Final Report for the Energy Modelling Initiative

Open and Accessible Renewable Electricity System Modelling for Prince Edward Island

January 20th, 2020

Matthew McCarville, Peter Rukavina, and Matthew Hall

Abstract

This report presents an open-source model of Prince Edward Island's electricity generation and consumption to enable more accurate and accessible exploration of ways to further decarbonize the province's energy system. The model is intended to be user friendly, customizable, and equally applicable to other regions of similar scale. It combines a spreadsheet-based user interface with a Python-based backend to provide accessibility as well as versatility, all while maintaining a fully visible and customizable process. The model operates at an hourly or sub-hourly time scale and models the energy balance from renewable energy sources, various inflexible and flexible loads, energy storage systems, and electric vehicles. These components are simulated together and then power time series, storage levels, and various performance metrics are calculated. The model provides levelized cost of energy and emissions estimates, which can then be used to inform assessment of decarbonization pathway alternatives. Demonstration of the model on three scenarios for PEI illustrates the model's outputs and highlights the value of demand response resources in accommodating high penetrations of renewable energy. Furthermore, the results show that with moderate cost estimates the overall electricity price does not seem to increase prohibitively even with very ambitious renewable energy and electrification scale-ups.

In concert with beta testing and feedback from users, the model will be verified and refined in preparation for public release. The model's simple interface and open-source composition are expected to make it attractive to other researchers and model developers, as well as less-experienced users with an interest in energy system decarbonization. The goal of this model is to reduce barriers to interested non-experts in engaging with the technical subject matter around renewable energy integration and energy system decarbonization pathways. The model should provide a new level of accessibility for engaging with energy system alternatives while maintaining the rigour necessary to give trustworthy and informative results.

Table of Contents

Introduction

This project brings together and builds on existing independent energy data and modelling efforts in Prince Edward Island (PEI) to create a modelling tool for electricity generation and consumption that is more accessible to a range of users, more comprehensive, and more geared toward policy-informing results than previous PEI-focused modelling efforts. These strengths are expected to make the model valuable for application in other locations as well.

The model development took place over the summer and fall of 2019, although its foundation is based heavily on a previous Python model that was used for more simplified studies of renewable energy mixtures and energy storage options for PEI in an isolated-grid context [1]. Relative to that model, the present model is more advanced and simultaneously more accessible to a broad community of advanced researchers, policymakers, and dedicated citizens. Electricity system modelling capabilities are extended further than the existing electricity sector. Electrification of carbon-intensive sectors, namely transportation and heating, can now be modelled and the effect on energy costs and emissions compared. This enables evaluation of the overall carbon abatement potential from the implementation of policies, the deployment of technologies, and from the pursuit of energy transition pathways. Thus the present model makes steps toward a more cross-sectoral and holistic approach to energy system transition than previously examined for PEI.

In the local context of Prince Edward Island, studies have used archived wind generation and temperature data to model the integration of wind electricity for space and water heating with thermal energy storage [2], [3]. More recently, the capture of wind energy using thermal energy storage devices for space and water heating has been implemented and studied within Summerside PEI's smart grid [4]. More recent studies looked at 100% renewable electricity systems for PEI using time-marching models for scenario cost optimization ([1], [5]). By combining these capabilities in an open and accessible way, the present model enhances the quantity and quality of renewable energy scenario modelling in PEI. Additionally, it serves as a prototype for how similar scenario explorations could be done in other comparable jurisdictions. Although PEI's electricity system is unique among provinces, its situation may be highly transferable to municipalities or communities looking to offset their electricity imports with community/municipality-owned renewable energy sources and storage systems.

At the time of writing, the model is functioning in a "beta" capacity. It can be used as desired to explore various electricity system scenarios, and the essentials of its user interface are in place so that new users can explore its functionality. Further improvements in error handling, user interface streamlining, and documentation are needed before releasing the model for public use. These improvements will be best made iteratively while gathering feedback from beta users who are interested in exploring the model with support from the authors.

The Model

The model simulates electricity demand, supply, and storage at an hourly time scale as is common practice for renewable energy integration modelling [6]. It includes features for simulating wind and solar energy generation, the behaviour of energy storage technologies, and province-wide electrical demand including the effects of increased electric heating adoption, electric vehicle use, and smart-grid technology. Key feature additions relative to previous modelling of PEI (e.g. [1], [5]) include demand response and smart charging of electric vehicles, both increasingly relevant opportunities for reducing heating and transportation emissions while enhancing renewable energy integration.

The model's main innovation is combining two views of the model that are both user-editable: a spreadsheet-based user interface that requires no programming to work with, and a Python-based model backend that gives full exposure and editability of the model's internal workings. The Excel frontend makes the model convenient to use and accessible to anyone with basic spreadsheet proficiency and energy knowledge. The Python backend enables more sophisticated simulation abilities and customization as needed for a given application, as well as deeper analysis of data results than is possible only through Excel. Both sides of the model are open source so that they can be used, audited, or extended by anyone with sufficient background.

Spreadsheet-Based User Interface

The Excel spreadsheet embodies the structure through which users can enter input data and settings to the model. It includes various sheets: an overview, loads, generation sources, storages, battery electric vehicles (BEVs), and performance curves (e.g. for wind turbine power and temperature-dependent heat pump performance). Time-series sheets include annual, weekly, and daily sheets for hourly or sub-hourly data to be used in the simulation. A time-series BEV sheet allows different categories of vehicle use patterns to be modelled.

The first sheet provides an overview of the model components, basic parameters for electricity exchange with an outside grid, and a button that executes the overall model when clicked. An example is shown in Figure 1.

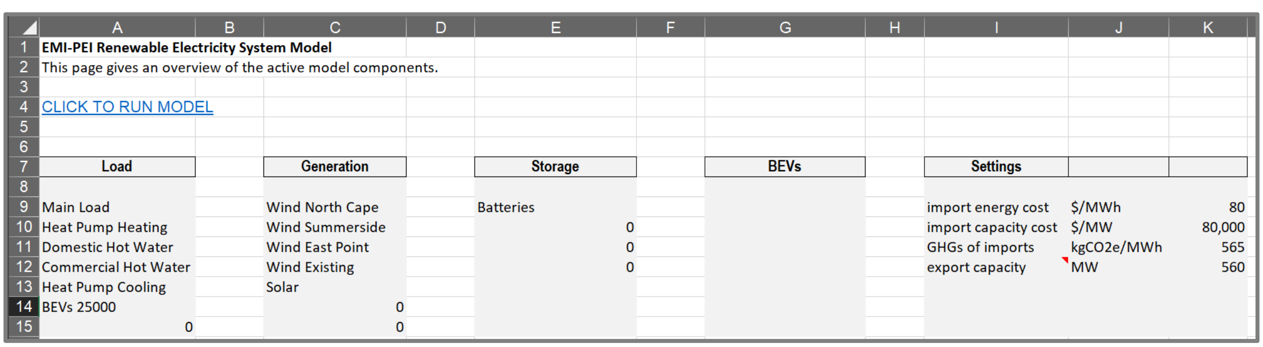

Figure 1: Model overview sheet

Loads Including Flexible Loads

The loads sheet, shown in Figure 2, lists all fixed and flexible loads. In the example shown, which is similar to one of the scenarios demonstrated later, loads include the existing hourly electric load in 2016, hourly space heating with electrification using heat pumps, and electricity-powered domestic and commercial hot water heaters.

	A	B	C	D	E	F	G	H
1	**Loads**							
2	List all fixed and flexible loads here.							
3			PREVIEW	PREVIEW	PREVIEW	PREVIEW	PREVIEW	PREVIEW
4	**Name**		**Main Load**	**Heat Pump Heating**	**Heat Pump Cooling**	**Domestic Hot Water**	**Commercial Hot Water**	**BEVs 25000**
5								
6	**Load time series**							
7	year long	select header	main load	HDH	CDH			BEVs 25000
8	week long	select header				Domestic Hot Wa	Commercial Hot Water	
9	day	select header						
10	week end day	select header						
11	seasonal adjustment							
12	seasonal scale	select header						
13	seasonal shift	select header						
14	**Conversion**							
15	performance curve	select header		ASHP Heating Mo	ASHP Cooling Mode COP Bins 21˚C Setpoint			
16	year long	select header		temperature	temperature			
17	week long	select header						
18	day	select header						
19	week end day	select header						
20	**Load shaping/scaling**							
21	energy	MWh						
22	peak power	MW		68.82	7.50			
23	**Demand response**							
24	flexload model	1 or 2	1	1	1	1	1	1
25	flexload fixed	MW	10					
26	flexload fraction	%		10%	10%			
27	fraction time series	select header						
28	***flexload model 1***							
29	nominal storage capaci	MWh				152	23.1	1500
30	max charge rate	MW				113.9	17.3	250
31	max discharge rate	MW				15.62	2.6	35.2
32	self discharge	%/hour				0.0%	0.0%	0.0%
33	charge efficiency	%				100%	100%	100%
34	discharge efficiency	%				100%	100%	100%
35	***flexload model 2***							
36	load shift type	0,1,2	0	0	1	1	1	
37	max time shift fwd	hr	4	2	2	4	4	
38	max time shift back	hr	4	2	2	4	4	

Figure 2: Load sheet

The most important input for a load is a time series. It can be selected from a year-long, week-long, or day-long set of values. Next, a performance curve can be applied to transform the values. For example, to model heat pumps, heating degree hours are used as the input time series and then a temperature-dependent performance curve for an air-source heat pump is applied to calculate the corresponding electricity demand. This functionality is important since heat pump efficiency varies with temperature, particularly in cold extremes.

Flexible loads with demand response can be modelled using one of two approaches. A storage-based approach mimics the behaviour of flexible loads that have an inherent storage element, such as electric thermal storage units. This model acts as a battery in parallel with the load that charges when there is a generation surplus and discharges when there is a generation shortage, within its limits. A time-shifting-based approach mimics the behaviour of loads that can simply be scheduled to occur earlier or later. Together, these models allow representation of various flexible loads. For example, water heaters with the right type of insulation can be set to an over-temperature, allowing them to operate longer without receiving a charge. A standard 55 gallon tank for a residential home can have greater than 6 kWh of storage capacity between the high and low temperature settings. This is already done for customers of the municipal electric utility in Summerside PEI.

The time-shifting-based demand-response model uses a convolution approach to shift load from a given hour to adjacent hours within a specified range. This allows loads to be shifted both backward and forward in time. The logic for when to shift loads can be set for three alternatives: minimizing shortages (which would be met by imports), minimizing load peaks, or minimizing exports.

Generation

Electricity generation is modelled similarly to load in that an input time series is provided, and also a performance or power curve can be provided to model the behaviour of specific technologies. For the simulations done in the current work, wind generation was modelled based on measured wind speed and weather condition data from three weather stations, then scaled to realistic hub heights and applied to a wind turbine power curve. "Preview" buttons in the spreadsheets call Python functions that load and process the respective input data and settings, providing the user a visual summary such as is shown in Figure 3.

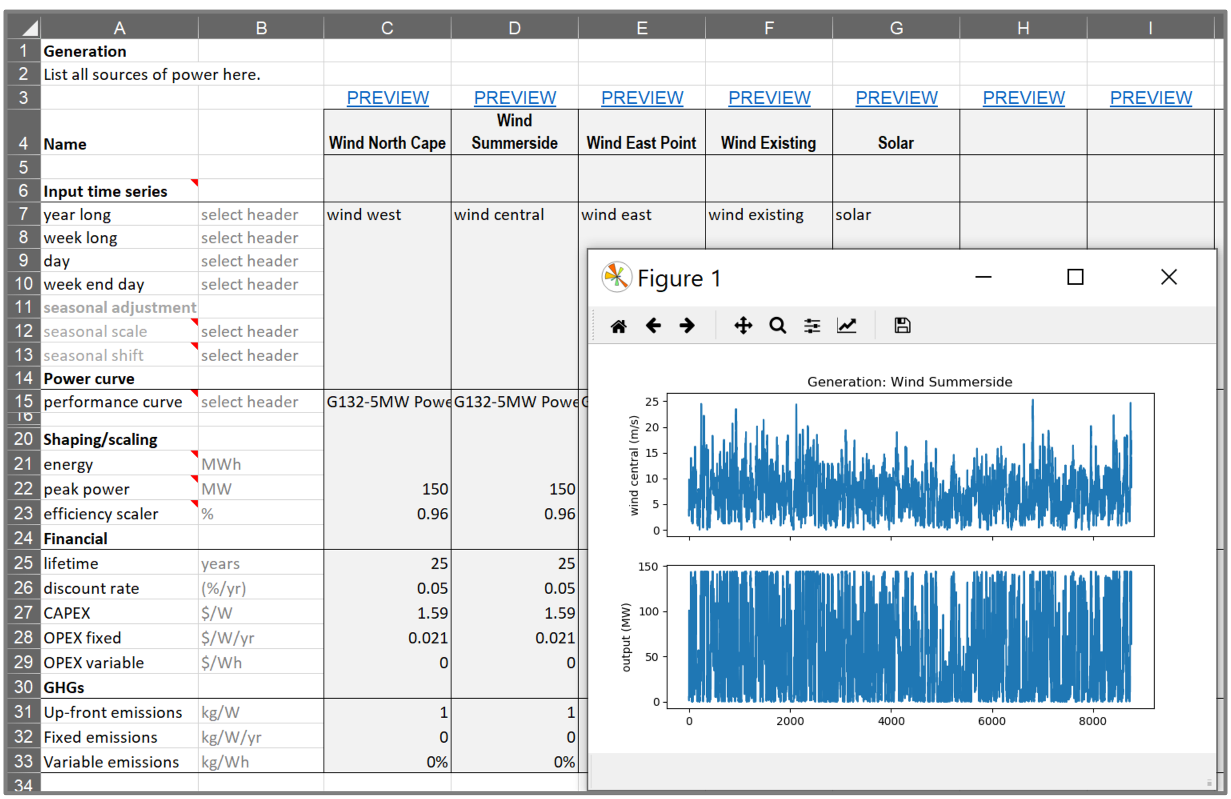

Figure 3: Generation sheet with preview shown

Storage Technologies

Electric energy storage technologies are represented by a model that accounts for storage capacity, charge and discharge limits and losses, self-discharge, and associated costs and lifetime limits. All of these parameters are input by the user. In addition, a time series can be provided to represent seasonal variation of the storage capacity. The inputs are shown in Figure 4.

	A	B	C	D	E
1	**Storage**				
2	List all energy storage capacities that are not flexible loads here.				
3			PREVIEW	PREVIEW	PREVIEW
4	**Name**		**Batteries**		
5	energy capacity	MWh	800		
6	max charge rate	MW	200		
7	max discharge rate	MW	200		
8	self discharge	%/hour	0.01		
9	charge efficinecy		0.95		
10	discharge efficiency		0.95		
11	**Variability**				
12	variation time series	select header			
13					
16	**Financial**				
17	lifetime cycles		7500		
18	lifetime	years	25		
19	discount rate	(%/yr)	0.05		
20	CAPEX	\$/Wh	0.23		
21	OPEX fixed	\$/Wh/yr	0.015		
22	OPEX variable	\$/Wh	0		
23	**GHGs**				
24	Up-front emissions	kg/Wh	0.65		
25	Fixed emissions	kg/Wh/yr	0		
26	Variable emissions	kg/Wh	0%		

Figure 4: Energy storage sheet

The storage model tracks the storage component's state of charge (SOC) over each interval and determines whether to charge or discharge based on the limits of the storage as well as the instantaneous needs of the grid.

Electric Vehicles

Electric vehicles (EVs) are handled with a separate modelling approach because they can involve both demand and storage aspects. EV batteries are modelled with the same performance traits as other energy storage technologies (charge rate, efficiency, etc.). However, the storage availability varies depending on whether vehicles are plugged in or not. Also, the change in state of charge resulting from vehicles departing (unplugging) and returning (plugging in), which incorporates EV energy consumption, is accounted for. Lastly, minimum SOC limits are imposed based on user-specified values for SOC expectations of departing vehicles. Two models have been developed to handle the separate cases of limited and ubiquitous charging infrastructure. The respective inputs are shown in Figure 5.

	A	B	C	D	E
1	**BEVs**				
2	List all groups of BEVs that will be modelled based on distinct plug/unplug periods here. (Use multiple groups to separate very different use patterns, since the model is based on an average SOC within the group.)				
3			PREVIEW	PREVIEW	PREVIEW
4	**name**		**Commuter group 1**	**Commuter group 2**	**Light Duty**
5	total battery capacity	MWh	200	750	375
6	minimum state of charge	%	50%	30%	50%
7	max charge rate	MW	12	100	50
8	max discharge rate	MW	10	0	50
9	self discharge	%/hour	0	0	0
10	charge efficinecy	%	1	1	1
11	discharge efficiency	%	1	1	1
12	annual energy consumption	GWh	200		
13	seasonal variation timeseries	select header			
14	BEV model	1 or 2	2	1	1
15	**BEV Model 1 (ubiquitous chargers)**				
16	**usage TS (add to 1 over time period)**				
17	year long	select header			
18	week long	select header			
19	day	select header	BEV Category 3 - weekday		
20	week end day	select header			
21	unavailable fraction%	%	5%		
22					
23	**BEV Model 2 (limited chargers)**				
24	**plug/unplug time series**				
25	year long	select header			
26	week long	select header			
27	day	select header	BEV Category 1 - weekday	BEV Category 2 - weekday	BEV Category 3 - weekday
28	week end day	select header	BEV Category 1 - weekend day	BEV Category 2 - weekend day	BEV Category 3 - weekend day

Figure 5: Electric vehicle sheet

Other Inputs

The remaining sheets in the spreadsheet allow input of time series or relationship data needed by any of the model components. A “Curves” sheet contains any power or performance curves, such as for wind turbines or heat pumps. These consist of matched sets of X and Y data. Four “TS” sheets hold temporal data for year-long, week-long, day-long and EV-specific quantities. The first three can be any type of needed quantity, such as load magnitude, wind speed, or temperature.

The BEV sheet contains a specific set of data for electric vehicle charging and discharging patterns. When using the limited-charger model, the inputs consist of four quantities for any given BEV fleet:

- % unplugging (fraction of fleet unplugging in a given hour)
- % SOC at departure (minimum SOC needed by departing vehicles that hour)
- % plugging (fraction of fleet plugging in in a given hour)
- % SOC at arrival (assuming departed with minimum)

These data are processed by the model to compute the energy consumption, storage availability, and charging requirements of each BEV fleet.

Python-Based Model Backend

The Python backend uses a simple object-oriented approach to automatically process the various energy system elements specified in the columns of the spreadsheet interface. A class exists for each system element type (load, generation, storage, and EV fleet) and an object is made for each element specified by the user. This makes model operation modular and efficient to change. Model behaviours can easily be modified, or a new component type could be added by following the structure of the existing spreadsheet pages and corresponding Python classes. By focusing on the minimum capabilities needed for the model at present, the code is relatively simple and navigable, making it well suited for expansion to suit others' needs.

The popular Anaconda IPython distribution is the recommended Python installation for use with the model, though many Python distributions will work. The one additional dependency required for full integration with the spreadsheet front end is the package xlwings. This package must be installed through Python, then its Excel add-in installed in order for the buttons in the spreadsheet to function. Otherwise, users can run the model by running a Python script.

Documentation of the specific implementation details in the model backend will be provided through extensive source code commenting, consistent with the goal of facilitating customization for more experienced users.

Model Outputs

The primary outputs of the model are hourly power quantities for all energy system components along with hourly state of charge quantities for storage and electric vehicle components. These outputs are displayed in various forms, including a spreadsheet of all power quantities, specific plots showing the power (and state of charge, if applicable) of each energy system component, and a master set of plots that visualizes the combination of all energy sources, loads, and storages. An example of the latter is shown in Figure 6. Additionally, high-level metrics are displayed to the user through the command console, for example:

```
Wind North Cape - generation COE: 30 $/MWh
Wind Summerside - generation COE: 42 $/MWh
Wind East Point - generation COE: 33 $/MWh
Wind Existing - generation COE: 62 $/MWh
Solar - generation COE: 47 $/MWh
Batteries - storage COE: 382 $/MWh
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Total generation:        2003.2 GWh
Total annual load:       1654.0 GWh
Integrated generation:   1596.0 GWh, 79.7%
Peak export (MW):         406.2 MW
Peak import (MW):         266.7 MW
Net import (GWh):        -296.5 GWh
Total (exports only):  407229.4 MWh
Total (imports only):  110739.4 MWh
Imports energy cost:   $     8.9M
Imports capacity cost: $    21.3M
```

```
Elec. import GHGs:        33221.8 tCO2e
Local renewable energy:      93.5%
LCOE:                       105.0 $/MWh
Overall GHG intensity:       20.1 kgCO2e/MWh
```

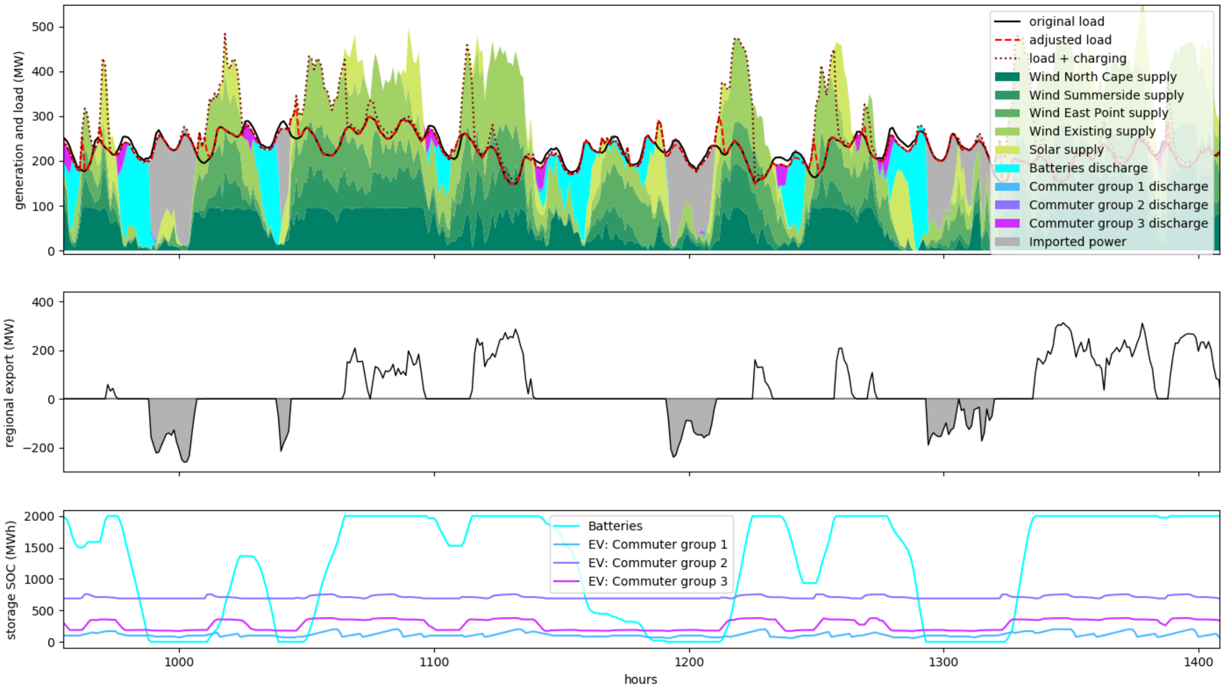

Figure 6: Sample model output plots

Model Summary and Contextualization

The developed model can best be described as a time-marching model with some simple storage and demand-response optimization capabilities. It has characteristics of both optimization models (i.e. unit commitment economic dispatch models), which optimize power flows using full knowledge of the yearly data, and time-marching models, which simulate grid behaviour one hour at a time with limited or no future knowledge. Before time marching, the model applies some foresight in its handling of demand response behaviour, intending to mimic the potential for load and supply forecasting in smart grid operation. This capability is very simplified and heuristic relative to forecasting models used in other research or by utilities, but it provides a practical estimation for high-level modelling needs.

Current features of the model include:

- Flexible incorporation of load, generation, and weather data sets;
- Capabilities for power and performance curves to account for time-varying generation and load performance changes based on user-specified technology specifications;

- Incorporation of temperature data to estimate heating demands, including heat pump specifications;
- Output of hourly electricity generation, load, demand response, and storage time series;
- Output of performance metrics (e.g. capacity factor, load factor, curtailment rate); and
- Output of policy-relevant metrics (e.g. cost of energy, GHG emissions).

The model's approach is simpler than most widely used optimization and time-marching models (e.g. Plexos and Homer Energy, respectively) because it is focused on the specific task of small-scale electricity system simulation. It is set up to evaluate and compare scenarios rather than to perform optimization of energy system options at this time. However, the backend of the model may still be programmed to enable least-cost and/or least-carbon or multi-objective optimization modelling in the future.

The model's spreadsheet-based front end streamlines incorporation of energy data from a variety of sources in a very generic way. Many other models streamline this process using global databases [7] but most of these models are not open-source and cannot be customized to meet the nuances of some situations. Meanwhile, models that are open source tend to lack the simplicity to be accessible to people who are not researchers. Because PEI-specific data comes from various sources, this project provides flexible options for accommodating different types of input data. The combination of flexibility, simplicity, ease of use, and customizability are what set the model apart from most other tools in the energy modelling ecosystem.

Model Demonstration on PEI Scenarios

In the scope of the present energy modelling initiative, the model is demonstrated to evaluate three scenarios: the existing state of PEI's electricity system in 2016 using existing data, a moderately renewable 2030 scenario with limited electrification, and a highly renewable 2030 scenario with ambitious electrification and demand response.

Ultimately, this tool is expected to facilitate greater involvement by stakeholders in exploring different scenarios, in turn providing greater insight to decision-makers about possible decarbonization pathways.

Scenario Setup

In the scenarios, existing data on PEI's electric load and wind generation at a 15 minute temporal resolution are used from the year 2016 using an open data archive [8]. These existing 2016 loads and generation are supplemented with additional estimated data to form new scenarios. The existing data for PEI in 2016 has an annual load of 1420 GWh, 580 GWh of which is met by on-Island wind generation. The peak load is 264 MW and the installed wind capacity is 204 MW. Although roughly half of this wind capacity is contracted to the mainland, for the purpose of energy balance modelling in this demonstration it is considered as meeting the PEI load, which is consistent with the physical power flows.

The following subsections overview the inputs and settings used for the two 2030 scenarios.

Generation

The generation sheet lists on-island power sources. The 204 MW of current installed wind capacity as of 2016 is included. Since new wind capacity involves higher hub heights, larger blades, and other technology advancements in wind turbines, the capacity factor for new wind generators is expected to be greater than for the existing ones. To account for this, additional wind generation is included and it is modelled based on measured wind speed and weather data from three weather stations scaled to realistic hub heights and applied to a wind turbine power curve. 180 MW of additional wind capacity is included in Scenario 1, and 420 MW in Scenario 2. The model distinguishes between nameplate capacity and actual peak output when determining levelized cost of energy (LCOE) for generation sources. For wind generation, a ratio of installed rated wind capacity to peak generation of 1.04 is used, consistent with the installed wind capacity (203.6 MW) and peak wind production (195.7 MW) in 2016.

For solar, the US National Renewable Energy Laboratory's (NREL's) System Advisor Model (SAM) is used to simulate hourly solar generation averaged across several geographically dispersed sites on PEI [7]. Use of historical wind, solar, load, and weather data for numerical simulations of increasingly weather-dependent energy systems better portrays a system's behaviour than using time-series solar data for a typical meteorological year. Solar generation from SAM was compared with data from an installed solar system in central PEI to validate the temporal variations from SAM to real-world data. Solar farm power output is generated by SAM, summed, and then applied as a model input. The modelled solar farms have nameplate DC capacity of 20 MW and total AC capacity of 16.94 MW (a DC to AC ratio of 1.18). 225 MW of solar capacity is added in Scenario 1 and 550 MW for Scenario 2.

Table 1 shows the installed capacity of wind and solar in each scenario, along with the power capacity required for electricity imports, and their respective capacity factors. Wind farm capacity factors increase for scenarios 1 and 2 due to assumed installation of more modern wind turbines.

Table 1: Installed capacity for each scenario

		Scenario 0	Scenario 1	Scenario 2
Installed capacity (MW)	Wind	204	384	624
	Solar	0	225	550
	Import	232	267	311
Capacity factor	Wind	34.6%	38.7%	41.0%
	Solar	n/a	14.7%	14.7%
	Import	41.1%	13.4%	4.2%

Loads

Additional loads beyond the 2016 load measurements are synthesized from several sources. The existing electric load from 2016 is left unchanged, except existing heat loads are estimated with thermal storage capacities incorporated. The new loads, considered to be a result of electrification and using new smart grid-enabled technology, are given demand response capabilities. The load quantities, in terms of electrification of previously fossil-fuel loads, are given in Table 2.

Table 2: Electrification amounts modelled for each scenario

	Scenario 1	Scenario 2
Electric cars, trucks and SUVs		
Number of BEVs	25,000	75,000
Typical km/year/vehicle	16,500	16,500
L gasoline avoided	41,250,000	123,750,000
tCO_2e avoided	94,463	283,388
Air-source heat pumps		
L oil avoided	45,000,000	90,000,000
tCO_2e avoided	123,075	246,150
Domestic hot water		
Number of hot water heaters[a]	25,300	50,600
L oil avoided	12,250,000	24,500,000
tCO_2e avoided	33,504	67,008
Commercial hot water		
L oil avoided	1,950,000	3,900,000
tCO_2e avoided	5,333	10,667
Total GHGs avoided from displaced fuels listed above		
tCO_2e avoided	256,375	607,212

(a) Residential water heaters electrified within the modelling include wood and propane but these fuels are excluded from the table.
(b) CO_2e avoided represents the potential reductions given a state of carbon-free electricity.

Increased use of heat pumps is modelled by assuming an installed quantity and then approximating temporal heating loads using hourly temperature data and typical coefficient of performance (COP) curves (Figure 7). Roughly 135 ML of light fuel oil were consumed in 2016. Of this, at least two thirds is assumed used for space heating with annual fuel utilization efficiency (AFUE) of 78%. Scenarios 1 and 2 assume 1/3 and 2/3 of the overall oil consumption is electrified using heat pumps, respectively. The end-use energy-to-work ratio improves with joule heat. The energy quantity of joule heating is used to calculate the load for cooling if the coefficient of performance (COP) is only 1. Then the cooling load can be calculated with the same approach as the heating load for heat pumps. 2.5% of the heat pump load is treated as flexible with a time shift of up to six hours in either direction. Figure 8 shows the heat pump plots for one of the scenarios, including a demonstration of the load shifting capability.

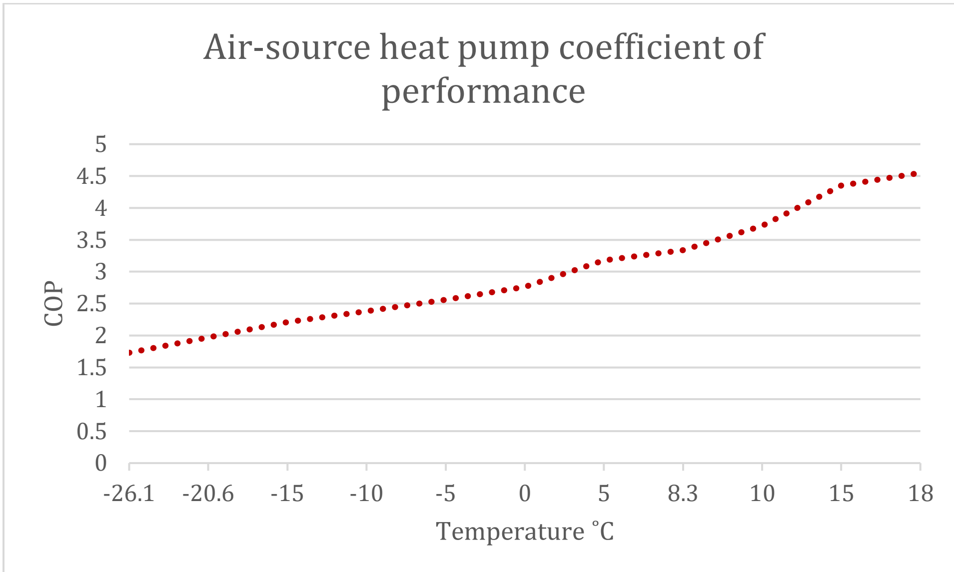

Figure 7: Heat pump performance curve

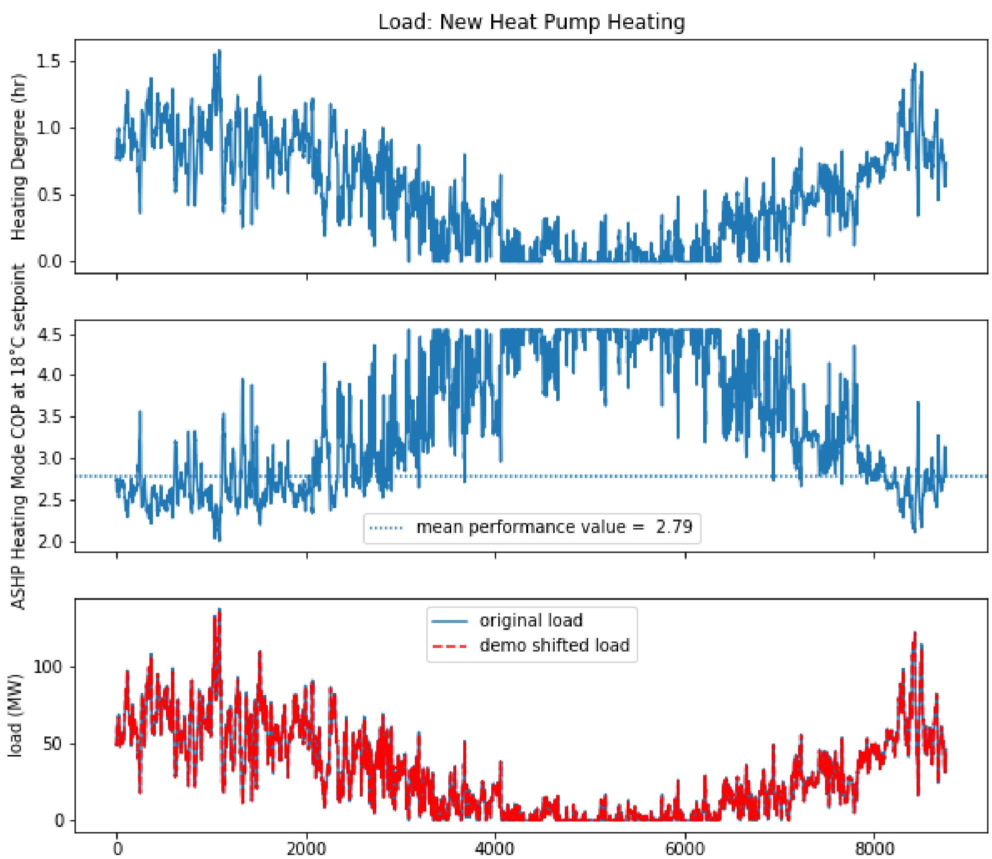

Figure 8: Sample heat pump load plots

Water heater electrification is represented by scaling reference weekly time series load profile data [9] to total consumption quantities based on the Comprehensive Energy Use Database (CEUD) for PEI's residential sector. Residential hot water largely uses oil according to available data. All residential hot water is converted to electricity in the high case and half in the low electrification case. The AFUE of oil, wood, and propane-based residential hot water tanks are assumed to be 55%, 50%, and 74% respectively, compared to electricity which assumed to be 90% efficient including standby losses.

The commercial hot water load is estimated by assuming 1.95 and 3.9 million litres of oil are electrified with low and high electrification by 2030. AFUE of oil hot water heaters is assumed to be 55% efficient while electric hot water is assumed to be 90% efficient accounting for standby losses. The hourly commercial hot water profile is derived from a Minnesota load profile reference [9]. Whereas the residential load profile varies a small amount from weekdays to weekends, there is greater variation in the commercial sector.

Hybrid heat pump water heaters are excluded to avoid undue model complexity. Figure 9 illustrates the weekly profiles of residential and commercial water heating loads that can be modelled.

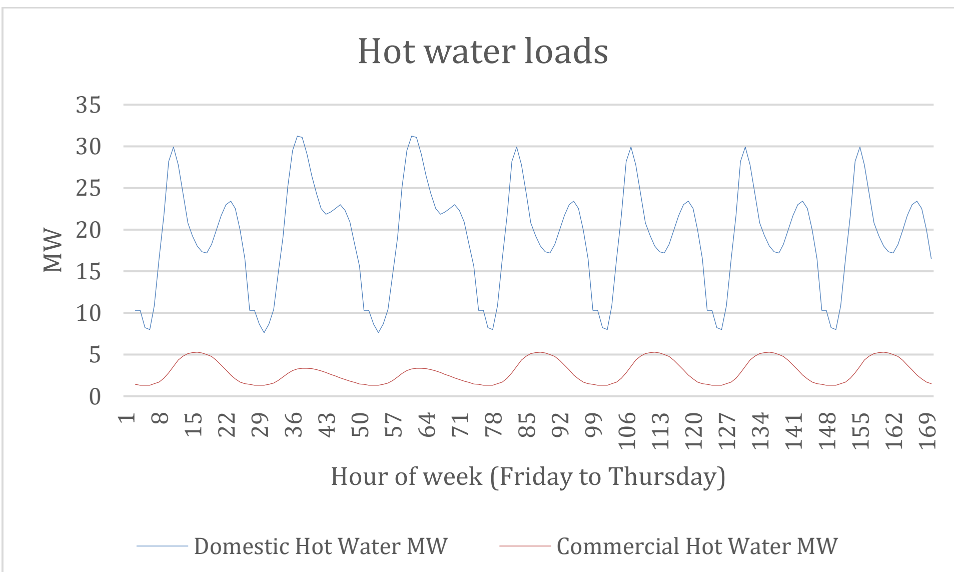

Figure 9: Sample of hot water load profiles

Energy Storage

Grid-scale battery energy storage is included in the scenarios to provide flexibility independent of interchange with the mainland grid. Electric vehicles, hot water heaters with demand response, and space heaters with electric thermal storage are also included forms of energy storage that aid flexibility. Table 3 shows the energy storage and power capacities modelled in each of the scenarios.

Table 3: Energy and power storage capacities

Types of Storage	Energy Capacity	Power Capacity
Scenario 1	MWh	MW
Batteries	500	125
BEVs	1500	250
Thermal	1006	222
Scenario 2	MWh	MW
Batteries	1000	250
BEVs	4500	750
Thermal	1931	383

Electric Vehicles

BEVs consume energy while driving and must be charged so as to allow for convenient travel. Scenarios model the fleet of BEVs with a maximum flexible energy storage capacity of 60 kWh per vehicle. This means if on average BEVs have 90-100 kWh of battery capacity onboard, the fleet's SOC can deplete by roughly two thirds before the load becomes inflexible. Vehicles with 450 km range are widely expected to be cost competitive by 2025, making the assumed flexible energy storage capacity reasonable.

The simulations treat access to EV chargers as ubiquitous such that vehicles are always plugged in when parked. Mostly, BEVs travel very short distances compared to their range. The BEVs are simulated, with 5% of them using on-demand charging at any given time. When parked for a duration and not in need or want of an immediate charge, BEVs participate in smart charging. The BEV fleet's average charging capacity per vehicle is modelled as 10 kW.

The simulations account for seasonal use and performance changes when modelling EVs. On PEI, greater distances are travelled in the summer compared to the winter; this is included in the use profiles. Electric vehicles require energy for both driving and climate control. A fleet's energy consumption per kilometre travelled has a degree of temperature-dependence. In this model the energy consumption from real-word driving of a large number of Nissan Leafs in Canada [10] parameterizes the effects of temperature on vehicle efficiency (Figure 10). Figure 11 shows the influence of temperature changes during a week in December on the energy consumption of 75,000 electric vehicles modelled in Scenario 2. The load is calculated as real-time energy consumption of the BEV fleet while vehicles are unplugged and driving.

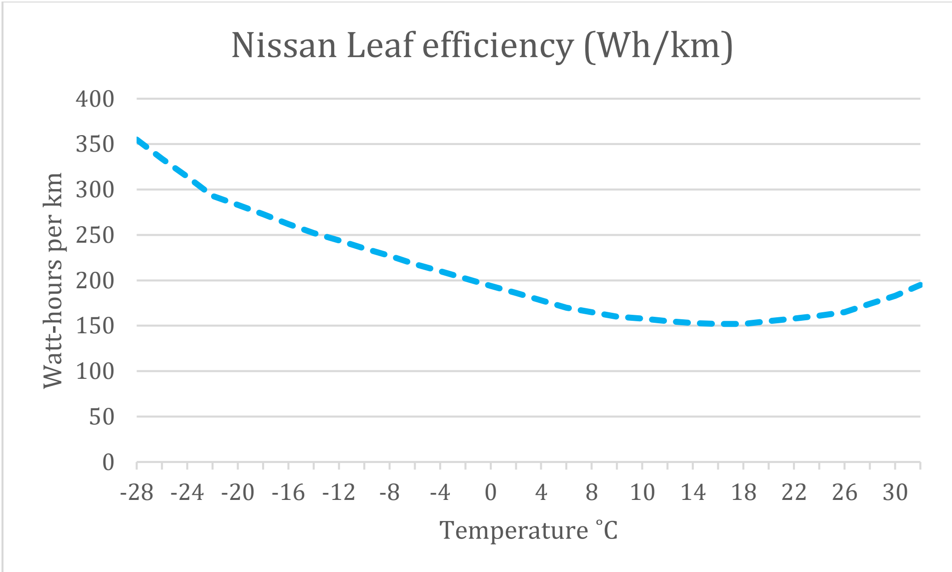

Figure 10: Nissan Leaf efficiency with temperature

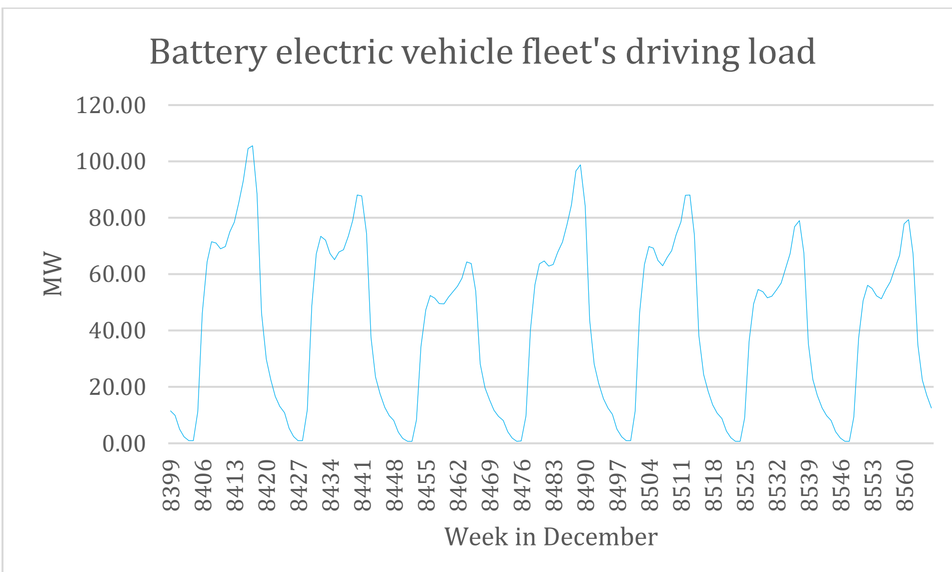

Figure 11: Sample BEV fleet load showing temperature dependence

Costs and Emissions

Costs and lifetimes of the energy system components are provided in Table 4. A 30 year lifetime is assumed for batteries and considered to be conservative for the use patterns considered given that lifetimes of between 5,000 and more than 10,000 cycles at the equivalent of 100% depth of discharge are expected in 2030 [11].

Table 4: Financial parameters of selected energy system technologies

Technologies		Units	2025
Solar PV optimally tilted[a]	Capex	$/kW	699
	Opex fixed	$/kW/yr	17.7
	Opex var	$/kWh/yr	0
	Lifetime	years	35
Wind onshore[a]	Capex	$/kW	1590
	Opex fixed	$/kW/yr	21.0
	Opex var	$/kWh/yr	0
	Lifetime	years	25
Batteries[b, c]	Capex	$/kWh	175
	Opex fixed	$/kW/yr	8.5
	Opex var	$/kWh/yr	0
	Lifetime	years	30
thermal energy storage[d]	Capex	$/kWh	50
	Opex fixed	$/kW/yr	0.65
	Opex var	$/kWh/yr	0
	Lifetime	years	30

(a) Ram M. et al. Global Energy System based on 100% Renewable Energy – Power, Heat, Transport and Desalination Sectors. Study by Lappeenranta University of Technology and Energy Watch Group, Lappeenranta, Berlin, March 2019.
(b) Cole, Wesley, and A. Will Frazier. 2019. Cost Projections for Utility-Scale Battery Storage. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-73222. https://www.nrel.gov/docs/fy19osti/73222.pdf.
(c) Battery cost assumptions are the average of 2027 and 2028 projects in reference b but half of batteries are co-located with PV. (Another NREL study shows co-location with PV may reduce costs.) For baseline 2016, same costs assumed, but greater power interface costs.
(d) Various sources (including confidential, 2009; 2018). Not represented in LCOE/LCOS as devices distributed across end-users.
1 USD to CAD = 1.25 1 EUR to CAD = 1.50

GHG emissions occur from the manufacture, construction, operation, and decommissioning of wind and solar. Estimates are derived from studies thereby providing emissions on lifecycle basis. GHGs associated with the manufacture of grid batteries are estimated at 65 kg CO_2e/kWh of storage capacity [11]. Lifecycle emissions of generation technologies are shown in Table 5. The model has the ability to include lifecycle emissions of wind, solar, batteries, and thermal power plants. However, in this demonstration some lifecycle emissions are excluded. The carbon intensity of the grid is estimated in alignment with Canada's national greenhouse gas inventory report protocol but emissions from electricity imports tied to PEI's are included in the results.

Table 5: Lifecycle CO_2e of generation technologies[a]

Technology	gCO_2e/kWh[b]
Solar PV	23
Wind	9
Natural gas combined cycle turbine	565

(a) Jacobson, M.Z., 100% Clean, Renewable Energy and Storage for Everything, Textbook in press, Cambridge University Press, 2020.
(b) CO_2e units expressed as GWP integrated over 100-y

Costs and emissions accompanying electricity interchange with New Brunswick (NB) are given in the table below.

Table 6: Import/export parameters

Cost of imports[a]	80	$/MWh
Capacity cost	80	$/kW
GHGs of imports[b]	300	kg CO_2e/MWh
Transmission capacity[c]	560	MW export/import

(a) Prince Edward Island Provincial Energy Strategy, 2016/2017.
https://www.princeedwardisland.ca/sites/default/files/publications/pei_energystrategymarch_2017_web.pdf
(b) Assumption for average carbon intensity of imports.
(c) Prince Edward Island Energy Corporation, Annual Report, 2017-2018.
https://www.princeedwardisland.ca/sites/default/files/publications/peiec_annual_report1718_final_1.pdf

The GHG emissions intensity of NB's electricity generation was 400 kg CO_2e/MWh in 2005 and 320 kg CO_2e/MWh in 2016 [12]. These carbon intensity values exclude some lifecycle emissions. Coal is continuously mined and transported over long distances by barges and trains to the Belledune coal-fired power plant in NB from Colombia (high-grade), the western United States (lower-grade), and the Great Lakes region (petroleum coke) [13]. Lifecycle emissions from natural gas-fired generation are higher than direct emissions at natural gas power plants due to methane venting and leakage over the lifecycle, etc. Emissions in PEI's inventory from end-use combustion of gasoline fuel and heating oil exclude lifecycle emissions which occur due to mining, refining, and transport.

Defining PEI's global-through-local obligations on climate change mitigation is outside of the scope of this energy modelling initiative. Authors quantify GHG reductions resulting from modelled scenarios through many lenses (unpublished). GHG reductions can be related to different baseline years, to only the energy sector, or with a view to total emissions within PEI's GHG inventory. Also GHG reductions including electricity imports have notable effects. Each is calculable. Quantification of the benefits of global warming and air pollution damage cost avoidance is not discussed. Yet, the model seems equipped to help inform how to seek and meet an objective of reducing emissions in an essential timeframe. Potential CO_2e reductions, within PEI's inventory, from modelled electrification scenarios are shown (Table 2).

Scenario Results

The results from each of the three scenarios are visualized in Figures 12-14 below.

Baseline Scenario

The baseline (Figure 12) reflects the status quo on PEI, with seasonally varying load and wind, and the wind generation stays below the load the vast majority of the time. There is no demand response nor noticeable energy storage impact. More than half the demand is met by imports.

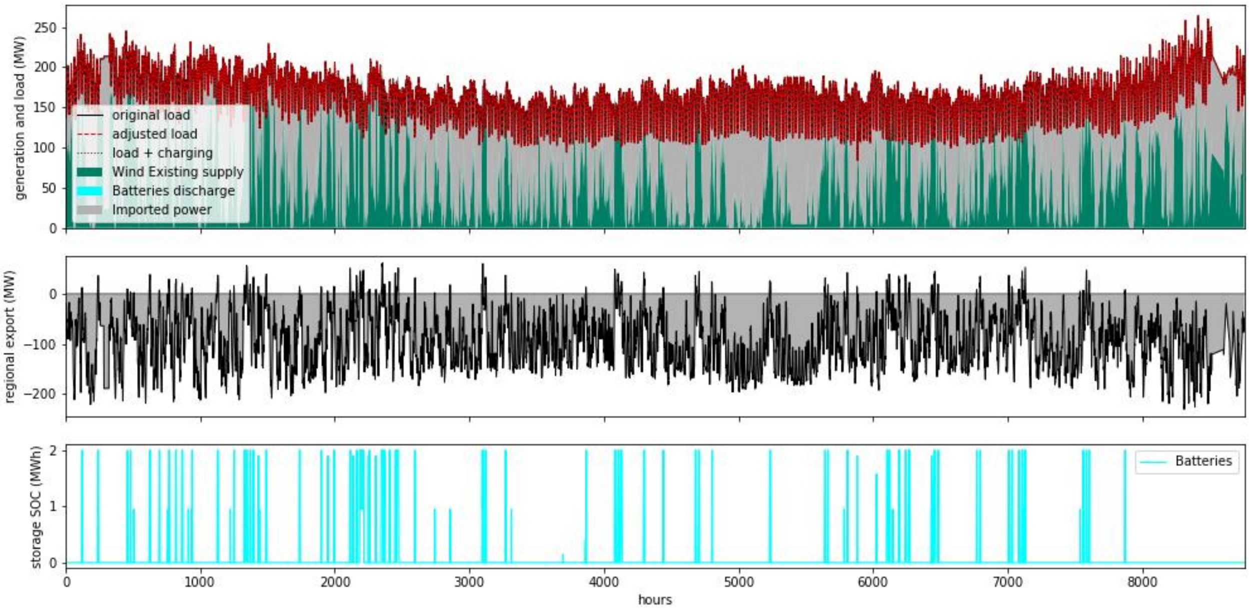

Figure 12: Scenario 0 (2016 baseline) illustration

<u>Generation and Storage:</u>

Wind Existing generation:
  Capacity factor: 34.6%
  LCOE: 59 $/MWh
Battery storage:
LCOS: 305 $/MWh

<u>Key Metrics:</u>

Total generation:	593 GWh
Total annual load:	1,420 GWh
Integrated generation:	583 GWh
Percent integrated:	98% of total generation
Peak export (MW):	63 MW
Peak import (MW):	232 MW
Net import (GWh):	828 GWh
Total (exports only):	9 GWh
Total (imports only):	837 GWh
Imports energy cost:	67.0 $M
Imports capacity cost:	18.5 $M
Elec. import GHGs:	251,135 tCO_2e
Local renewable energy:	41%
Overall LCOE:	85 $/MWh
Overall GHG intensity:	177 $kgCO_2e$/MWh

Moderate Scenario

The moderate 2030 scenario in Figure 13 shows significantly more renewable energy generation than the baseline case, with considerably reduced imports. Exports only moderately increase over the baseline case, due to the availability of demand response and storage to integrate excess renewables. Energy storage plays a noticeable role in balancing short-term supply fluctuations.

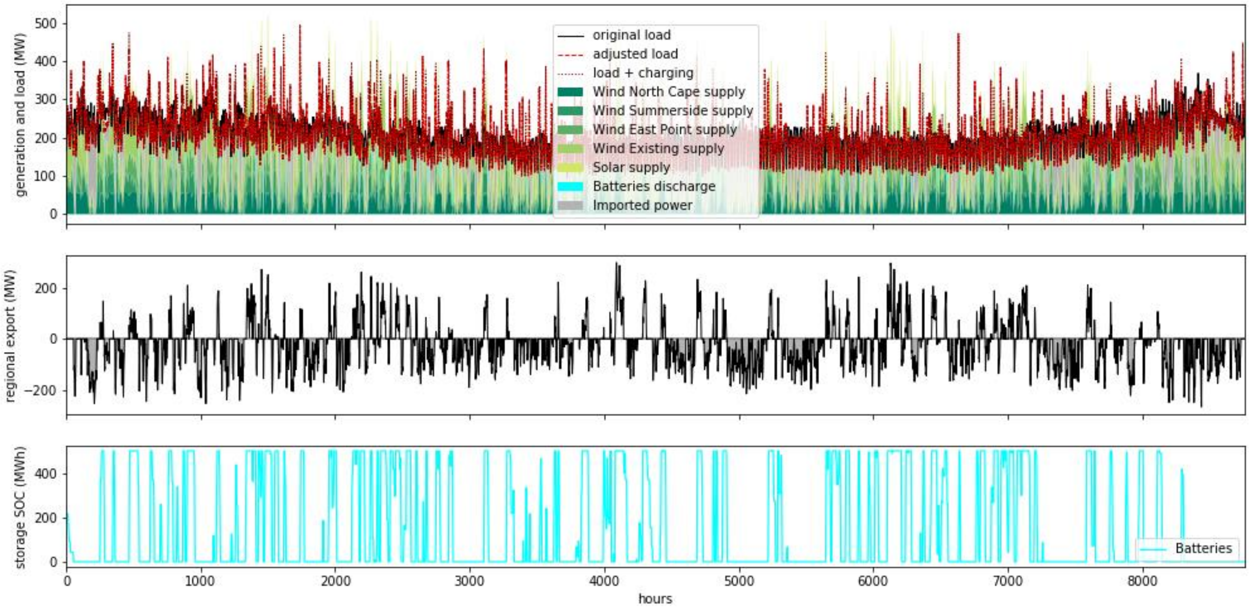

Figure 13: Scenario 1 (2030 moderate) illustration

Generation and Storage:

Wind North Cape generation:
  Capacity factor: 51.7%
  LCOE: 30 $/MWh
Wind Summerside generation:
  Capacity factor: 36.5%
  LCOE: 42 $/MWh
Wind East Point generation:
  Capacity factor: 46.3%
  LCOE: 33 $/MWh
Wind Existing generation:
  Capacity factor: 34.6%
  LCOE: 59 $/MWh
Solar generation:
  Capacity factor: 14.7%
  LCOE: 47 $/MWh
Battery storage:
  LCOS: 248 $/MWh

Key Metrics:

Total generation:	1,590 GWh
Total annual load:	1,753 GWh
Integrated generation:	1,444 GWh
Percent integrated:	91% of total generation
Peak export (MW):	299 MW
Peak import (MW):	267 MW
Net import (GWh):	169 GWh
Total (exports only):	146 GWh
Total (imports only):	315 GWh
Imports energy cost:	25.2 $M
Imports capacity cost:	21.4 $M
Elec. import GHGs:	94,484 tCO_2e
Local renewable energy:	82%
Overall LCOE:	74 $/MWh
Overall GHG intensity:	54 $kgCO_2e/MWh$

Ambitious Scenario

The ambitious 2030 case in Figure 14 shows frequent over-supply and export of excess, although increased demand response and storage resources are very active in absorbing a good portion of the excess. Supply fluctuations are much higher in this scenario by virtue of the larger overall renewable capacity.

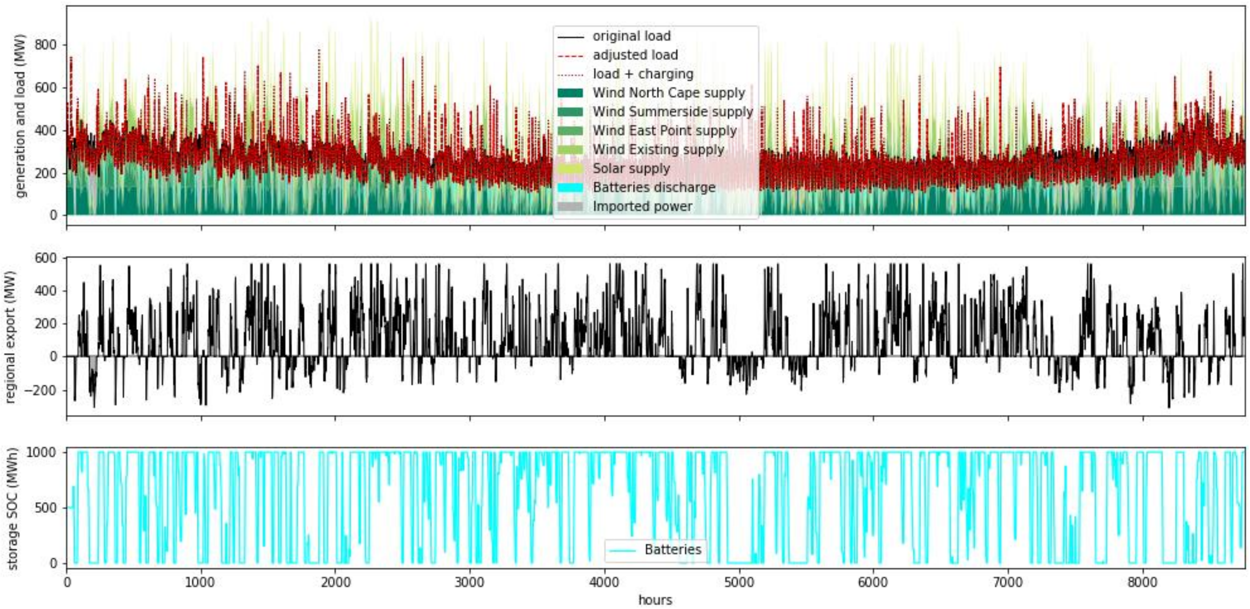

Figure 14: Scenario 2 (2030 ambitious) illustration

<u>Generation and Storage:</u>

Wind North Cape generation:
  Capacity factor: 51.7%
  LCOE: 30 $/MWh
Wind Summerside generation:
  Capacity factor: 36.5%
  LCOE: 42 $/MWh
Wind East Point generation:
  Capacity factor: 46.3%
  LCOE: 33 $/MWh
Wind Existing generation:
  Capacity factor: 34.6%
  LCOE: 59 $/MWh
Solar generation:
  Capacity factor: 14.7%
  LCOE: 47 $/MWh
Battery storage:
  LCOS: 180 $/MWh

<u>Key Metrics:</u>

Total generation:	2,952 GWh
Total annual load:	2,186 GWh
Integrated generation:	2,092 GWh
Percent integrated:	71% of total generation
Peak export (MW):	560 MW
Peak import (MW):	311 MW
Net import (GWh):	-740 GWh
Total (exports only):	856 GWh
Total (imports only):	116 GWh
Imports energy cost:	9.3 $M
Imports capacity cost:	24.9 $M
Elec. import GHGs:	34,739 tCO_2e
Local renewable energy:	95%
Overall LCOE:	81 $/MWh
Overall GHG intensity:	16 $kgCO_2e/MWh$

Costs and Emissions

Table 7 provides a comparison of the levelized costs and energy and of storage (LCOE and LCOS, respectively) calculated by the model for each scenario. It also shows the various metrics output by the model. Integrated generation and load factor after demand response can both be seen to drop noticeably with increasing renewable penetration levels, while the associated emissions fall and the overall LCOE changes relatively little. This suggests that electricity prices would not change significantly in a highly renewable scenario, subject to the assumptions made in this comparison. It should be noted that transmission infrastructure limits or costs are not considered in the model.

Table 7: Summary results comparison

	Scenario 0	Scenario 1	Scenario 2	
Generation and Storage Costs				
Wind North Cape generation LCOE:		30	30	$/MWh
Wind Summerside generation LCOE:		42	42	$/MWh
Wind East Point generation LCOE:		33	33	$/MWh
Wind Existing generation LCOE:	59	59	59	$/MWh
Solar generation LCOE:		47	47	$/MWh
Battery storage LCOS:	305	252	180	$/MWh
Key Metrics:				
Total generation:	593	1,590	2,952	GWh
Total annual load:	1,420	1,753	2,186	GWh
Integrated generation:	583	1,442	2,088	GWh
Integrated generation fraction:	98%	91%	71%	
Peak export (MW):	63	299	560	MW
Peak import (MW):	232	267	311	MW
Net import (GWh):	828	169	-740	GWh
Total (exports only):	9	147	856	GWh
Total (imports only):	837	316	116	GWh
Imports energy cost:	67.0	25.3	9.3	$M
Imports capacity cost:	18.5	21.4	24.9	$M
Elec. import GHGs:	251,135	94,946	34,739	tCO_2e
Local renewable energy:	41%	82%	95%	
Overall LCOE:	85	74	81	$/MWh
Overall GHG intensity:	177	54	16	tCO_2e/MWh

Electrification and Efficiency

One benefit of electrification is increased efficiency resulting in a net decrease of total energy consumption. Table 8 gives estimates of the end-use energy consumption reductions resulting from the electrification modelled in scenarios 1 and 2. Additional cooling loads are modelled but are not listed due to their small size. The reductions from switching to heat pumps and electric vehicles are in the order of 72% and 75%, respectively.

Table 8: End-use energy reductions due to electrification of transportation and heating[a]

		Scenario 1	Scenario 2
Cars, trucks and SUVs to battery electric vehicles			
Displaced gasoline fuel use	MWh/yr	401,042	1,203,125
New electrified load	MWh/yr	100,260	300,781
Net energy use reduction	%	75.0%	75.0%
Oil space heating to air-source heat pumps			
Displaced light fuel oil use	MWh/yr	483,500	967,000
New electrified load	MWh/yr	134,504	269,007
Net energy use reduction	%	72.2%	72.2%
Oil domestic hot water to joule heat			
Displaced light fuel oil use	MWh/yr	131,619	263,239
New electrified load	MWh/yr	80,434	160,868
Net energy use reduction	%	38.9%	38.9%
Oil commercial hot water to joule heat			
Displaced light fuel oil use	MWh/yr	20,952	41,903
New electrified load	MWh/yr	12,804	25,608
Net energy use reduction	%	38.9%	38.9%
Total energy reductions due to modelled electrification of transportation and heating [a]			
Displaced gasoline and oil use	MWh/yr	1,037,113	2,475,267
New electrified load	MWh/yr	328,002	756,264
Net energy end-use reduction	MWh/yr	709,111	1,719,003
Reduction in electrified end-use	%	68.4%	69.4%

(a) Residential water heaters electrified within the modelling include wood and propane but these fuels are excluded from the table.

As indicated by Table 8, the electrification of transportation and heating modelled in scenarios 1 and 2 gives noticeably reduced overall energy end use, even if electrical load is increased. Although scenario 1 sees a 328 GWh increase in annual electrical load, efficiency gains result in a net reduction in total energy end use of more than double that amount, 709 GWh. Meanwhile, scenario 2 sees an increase in electrical load of 756 GWh but a reduction in total energy end use of 1719 GWh. Both electric vehicles and heat pumps play critical roles in reducing energy usage through high efficiencies and the avoidance of inefficient and polluting combustion processes. Residential water heating involves switching from mainly fuel oil, with small amounts of wood and propane fuels, to electric resistive heating. Switching to electricity for both residential and commercial hot water reduces energy use in 2030 compared to 2016. Moreover, the electrification of water heating could be made more efficient by using heat pumps.

Discussion of Model Applicability

The scenario results show clearly that electrification coupled with demand response can significantly reduce emissions while improving renewable energy integration abilities. Both transportation and heating are carbon-intensive sectors in PEI that can be decarbonized through electrification while also boosting demand response capacities in the electricity grid.

Further experimentation with the model suggest that in PEI's electric system when there are high penetrations of electric vehicles that have vehicle-to-grid power flow it will reduce the amount of stationary energy storage capacity needed to cover prolonged periods of low wind and solar towards a fully renewable province. Such events of low wind and solar are rare, but do occur. Interestingly, the price sensitivity to even large sizings of renewable generation capacity is very small provided that demand response capacities are also scaled up similarly. These are topics that could be explored further by running additional cases with the model.

Value to Informing Policy

Scenario modelling as demonstrated above can be informative to energy policy in PEI, having direct implication to emission reduction strategy decisions. In 2019 the Legislative Assembly of PEI adopted a new target to reduce GHGs from 2005 levels to 1.2 megatonnes of CO_2e in 2030. This will be challenging as PEI's population grows. In mid-2005 the official population of PEI was fewer than 138,100. As of mid-2017, PEI's official population had increased to more than 150,500 and the population currently is expected to continue growing to over 183,000 in 2030 and to more than 220,000 by 2050 [14]. Electrical energy demand will furthermore be increased by rising electrification of heating and transportation.

In considering emissions reductions pathways, it is notable that PEI's energy system is atypical in its low level of industrial activities compared to other jurisdictions. The Canadian Energy System Simulator (CanESS) shows that of the 24.33 petajoules (PJ) of energy use in 2013 (excluding non-energy purposes), only 2.74 PJ was in the industrial sector [15]. Whereas less than 11.3% of PEI's energy use occurred in the industrial sector, more than 34.4% of Alberta's end-use energy (excluding non-energy use) was in that sector the same year. As a result, population change is an especially relevant consideration in energy usage and in planning for a sustainable energy system.

The previous published renewable energy studies in PEI focused on some of the possibilities to transform the electricity sector only as its demand profile exists today, e.g., without a cross-sectoral approach to deep electrification and decarbonization of the Island's energy system (e.g. [1], [5]). These studies sought cost minimized combinations of wind, solar, and storage with a constraint of 100% wind and solar supply with no mainland power exchange. The first study found that such a 100% renewable electricity system was a compelling scenario, especially with low storage costs. The second study offered an initial comparison of deploying lithium batteries or high-temperature thermal-turbine electricity storage in the design of a 100% renewable electricity system on PEI.

Relative to the simplifications of the previous studies, the present model allows more realistic scenario options, such as energy exchange with the mainland, better load detail including demand response, energy storage inefficiencies, and electric vehicle charging and discharging. Users can include most considerations within the scope of hourly electricity flows. For example, hot water reductions from low-flow showerheads can be quantified and used to reduce the hot water loads in residential dwellings or in the commercial sector (e.g. in accommodations) within the model. Another example could be to reduce the load for space heating using heat pumps by considering the viability of energy retrofits to reduce demand in existing buildings.

Utilizing these new abilities, future studies might include the following:

- the use of vehicle-to-grid technology to leverage EV-based energy storage;
- distributed thermal energy storage for heating and cooling;
- centralized large-scale thermal energy storage systems; and
- electrification of additional sectors (e.g. manufacturing, agriculture, fishing).

More broadly, the high-level metrics provided by the model, such as energy costs and GHG emissions changes, can be useful to policymaking in general in areas of both general sizing of energy system components, and examining trade-offs and cost-benefit comparison of energy transition alternatives.

Alignment with Open Data and Standard Data Sources

The model aligns with and promotes open data from well-respected sources. The existing model demonstration uses only publicly available data sets, and the model itself is fully open-source. This means the presented results can be replicated or extended using this existing model or other models, and also that the model itself can be extended and applied to other scenarios and data sets. Making transparent use of these data sets in the model will hopefully also help bring greater visibility to the open data available that can be applied to these energy modelling initiatives.

The open data sets used include the following:

- Sub-hourly electricity load and wind data for PEI
- Environment and Climate Change Canada weather data

- Solar data accessible through the NREL System Advisor Model

Areas for improvement in the use of open data include improving automatic attribution of data sources used in the model, dealing with quality concerns in some data sets, and navigating contradictory data sources. For example, industry data, as well as end-use energy data for agriculture, fishing, and forestry sectors is difficult to find. Marine and aviation sectors also have some data availability challenges. Furthermore, contradictory data from one source to the next makes it challenging to estimate current fuels being consumed in different end-uses.

Areas for Model Improvement and Extension

Although the model is complete in addressing the main electric energy system components commonly discussed in the PEI context, there are a number of improvements that could increase its scope in a useful way.

Better modelling tools for including electrification of commercial/institutional, industry, agriculture, fishing, and forestry sectors would facilitate a broader decarbonization scenario exploration. Broader electrification modelling could be extended to add more storage of heat and cold in water, rocks, ice, and phase-change materials. There are a variety of storage options that exist but are not modelled in the current demonstration. Long duration storage options may include underground thermal energy storage in pit thermal energy storage, boreholes, or aquifers. Heat or cold can also be stored in long durations but shorter timescales than seasonally, within large storage tanks.

The current approach lacks intelligent or adaptive prioritization of the various storage and demand response resources. A prioritization strategy could allow the model to optimize battery lifetimes and costs of energy by using the least-cost resource at a given time. There are also improvements needed in finalizing the vehicle-to-grid model approaches.

Hydrogen could be introduced to the model, where it is produced using electrolysis with surplus wind and solar energy. This could help for fuel cell applications in long-distance heavy duty ground transportation, marine, and someday in aviation sectors. Hydrogen may become a viable power source for backup generation or it could be used in industrial activities.

Lastly, the model results would be improved by improved data sets. To further characterize the behaviour of future electric systems with deep electrification there would be advantages to having additional data to better support projections about future electricity demands.

Interfacing and Data Exchange with Other Modelling Tools

The model facilitates input and output of time series with other models through its spreadsheet-based interface and output files. In some respects the model can indirectly feed on the output from other models. For example, the US National Renewable Energy Laboratory's (NREL's) System Advisor Model (SAM) is freeware that is used in our demonstration. Across PEI, SAM is used to model hourly PV output in year 2016 across 15 geographically-dispersed solar farms with 20 MW (DC) of installed capacity and approximate DC:AC oversizing of 1.18 (rated AC capacity is 16.94 MW). At each location there is variability compared to other sites due time-varying local differences in solar irradiance, etc. However, when hourly outputs from the 15 sites are averaged, the combined variability is reduced considerably. In other words, connecting geographically-dispersed solar farms helps to smoothen the overall PV output. Since the model is used in the context of PEI, for now this process is done manually in SAM and Excel to create the average solar generation time series across the sites. However, it is a process that can be automated in future iterations of the model's development.

The model compiles various data and many of these could be used as inputs for others. The model also produces a file of outputs from model runs. For example, the hourly load of heat pumps is an output that could be used by others as an input in modelling efforts.

Conclusion

In response to a void in modelling tools that can be applied to small-scale highly-renewable energy systems, that are open source, and that are easy to use, a new electricity system model has been created. The model combines a spreadsheet-based user interface with a Python-based backend to provide accessibility as well as versatility, all while maintaining a fully visible and customizable process. The model operates at an hourly or sub-hourly time scale and models the energy balance from renewable energy sources, various inflexible and flexible loads, energy storage systems, and electric vehicles. As such, it provides high-level findings on the economic and emissions performance of different electricity system scenarios.

The model is demonstrated on three scenarios based in PEI, illustrating the data sources available and how they can be used to evaluate energy alternatives. The low electrification case provides a clear quantification showing that a lot will be needed to reduce energy-related emissions in line with the province's stated targets. Results suggest costs do not change significantly. The high electrification case shows a rapid electrification of transportation and heating. It seems to push the envelope in terms of what is possible in the specific sectors analyzed and an interesting result is that the overall energy costs in the ambitious scenario may be slightly lower while the benefits of avoided climate and health damage costs will be superior. These results should be verified in terms of both the model's calculations and the assumptions and inputs used in formulating the scenarios.

A basic working version of the model has been created. Going forward, it will be refined and further documented, and verified against other modelling tools, in preparation for a full public release. By creating this open-source model and sharing it with the community, we hope to spur increased energy system modelling by non-experts and lower the threshold for newcomers to the field to engage hands-on in exploring energy system alternatives.

References

[1] M. Hall and A. Swingler, “Initial Perspective on a 100% Renewable Electricity Supply for Prince Edward Island,” *International Journal of Environmental Studies*, vol. 75, no. 1, pp. 135–153, 2018.

[2] L. Hughes, “Meeting residential space heating demand with wind-generated electricity,” *Renewable Energy*, vol. 35, no. 8, pp. 1765–1772, Aug. 2010, doi: 10.1016/j.renene.2009.11.014.

[3] L. Hughes, M. Dhaliwal, A. Long, and N. Sheth, “A Study of Wind Energy Use for Space Heating in Prince Edward Island 1,” 2006.

[4] S. Wong, G. Gaudet, and L. P. Proulx, “Capturing Wind with Thermal Energy Storage; Summerside’s Smart Grid Approach,” *IEEE Power and Energy Technology Systems Journal*, vol. PP, no. 99, pp. 1–1, 2017, doi: 10.1109/JPETS.2017.2754139.

[5] A. Swingler and M. Hall, “Initial comparison of lithium battery and high-temperature thermal-turbine electricity storage for 100% wind and solar electricity supply on Prince Edward Island,” *Energies*, vol. 11, no. 12, 2018.

[6] D. Connolly, H. Lund, B. V. Mathiesen, and M. Leahy, “A review of computer tools for analysing the integration of renewable energy into various energy systems,” *Applied Energy*, vol. 87, no. 4, pp. 1059–1082, Apr. 2010, doi: 10.1016/j.apenergy.2009.09.026.

[7] “System Advisor Model (SAM),” *US National Renewable Energy Laboratory*. [Online]. Available: https://sam.nrel.gov.

[8] P. Rukavina, “Prince Edward Island Electricity Data,” *Reinvented Inc.* [Online]. Available: energy.reinvented.net.

[9] “Minnesota Technical Reference Manual (TRM) on Electricity End Use Load Profiles,” 2016.

[10] T. Yuksel and J. J. Michalek, “Effects of Regional Temperature on Electric Vehicle Efficiency, Range, and Emissions in the United States,” *Environ. Sci. Technol.*, vol. 49, no. 6, pp. 3974–3980, Mar. 2015, doi: 10.1021/es505621s.

[11] A. Hoekstra, “The Underestimated Potential of Battery Electric Vehicles to Reduce Emissions,” *Joule*, vol. 3, no. 6, pp. 1412–1414, Jun. 2019, doi: 10.1016/j.joule.2019.06.002.

[12] “National Inventory Report 1990-2017: Greenhouse Gas Sources and Sinks in Canada,” Environment and Climate Change Canada, 2019.

[13] “Thermal,” *NB Power*, 2015. [Online]. Available: https://www.nbpower.com/en/about-us/learning/learn-about-electricity/thermal. [Accessed: 22-Jan-2020].

[14] “Prince Edward Island Population Projections 2019 – 2058.” PEI Statistics Bureau, Department of Finance, 2019.

[15] “End-use sectors: energy use and greenhouse gas emissions in Canada and its provinces,” *Canadian Energy Systems Analysis Research*. [Online]. Available: https://www.cesarnet.ca/visualization/end-use-sectors-energy-use-and-greenhouse-gas-emissions-canada-and-its-provinces. [Accessed: 28-Nov-2019].