showed that with high accuracy control 1% standard deviation in load forecast was expected, with 0% real-time mean error at 0.15% standard deviation at peak load. However, for the purposes of a preliminary study like the one presented in this paper, we will consider the scheduling error to be Gaussian with a mean error of 0 MW and a standard deviation of 100 MW. We believe that energy and flexibility markets should be efficient enough to remove all systematic error from the price signals leaving only the random noise that is satisfactorily modeled by Gaussian noise.

The comparison of the conventional and optimal dispatch for a typical case is shown in Figure 5. The conventional control strategy is shown in dotted lines, with the 10 minute optimal-dispatch trajectory shown as solid lines. Note that the ramp rate is constant between discrete control updates. The evaluation is completed with the marginal prices and marginal costs at 100 GW, as shown in Table 1. The dispatch changes according to a varying energy production error remaining at the end of the previous dispatch interval. These production errors typically arise from renewable, load, and demand response forecasting errors and the results show how these errors can be corrected by optimal redispatch during the upcoming interval, regardless of the previous production schedule. A -5% error represents an accrued energy deficit of 5 GWh for a 105 GWh schedule, while a $+5\%$ error represents an energy surplus of 5 GWh.

The marginal prices in Table 1 are chosen to satisfy the following conditions:

Table 1: Marginal prices and marginal costs cases in Figure 5.

Variable	Base case	Study case	Units
Marginal prices:			
a	1.27×10^{-3}	6.34×10^{-4}	\$/MW^2·h
b	1.27×10^{-3}	6.34×10^{-4}	\$/MW^2
c	4.23×10^{-6}	3.09×10^{-2}	\$·h/MW^2
Marginal costs:			
P	133.09	66.55	\$/MW·h
R	133.13	375.19	\$/MW
ω	17.3	0.1433	h^{-1}

1. The system operating cost is roughly \$100/MWh at a system load of 100 GW.
2. For the low renewables case, the energy cost is roughly 10 times the ramping cost, while for the high renewables case the ramping cost is roughly 10 times the energy cost for the nominal schedule. This was necessary to ensure that costs were the same for both cases.
3. The marginal power price b for both cases is equal to the marginal energy price a of the respective case.

We considered the performance degradation resulting from longer dispatch intervals by evaluating the performance using 5 minute updates, 1 minute updates, and 4 second discrete control timesteps but found no appreciable difference in the economic performance. The results shown in Table 2 are shown for the 5 minute dispatch interval. The output of the presented discrete control method is a load profile that does not necessarily lead to the scheduled hourly energy, because the load trajectory over each time intervals (which is linear) is slightly different from the optimal load trajectory (that often has a curvature). One approach to deal with this energy deficiency is to use a higher time resolution, so that the trajectories lay on each other more precisely. Another approach is to adjust the targeted load such that it delivers the scheduled energy over each time interval. In this case, the discrete control load is not necessarily equal to the optimal load.

Generally at low levels of renewables savings are not possible using the optimal control strategy. The cost savings observed in the extreme low renewables dispatch cases in Table 2 are due to the fact that discrete dispatch control follows the optimal trajectory sampling every t_s seconds. This dispatch error can result in small over or underproduction depending on the degree of asymmetry in the optimal trajectory.

At higher levels of renewables the savings are potentially more significant. In addition, the savings are maximum when dispatch tracks the original schedule, which suggests that there may be a strong economic incentive to avoid carrying over energy tracking error from one schedule interval to the next.

Table 2: Single hour cost savings under low and high renewable for a case shown in Figure 5.

Dispatch Energy (GWh)	Reference Cost Energy ($M)	Ramp ($M)	Total ($M)	Price ($/MWh)	Optimal Cost Energy ($M)	Ramp ($M)	Total ($M)	Price ($/MWh)	Cost Savings ($M/h)	(%)	Dispatch Error (%)
Low renewable scenario											
110.3	10.8	1.2	12.0	108.62	10.8	1.1	11.9	107.93	0.1	0.6	-0.8
107.1	10.1	0.9	11.0	102.50	10.1	0.9	11.0	102.50	0.0	0.0	-0.4
105.0	9.6	0.9	10.5	100.00	9.6	0.9	10.5	99.98	0.0	0.0	0.0
102.9	9.1	0.9	10.0	97.53	9.1	0.9	10.0	97.51	0.0	0.0	0.4
99.8	8.4	1.1	9.6	96.06	8.4	1.1	9.5	95.42	0.1	0.7	0.9
High renewable scenario											
110.3	1.6	24.1	25.7	232.77	1.6	13.5	15.1	136.75	10.6	41.3	-2.0
107.1	1.3	11.7	13.0	121.55	1.3	4.8	6.1	57.27	6.9	52.9	-0.8
105.0	1.1	9.4	10.5	100.00	1.1	3.2	4.3	41.25	6.2	58.8	-0.0
102.9	1.0	11.7	12.7	123.35	1.0	4.8	5.8	56.43	6.9	54.2	-0.7
99.8	0.7	24.1	24.8	248.95	0.8	13.4	14.2	142.37	10.6	42.8	-1.9

Table 3: WECC 2024 cost savings from optimal dispatch under different transmission constraint and renewable scenarios.

Scenario Model	Cost Base case ($B/y)	Optimal ($B/y)	Savings ($B/y)
Unconstrained:			
Low	126.0	125.9	0.16 (0.1%)
High	108.6	77.8	30.85 (28.4%)
Constrained:			
Low	184.4	184.1	0.26 (0.1%)
High	388.3	231.2	157.12 (40.5%)

Table 4: Energy and price impacts of optimal dispatch for the WECC 2024 base case.

Scenario Model	Total Energy (TWh)	Price Base case ($/MWh)	Optimal ($/MWh)
Unconstrained:			
Low	1054.6	119.5	119.35 (-0.1%)
High	1067.2	101.8	67.29 (-51.2%)
Constrained:			
Low	1054.5	174.8	174.55 (-0.2%)
High	1055.7	367.8	87.96 (-318.2%)

The interconnetion-wide scheduling solution in [12] includes a 20-area constrained solution. The hourly energy prices for each area are computed considering both supply and demand energy price elasticities. The energy prices are computed for the interconnection-wide surplus-maximizing schedule over the entire year. The marginal power price is the price of energy for the schedule hour. The marginal price of ramping is 1/300 marginal price of power in the low renewable case, and 49 times the marginal price of power in the high renewable case. The costs, savings and price impact of using this scheduling solution

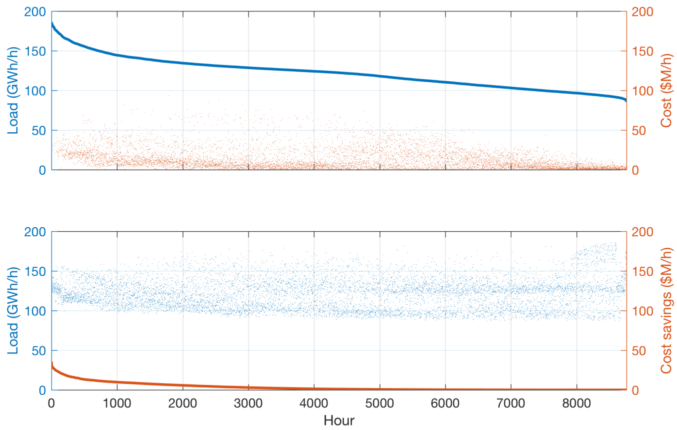

Fig. 6: WECC 2024 unconstrained load (top) and cost savings (bottom) duration curves.

compared to the base case are presented in Tables 3 and 4. The unconstrained solution is evidently less costly because the combined system-wide fluctuations are smaller than the sum of the individual of the variations in each balancing authority.

The WECC 2024 system-wide load and savings duration curves[4] are shown in Figures 6 and 7 for the constrained and unconstrained cases, respectively. The load duration (top) and optimal dispatch savings duration (bottom) using discrete optimal control at 5-minute dispatch rate are shown with scatter plots for the corresponding cost (red) and load (blue) values for the durations curves shown. The potential savings are very significant for all scenarios, with the highest savings being found when high levels of renewable resources are available. The savings

[4]A duration curve shows the number of hours per year that a time-series quantity is above a particular value. It is obtained by sorting the time-series data in descending order of magnitude and plotting the resulting monotonically descending curve.

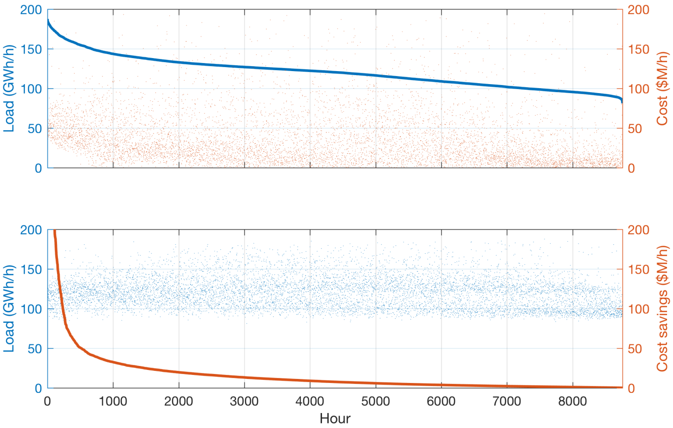

Fig. 7: WECC 2024 constrained duration curves for load (top) and cost savings (bottom).

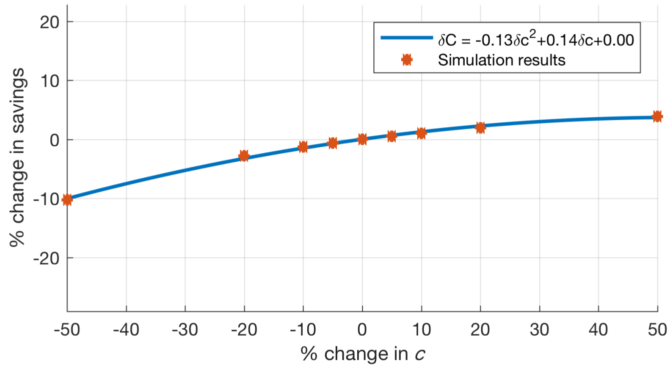

Fig. 8: Sensitivity of savings to marginal price of ramping resources.

when more transmission constraints are active are augmented considerably with respect to unconstrained system conditions.

6. Discussion

The significance of the results shown in Figure 3 cannot be understated. First we observe that when $a >> c$, the optimal response is very similar to the conventional dispatch strategy, giving us some assurance that today's operations are very nearly optimal. However, when $a << c$ today's hourly dispatch strategy is not optimal. As the fraction of cost attributed to energy decreases relative to the cost attributed to ramping, we see that ω decreases and the value of changing the dispatch strategy increases dramatically. In the limit of a very high renewable scenario the savings achievable using the optimal dispatch strategy can be extremely significant. Failure to adopt an optimal dispatch such as the one proposed could result in major and likely unnecessary costs. Utilities will inevitably find it necessary to mitigating these costs, either by reducing the amount of renewables, by increasing the revenues from their customers, or by developing some kind of optimal resource allocation strategy such as the one proposed.

A sensitivity analysis of the savings as a function of the marginal price of ramping c shows that the savings are not overly sensitive to changes in our assumption of the cost of ramping scarcity. Figure 8 shows that for a 50% decrease in c, we observe a 10.3% decrease in savings, while a 50% increase in c results in a 3.9% increase in savings. This suggests that the savings from employing the optimal dispatch strategy is quite robust to our uncertainty about the marginal price of ramping resources.

In any financially sustainable future scenario, we must consider how the long-term average costs and fixed costs are recovered under the pricing mechanism. We have assumed in this study that renewable generation and utilities cannot sustainably continue employing complex power purchasing agreements and subsidies to hedge against energy price volatility. Instead all parties should come to rely on separate real-time pricing mechanisms for energy, power and ramping response of the resources they control.

Shifting revenue from resource allocation mechanisms based primarily on energy resource scarcity to ones based primarily on flexibility resource scarcity can be expected to have a significant impact on the cost of subhourly resource dispatch. The optimal strategy for low renewable conditions very closely matches the strategy employed today when moving hour-to-hour from one scheduled operating point to another. Indeed, the optimal dispatch strategy does not offer any significant cost savings when overall pricing is dominated by energy resource scarcity.

However, as increasing amounts of renewables are introduced, the scarcity rents may shift from energy to flexibility resources. The optimal subhourly dispatch strategy may be expected to change with increasing emphasis on avoiding high ramp rates over sustained periods at the expense of maintaining a constant power level over the hour.

The relationship between existing price signals for various grid services and the three principle price components needed to implement this optimal strategy requires further investigation. It is evident that the marginal price a represents a linearization of the energy price itself at the current operating point. But it is not clear yet whether and to what degree the marginal prices b and c can be connected to any existing price signals, such as the capacity price or the price of ancillary services like frequency regulation resources, generation reserves, and demand response. The links do suggest themselves based on both the resource behaviors and physical dimensions of the parameters. However, it is not certain yet whether this will be simply a matter of obtaining a linearization of the services' cost functions at the appropriate operating point.

Additionally, it is instructive to note that the marginal price of redispatched power b is not important to the optimal dispatch strategy, insofar as the parameter does not appear in Eq. 6. This leads one to conclude that to the extent capacity limits do not affect either energy or ramping scarcity rents (or are already captured in them), the marginal cost of additional resource capacity is never considered for optimal subhourly dispatch control. This is consistent with the expectation that sunk costs should not be a factor in the selection of which units to dispatch at what level, at least to the extent that these costs are not entering into the energy or ramping costs.

In the presence of significant renewables, the energy marginal cost does not entirely reflect the grid condition without considering the cost of ramping up and down services. Therefore, the energy price cannot be solely used as a control signal to the generation and load units to achieve the optimal utilization of resources. In order to quantify the value of ramping product we suggest using a market framework in which flexible generation and load resources compete to sell their ancillary service products at the bulk electric system level. As renewable level rises the energy marginal cost decrease (smaller a value) because renewables are zero-generation cost resources, but the ramping marginal cost increases (larger c value) because the system requires more flexibility to handle the generation variation. In long run, inflexible units get retired and more flexible units are built to support the renewable integration since flexibility will be a revenue source rather than energy.

The availability of high renewables can lead to situations where low cost energy is being supplied to areas with high cost flexibility resources through constrained interties. The optimal strategy avoids dispatching these high cost flexilibity resources to the extent possible by reducing the ramping schedule. The more transmission capacity is available, the lower the overall cost, but we note that even when the system is constrained, the cost of optimally dispatching flexibility resources can be significantly lower under the high renewables case than under a low renewables scenario.

It seems that the use of energy-only market designs run counter to the results of this study. Flexilibity resource markets may become increasingly important, even in regions that are not dominated by local renewable generation. This is especially true in cases where adequate transmission capacity is available for renewables in remote regions to displace local dispatchable generation. This may give rise to a new set of challenges for utility and system operators as they seek a revenue model that not only provides for operating costs, but also maintains the coupling between retail demand response and wholesale supply and retail delivery constraints. If the cost of the wholesale system becomes increasingly dominated by ramping resource constraints, while retail continues to use energy prices to encourage consumer efficiency, then retail behavior will be not affected as much by short-term wholesale price fluctuations. This trend runs against the desire for more engaged consumers who can respond to system conditions in real time. Clearly a new utility revenue model is needed if the transformation to a high renewable *modus operandi* is to occur successfully in the coming decades.

7. Conclusions

The principal finding of this paper is that the use of an optimal dispatch strategy that considers both the cost of energy and the cost of ramping resources simultaneously leads to significant cost savings in systems with high levels of renewable generation. For the WECC 2024 common case the savings can exceed 25% of total operating costs in a 50% renewables scenario.

As the bulk power interconnection resource mix shifts from primarily dispatchable non-zero marginal cost resources (e.g., natural gas) to primarily non-dispatchable zero marginal cost renewable resources (e.g., run-of-river hydro, wind, solar) we expect a steady shift in bulk system costs from energy resource scarcity rent to ramping resource scarcity rent. While the total revenue must remain largely the same for financial sustainability, operating strategies must adapt to reflect changes in resource scarcity costs.

Acknowledgments

This work was funded in part by the Pacific Institute for Climate Solutions at the University of Victoria and the California Energy Commission under Project EPC-15-047. SLAC National Accelerator Laboratory is operated for the US Department of Energy by Stanford University under Contract No. DE-AC02-76SF00515. The authors also thank Francesco Carducci for his very helpful suggestions during the preparation of this paper.

Nomenclature

$\ddot{Q}$	Ramping rate of change in MW/h^2.
$\dot{Q}$	Ramping in MW/h.
$\dot{Q}^*$	Discrete power at next time step in MW.
$\dot{Q}_0$	Initial ramping in MW/h.
$\dot{Q}_T$	Terminal ramping in MW/h.
λ	Lagrange multiplier (excluding Q_z) in \$/MWh.
μ	Lagrange multiplier (including Q_z) in \$/MWh.
ω	Square root of energy to ramping marginal price ratio in h^{-1}.
A	A cost parameter (unit varies according to context).
a	Marginal price of energy in \$/MW^2·h.
B	A cost parameter (unit varies according to context).
b	Marginal price of power in \$/MW^2.
C	A cost parameter (unit varies according to context).
c	Marginal price of ramping in \$·h/MW^2.
$C(t)$	Cost over the time interval 0 to t in \$.

C^* Cost associated with discrete time control in \$.

C_{base} Cost associated with base case control in \$.

D A cost parameter (unit varies according to context).

$E(t)$ Energy over the time interval 0 to t in MWh.

E_Δ Energy demand parameter in MWh.

E_T Energy over T in MWh.

$G(t, Q, \dot{Q})$ Cost Lagrangian in \$.

k Discrete time step in p.u. t_s.

$P(Q)$ Power price function in \$/MWh.

$Q(t)$ Power in MW.

Q^* Discrete power in MW.

Q_0 Initial load in MW.

Q_Δ Power demand parameter in MW.

Q_E Scheduled load in MW.

Q_T Terminal load in MW.

Q_z Must-take generation in MW.

$R(Q, \dot{Q})$ Ramping price function in \$/MW.

s Frequency domain complex variable in h^{-1}.

T Interval terminating time in hours.

t Time domain real variable in hours.

t_s Time step in seconds.

References

[1] M. S. Markoff and A. C. Cullen. Impact of climate change on Pacific Northwest hydropower. *Climatic Change*, 87(3-4):451–469, 2008.

[2] M. K. Chandel, L. F. Pratson, and R. B. Jackson. The potential impacts of climate-change policy on freshwater use in thermoelectric power generation. *Energy Policy*, 39(10):6234 – 6242, 2011. Sustainability of biofuels.

[3] S. C. Parkinson and N. Djilali. Robust response to hydroclimatic change in electricity generation planning. *Climatic Change*, 130(4):475–489, 2015.

[4] M. A. Ortega-Vazquez and D. S. Kirschen. Estimating the spinning reserve requirements in systems with significant wind power generation penetration. *IEEE Transactions on Power Systems*, 24(1):114–124, Feb 2009.

[5] G. Blackburn, C. Magee, and V. Rai. Solar valuation and the modern utility's expansion into distributed generation. *The Electricity Journal*, 27(1):18–32, 2014.

[6] M. J. E. Alam, K. M. Muttaqi, and D. Sutanto. Mitigation of rooftop solar PV impacts and evening peak support by managing available capacity of distributed energy storage systems. *IEEE Transactions on Power Systems*, 28(4):3874–3884, Nov 2013.

[7] P. Denholm, M. O'Connell, G. Brinkman, and J. Jorgenson. *Overgeneration from solar energy in California: A field guide to the duck chart*. National Renewable Energy Laboratory, 2015.

[8] I. Dobson, B. A. Carreras, V. E. Lynch, and D. E. Newman. Complex systems analysis of series of blackouts: Cascading failure, critical points, and self-organization. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 17(2):026103, 2007.

[9] G. Boyle. *Renewable electricity and the grid: the challenge of variability*. Earthscan, 2012.

[10] Y.V. Makarov, C. Loutan, J. Ma, and P. de Mello. Operational impacts of wind generation on California power systems. *IEEE Transactions on Power Systems*, 24(2):1039–1050, 2009.

[11] M. Nyberg. Thermal efficiency of gas–fired generation in California: 2012 update. *California Energy Commission*, 2013.

[12] S. Behboodi, D. P. Chassin, N. Djilali, and C. Crawford. Interconnection-wide hour-ahead scheduling in the presence of intermittent renewables and demand response: A surplus maximizing approach. *Applied Energy*, 189:336–351, 2017.

[13] S. Behboodi, D. P. Chassin, N. Djilali, and C. Crawford. Transactive control of fast-acting demand response based on thermostatic loads in real-time retail electricity markets. *Applied Energy*, 210:1310–1320, 2018.

[14] D. P. Chassin, S. Behboodi, Y. Shi, and N. Djilali. H2-optimal transactive control of electric power regulation from fast-acting demand response in the presence of high renewables. *Applied Energy*, 205:304–315, 2017.

[15] G. A. Stern, J. H. Yan, P. B. Luh, and W. E. Blankson. What objective function should be used for optimal auctions in the iso/rto electricity market? In *Power Engineering Society General Meeting*, pages 10–pp. IEEE, 2006.

[16] Y. T. Tan and D. S. Kirschen. Co-optimization of energy and reserve in electricity markets with demand-side participation in reserve services. In *Power Systems Conference and Exposition*, pages 1182–1189. IEEE, 2006.

[17] G Irisarri, LM Kimball, KA Clements, A Bagchi, and PW Davis. Economic dispatch with network and ramping constraints via interior point methods. *IEEE Transactions on Power Systems*, 13(1):236–242, 1998.

[18] H Glatvitsch and Fernando Alvarado. Management of multiple congested conditions in unbundled operation of a power system. *IEEE Transactions on Power Systems*, 13(3):1013–1019, 1998.

[19] D. J. Hammerstrom, R. Ambrosio, J. Brous, T. A. Carlon, D. P. Chassin, J. G. DeSteese, R. T. Guttromson, G. R. Horst, O. M. Järvegren, R. Kajfasz, et al. Pacific Northwest GridWise Testbed Demonstration Projects: Part I. Olympic Peninsula Project. Technical Report PNNL-17167, Pacific Northwest National Laboratory, October 2007.

[20] GB Shrestha, Kai Song, and L Goel. Strategic self-dispatch considering ramping costs in deregulated power markets. *IEEE Transactions on Power Systems*, 19(3):1575–1581, 2004.

[21] Miao He, Sugumar Murugesan, and Junshan Zhang. Multiple timescale dispatch and scheduling for stochastic reliability in smart grids with wind generation integration. In *INFOCOM, 2011 Proceedings IEEE*, pages 461–465. IEEE, 2011.

[22] Makoto Tanaka. Real-time pricing with ramping costs: A new approach to managing a steep change in electricity demand. *Energy Policy*, 34(18):3634–3643, 2006.

[23] Nivad Navid and Gary Rosenwald. Market solutions for managing ramp flexibility with high penetration of renewable resource. *IEEE Transactions on Sustainable Energy*, 3(4):784–790, 2012.

[24] Erik Ela, Brendan Kirby, Nivad Navid, and J Charles Smith. Effective ancillary services market designs on high wind power penetration systems. In *Power and Energy Society General Meeting, 2012 IEEE*, pages 1–8. IEEE, 2012.

[25] Shahab Shariat Torbaghan, Niels Blaauwbroek, Phuong Nguyen, and Madeleine Gibescu. Local market framework for exploiting flexibility from the end users. In *European Energy Market (EEM), 2016 13th International Conference on the*, pages 1–6. IEEE, 2016.

[26] Cherrelle Eid, Paul Codani, Yurong Chen, Yannick Perez, and Rudi Hakvoort. Aggregation of demand side flexibility in a smart grid: A review for european market design. In *European Energy Market (EEM), 2015 12th International Conference on the*, pages 1–5. IEEE, 2015.

[27] Aleksandra Roos, Stig Ø Ottesen, and Torjus F Bolkesjø. Modeling consumer flexibility of an aggregator participating in the wholesale power market and the regulation capacity market. *Energy Procedia*, 58:79–86, 2014.

[28] He Hao, Abhishek Somani, Jianming Lian, and Thomas E Carroll. Generalized aggregation and coordination of residential loads in a smart community. In *Smart Grid Communications (SmartGridComm), 2015 IEEE International Conference on*, pages 67–72. IEEE, 2015.

[29] N Siebert, S Ammari, X Cao, T Delaplagne, K Mamadou, M Chouiter, H Buttin, O Gaci, J Lagorse, and Y Bertone. Scheduling demand response and smart battery flexibility in a market environment: Results from the reflexe demonstrator project. In *PowerTech, 2015 IEEE Eindhoven*, pages 1–6. IEEE, 2015.

[30] Flexibility EDSO. The role of DSOs in tomorrow's electricity market. Technical report, Tech. Rep, 2014.

[31] WECC's System Adequacy Planning Department. WECC 2024 common case. https://www.wecc.biz/SystemAdequacyPlanning/Pages/Datasets.aspx. [Online; accessed 21-July-2017].

[32] R. Diao, N. Samaan, Y. Makarov, R. Hafen, and J. Ma. Planning for variable generation integration through balancing authorities consolidation. *IEEE Power and Energy Society General Meeting*, pages 1–8, 2012.