Renewable Resources Portfolio Optimization in the Presence of Demand Response

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Abstract

Demand response is viewed as a practical and relatively low-cost solution to increasing penetration of intermittent renewable generation in bulk electric power systems. This paper examines the question of what is the optimal installed capacity allocation of renewable resources in conjunction with demand response. We introduce an integrated model for total annual system cost that can be used to determine a cost-minimizing allocation of renewable asset investments. The model includes production, uncertainty, emission, capacity expansion and mothballing costs, as well as wind variability and demand elasticity to determine the hourly cost of electricity delivery. The model is applied to a 2024 planning case for British Columbia, Canada. Results show that cost is minimized at about 30% wind generation. We find that the optimal amount of renewable resource is as sensitive to installation cost as it is to a carbon tax. But we find the inter-hourly demand response magnitude is much less helpful in promoting additional renewables than intra-hourly demand elasticity.

Keywords: Demand response, Renewable integration, Power market, Portfolio optimization

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- Adding renewable resources can reduce uncertainty costs more than production costs.
- Inter-hourly demand response is not as useful as intra-hourly demand response.
- Optimal renewable resource level is as sensitive to carbon tax as to first cost.

Nomenclature

C	Annual cost, in \$/y.
c	Hourly cost, in \$/h.
G	Annual generation, in MWh/y.
g	Hourly generation, in MWh/h.
p	Price, in \$/MWh.
Q	Quantity, in MW.
q	Hourly demand, in MWh/h.
t	Time, in hours.
v	Normalized hourly wind production, per unit of installed wind capacity.
Greek symbols	
α	Magnitude of the variable cost component of supply curve, in \$/MWh.
β	Curvature of the supply curve, in a non-dimensional unit.
γ	Base price of the first dispatchable generation, \$/MWh.
ϵ	Emission factor of a resource, in tCO ₂ /MWh.
κ	Curvature of the demand curve, in a non-dimensional unit.
τ	Time-substitution delay of inter-hourly demand response, in hours.
ω	Fractional resource allocation, per unit of installed capacity.
Subscripts	
BG	Base load generation
D	Demand response
E	Emission
IG	Intermediate load generation
M	Market
P	Production
PG	Peak load generation
R	Reserve
SV	Scarcity value

CT	Carbon tax
U	Uncertainty
W	Wind

1. Introduction

According to the Energy Information Agency (EIA) International Energy Outlook developing economies have seen a steady growth in renewable energy resources in recent years. Wind and solar resources in particular show the strongest growth with EIA projecting that more than three quarters of all new additions in 2015 will be renewable [1]. The advantages of renewable energy are manifest and in the absence of viable alternatives to reducing greenhouse gas emissions, they are expected to remain the electricity generation resource of choice for new additions for many years to come. Unfortunately, all is not well where renewable electricity generating resources are concerned. Significant economic and operational considerations impose practical limits on the total amount of renewables that can be deployed in bulk electric power systems. Land use considerations, power system reliability, and electricity market design are among the many issues that contribute to constraints on the total deployment of renewables, particular those that rely on intermittent prime-movers, like wind and solar energy. Hydro-electric generation has long been employed as a significant renewable source of electricity. But climate change may jeopardize the magnitude and certainty with which the existing asset base can meet demand [2, 3], while lack of productive new dam siting options, population displacement, habitat destruction and fish stock degradation limit the growth of new assets. Wind power has seen rapid growth in recent years, but the need for reliable resources limits the penetration of wind generation unless additional intermittency mitigation measures are considered [4]. Solar resources are also becoming increasingly available but have intermittency challenges similar to those of wind. In addition residential rooftop solar resources are challenging the classical utility revenue model [5] and are known to cause voltage control issues in distribution systems in response to cloud transients and the diurnal cycle [6, 7]. There are also early signs that the wholesale market designs are not well suited to high penetration of renewables and the specter of revenue adequacy problems has been raised [8, 9]. Finally, the reliable, robust control and optimal operation of an increasingly complex bulk electricity system has become a very real concern [10].

The traditional utility approach to renewable intermittency is to allocate additional firm resources to replace all potentially non-firm renewables resources. These firm resources are generally provided by fast-responding fossil-fuelled thermal plants and hydro (where available) power generation as well. The need for fast-ramping resources discourages the dispatch of high-efficiency fossil and nuclear generation assets while promoting low-efficiency fossil for regulation and reserve services. The early state of development of many wholesale regulation markets precludes consideration of market-based remedies at this time, although arguably one should consider renewables before committing to any particular market design.

Demand response is generally regarded as a lower-cost alternative to fast-response generation reserves that reduces the dispatch of expensive generation resources [11, 12, 13, 14], although the response speed, magnitude and duration are important considerations [15]. The effect of demand response on the daily generation schedule is known [16] and sometimes demand response is even presented as a virtual power plant [17]. But load control strategies for demand response can be challenging to deploy [18] in part due to competing local and global objectives [19, 20] and in part due to the complexity of the load control modeling and design problem itself [21]. Numerical modeling of resource adequacy for large-scale planning problems is difficult to implement [22] and demand response models typically do not capture the salient features of load necessary to make optimal resource allocation decisions. This is particularly true when considering the interaction of renewable intermittency and demand response capabilities [23].

Effective and widely used strategies for optimizing the scheduling and operation of bulk-system resources have used markets to solve the cost-minimizing resource-allocation problem since they were proposed in the early 1980s [24]. Market-based control strategies were later adapted to building control systems [25], generalized to feeder-scale operations [26], then utility-scale operations [27], and most recently proposed for ancillary services [28]. Integrated demand dispatch mechanisms allow consideration of the combined economic impact of both intermittent generation under traditional wholesale markets and so-called “transactive” retail-side demand response dispatch system. It seems therefore possible to define global cost functions that incorporate the essential characteristics of both intermittent generation and demand response.

In recent years many have contributed relevant and very detailed models [29, 30, 31, 32] addressing the individual aspects discussed above. Wang

et al. [33] reviewed prototyped real-time electricity markets, focusing on their market architectures and incentive policies for integrating distributed energy resources and demand response. Kwag and Kim [34] introduced a new concept of virtual generation resources, according to which marginal costs are calculated in the same manner as conventional generation marginal costs using demand response information: magnitude, duration, frequency and marginal cost. Sreedharan *et al.* [35] determined the avoided cost of demand response in a restructured market with renewables in California. Dallinger *et al.* [36] showed that a demand response program based on smart charging of electric vehicles can facilitate the integration of intermittent resources in California and Germany. Mahmoudi *et al.* [37] proposed a new wind offering strategy in which a wind power producer employs demand response to cope with power production uncertainty and market violations. To this end, the wind power producer sets contracts with a demand response aggregator. Rajeev and Ashok [38] proposed a dynamic load shifting program using real-time data in a cloud computing framework to enable the effective capacity utilisation of renewable resources. Heydarian-Forushani *et al.* [39] investigated the impacts of different electricity markets on the optimal behavior of a demand response aggregator in a renewable-based power system. Fripp [40] introduces Switch, a new open-source optimization model for long-term planning of power systems with large shares of renewable energy. Santoro *et al.* [41] used a stochastic approach based on Monte Carlo simulation technique to simulate the impacts of demand response in power systems with integrated renewable resources over one year period. They showed the optimization of demand response and renewable production reduces locational marginal prices.

Electricity consumers behavior, and in particular their response to price fluctuations is challenging to characterize and model, and researchers have modeled the behavior by using a linear demand curves to represent price responsiveness [42], invoking new methods to calculate a demand reserve offer function [43], or assuming consumers use day-ahead prices to shift daily energy consumption from hours when the price is expected to be high to hours when the price is expected to be low while maintaining total net energy consumption [44]. The results from the Olympic Peninsula demonstration project [26] and American Electrical Power gridSMART project [27] showed that the demand curves of thermostatic loads are generally sigmoid with asymptotes at the unresponsive quantity and the maximum load.

For the most part, these contributions do not collectively answer the larger question of how to determine the optimal installed capacity allocation

of renewable resources when demand response is considered simultaneously. This paper introduces a model for total annual system cost that integrates renewable resource intermittency and demand response impacts in a global cost function that can be used to determine the optimal allocation of new asset investments. The new contributions of this work are: (i) formulation of the uncertainty cost of intermittent renewable resources and demand response acting jointly; (ii) an economic model of demand response interacting with renewables in markets; (iii) separation of the impact of intra-hour (short-term) demand response from inter-hour (mid to long-term) demand response; and (iv) a joint demand response/renewables portfolio study for British Columbia.

In Section 2 the model is described in detail, and in Section 3 we propose a resource portfolio optimization formulation that addresses the question of how much renewable and demand response is necessary to minimize annual cost in any given system. In Section 4 the model is applied to a system loosely based on the power grid of British Columbia, Canada and sensitivity analyses of the results are presented in Section 5.

2. System Description

In this section we describe the system models employed to solve the general annual-cost minimizing resource allocation problem. The model includes three categories of elements: (i) the resource models, (ii) the temporal models, and (iii) the economic models.

2.1. Resource Model

System resources are modeled with five classes of generation and two classes of load:

Base: Baseload generation includes all generators that are presumed to be always running when available. Baseload generation usually has a very low marginal cost but is not expected to respond to intra-hour load changes or intermittency in other generation assets.

Intermediate: Intermediate generation includes all the main energy production assets that are used to follow the normal diurnal fluctuations in demand. Intermediate generation is usually also relatively low marginal cost but is expected to have at least some ability to change output in response to intra-hour imbalances.

Peak: Peak generation usually includes only low efficiency energy production assets that are used to meet peak load events that happen infrequently. These assets are typically low capital-cost assets with high marginal costs of production, but they are expected to have excellent ability to change output quickly in response imbalances.

Intermittent: Intermittent generation generally has high first cost, but effectively zero marginal production cost. The main feature of intermittent resources is that they are essentially non-dispatchable because their production capacity is subject to uncontrollable fluctuations in the prime mover, e.g., wind, solar, or wave. As a result not only intermittent resources cannot provide any useful load following capability, but they may also contribute to increasing imbalances due to forecasting uncertainty.

Reserve: Reserve generation is usually comprised of peak generation units that are effectively never used and only held in reserve in the event of a system contingency. Because many of these non-spinning reserve units typically are not dispatched, they effectively do not generate revenue directly from production. Instead they are a cost which is typically recovered through scarcity rent on the other assets in a vertically integrated systems, or by participating in reserve markets, when they exist.

Unresponsive: Unresponsive loads include the vast majority of load in most systems. Unresponsive load generally has five components: (i) the base load, which is always present; (ii) the seasonal load, which varies according to the time of year; (iii) the long term weather component, which changes with weather; (iv) the diurnal component, which fluctuates with the daily solar cycle; and (v) the short term weather and human activity disturbances, which fluctuate on a subdaily and often subhourly basis.

Responsive: Responsive loads are all the loads that can respond to signals of various kinds, including direct and indirect (e.g., price-based) load control signals. Responsive load is generally divided into three categories: (i) curtailable load, where energy use is reduced and not replaced later, e.g., by industrial load curtailment; (ii) deferrable capacity or inter-hourly demand response, where peak demand is cut and energy use

is replaced in subsequent hours, e.g., by direct load control; and (iii) fast-acting ramp response or intra-hourly demand response, where load is shifted momentarily and typically replaced within one hour, e.g., by real-time price signals.

Elasticity represents the response of consumers to dynamic pricing. The price elasticity of demand is the fractional change in demand to a given fractional change in price:

$$\eta = \frac{p}{q} \frac{dq}{dp}$$

where η , p and q respectively are elasticity, price and demand. Numerous studies in recent decades have examined the elasticity of demand under various tariffs. However, few of those studies [45, 46] address real-time price tariffs. In their survey of 15 demand response studies, Faruqui and Sergici [47] identified the likely range of inter-hourly elasticity of substitution as between -0.07 and -0.21 . For the purposes of this paper, we use the suggested average value of -0.14 . It should be noted that the long-term demand elasticity is taken out from consumers' behaviour before estimating the short-term elasticity. Sensitivity analysis on the elasticity is formed to gauge the impact of this estimate on the results.

2.2. Temporal Model

All system assets are typically scheduled for operation on an hourly basis in a day-ahead electricity market. Fast-acting controllable assets can be dispatched subhourly, with some assets responding at a five-minute time-scale (e.g., demand response), some at the 4 second control time-scale, and some at a subsecond electromechanical dynamic response and sub-cycle relay/protection control time scale. However, in general these are only considered insofar as they may reduce the backup reserve requirement and they do not affect the energy component of the hourly dispatch schedule.

The potential magnitude of demand response resources must be considered in terms of the bandwidths over which they can operate [48]. In general demand response that addresses intermittency is based on load resources that respond only within a time no greater than about a few hours and no less than a few minutes, the upper limit arising from limits on the customer's willingness to forgo or defer consumption, and the lower limit arising from the time update rate of the load control signal or load control lockout. For

example, building thermostat-based demand response is relatively fast and essentially subhourly, whereas electric vehicle charging demand response is relatively slow and primarily super-hourly. The magnitude of the intermittency within that frequency band is the only intermittency that demand response can mitigate and therefore the only intermittency that we can consider being cancelled in the total resource pool [49].

The production cost for energy is determined hourly based on the variation in load for each hour of the year. In this study, demand response with inter-hour capability is assumed to not be significant beyond 4 hours. The proposed model dispatches price-sensitive load by comparing the real-time price and the average price over the next 4 hours. In the case of subhourly response, we assume that all fast dynamics have mean zero contribution to the hourly energy demand, but they do have a non-zero variance contribution to the power imbalance. For intermittent generation the cost of mitigating this variance is included in the cost function through the variability of the wind production. With fast-acting demand response the magnitude of its contribution is assumed to be always less than the subhourly intermittency of wind but effectively mitigates intermittent generation. Because the marginal cost of fast-acting demand response and the marginal cost of intermittent generation are both zero, they are simply cancelled and the total intermittent wind subhourly impact on the system is reduced by the amount of demand response available. The first cost of fast-acting demand response is assumed to be in addition to the deferrable load control infrastructure cost. Where automated metering infrastructure is already in place, this additional first cost should in principle be nearly zero.

2.3. Economic Model

The global cost function consists of variable and fixed costs. The variable costs include the following components:

Production: This cost includes the hourly cost of producing energy from the resources that were dispatched. In principle this should include subhourly cost of production as a result of redispatch to follow load and mitigate forecast deviations in intermittent resources, but we assume that this cost has zero mean over the hour.

Uncertainty: This is actually defined as producer surplus [50]. But because this cost arises primarily from the requirement to maintain dispatchable

resources with non-zero marginal costs to mitigate for the uncertainty in non-dispatchable resources with zero marginal (as well as variability in the unresponsive load) we choose to call this *the cost of uncertainty* due to the intermittency of lower or zero cost resources. As we will see below, this definition has the significant advantage of allowing us to easily relate the magnitude of the resource uncertainty to the cost impact of that uncertainty as the allocation of that resource changes. For example, the uncertainty cost of a small allocation of wind is counterintuitively much higher than it is for a large allocation of wind simply because as we add more wind, the resources being used to mitigate its intermittency are dispatched from lower down the supply curve. This effect is independent of and in addition to smoothing effects [51] that results from geographic resource diversity.

Emission: This cost is considered by the introduction of a carbon tax at the point of CO₂ emission.

The fixed costs include the following components:

Wind: Increasing wind allocation requires an investment in the installation of new units, which is represented by a levelized cost of energy on what would otherwise be a zero production cost. However, strict application of market-pricing regards this as a sunk cost once the unit is installed, which is why intermittent wind, solar and wave units are effectively zero-marginal cost relative to fossil units. Thus the first cost of new units is captured separately in the model in order to avoid having to account for these in the production cost.

Demand response: There is very little recent data on the first cost of demand response installation. Borenstein provided a quote from Comverge in 2002 where the estimate was \$1000 per customer [52]. If we assume that each customer can provide about 10 kW of controllable load on peak, the cost of controllable demand response capacity is around \$50,000/MW.

Reserve: As the allocation of wind is increased, a proportion of non-spinning reserve is not required but continues to incur costs.

3. Problem Formulation

In this section, the cost minimization problem is stated in the standard form, and its components are quantified considering renewable intermittency and demand response effects.

3.1. Hourly Cost

To derive the annual cost function we begin with the hourly costs, which will then be integrated over a year. The hourly cost includes the market-based energy cost, and the intermittency and the demand response impacts discussed above.

Market Cost

We use a mathematical formulation for the market cost based on an asymptotic supply curve for production cost, which is combined with a cost arising from the producer surplus, which we refer to as the uncertainty cost when intermittent resources are considered. Consider the supply curve illustrated in Figure 1a where producers bid their marginal costs (which is zero for wind) and are paid the clearing price, which is the marginal cost of the last unit dispatched. At any given time, the region enclosed by the market clearing quantity q_M and price p_M is the market cost $c_M = p_M q_M$. So the region under the supply curve is the total production cost which is the sum of the individual production costs of the each generating unit $c_P = \sum_{n=1}^N p_n g_n$ and the region above the curve but below the clearing price is total producer surplus associated with each unit $c_U = \sum_{n=1}^N (p_M - p_n) g_n$. The supply curve can be expressed as an asymptotic function of the quantity:

$$p = \alpha \left(1 - \frac{q}{Q_{cap}} \right)^{-\beta} + \gamma$$

where α and β determine the magnitude of the scarcity rent and the curvature of the supply curve respectively, and γ is the minimum bidding price of the first dispatchable unit. The system capacity Q_{cap} is the maximum observed demand

Q_{max} with the supply requirement reserve factor ω_R , so $Q_{cap} = Q_{max} (1 + \omega_R)$. The cost function for any particular time t is then:

$$c_{M[t]} = \alpha q_{M[t]} \left(1 - \frac{q_{M[t]}}{Q_{cap}} \right)^{-\beta} + \gamma q_{M[t]}$$

We can express the energy production cost as:

$$c_{P[t]} = \int_0^{q_{M[t]}} p dq = \frac{\alpha Q_{cap}}{\beta - 1} \left\{ \left(1 - \frac{q_{M[t]}}{Q_{cap}} \right)^{-\beta+1} - 1 \right\} + \gamma q_{M[t]}$$

Then the uncertainty cost $c_U = c_M - c_P$ at any particular time is:

$$c_{U[t]} = \int_0^{p_{M[t]}} q dp = \frac{\alpha Q_{cap}}{\beta - 1} \left\{ 1 - \left(1 - \frac{q_{M[t]}}{Q_{cap}} \right)^{-\beta} \left(1 - \frac{q_{M[t]}}{Q_{cap}} \beta \right) \right\}$$

Wind Intermittency Effect

When renewable resources are active, they are dispatched below the baseload resources in the supply merit order, and therefore they shift supply curve accordingly. We assume that renewable production cost is zero because the marginal cost of all wind is zero. But the producer surplus can be large, as shown in Figure 1b. Deducting the wind generation g_W from the demand, the clearing price is:

$$p_M = \alpha \left(1 - \frac{q_{M[t]} - g_{W[t]}}{Q_{cap}} \right)^{-\beta} + \gamma$$

where wind generation is $g_{W[t]} = v_{W[t]} \omega_W Q_{max}$, and v_W is the normalized wind generation pattern taken from historical data.

We make an important observation about the cost of uncertainty: if the supply curve is flat, the cost of uncertainty is zero even though there may be very high variability associated with the lowest cost resource. In other words, if the lowest cost resource is highly uncertain, but can be replaced by other similarly low-cost resources, then the cost of uncertainty may be in fact near zero. Of course, this condition is predicated on the notion that excess resources are “curtailed”, which may not always be the case with today’s wind resources. But this possibility suggests that any attempt to optimize a resource portfolio where unlimited highly uncertain resources are permitted

Figure 1: Single auction electricity market: demand curve (blue) and supply curve (red)

will necessarily result in an optimal allocation where a large amount of low cost/high uncertainty resources are acquired and only the uncertain resources are used.

Demand Response Effect

Being sensitive to electricity price, customers change their demand in response to price fluctuations. With demand response included, the total quantity consumed is given as the summation of price unresponsive and responsive demands. The particular form of the sigmoid function is not readily deduced from the field data, but one can presume that it arises from the discrete choice statistics of the consumers based on the random utility model [53]. According to this model, comfort governs the outcome with the highest utility going to the customers with the highest demand for comfort. The net benefit to each customer depends on an unobservable characteristic a and an observable one b , such that the utility of choosing x is $a + bx + \delta$ where δ is a random independent error. The action corresponding to that choice is taken when $a + bx + \delta > 0$. The probability of taking the action is then proportional to $(1 + e^{-(a+bx)})^{-1}$. The behavior of the demand response model under curtailment and recovery is illustrated in Figure 2a and Figure 2b respectively.

The proposed model determines the active responsive load considering the mean of expected prices $\bar{p}$ within the next τ hours. We use this model to

Figure 2: Behavior of price-responsive demand

express all demand curves from automated demand response agents such as HVAC thermostats and electric vehicle chargers as taking the form:

$$q_D^{[t]} = \frac{2 \omega_D \bar{q}^{[t]}}{1 + e^{\kappa \left(\frac{p_M}{\bar{p}} - 1 \right)}}$$

where ω_D is demand response allocation and κ is the demand response function curvature. It should be noted that q is the total load when the demand is completely blind to the price. The responsive demand q_D changes to clear market at quantity of $q_M = \bar{q} (1 - \omega_D) + q_D$ and its associated price p_M . We consider only demand response that is capable to shift the load for more than 1 hour and treats all subhourly demand response as mean-zero magnitude. The average elasticity of demand $\bar{\eta}$ is then given over a τ hours time window, and defined based on the instantaneous elasticity. Combining this definition with the equation for the demand response we find: $\kappa = -2 \bar{\eta}$. Figure 3 illustrates the interaction between the proposed demand response model (under curtailment) and supply model in a double auction market. The horizontal and vertical shades respectively show the reduction of uncertainty and production costs as a result of demand response implementation.

Figure 3: Double auction electricity market

3.2. Annualized Effective Electricity Price

Our objective is to minimize the total annual cost, which is a function of the renewable resource and demand response penetration levels. The total annual cost, consisting of annual production, uncertainty, emission, wind capacity expansion, supply reserve and demand response (e.g. labor and hardware) installation costs, is computed for different combinations of design variables ω_W and ω_D . We express results in annualized effective electricity price p_{eff} , which is a more easily understood criterion, and by definition is the total annual cost divided by the annual demand:

$$p_{eff}(\omega_W, \omega_D) = \frac{C_P + C_U + C_E + C_W + C_R + C_D}{\sum_{t=1}^{8760} q_M^{[t]}}$$

where $C_P = \sum_{t=1}^{8760} c_P^{[t]}$ and $C_U = \sum_{t=1}^{8760} c_U^{[t]}$ are the annual production and uncertainty costs. These costs are obtained across the entire year with a hourly time resolution. The emission cost C_E is:

$$C_E(\omega_W, \omega_D) = F_{CT} (\epsilon_{BG} G_{BG} + \epsilon_{IG} G_{IG} + \epsilon_{PG} G_{PG})$$

where ϵ and G are the carbon intensity and annual generation of base, intermediate and peak load generation units; F_{CT} is the carbon tax. The cost of adding a new wind unit is assumed quadratic due to market scarcity for large magnitude resource additions. The wind installation cost C_W therefore

is computed as:

$$C_{W(\omega_W)} = F_{SV} (\omega_W Q_{max})^2 + F_W \omega_W Q_{max}$$

where F_{SV} and F_W are scarcity value and average wind initial cost. The cost of unused supply reserves C_R is:

$$C_{R(\omega_W, \omega_D)} = F_R (Q_{cap} - (1 + \omega_R) [q_{[t]} - g_{W[t]}]_{max})$$

where F_R is the average cost for unused reserve capacity. Finally, the cost of demand response C_D infrastructure is assumed as:

$$C_{D(\omega_D)} = F_D \omega_D Q_{max}$$

where F_D is the estimated cost for demand response.

4. Application

We apply the proposed model to a hypothetical electric system based on the planning model for the province of British Columbia, Canada used by the Western Electricity Coordinating Council for the year 2024 [54]. The hourly load forecast and wind generation profiles of the province are taken from a 10 year-ahead planning case. British Columbia's power system is not deregulated, so we use a hypothetical energy market with characteristics of a deregulated market, as shown in Table 1. To estimate the emission costs, the baseload generation type is assumed to be a zero emission resource (e.g. hydro), and intermediate and peak units are combined and simple cycles respectively. Figure 4 shows the supply curve with a supply reserve requirement of 14%.

Table 1: Market characteristics

Variable	Base	Intermediate	Peak	Reserve	Unit
Capacity	5300	3500	3500	1700	MW
Emission factor [55, 56]	5	450	670	670	tCO ₂ e/MWh
Minimum bid	15	25	65	1006	\$/MWh

The first cost of wind is determined by averaging the direct capital cost of 111 potential onshore wind site in British Columbia [57]. The assumed costs and demand response parameters are tabulated in Table 2. We estimate the

Figure 4: Supply curve

scarcity value based on the wind turbine price trends in the US over the past decade [58].

Table 2: Assumed values

Variable	Symbol	Value	Unit	Source
Carbon emission tax	F_{CT}	30	\$/tCO ₂	[59]
Demand response cost	F_D	50000	\$/MW	[52]
Interest rate	i	3	%	
Elasticity	η	-14	%	[47]
Peak load	Q_{max}	12300	MW	Table 1
Scarcity value	F_{SV}	7	\$/MW ²	
Time-substitution	τ	4	h	
Unnecessary supply reserve cost	F_R	100000	\$/MW-year	
Wind installation cost	F_W	3210000	\$/MW	[57]

The cost model is applied across a range of wind penetration levels. Figure 5 is a plot of objective function, allowing identification of an optimal level. The penetration level of 100% is the case where the wind capacity equals to the maximum demand Q_{max} . With demand response considered, the optimal wind capacity is slightly less than 3860 MW, or 31.2% of the system load on peak. In other words, the reduction in the combined annual production and uncertainty costs is greater than the wind installation capital

cost up to 3860 MW. By May 2015, British Columbia had 4 wind farms currently supplying power to the grid with a nameplate capacity of 487 MW, and another 4 wind farms in development with a nameplate capacity of 230 MW [60].

Figure 5: Objective function for various possible renewable capacity allocations with active demand response

The scenarios presented in Figure 6 and Figure 7 are as follows:

- (1) No wind and no demand response;
- (2) Optimal wind and no demand response;
- (3) No wind and maximum demand response; and
- (4) Optimal wind and optimal demand response.

The fraction of maximum responsive demand to total demand was established at 10% and the optimization determined that this is the corner solution for the optimal demand response. A logarithmic scale on the duration axis is

used to emphasize the results during peak hours where they have the greatest impact on overall costs. Table 3 compares annual generation of all scenarios.

Figure 6: Load duration curve

Figure 7: Cost duration curve

Figure 8 illustrates the impact of the demand response fraction on the annual production and uncertainty costs and also on its installation cost. The saving impact of demand response on the uncertainty cost is much greater than its impact on production cost.

Table 3: Annual generation by type

Resource	Scenario				Unit
	(1)	(2)	(3)	(4)	
Intermittent	0	8500	0	8515	GWh
Base	46555	46555	46555	46555	GWh
Intermediate	19845	12635	19862	12636	GWh
Peak	1753	464	1729	453	GWh

Figure 9 shows the behaviour of demand response pricing over the study year. This illustrates the degree to which demand response is reacting when hourly prices are different from expected price. The negative points (red) are hours during which the market price is higher than the average of the next 4 hours; therefore, the responsive demand is postponed.

Figure 8: Demand response cost and benefits

5. Discussion and Sensitivity Analysis

At the hourly scale of energy markets, only a slight benefit from demand response can be observed. The sensitivity of the optimal wind allocation to elasticity and time-substitution of demand response are shown in Figure 10. This result shows that strategies to increase load shifting horizon and demand elasticity have no significant impact on the effective electricity price for the

Figure 9: Demand response behaviour

optimal wind case. This suggests that reasoning based on the inter-hour forward energy prices does not offer a significant benefit when compared to accounting for only the intra-hour price fluctuations. This emphasizes the importance of analyzing thermostatic (intra-hourly) demand response using short-term fluctuations in prices, separately from storage-based (inter-hourly) demand response using slow price fluctuations.

The nominal wind installation cost assumed for this study is \$3.21 M/MW. However wind turbine costs are expected to decrease over time. Figure 11 shows the sensitivity on the wind installation cost. For a 30% decrease in wind capacity cost, we observe a 5.5% increase in wind capacity and a corresponding 0.28 ¢/kWh decrease in electricity price.

A carbon tax is widely regarded as one of the most effective tools regulators have to encourage power producers to invest on clean energy resources. Figure 12 shows the sensitivity to the level of carbon tax and suggests the optimal wind penetration changes more than 10% for a range of reasonable carbon taxes expected in the foreseeable future.

Since we consider a fixed generation schedule for baseload units, we must assume excess wind generation is curtailed rather than redispatching baseload

Figure 10: Demand response impact on optimal wind allocation and effective electricity price (¢/kWh)

Figure 11: Wind installation cost impact on optimal wind allocation and effective electricity price (¢/kWh)

Figure 12: Carbon emission tax impact on optimal wind allocation and effective electricity price (in ¢/kWh)

units. However if the baseload generation can go to part load, renewable curtailment is reduced. Figure 13 shows the sensitivity on the part load factor range. From this analysis, part load does not have an appreciable impact on the optimal allocation intermittent resources. The cost impact of curtailing wind rather than redispatching baseload is insignificant because of the low cost during off peak load hours when this is expected to occur.

6. Conclusions

In this paper we introduce a simple cost model of renewable integration and demand response that can be used to determine the optimal mix of generation and demand response resources. We use numerical methods to obtain the optimal mixtures of renewable generation and demand response resources given a fixed portfolio of conventional generation assets, wind patterns and energy use. The model incorporates production, uncertainty, emission costs, as well as capacity expansion and mothballing costs, and considers wind variability and demand response impacts to determine the hourly price of electricity delivery. Supply is divided into intermittent, base, intermediate, peak and reserves, while load is divided into unresponsive and responsive. The load model includes inter-hourly impact of fast (e.g. building thermostat) and slow (e.g. electric vehicles) responses to price variations. The temporal model includes time-substitution in demand up to 4 hours.

Figure 13: Part load factor impact on useful wind generation fraction and optimal wind allocation

The model is tested by optimizing the 2024 planning case for British Columbia at the hourly level. We find that cost is minimized with about 31.5% renewable generation. The cost reduction relative to the current level is about 15%. The optimal renewable mix decreases to 31.2% when 10% demand response is considered with a very small cost impact. We find that demand response does not have a significant impact on cost at the hourly level, which suggests that future work must include sub-hourly load behavior to properly consider its full potential. The results also suggest that the optimal level of renewable resources is not very sensitive to demand elasticity, but it is highly sensitive to a carbon tax and renewable resource first cost.

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