## Optimizing renewables, storage and demand response to replace fossil fuels: Assessing the use of capacity credit analysis

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### Abstract

Capacity credit analysis is often used to determine how much traditional generation capacity can be replaced by a given capacity of new resources. This paper assesses the suitability of a capacity credit methodology for high-level estimates of the mix of renewables, demand response and energy storage necessary to carry out the following sequential scenarios in Ontario: displacing fossil fuel generation, electrifying passenger vehicles, and retiring nuclear generation. The capacity credit methodology requires excess capacity, increasing system costs; an alternative load matching model is employed. The transitions are technically feasible but require significant investment.

**Keywords**: renewable energy, energy storage, demand response, capacity credit, wind, solar, bioenergy, electric vehicles

### Résumé

Si l’article est en français, le résumé français sera le premier.

**Mots clés** : conférence, article, modèle, dix mots maximum

## 1. Introduction

Renewable energy offers the opportunity to shift away from carbon-emitting fossil fuels, potentially mitigating the effects of climate change. Some authors have postulated that the amount of available renewable supply is sufficient to meet current demand [1, 2]; however, there is still concern that excessive fossil fuel back-up generation will be required in order to accommodate the variable output from renewable energy sources, such as wind and solar photovoltaic (PV) [3]. Distributed resources, like demand response and energy storage, can help smooth out fluctuations in supply, increasing system reliability. The capacity credit, or capacity value, of a new electric grid resource is the fraction of that resource that can be counted on to replace conventional generation. Capacity credit analysis is often proposed as a tool for estimating the reliability of electricity systems as renewable and distributed resources are introduced into the grid [4, 5].

The capacity credit of a grid resource is generally calculated by comparing the electricity system’s reliability before the addition of a new resource to its reliability after the new generator is brought on-line. A variety of methods have been designed for assessing system reliability and capacity credits. The methods can be broadly categorized into two camps: full system reliability simulations, and statistical approximations. Numerous authors have reviewed the available methods [4, 5, 6] for both renewable and conventional generators. The Garver approximation [7] is a statistical approach that is often recommended for a variety of generating units.

Various studies have used the Garver method, or other similar techniques, to assess the capacity credit for one grid resource. Analysis has been conducted for wind [8, 9], solar PV [5, 10, 11], micro-combined heat and power [12], demand response [13], and plug-in electric vehicles (PEVs) [14]. Recently, Chakraborty et al. [15] used capacity credit methodology to assess the system impacts of two combined resources. The authors determined an optimal combination of solar PV and PEVs, with a vehicle-to-grid (V2G) connection, in New York City. However, this study considered only the marginal benefit of each generating source, without any regard for cost constraints. The trade-off between costs and system reliability is an essential consideration as more renewable and distributed grid resources are integrated into current electricity systems. Furthermore, capacity credit analysis has only been applied to one or two resources in a grid; it is unknown if this method is suitable for modelling multiple resources interacting on a large scale in the grid.

Consideration of costs and resource performance, using a capacity credit statistical approximation technique, allows for a high-level estimate of the mix of grid resources required to move away from fossil fuels and other conventional energy sources. This paper investigates the use of the Garver approximation to estimate optimal combinations of renewable energy resources, along with demand response and energy storage, to replace conventional energy sources in Ontario, Canada. Given supply, reliability and price constraints, the optimal mix of renewable and distributed resources is investigated for three sequential scenarios: displacing fossil fuel electricity generation, converting the passenger vehicle fleet to PEVs, and retiring nuclear generation. The usefulness of the Garver approximation is assessed. The results are meant to be indicative of the scale, and approximate proportions, of these resources that will be needed to transition to a carbon-free, sustainable energy system.

## 2. Methods

The Garver approximation, shown in Equation (1), calculates capacity credit as equivalent to the effective load carrying capability (ELCC). ELCC, or capacity credit, is the displaced conventional generation as a fraction of the new installed capacity.

$$ELCC = m\mathrm{Ln}\left[\frac{\sum_i \exp(-(L_P - l_i)/m)}{\sum_i \exp(-(L_P - l_i + x_i)/m)}\right]/X \qquad (1)$$

where $L_P$ is peak load, $m$ is the Garver coefficient set to equal $0.03L_P$, $l_i$ is the load at hour $i$, $X$ is the capacity of the new generator, and $x_i$ is the output or availability of the new generator at hour $i$. For dispatchable resources such as biomass or demand response, $x_i$ is hourly availability because it represents the capacity that could be available if needed. In the case of intermittent resources like wind or solar, $x_i$ is the hourly output as this value represents the actual availability of those resources.

The firm capacity contribution of a resource is the amount of existing supply that can be replaced by that resource while serving the same load and maintaining reliability. Firm capacity contribution is equal to ELCC*X. ELCC varies with X, the correlation of a given resource with demand, and the capacity factor of that resource

The performance of the Garver approximation is investigated for determining the optimal installed capacities of renewable energy (biomass, solar PV, and wind), demand response, and energy storage that could manage the aforementioned three sequential scenarios. The analysis is performed such that the total costs of the additional generation were minimized.

## 2.1 Data and modelling

### 2.1.1 Data sources

Performance of the renewable energy technologies is modelled using various data sources such as actual recorded generation and hourly satellite time-series data. Historical fossil fuel and wind generation and availability data were acquired from the Independent Electricity System Operator (IESO). Solar PV production is modelled based on input data from four sites in the province: Ottawa, Toronto, London, and Thunder Bay. Hourly satellite solar radiation data from Natural Resources Canada [16] are used to model the PV production. An additional GW of new hydroelectric capacity is incorporated into the model, based on the medium term plans of for Ontario [17].

### 2.1.2 Generating capacity and ELCC

The ELCC calculation is based on the available capacity of each generating source to cover demand in a given hour. For each generation source, the hourly availability is calculated using the source's availability fraction for that hour, multiplied by the modelled installed capacity. The hourly available capacity, or availability, for biomass plants is assumed to be the same as that of fossil fuel power plants in the province.

The hourly availability of wind and solar power is equal to the hourly capacity factor of those resources. Wind power is scaled up based on hourly capacity factors from existing Ontario wind farms. Solar power is modelled for an even distribution of fixed panel orientations at each site (based on [18]): flat, south-facing at a $10^{o}$ tilt, south-facing tilted at latitude, southwest facing at a $10^{o}$ tilt, and southwest facing tilted at latitude. The hourly production for each site and each orientation is combined to create an hourly availability factor.

Demand response and energy storage are modelled using a similar approach. Demand response is assumed to be available at all times, unless it has recently been deployed for a number of hours, in which case the availability is zero. If a customer provides 1kW of demand response for one hour, it is assumed that their demand will increase by 0.4kW for two hours at a later off-peak period; this results in a slight overall decrease in electricity use. Energy storage is available when electricity has been stored for later use. Electricity is stored during periods of low demand and/or high renewable availability. Round-trip efficiency is assumed to be 80%, and 10Wh of storage are assumed to be available for each watt of charge/discharge capacity.

### 2.1.3 Matching supply and demand

To ensure that the modelled system, based on the ELCC criteria, is actually able to maintain system reliability, generation for each hour is dispatched to cover demand. Generating sources are deployed in the following manner to meet demand. Nuclear, in the scenarios that consider nuclear, is deployed first using the actual historical output, followed by wind and solar. If there is excess capacity available, electricity is diverted to storage and/or increased demand from demand response. Hydroelectric power is then deployed, followed by storage, demand response and finally biomass as a peaking resource. In the event that the sum of these resources can't meet demand, electricity imports are allowed.

The deployment of some resources is subject to constraints. The maximum ramp rate for bio-electricity is assumed to be equal with that of coal generation. Estimates for the amount of sustainable bio-electricity that can be produced on a yearly basis in Ontario range from 14TWh [19] to 87TWh [20]; due to concerns about the actual availability of biomass, only 15TWh per year is assumed to be available. The maximum ramp rate for hydro is equal to the historical ramp rates. The total capacity factor for hydro is limited to the historical capacity factor. Demand response and storage can only be called upon when available. Imports are subject to historical hourly limits, and cumulative imports are limited to the historical yearly imports.

2.1.4 Costs

Costs for each resource are calculated on a per kWh basis using Equation 2.

$$LCOE = \frac{CRF \times C_{cap} + OM_{fixed}}{8760\,CF} + OM_{variable} + \frac{C_{fuel}}{\eta} \quad (2)$$

where *LCOE* is the levelized cost of electricity ($/kWh), *CRF* is the cost recovery factor based on a 5% interest rate and 20 year project life (10 years for demand response), $C_{cap}$ is the capital cost ($/kW), $OM_{fixed}$ is the fixed operations and maintenance (O&M) cost ($/kW/year), *CF* is the capacity factor, $OM_{variable}$ is the variable O&M cost ($/kWh), $C_{fuel}$ is the cost of fuel ($/kWh) and $\eta$ is the efficiency in generating electricity from fuel. The fuel cost for storage is based on the assumption that cheap, off-peak electricity will be purchased at the market clearing price determined by the IESO. The assumed cost for each resource is shown in Table 1.

Table 1. Assumed costs for each resource

| **Resource** | **Capital Cost ($/kW)** | **Fixed O&M ($/kW)** | **Variable O&M ($/kWh)** | **Fuel Cost ($/GJ)** | **Efficiency** |
|---|---|---|---|---|---|
| *Wind* | 2100.0[a] | 0.0 | 0.01[a] | 0 | |
| *Biomass* | 2000.0[b] | 55.0[c] | 0.005[c] | 8.2[c] | 0.31[c] |
| *Solar* | 3500.0[d] | 52.5[e] | 0 | 0 | |
| *Demand Response (Residential)* | 511.5[f] | 26.3[f] | 0 | 0 | |
| *Demand Response (Commercial & Institutional)* | 170.8[g] | 1.0[g] | 0 | 0 | |
| *Storage (Pumped Hydro)* | 1650.0[h] | 24.8[e] | 0.005 | 0.02 ($/kWh) | 0.8 |
| *Storage (Battery)* | 1800[i] | 37.5[i] | 0.005[i] | 0.02 ($/kWh) | 0.8 |

a- From [21]; b- From [1]; c- From [22]; d- From [23]; e- From [24]; f- Based on data from [25, 26, 27];; g- Based on data from [28, 29]; h- Based on proposed pumped hydro project in Ontario [30]; i- From [31]

Capacity factors are based on the actual modelled performance of the resource. Thus, the per kWh costs of generation for each source are determined in the model. A constant cost of 3.8 [32] and 9.0¢/kWh [33] are assumed for hydro power and imports, respectively.

### 2.2 Analysis

Analysis is performed using hourly data from March 1, 2006 to December 31, 2008. Total cost is calculated using Equation 3

$$Cost = \sum_j \sum_i X_j CF_{i,j} c_j \tag{3}$$

where $X_j$ is installed capacity for resource *j*, $CF_{i,j}$ is the hourly capacity factor for resource *j*, and $c_j$ is the unit cost for resource *j*. The objective function is to minimize cost, such that ELCC*X is equal to a minimum firm capacity.

The performance of the ELCC method is assessed based on its ability to create a modelled system that matches supply and demand while minimizing costs.

#### 2.2.1 Scenario 1: Displace fossil fuel generation

The first step in the analysis is to calculate the combined ELCC for coal and natural gas generation in Ontario. This is done using hourly generator output, capability and planned outage data obtained from the IESO for the time period given above. The optimal lowest-cost combination of biomass, wind, solar, demand response, and storage is calculated such that to meet the ELCC requirements.

#### 2.2.2 Scenario 2: Convert passenger fleet to PEVs

For the second scenario, an EV charge plan is introduced based on a complete conversion of the passenger vehicle fleet from internal combustion engine to PEV. The number of vehicle kilometres per year was obtained from Statistics Canada [34]. The yearly energy demand for PEVs is computed by assuming an average vehicle fuel economy of 6km/kWh and a battery charging efficiency of 0.9. Vehicle charging is scheduled to occur during periods of low demand and high renewable availability, while still meeting daily driving energy requirements. The PEV demand is added to the existing demand in the model. In a very few high demand days (6 out of 1037 days in the study) the full daily energy requirement is not met; it is assumed that this shortfall is manifested in slightly lower battery levels across many drivers and does not cause any consumer inconvenience. In the optimisation for this scenario, the hourly EV demand is added to the load profile.

#### 2.2.3 Scenario 3: Retire nuclear generation

Combined nuclear and fossil fuel generator firm capacity is calculated using the same method outlined for Scenario 1. The model has to provide the equivalent firm capacity of the nuclear and fossil fuel generators, while satisfying the demand from PEVs.

## 3. Results & Discussion

The modelled installed capacities for the first scenario are shown in Figure 1. Installed capacities are shown for the ELCC approach and a 'load matching' approach. In the load matching approach, the model is run as described in Section 2, except the ELCC constraint is lifted. The model is only required to match supply and demand at a minimum total cost. A comparison of the performance of the two approaches is shown in Table 2, which shows the firm capacity contribution, average non-nuclear cost of electricity, and the number of hours that demand exceeds supply.

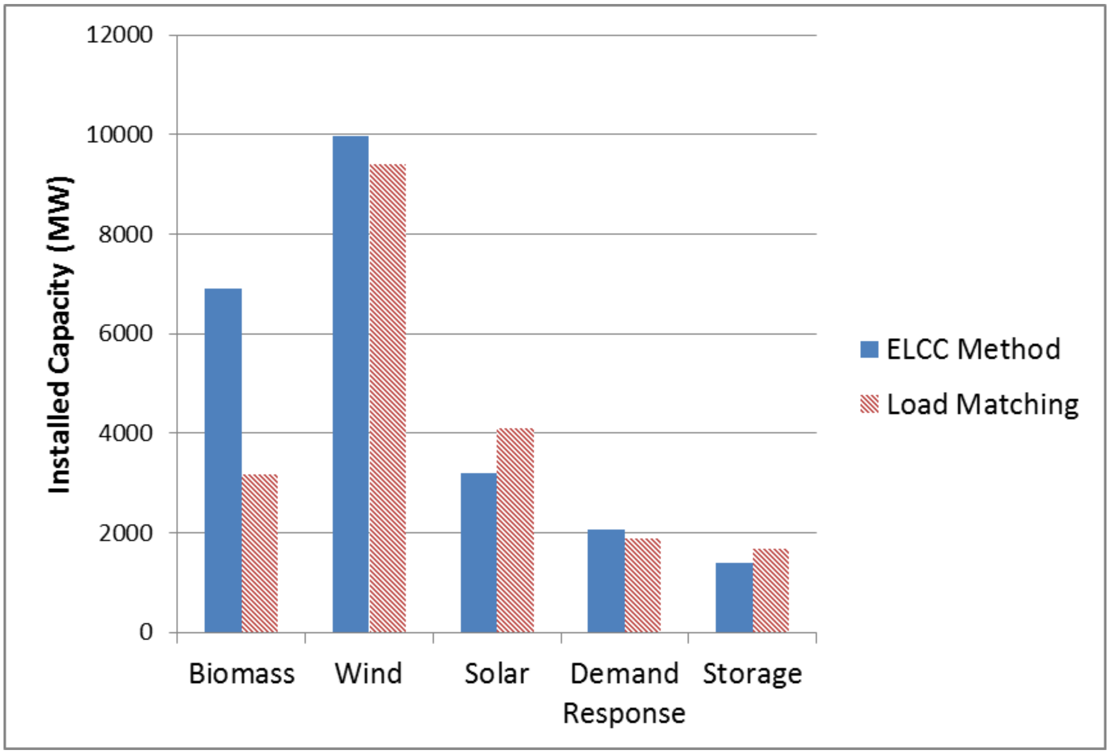


Figure 1. Installed capacity by resource, for ELCC and load matching methods.

| | Firm Capacity Contribution (MW) | Cost ($/MWh) | # Hours Demand>Supply |
|---|---|---|---|
| *ELCC* | 9200.4 | 93.5 | 3 |
| *Load Matching* | 6042.8 | 85.4 | 0 |

Table 2. Comparison of ELCC and load matching methods

Figure 1 and Table 2 show that the ELCC method is not an effective method for optimizing an electricity system to meet performance requirements. The ELCC method requires a much greater installed capacity, particularly biomass, for backup reliability concerns. However, despite the greater installed capacity there are still three hours during the modelled time period in which demand exceeds supply. Furthermore, the levelized non-nuclear cost of electricity generation for the load matching technique is nearly 1¢/kWh less than the ELCC approach, primarily because the extra biomass capacity lowers the average capacity factor for bioelectricity, which increases the LCOE.

The relative performance between the ELCC method and load matching approaches is similar for the second and third scenarios. The ELCC method requires excess capacity to be built, increasing system costs without appreciably improving system performance. Thus, the ELCC method is not a useful tool for large scale system estimates. It is likely more suited for evaluating the relative contribution of a single resource at a smaller scale contribution to the system, as opposed to being used as a criterion for larger scale system modelling.

This finding is somewhat surprising; it was hypothesized that ELCC would be a useful tool for creating a high-level estimate of the capacity of new grid resources necessary to replace conventional energy supply. Given the method's short comings, it is suggested that the ELCC method and other statistical approximations for capacity credit be further evaluated for their suitability in this regard.

Despite the conclusions about the ELCC approach, the constructed model is able to give high level estimates for each of the scenarios based on the load matching approach. The results from this approach, for all three scenarios, are shown in Figure 2. The non-nuclear electricity costs are 8.5, 9.5, and 12.5¢/kWh for the first, second and third scenarios, respectively.

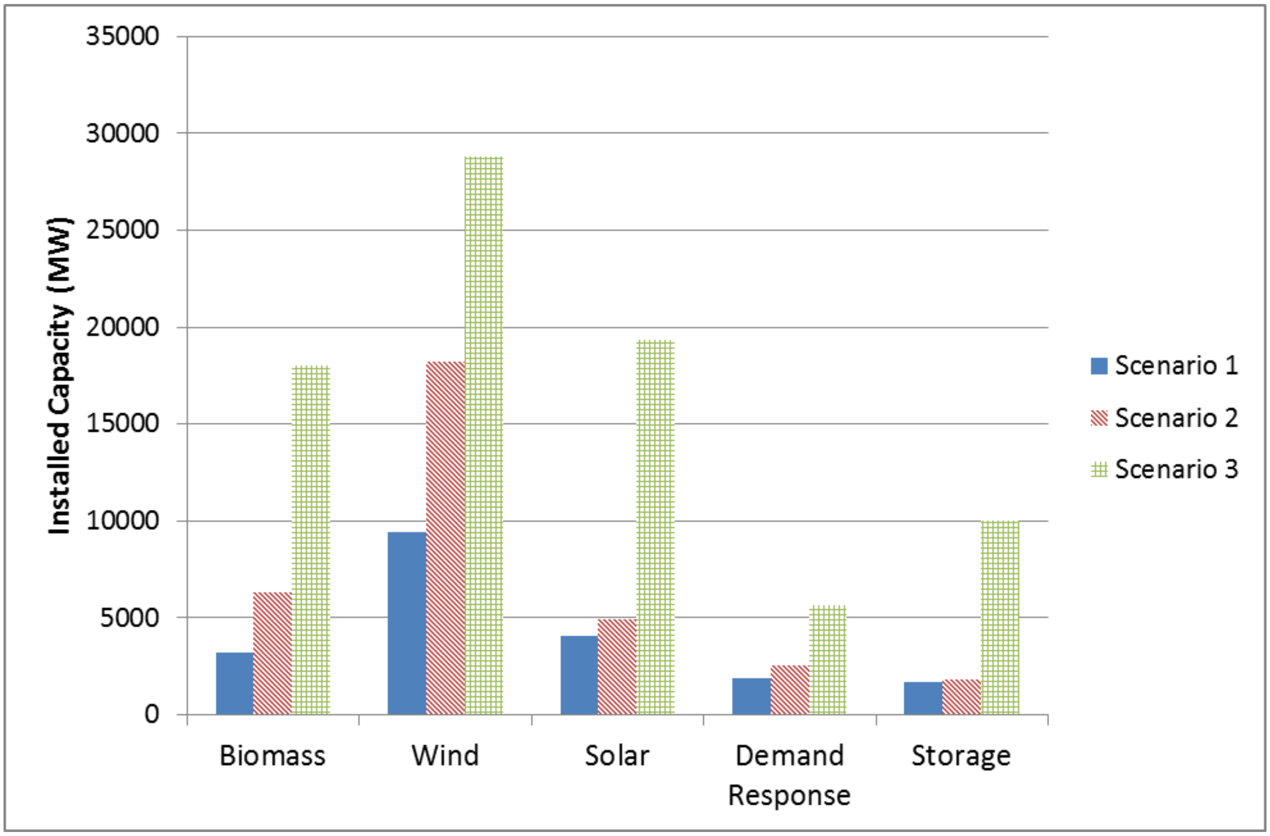


Figure 2. Installed capacity by resource, three scenarios using the load matching approach

The results in Figure 2 show that each of the three transitions is technically possible. The systems, excluding the contributions of nuclear and hydro, are predominately wind based with smaller amounts of the other resources for support. The bioelectricity capacity factor is around 8% for the first two scenarios, increasing to 20% for the third scenario. As a result, the LCOE for biomass is quite high, consistent with its modelled deployment as a peak and backup source of generation.

The large installed capacities modelled to replace nuclear power are not surprising. Nuclear power currently provides around 50% of Ontario's electricity, and the low capacity factors for wind, solar and biomass mean that large capacities will need to replace nuclear generation. It should be noted that the average LCOE of 12.3¢/kWh to replace nuclear is substantially less than most estimates for new or refurbished nuclear power [1, 33].

Relatively small amounts of demand response and storage were selected by the model for all scenarios, despite being dispatchable for peak demand hours or periods of low renewable supply. The reason for this is that every period of peak shaving by demand response or storage is accompanied by a period of increased demand later. The model finds an optimal balance between the marginal benefit of peak shaving and the marginal cost of increased load.

The optimal combination of resources could likely be further optimised through the use of more detailed models and analysis. This paper uses a static approach for deploying grid resources and modelling the interactions of various sources and services. The paper is intended as a 'first draft' of the mix of resources required to change the energy supply in the province. The results are useful as a starting point, for discussion as well as more detailed analysis. An in-depth hour-by-hour reliability assessment using a 'smart-grid' methodology could deploy resources in a more reactive manner. For example, PEVs with V2G could be considered as a method of improving system reliability while moving away from fossil fuel energy sources.

## 4. Conclusion

The goal of this paper is to provide high level estimates of the combination of renewables, storage, and demand response that would be required to replace conventional energy generation in Ontario. High level estimates are useful for policymakers in determining the plausibility of meeting certain policy goals, and the scope of investment and change that would be required to meet those goals. The analysis presented in this paper provides an initial estimate of how to move sharply away from fossil fuels, and to a lesser extent nuclear power, as an energy source in the province without requiring extensive data and computationally intensive probability analysis.

A further goal was to assess the suitability of the ELCC method for modelling an electricity system based on new grid resources while maintaining system reliability. The findings in this paper suggest that the ELCC method requires unnecessary excess capacity, which increases system costs without substantively improving system performance. A load matching methodology was employed instead to model the transition away from conventional energy.

The results indicate that system reliability can be maintained as we move away from fossil fuels for electricity generation and passenger transportation. Reliable and dispatchable resources are essential in meeting these goals. The model used in this paper also finds it is technically feasible to replace nuclear generation, in addition to fossil fuels, while maintaining system reliability. Transitioning away from nuclear power requires substantial investments in new capacity.

Future research is suggested in a number of areas: detailed consideration of the potential for sustainable biomass energy production in Ontario, the potential for increased imports of hydroelectricity from neighbouring provinces, the impact of geographically diverse wind farms optimized for consistent supply, and more detailed hourly analysis which optimizes the coordination of energy storage and excess renewable generation. The results of this and of future research can be used as a guide for how to begin the transition to a carbon-free energy system in Ontario.

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