Project Report

Smart Microgrid Solutions to Reducing Fossil Fuels Dependence in Canada's Rural and Remote Communities

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by

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Executive Summary

To combat climate change and achieve deep decarbonization of the Canadian economy, new and innovative modelling approaches are required for policy makers and stakeholders to accelerate electrification of Canada's energy systems. With this incentive, the University of New Brunswick (UNB) is supported by Natural Resources Canada (NRCan) energy modelling initiative (EMI) funding to conduct a project on smart microgrid solutions to reducing diesel reliance in Canada's rural and remote communities using a variety of renewable energy resources (DERs). The main objectives of this project are:

- To develop a strategic framework of smart microgrid planning and design for rural and remote communities in Canada;
- To study the DER models which primarily include wind, solar photovoltaic (PV), controllable loads, and battery energy storage systems;
- To establish a decision-making model to help choose an optimal microgrid solution taking account of multiple factors which may affect the success of the application.

The purpose of modeling DERs is to better understand and determine the contribution of these individual components to the community-scale microgrid design taking both dispatching capacity and cost difference into consideration. The per unit (p.u.) generation/load profiles of each DER can be obtained either from direct data import or through simulation models developed by the UNB team. Combined with the annual load profile of the investigated community, various combinations of available DERs can be evaluated to meet the requirement of the local electric power system. An Analytica Hierarchy Process (AHP) based decision-making model is then designed to help system planners to choose the optimal microgrid solution based on not only environmental benefits, technique challenges and cost budgets but also consideration for practical limitations, such as social acceptability.

The smart microgrid design framework proposed in this project enables to bridge the gap between a government initiative to help reduce diesel energy in rural and remote communities and in-depth knowledge about benefits, risks, limitation, and costs of smart microgrid implementation in practice. A Python-based microgrid design application has been developed by the UNB team integrated with proposed models which can be used as the first version of a public tool for microgrid design and planning for Canada's rural and remote communities.

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1. Introduction

Even though considerable effort has been made to promote rural electrification in the past decades, there are still approximately 260 remote and northern communities and industrial sites across Canada that lack access to the national power grid. The majority of these communities rely on diesel for electricity generation and heat, which is a well-known reliable but costly, low efficiency and non-eco-friendly energy source. The application of smart microgrids gaining in popularity presents an opportunity to overcome the dependence on diesel in these communities due to their adaptability and flexible expandability. Fed by a variety of distributed energy resources (DERs), renewable energy integrated microgrids enable to provide a clean, efficient, reliable and affordable solution for supplying energy to off- and weak-grid communities.

The objectives of of this project are to develop a generic framework for the microgrid planning and design using the worst-case scenario analysis to achieve 100% renewable energy for heating, electricity generation and transportation in off grid communities, and to establish an evaluation model to determine the optimal combination of available DERs in a microgrid considering the minimization of capital and operational costs subject to reliability constraints as well as practical limitations specific to the investigated community. The remainder of this report is organized as follows: Section 2 details the simulation models of community load profiles and typical DERs which include solar photovoltaic (PV), controllable loads, and battery energy storage systems. Section 3 proposes an approach adapted to optimize microgrid solutions and a strategic framework of the microgrid planning and design for off-grid rural and remote communities. The development of a Python-based microgrid design tool has been introduced in Section 4 with a case study. And the main findings and recommendations for policy makers can be found in Section 5.

2. Modelling of Microgrid Components

The components within microgrids form a wide variety. The electric power systems in rural and remote areas are normally off-grid and use diesel as their main power source. The power network characterized by low population density. A small number of homes is facing a relatively high number of farms dispersed over a large area, characterized by long low-voltage transmission lines in the form of overhead lines. The vast territory of meadows and arable land offers ideal conditions for wind turbines. And large roof areas also make PV systems available. Furthermore, battery energy storage systems and controllable residential thermostatically controlled loads (TCLs) such as domestic electric water heaters (DEWHs), electric thermal storages (ETSs) can be used as an energy buffer to balance the demand and load of the community as well as act against abnormal operation of the electric power system. Thus, the models of wind, solar, TCLs and batteries are presented in this section as the major DERs of a microgrid for rural and remote communities. In addition, a model employed to simulate the electrical load profiles of communities is also proposed using transfer learning technologies.

2.1 Wind power production model

Wind is one of the most promising renewable energy sources. Wind turbines convert kinetic energy from wind into electrical energy. The primary benefits of wind power over diesel generation are there are no fuel costs to operate them, and they have very little environmental impact [1]. In addition, some general drawbacks to wind generation such as not the most profitable use of the land and site selections normally far from cities with few already-proposed transmission lines can be significantly ameliorated in rural and remote areas, that makes wind energy become one of the most prevalent DERs in a microgrid.

In order to estimate the potential contribution of wind energy to a microgrid, the per unit (p.u.) power production profile of selected wind turbines should be prepared taking account of both wind turbine's characteristics and weather conditions in the investigated communities. However, it is hard in practical. The power curves from wind turbine manufactures are normally used to represent the relationship between wind power production and wind speed, however, as the manufacturers' curves are created under standard conditions, they cannot represent the realistic characteristic of the wind turbine. Fig. 2.1 gives an example of difference between the manufacture's power curve and the one extracted from a three-year period of telemetry data of an investigated wind farm in New Brunswick (NB).

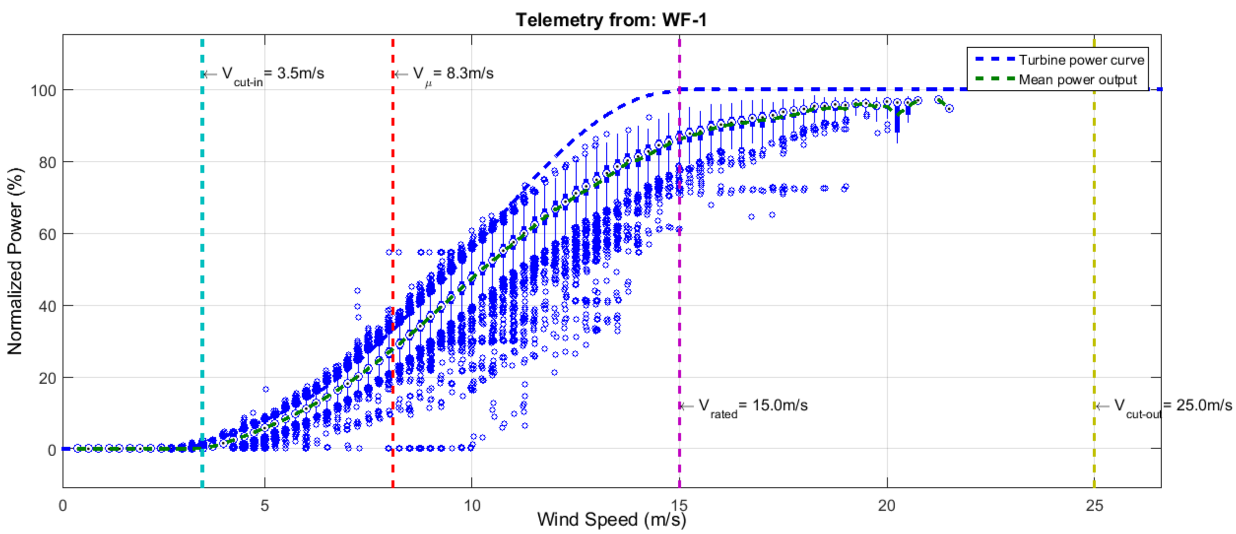


Fig. 2.1 Measured power curve for an investigated wind farm in NB. Blue dashed line corresponds to the manufacturer's power transfer curve. Green line is the average power curve calculated from the data. Boxplots allow to identify the maximum, minimum power curves and data outliers (blue circles)

To accurately characterize the relationship between wind speed and wind power production, a non-linear auto-regressive exogenous (NARX) power transfer model has been developed from a previous study carried by the UNB team on development of wind power production forecasting algorithm, shown as Fig. 2.2. A NARX network is a powerful class of dynamical models that have demonstrated its capacity to model nonlinear time series. In our approach, the inputs are both the wind speed and the last output power of the turbine, which acts as the exogenous input. The number of neurons in the hidden layer is set to five and the Levenberg-Marquardt method is employed as the training algorithm. The idea behind the use of an exogenous input here is to account for the inertia of the wind turbine that cannot change abruptly with sudden changes in the wind speed.

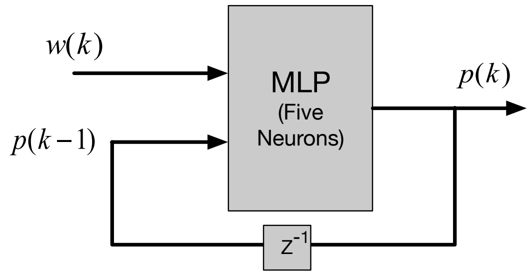


Fig. 2.2 UNB developed NARX-based power transfer model

However, the proposed UNB developed NARX-based power transfer model requires a considerable amount of historical data for training the network which is normally not available for a specific wind turbine. In order to solve this problem, transfer learning technologies have been implemented in this research to build accurate wind power production models of investigated wind turbines with limited historical data through starting from knowledge that has been learned when modeling for an existing wind turbine. As shown in Fig. 2.3, a deep neural network (DNN) is developed to establish a relationship function between wind power production and manufacture power curve-based output using Keras library in Python [2]. And this pre-trained DNN can be also used to simulate the generation profiles of any other wind turbines once their manufactures' power curves are available.

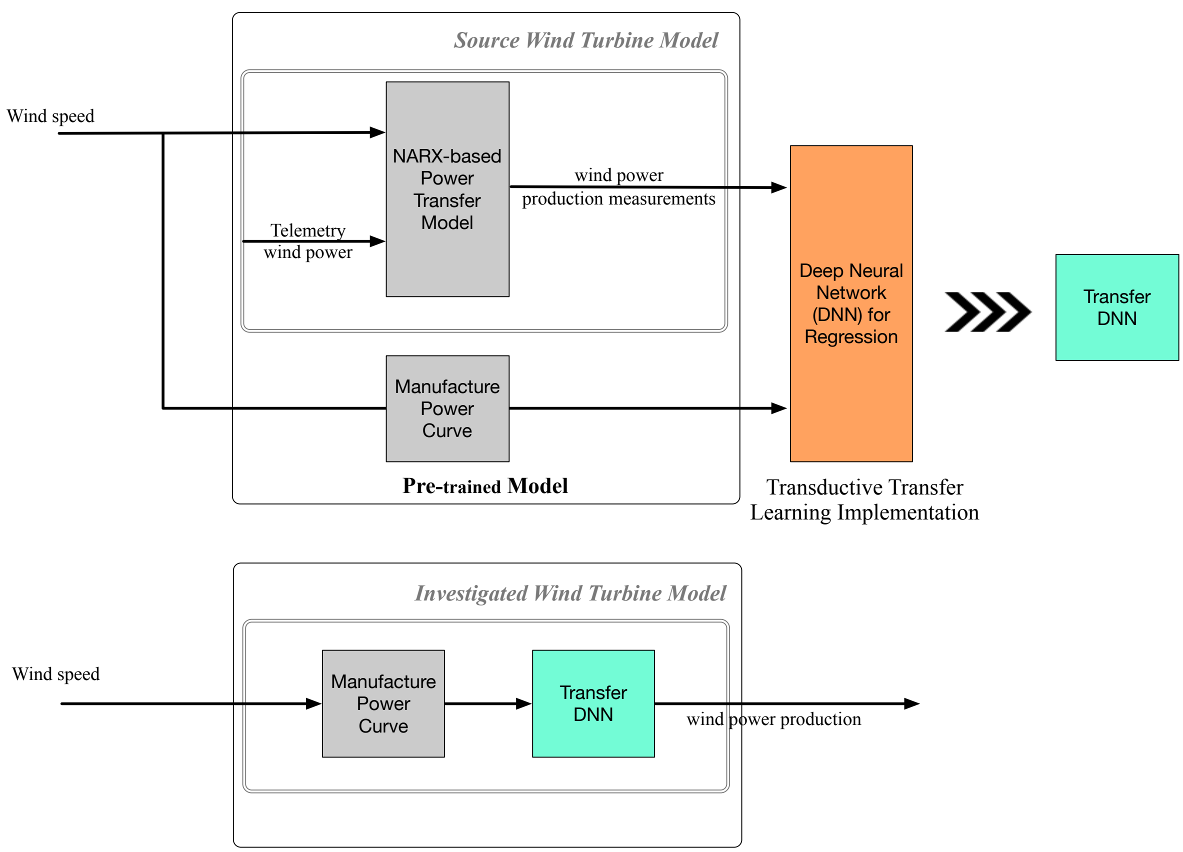


Fig. 2.3 Transfer learning architecture with a pre-trained power transfer model

Here, the wind speed data is collected from Canadian Weather Energy and Engineering Datasets (CWEEDs) with an hourly time resolution. CWEEDS provides statistical weather records from 492 Canadian locations with at least 10 years of data for the period between 1998 and 2014 [3]. In order to estimate wind speed values for a location not included in CWEEDS, a spatial interpolation method called "inverse distance weighting (IDW)" is implemented by using a linear combination of the data from the CWEEDS locations surrounding the study areas. IDW assumes that the wind speed indicates a local influence that diminishes with distance, which can be expressed as

$$\hat{u}(x_p) = \sum_{i=1}^{N} w_i(d_{i,p})u(x_i)/\sum_{i=1}^{N} w_i(d_{i,p}) \quad (2.1)$$

where $\hat{u}(x_p)$ is the estimated variable at the wind turbine site, $u(x_i)$ is the corresponding variable at the neighbor CWEEDS locations, and $w_i(d_{i,p})$ is the weight value determined by the distance between the investigated area and surrounding CWEEDS locations. But if the second nearest neighbor is more than three times further than the nearest one, the wind speed records from the nearest location will be used for the investigated wind turbine.

2.2 PV generation model

Solar PV is another mature renewable energy source as an alternative to the diesel generation. Like wind turbines, there is no negative impact made by PV panels on environment as well as no significant operation and maintenance costs. The rural and remote communities normally have potential for large-scale distributed PV system installation based on rich available land resources, but the performance of these PV systems is geographical-oriented, highly dependent on the local solar resources. Thus, the PV generation can be modelled by a linear power source based on the ambient temperature and the irradiance level [4]. Assuming that every PV panel can work at its maximum power point when a proper maximum power point tracking (MPPT) is applied, the power production of a PV system at time *t* can be expressed as

$$P_{PV,t} = P_{PV\_Cap} \times \frac{I_t}{1000} \times [1 - \gamma \times (T_{PV,t} - 25)] \quad (2.2)$$

where $P_{PV,t}$ is the output power of the PV system at t, P_{PV_Cap} is the capacity of the PV system, I_t is the irradiance at t (W/m^2), γ is the power temperature coefficient which equals to 0.043%/°C here, and $T_{PV,t}$ is the temperature of PV panels at t.

Fig. 2.4 gives an example of a simulated PV generation profile for seven days produced with inputs of ambient temperature and irradiation. Both information could also be obtained from CWEEDS using the average hourly measurements of dry bulb temperature (DBT) and global horizontal irradiance (GHI), respectively. Here, the DBT, usually referred to as "air temperature", is the air property that is most commonly used. When people refer to the temperature of the air, they are normally referring to the DBT. And the GHI which is used as I_t for PV generation estimation. It can be expressed by the sum of direct and diffuse radiation as

$$GHI = DHI + DNI \times \cos(Z) \quad (2.3)$$

where *DHI* represents diffuse horizon irradiance, *DNI* represents direct normal irradiance and *Z* is the solar zenith angle.

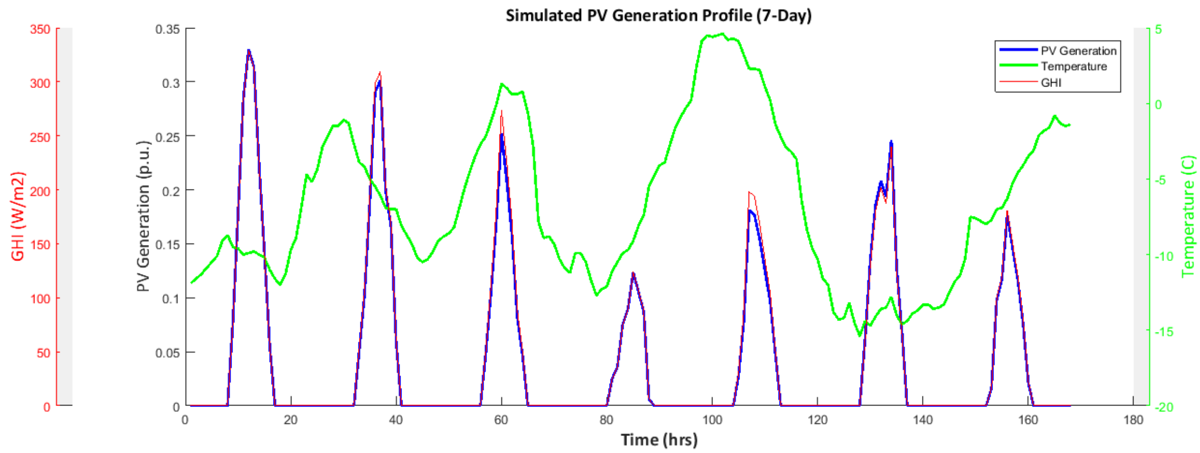


Fig. 2.4 An example of a 7-day simulated PV generation profile

2.3 Battery model

According to the wind and PV generation models discussed above, it is clear that the intermittency is the main challenge for rural electrification with renewable energy sources. In a microgrid, like in any other electric power systems, generation and consumption must be tuned permanently to each other. If the power production is based mainly or partly on renewable energy sources, the balancing of these sources by an energy storage system can take place.

Depending on the design objectives, the appropriate energy storage technology can be determined for the planned microgrid. A battery energy storage system is normally selected as stationary storage within renewable energy integrated microgrids due to its relatively low cost, technical maturity, market availability and reliability [5]. In modeling, the state of charge (SOC) and capacity ($C_{battery}$) are two of the key parameters for battery storage system operation. The most common method for state of charge estimation is coulomb counting based on the introduction of the charging/discharging current [6], which can be described by

$$SOC_t^{\%} = SOC_{t-\Delta T}^{\%} + \eta \times \frac{100}{C_{battery}} \int_{t-\Delta T}^{t} charge(\tau) d\tau - \frac{100}{C_{battery}} \int_{t-\Delta T}^{t} dis(\tau) d\tau \,, when\ SOC_t^{\%} \leq 1 \quad (2.4)$$

where $SOC_t^{\%}$ is SOC of the battery expressed in percentages, ΔT is the sampling period, η is the charging efficiency, $C_{battery}$ is the battery capacity (kWh), and $charge(\tau)$ and $dis(\tau)$ are the charging and discharging power (kW), respectively.

As the battery is connected via an inverter to the microgrid, it can be assumed that there is no delay between the load demand and infeed from the storage. Thus, the capacity of the battery becomes the main concern of the planner which can be determined based on the high-level operational and investment objectives and constraints of microgrid design via an optimization function detailed in Section 3.

2.4 TCL model

Besides the battery energy storage systems, load control also shows considerable dispatch potential to help address the intermittency, thereby supporting the balance and reliability of the local electric power system. In rural and remote communities, conventional generation dispatch using diesel generators is subject to physical constraints, operating expenses and particularly environmental concerns [7], while load control can alleviate these limitations by managing dispatchable loads on demand side. Typical examples of dispatchable loads are thermostatically controlled loads (TCLs) that have inherent operation flexibility. Such flexibility results from the energy storage capacity that can help "decouple" the electricity consumption and thermal energy demand. TCLs which could be used in rural and remote areas include many widely used appliances, such as domestic electric water heaters (DEWHs) and electric thermal storage units (ETSs). Their wide use means massive "usable" capacity, and therefore the aggregation of a large number of controllable TCLs shows great potential for system balancing in a microgrid. In this report, a differential equation-based model [8] has been presented to simulate the TCL characteristics, which can be formulated as

$$\theta_i(k+1) = a_i\theta_i(k) + (1-a_i)\big(\theta_{a,i}(k) - m_i(k)\theta_{g,i}\big) + \epsilon_i(k) \tag{2.5}$$

where $\theta_i(k)$ and $\theta_{a,i}(k)$ are the internal and ambient temperature for the i^{th} TCL at time step k. $a_i = e^{-h/RC}$, with h being the sampling period, C the thermal capacitance and R the thermal resistance of the TCL. The parameter $\theta_{g,i}$ is the temperature gain when the i^{th} TCL is ON ($\theta_{g,i} = R_i P_{trans}$, with P_{trans} being the energy transfer rate of the TCL). The term ϵ_i denotes a random disturbance. The local control variable m_i equals 1 when the i^{th} TCL is ON and 0 when it is OFF.

The power consumption of each TCL in the ON state is $P_i = P_{trans}/COF$, where *COF* represents the coefficient of performance. In addition, $\theta_{set,i}$ is the temperature setpoint and δ_i is the width of the temperature hysteresis band.

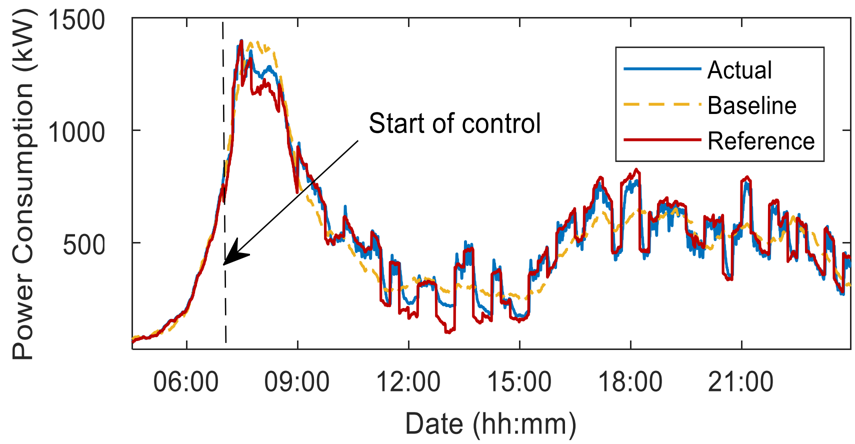
Load control can be exercised either indirectly or directly. Direct Load Control (DLC) is more straightforward and precise than Indirect Load Control (ILC), and more suitable for real-time power tracking. This is so because, ILC implicitly influences power consumption behavior through price incentive policies without guarantee on real-time tracking performance, while DLC directly regulates load profiles to desired shapes via ON/OFF control or setpoint control on individual loads. TCLs automatically turn ON and OFF by their intrinsic hysteresis temperature bands, but ON/OFF control of TCLs may override the hysteresis bands altering the end use of appliances and possibly disrupting the user's comfort or safety. Such control may also be implemented without changing the setpoints or the hysteresis bands of TCLs with less impact on end-user comfort levels.

In this project, a UNB developed bottom-up forecasting with Markov-based error reduction method has been implemented for TCL control in a microgrid [9]. This DLC algorithm had been verified to have outstanding performance particularly when the aggregation size of TCLs is small. Fig. 2.5 shows an example of the proposed DEWH control using an aggregation of 1000 simulated units. Two DEWH models (listed in Table 1) have been used, assigning half units to each model. The simulation considers the reference power equal to the 15-minute piecewise capacity provision load request plus the baseline with the control starting at 7:00AM. Fig. 2.5(a) shows the reference power, actual load and baseline load. Fig. 2.5(b) shows the capacity provision request at each time step and the actual capacity provision. It is clear that the DEWHs can track the power reference and provide appropriate response to requests.

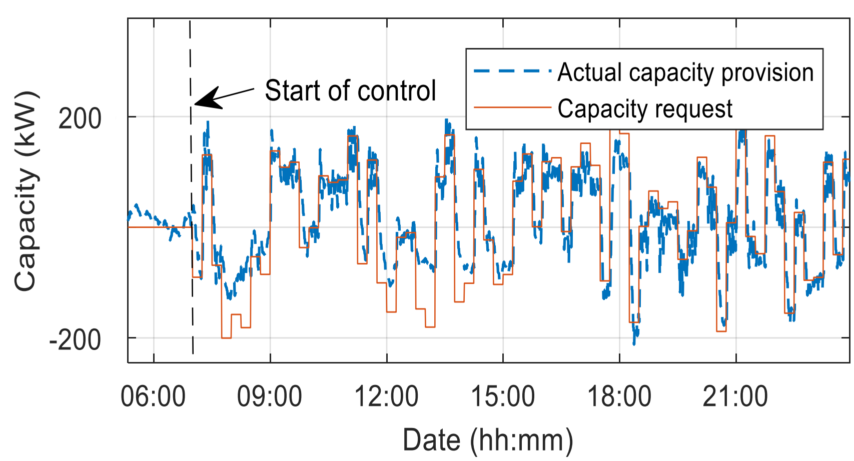
TABLE I PARAMETERS OF SIMULATED DEWHS

Parameters	Model I	Model II
Upper limit of water temperature	55°C	50°C
Lower limit of water temperature	50°C	45°C
Volume of water tank	300 L	150 L
Rated power	6 kW	4.5 kW
Default house temperature	**N** (20, 9) °C	**N** (20, 9) °C
Inlet water temperature	5-15°C	5-15°C

N (20, 9): Normal distribution with the mean of 20 and the variance of 9.



(a)



(b)

Fig. 2.5 Capacity provision using 1000 simulated DEWHs

2.5 Community load profile model

In order to design a microgrid, preparing the electrical load profiles of the investigated community is normally the first step in determining the electrical sizing of the energy system. However, this data is often non-existent or unreliable, especially when looking into the rural and remote communities. In this project, one year of the hourly-averaged electrical load data is preferable for microgrid design and planning. The main challenge of simulating the community load profile is estimation of the energy consumption behaviour in these diverse communities. As a result, a multilayer perceptron (MLP) neural network model has been developed for the load profile construction via a data-driven approach. The electrical consumption data from four distinct remote communities across Canada (two in Newfoundland and Labrador, one in Quebec and the other one in Nunavut) over a period of at least one year has been collected for this study.

The important load profile parameters for modelling in this project include population, temperature information, and annual total/average electric energy consumption (MWh/yr), all of which can be found in NRCan Remote Communities Energy Database and CWEEDS. Fig. 2.6 shows the architecture of the propose MLP, which develops a relationship between basic information of the investigated community and hourly-averaged consumption bias for the community load profile simulation.

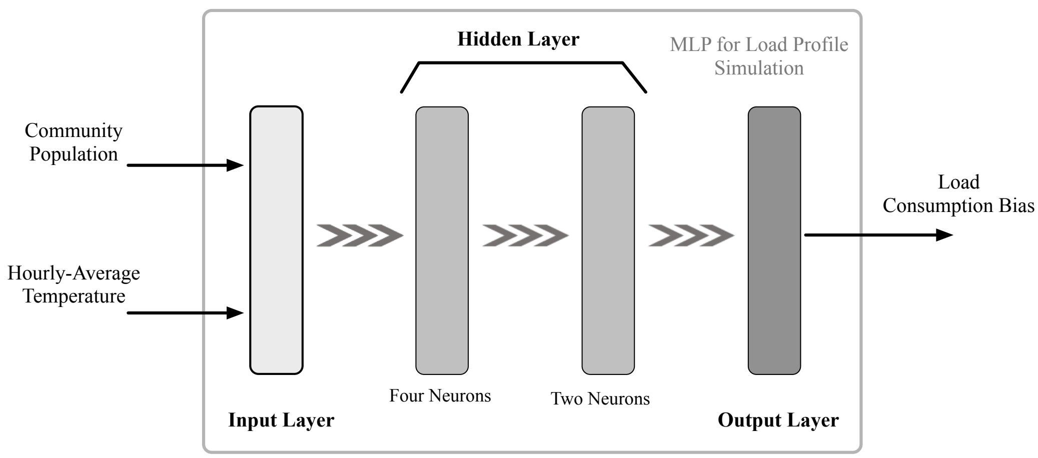


Fig. 2.6 MLP architecture for community load profile simulation model

Fig. 2.7 gives an example to compare the simulated load profile and the actual one based on a community located at Cambridge Bay, NU with a yearly eclectic energy consumption of 11929MWh. The population of Cambridge Bay, NU is about 1766 [3]. Two global metrics, root mean squared errors (RMSEs) and mean absolute percentage errors (MAPEs) have been employed to evaluate the performance. RMSE is a good estimator of the accuracy of mean simulated values. Its nonlinear form penalizes larger errors as it becomes larger upon the existence of large errors. While MAPE expresses accuracy of the model in a percentage term. Both of these can be given as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(e_i)^2} \tag{2.6}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{|e_i|}{|y_i|} \tag{2.7}$$

where e_i is the error and y_i is the actual consumption value. Limited by the small training and validation datasets collected in this project, the output of the simulation model in this example has a RMSE value of 269.0kW while reaches 17.0% of MAPE.

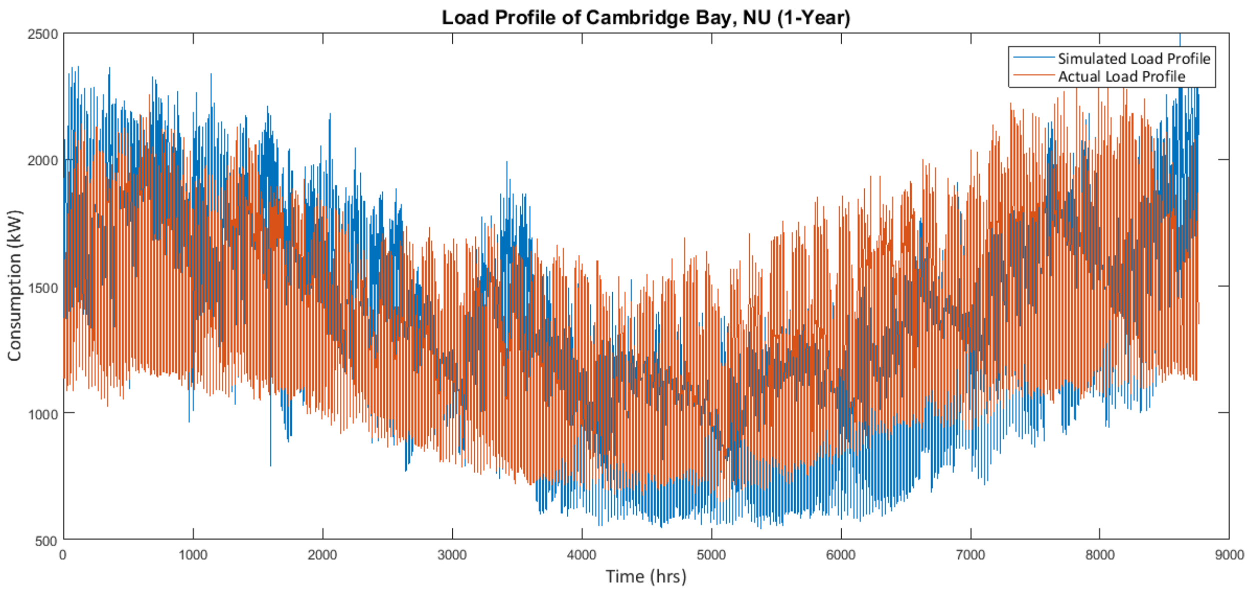


Fig. 2.7 An example of a simulated load profile for Cambridge Bay, NU

3. Framework for microgrid design

The main goal of this project is to develop a comprehensive strategic framework for community-size microgrid design and optimization, taking multiple objectives into consideration. The optimal system configuration for a rural or remote community normally addresses several requirements, such as economic feasibility, renewability assessment, demand management and reliability of the local electric power system, etc. In this project, two of the optimization objectives we pursue include the best Return on Investment (ROI) with the minimum diesel generation and an achievement of 100% renewable energy in the community.

The strategic framework for microgrid design is proposed as a flowchart shown in Fig. 3.1. The flowchart consists of three core processes: building generation profile evaluation model, carrying out modelling optimization and making a decision using Analytica Hierarchy Process (AHP). The generation profile evaluation model is used to collect the p.u. profiles of each available DER via direct data import or simulation using proposed DER models taking account of their individual requirements and limitations specific to the investigated community. The modelling optimization is carried out using convex optimization techniques [10] to provide optimal DER combinations of a microgrid to attain objectives such as maximizing the ROI or achieving 100% renewable energy supply. And AHP as one of the most effective multi-criteria decision-making (MCDM) methods can be implemented to select the best microgrid solutions focusing on both quantitative and qualitative attributes.

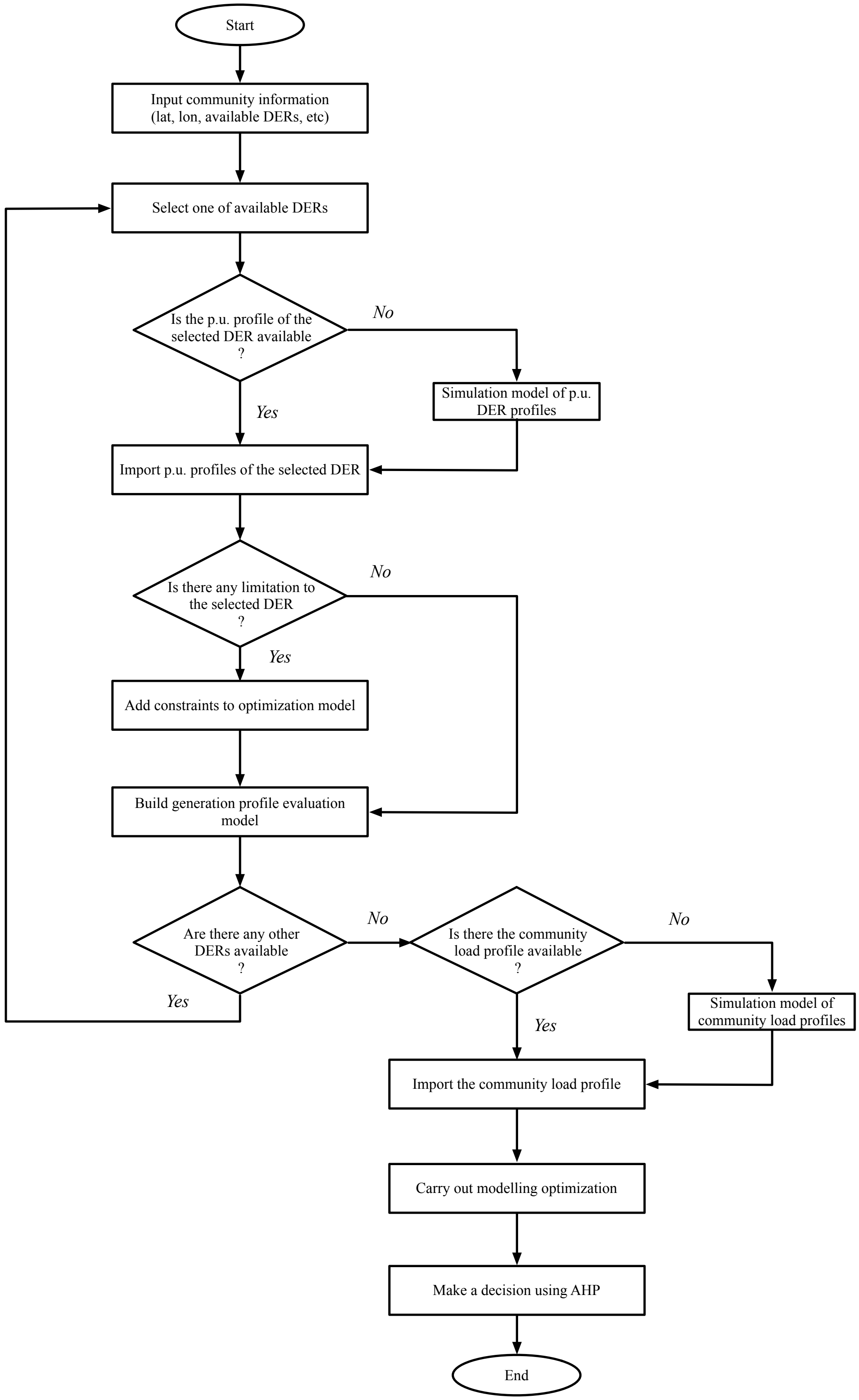


Fig. 3.1 Flowchart of proposed microgrid design framework

3.1 Scenario selection

Two daily scenarios extracted from a yearly community load profile have been evaluated for determining capacities of each available DER to meet the objectives of microgrid design, which include a yearly-averaged daily load profile and a worst-case daily load profile.

The yearly-averaged load profile is used to estimate the size of renewable generators to have the best ROI, particularly focusing on the operation cost. In a microgrid, the main operation cost is usually from the diesel generators, hence, minimizing the operation cost is the same word as minimizing the diesel emissions. The yearly-averaged daily load profile can be generated by

$$L_{ave,k} = \frac{1}{N_{days}} \sum_{n=1}^{N_{days}} l_k^n,\ k = 1,2,\ldots,2 \tag{3.1}$$

where $L_{ave,k}$ is the average load at the at the k^{th} hour in the daily profile, l_k^n is the actual load at the k^{th} hour in the n^{th} day, N_{days} is the number of days in the yearly load profile dataset.

And the worst-case scenario analysis is motivated to seek for a possible solution to having a 100% renewable energy microgrid for rural and remote communities. The worst-case daily load profile then can be expressed as

$$L_{max,k} = \max_n (l_k^n),\ n \in [1,2,\ldots,N_{days}] \tag{3.2}$$

Fig 3.2 shows the measurement of one-year electrical consumption load for Ramea, NL, a small village located on Northwest Island, NL. According to (3.1) and (3.2), two typical daily load profiles of Ramea can be obtained as shown in Fig. 3.3, both of which can be used for objectives-oriented optimization in the next step.

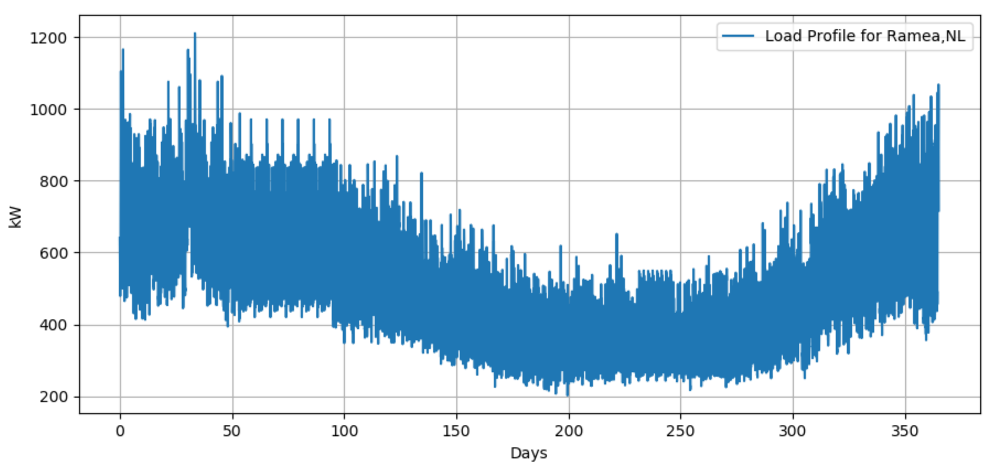


Fig. 3.2 Actual load profile for Ramea, NL

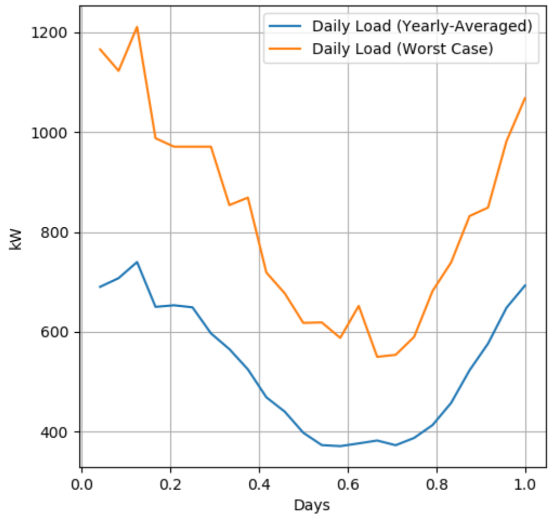


Fig. 3.3Typical daily load profiles for Ramea, NL

3.2 Modelling optimization

The microgrid for a rural and remote community is required to maintain a balance of load and generation, which is a prerequisite for further optimizing the combinations of available DERs. Fig. 3.4(a) gives an example of a microgrid fed with multiple DERs, where batteries and diesel generators are used to reduce the impact of renewable energy intermittency. Fig. 3.4(b) represents load and the sum of DERs.

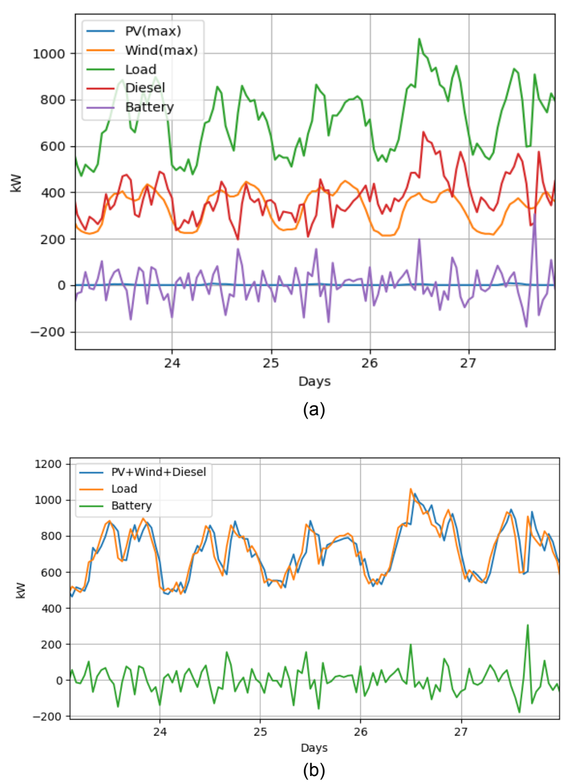


Fig. 3.4 An example of a microgrid integrated with multiple DERs

Two optimization objectives set in this project are: (1) to minimize the cumulative cost including investment and operation cost for *N* years (Best ROI); (2) to achieve 100% renewable energy supply. Accordingly, a two-stage optimization model has been developed for the optimal system configurations of microgrid design, which can be described as

- Stage I: to select optimal capacities of wind turbines and PV panels based on typical daily load profile analysis introduced in Subsection 3.1.
- Stage II: to optimize the battery size to support the balance of load and generation with a minimum investment.

In Stage I, when the objective is to minimize the total cumulative cost, the objective function can be formulized as

$$\min_{x_{pv},x_w,P_k^D,P_k^B} \left[\frac{1}{N_{days}}\left[c_{pv}\cdot P_k^{1PV}\cdot x_{pv}+c_w\cdot P_k^{1W}\cdot x_w\right]+\beta_1\cdot\sum_{k=1}^{24}\left[a\cdot(P_k^D)^2+b\cdot P_k^D\right]+\beta_2\cdot\left|\sum_{k=1}^{24}(c_B\cdot P_k^B)\right|\right] \tag{3.3}$$

Subject to

$$\begin{cases} x_{pv},\ x_w \in \mathbb{Z} \\ P_k^{1PV}\cdot x_{pv}+P_k^{1W}\cdot x_w+P_k^D+P_k^B \geq L_k, \quad \text{for } \forall\, k=1,2,\dots,24 \\ P_k^{PV}\geq 0 \\ P_k^W \geq 0 \\ P_{min}^D < P_k^D \leq P_{max}^D \\ P_{min}^B < P_k^B \leq P_{max}^B \\ \sum_{k=1}^{24} P_k^B \leq 0 \end{cases} \tag{3.4}$$

where P_k^{1PV} is the generation profile of a unit PV system, P_k^{1W} is the generation profile of a unit wind turbine, x_{pv} is the number of the unit PV systems, P_k^{PV} is the total PV capacity which equals to $(P_k^{1PV}\cdot x_{pv})$, x_w is the number of wind turbines, P_k^W is the total wind capacity which equals to $(P_k^{1w}\cdot x_w)$, c_{pv} is the capital cost of PV generation (\$/kW), c_w is the capital cost of wind turbine generation (\$/kW), c_B is the capital cost of batteries (\$/kWh), P_k^D is the output power of diesel generators in the k^{th} hour, P_k^B is the output power of batteries in the k^{th} hour, N_{days} is the expected return period, β_1 is the coefficient that weights diesel generation (when looking for solutions for a 100% renewable energy application, β_1=0), β_2 is the coefficient that weights battery supply, and a (\$/kWh)^2, b (\$/kWh), c (\$/kWh) are the coefficients of the diesel generation cost model presented in [11].

In addition, L_k here represents the daily load profile from the selected typical scenario: when optimized for the minimum cumulative cost, $L_k = L_{ave,k}$; while the optimization is employed for more renewable energy integration, $L_k = L_{max,k}$.

In Stage II, the battery size could be optimized using a net load calculation method that using battery energy management system to compensate the difference between load and generation. Thus, the objective function can be given by

$$\min_{E_{Bsize},P_k^D} \left[\frac{c_B}{N} \cdot E_{Bsize} + \sum_{k=1}^{N}[a \cdot (P_k^D)^2 + b \cdot P_k^D + c_k]\right], \text{ for } \forall\, k = 1,2,\dots,N \tag{3.5}$$

Subject to

$$\begin{cases} P_{min}^D < P_k^D \le P_{max}^D \\ E_{Bsize} \ge 0 \\ E_{Bsize} \le \left|\max\limits_{i\in[1,2,\dots,N]} \sum_{k=1}^{i}\left(L_k - P_w \cdot x_w^* - P_{pv} \cdot x_{PV}^*\right)\right| \end{cases} \tag{3.6}$$

where * represents the optimal solution, E_{Bsize} is the battery size (kWh) and N is the expected return period in hour.

Then, the minimum operation cost can be reached through an optimal quadratic algorithm [12] , which can be expressed by

$$\min_{P_k^D, P_k^B} \; [a \cdot (P_k^D)^2 + b \cdot P_k^D + c], \;\; x_{pv}, x_w \in \mathbb{Z} \tag{3.7}$$

Subject to

$$\begin{cases} P_k^{PV} + P_k^W + P_k^D + P_k^B = L_k, \;\text{ for } \forall\, k = 1,2,\dots,24 \\ \left|\sum_{k=1}^{i} P_k^B\right| \le \gamma \cdot E_{Bsize} \\ P_{min}^D < P_k^D \le P_{max}^D \\ P_{min}^{PV} < P_k^{PV} \le P_{max}^{PV} \\ P_{min}^W < P_k^W \le P_{max}^W \end{cases} \tag{3.8}$$

Therefore, the total optimal cost can be calculated by

$$\text{Cost}_{total}{}^* = c_{pv} \cdot P_k^{1PV} \cdot x_{pv}^* + c_w \cdot P_k^{1W} \cdot x_w^* + c_B \cdot E_{Bsize}{}^* + \sum_{k=1}^{N}[a \cdot (P_k^{D*})^2 + b \cdot P_k^{D*} + c_k] \tag{3.9}$$

3.3 AHP-based decision-making model

The optimization discussed in the previous subsection provides optimal combinations of available DERs to achieve the microgrid design objectives. However, the selected optimized system configuration may not be considered as the best microgrid solution to the investigated community in terms of reducing the diesel reliance, as system planners may need to add more specific criteria to evaluate the existing options to make a decision. Many factors influence which criteria to use, and how to select criteria is also an important part of the decision-making process. Consequently, AHP has been implemented in this project to evaluate alternative microgrid solutions taking account of scales of each criterion [13] for making improvements to the electricity supply system in rural and remote areas.

AHP as one of the most effective and efficient MCDM methods provides a convenient approach to analyse decision problems preferred in group decision-making applications, which is capable of guiding the decision-makers for achieving the best and optimal judgment for their problem rather than to get "correct" answers [14]. The approach of APH is to simplify the MCDM problems by breaking it down into a hierarchical system, which allows the decision-makers to integrate the entire range of elements into a single analysis, as shown in Fig. 3.5. Here, the elements can relate to any aspect of the presented decision problem including criteria, options, or anything that applies to the decision at hand. In addition, AHP helps quantify the weight of the appraised criteria in the form numeric basis. The criteria weight of each element determines its relative importance with the other elements of the hierarchy. Hence, it facilitates the decision-makers to identify and prioritize significant factors. Besides this, the calculation of the inconsistency index is another salient feature of AHP. It makes possible for the decision-makers to check the consistency of their judgments.

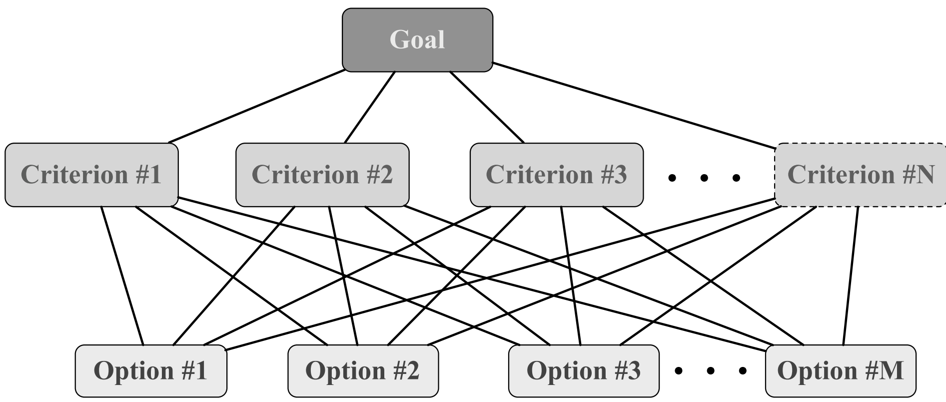


Fig. 3.5 Architecture of AHP

Applying an AHP-based decision-making model involves the following steps, which are described as:

- Establish the hierarchical structure of AHP: the construction of hierarchy is a top-down process and comprises of several levels. The elements of the same hierarchy level must be correlated with the other corresponding factors of the structure. The formation of AHP hierarchy normally starts from the higher-level goal and subdivides into lower-level decision factors [15]. A four-level AHP model including both criteria and sub- criteria has been implemented in this project.
- Determine the goal and criteria used for decision-making: when evaluating potential renewable energy integrated microgrid solutions in rural and remote communities, a set of 10 criteria (sub-criteria) has been selected as an example and grouped into four broad categories (criteria): technical, economic, environmental and social, which is shown on the hierarchy depicted in Fig. 3.6.
- Determining the Comparison Matrix and the Priority Vector (eigenvector): after the hierarchy has been established, the criteria must be evaluated in pairs so as to determine the relative importance between them and their relative weight to the global goal. A Comparison Matrix is used to measure this relative importance of each criterion represented using the normalized

number scale. The weights can be derived by calculations made using the eigenvector method introduced in [13].

- Check the Consistency Ratio: The measure of "Consistency Ratio" is an important aspect of AHP. The optimal decision-making in pairwise comparison is mainly associated with the permissible value of consistency ratio. This step acts as a gateway to observe the consistency and inconsistency of the decision matrix [15].

- Synthesize results: the final step starts from the summation of relative values for each set of alternatives on all hierarchy levels. These values are combined together to establish the overall score or criteria weights of each alternative. And the final priorities are synthesized by aggregating the product of local eigenvector and the relative weights of the respective alternative.

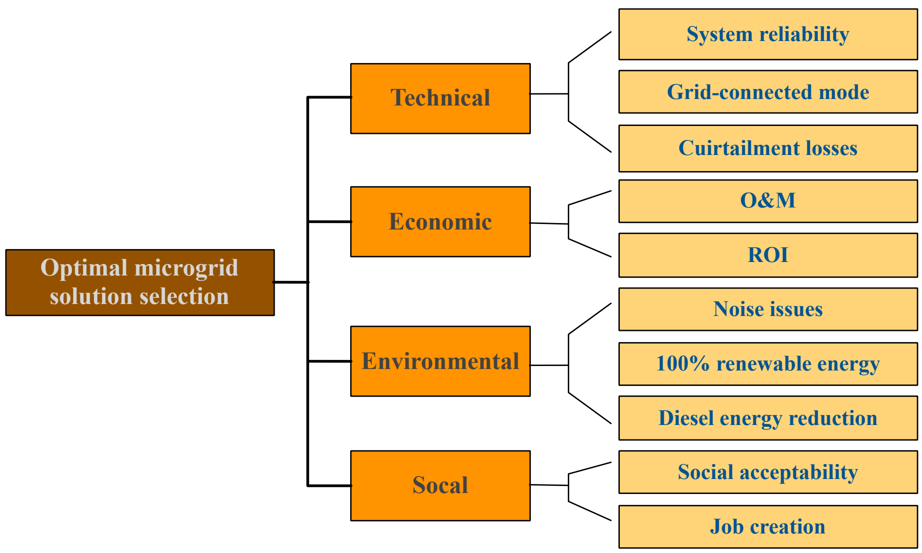


Fig. 3.6 Hierarchy of Criteria for microgrid selection

4. Application development of microgrid design

A framework of microgrid design provides value only when policy makers and system planners can use it in a manner that is convenient, and have the necessary resources and mechanisms in place that helps them to make a decision. Accordingly, a Python-based desktop application has been developed as a toolkit for microgrid design and planning.

4.1 Toolkit development

The proposed "UNB Smart Grid Design Tool for Rural & Remote Communities" is developed based on two key parts: the frontend data input & display panel and the backend optimizer design. Both the frontend and the backend parts are developed using Python script. The frontend panel is built within wxFormBuilder first, which is an open source Python GUI designer application. By using this software, the layout of the toolkit frontend panels, button functions, file selection units, display modules and etc. are all placed. Once the frontend panel design is completed, all the elements are converted into python script using wxFormBuilder with embedded pre-defined functions. These pre-defined functions will be filled with the developed optimizer later on to link the backend code. Fig. 4.1. give an overview of the proposed toolkit, followed by a detail description of the functions. This toolkit consists mainly of four sections, which include general community information import, DER parameter settings, design optimization and result visualization.

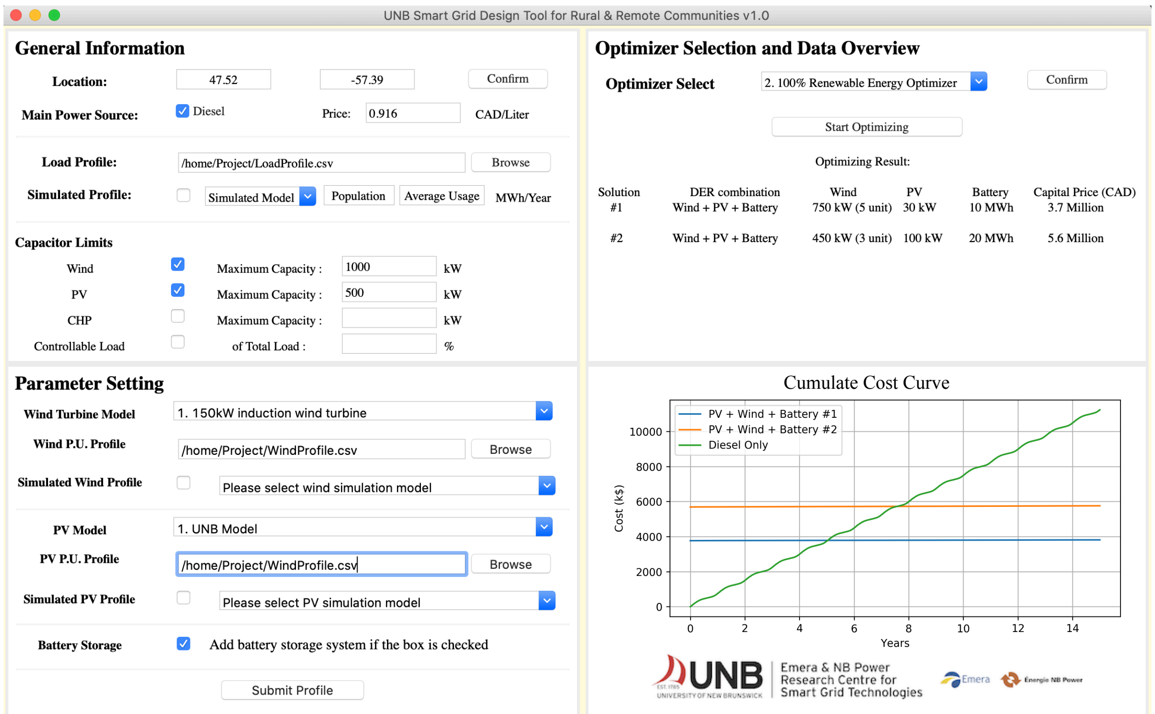


Fig. 4.1 UNB Smart Grid Design Tool for Rural & Remote Communities

- General community information import (shown in Fig. 4.2): this section inputs the basic information of the investigated rural or remote community. Specific requirements and limitations are also taken into consideration.

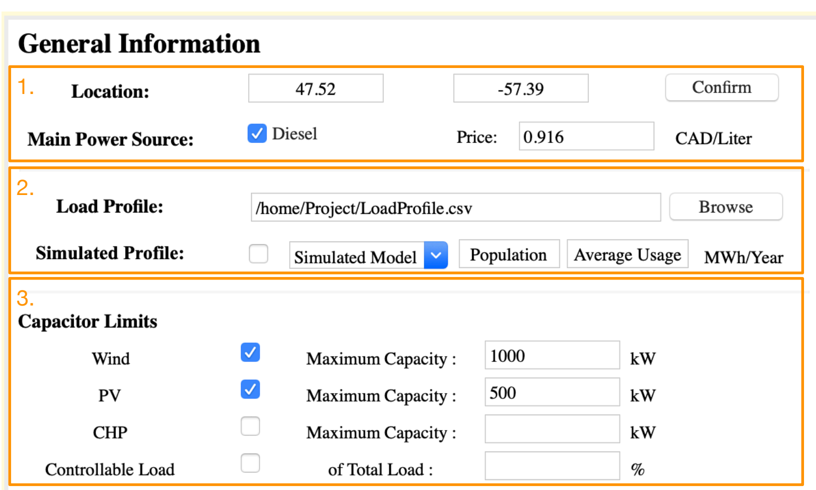


Fig. 4.2 Overview of general community information import section

where,
Box 1: Input the community location as well as check box to illustrate whether this investigated community uses diesel as its main power source or not;

Box 2: Import the electrical load consumption profile of the community using a .csv or .xlsx format or simulate the profile via the internal UNB developed model (or other third-party models) when checking box;

Box 3. Set the capacity limitations of each of available DERs which comprise wind, PV, Combined Heat and Power (CHP) and controllable loads. Checking box will add the selected DER into the optimization process.

- DER parameter settings (shown in Fig. 4.3): this section inputs the parameters and p.u. generation profiles of wind turbines and PV panels.

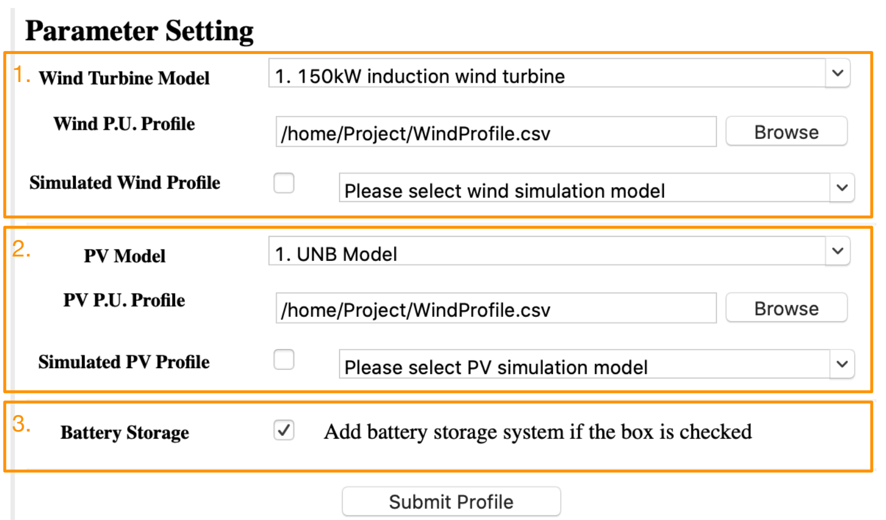


Fig. 4.3 Overview of DER parameter settings section

where,
Box 1: Select the specification of the wind turbines that will be used in the investigated community and add the wind turbine p.u. profile to the optimizer. If the actual p.u. prolife is not available, a simulated profile can be generated via a selected simulation model;

Box 2. Select the specification of the PV panels that will be used in the investigated community and add the PV p.u. profile to the optimizer. If the actual p.u. prolife is not available, a simulated profile can be generated via a selected simulation model;

Box 3. Add battery storage into the optimization if the box is checked.

- design optimization (shown in Fig. 4.4): this section works together with the backend to optimize the microgrid solutions within different design objectives.

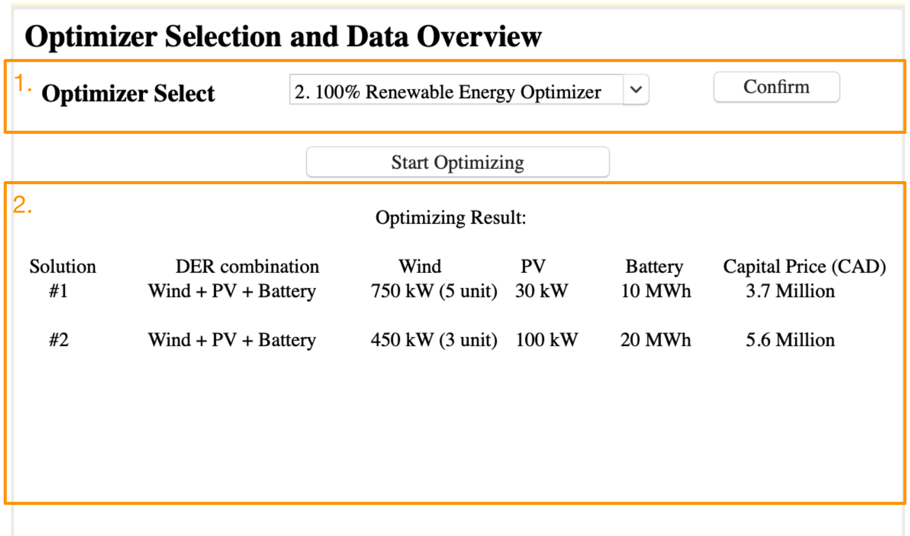


Fig. 4.4 Overview of design optimization section

where,

Box 1: Select one of the optimizers to evaluate available microgrid solutions in terms of the DER combination, the capacity configurations and the capital price. Currently there are three selectable optimizers which are Best ROI Optimizer, 100% Renewable Energy Optimizer, and customized one.

Box 2: List all the available optimization solutions based on the objective set by the optimizer selection.

- result visualization (shown in Fig. 4.5): this section displays the cumulate cost curves for every optimized solution.

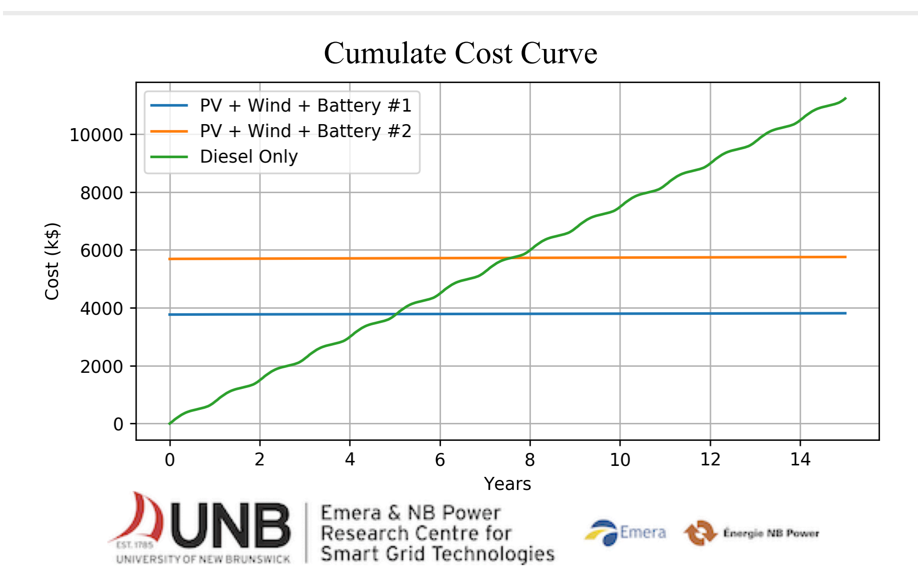


Fig. 4.5 Overview of result visualization section

4.2 Case study

To test and demonstrate the proposed framework, the microgrid design for Ramea Island, NL has been selected as a case study. A previous pilot project led by Newfoundland and Labrador Hydro, with funding support from the Atlantic Canada Opportunities (ACOA), the Government of Newfoundland and Labrador, and from NRCan was commissioned in 2009 with development of a wind-hydrogen-diesel system used for reducing the dependence on diesel power. The UNB, Frontier Power System in P.E.I and Memorial University were the main technical partners. The updated information of Ramea, NL can be found NRCan Remote Communities Energy Database as the initial data collection for the microgrid design, as shown in Fig. 4.6, which includes population, coordinates, total fossil fuel generating capacity (kW), diesel price ($/L) annual fossil fuel generation (MWh/yr), and etc.

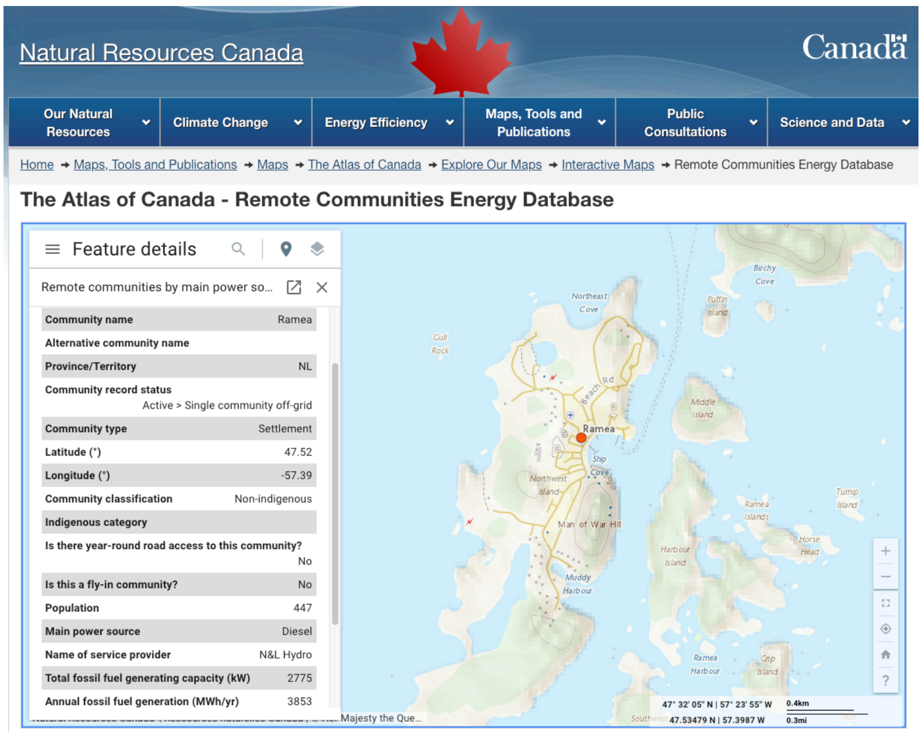


Fig. 4.6 Basic information of Remea, NL

When designing a microgrid for Remea using the proposed framework, three scenario studies presented in this project have been evaluated, which can be described as

a) Best ROI microgrid solution

b) 100% renewable energy supplied microgrid solution

c) 100% renewable energy supplied microgrid solution with a limitation of the maximum capacity of deployed wind generation ($\leq$ 1.5MW)

Fig. 4.7 shows the simulated yearly p.u. generation profiles of wind and PV using the models presented in Section 2. In this case study, an 150kW induction-generator-based wind turbine system is used as the standard wind turbine unit for planning. And a 2kW rooftop PV power station is used as the standard PV panel unit. Then, an averaged daily p.u. profile of wind and PV generation can be obtained in a similar way developed in (3.1), which is illustrated in Fig. 4.8. The electrical consumption load profile of Remea come from the measurement which was shown in Fig. 3.2. However, a 20% margin is left for the design taking account of the increasing electricity demand growth.

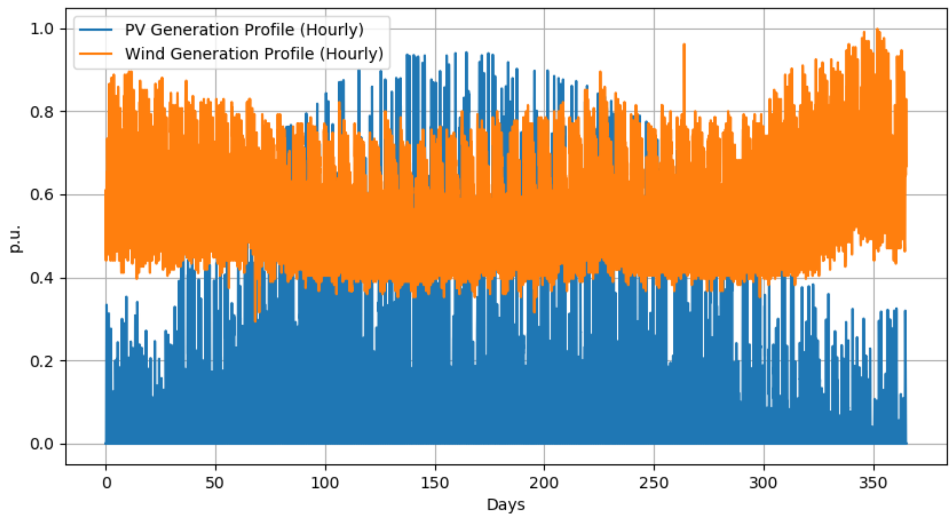


Fig. 4.7 Simulated generation profile of p.u. wind and PV for Remea, NL

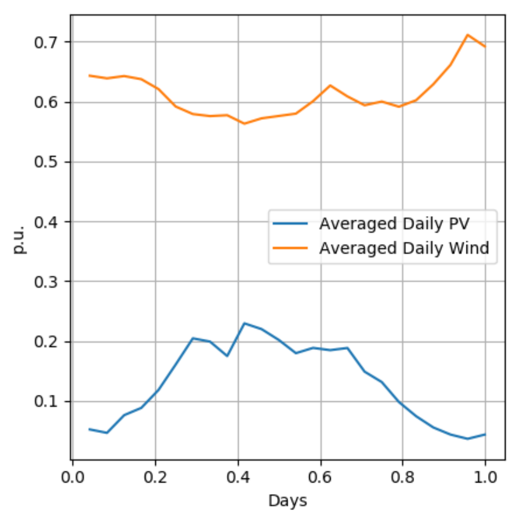


Fig. 4.7 Averaged daily generation profiles of wind and PV for Ramea, NL

Table II provides the necessary parameters used for this case study. Table III lists the optimized solutions to three scenario studies, respectively. Fig. 4.8 gives a screenshot of the operation in scenario b as an example to understand how the battery works in a microgrid to compensate the intermittency of integrated renewable generation.

TABLE II PARAMETERS FOR MICROGRID DESIGN IN REMEA, NL

PV Capital Cost c_{pv}	3000 $/kW	a	$0.0002484\ (\$/\mathrm{kWh})^2$
Wind Capital Cost c_w	3500 $/kW	b	$0.3312\ \$/\mathrm{kWh}$
Battery Capital Cost c_B	609 $/kWh	c	$0.0156\ \$/\mathrm{kWh}$
P_{rated}^{1PV}	2KW	P_{max}^{D}	1500 kW
P_{rated}^{1W}	150 kW	P_{min}^{D}	20 kW
N	131,400 hrs (15-year)	N_{days}	5,475 days (15-year)

TABLE III MICROGRID SOLUTIONS TO SCENARIO STUDIES

Scenario Study	DER Solution	Wind Turbine (kW)	PV Panel (kW)	Battery (kWh)	Capital Investment (k$)
a	Diesel + Wind + PV	600 (150×4)	30 (2×15)	0	$1,875.00
b	Wind + PV + Battery (#1)	1650 (150×11)	30 (2×15)	1293	$6,604.00
c	Wind + PV + Battery (#2)	1500 (150×10)	630 (2×315)	1386	$7,984.00

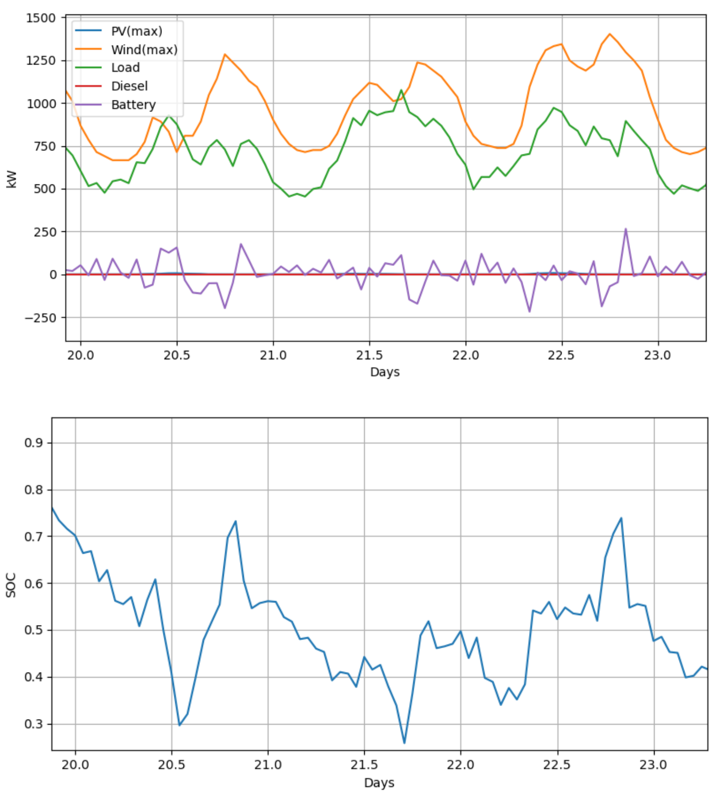


Fig. 4.8 Operation of a microgrid with 100% renewable DERs

Fig. 4.9 illustrates the cumulative costs of each microgrid solution listed in Table III during a period of 15 years. It is clear that the microgrid integrated with renewable DERs can offer not only the environment benefits, but also a significant savings of the fuel cost, and the main barrier to deployment of renewable electric energy in rural and remote communities is still the up-front cost. In addition, when comparing two 100% renewable energy solutions, it is easy to find that adoption of wind turbines in Ramea, NL is more efficient and cost-effective than PV panels for energy supply. There is no one-size-fits-all solution to microgrid design for all of Canada's rural and remote communities -- any renewable technology is only truly effective when located in an area with appropriate natural resources such as solar or wind. Thus, when planning to design a microgrid integrated with renewable energy, the proposed framework becomes beneficial due to the help for identifying the optimal DERs through evaluating the different system configurations. However, there are still some important factors in microgrid design not included in this study, such as ancillary services provided by DLC, maintenance cost of DERs, sensitivity analysis, connection issues with a national grid and etc., all of which will be evaluated in the future research.

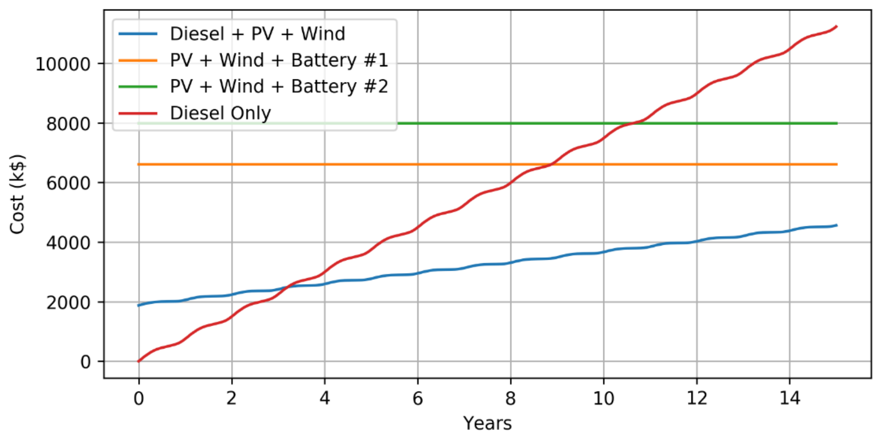


Fig. 4.8 Cumulative cost curves for microgrid solutions

5. Conclusions and Recommendations

This report proposed a strategic framework for designing a renewable energy integrated microgrid for Canada's rural and remote communities to reduce fossil fuels dependence. The proposed framework is composed of three primary processes: building generation profile evaluation model, carrying out modelling optimization and making a decision using AHP. The framework serves as a guide of how policy makers and system planners will make a decision on the optimal microgrid solution selection to meet the goal of reducing fossil fuel emissions in rural and remote communities as well as accelerating the rural electrification across Canada. In addition, the profile simulation models of a variety of DERs and the community demand proposed in this report are highly beneficial for narrowing the gap between microgrid design and development.

Compared to the existing methodological framework design for microgrids, this project proposes a specific one applied for microgrids in rural and remote communities in Canada. All the mandatory information and data can be available in Canada's public database. And all the simulation models are also developed specific to rural and remote applications. In addition, considering that the framework is established to support a high-level decision-making, the AHP-based MCDM model is developed to build the potential of cross-sectoral cooperation, which makes the decision-making process more efficient. Furthermore, the presented optimization method is capable of not only offering economic and reliability analysis of a microgrid design like most of the other framework did, but also providing suggestion to power the future such as design of a 100% renewable energy microgrid.

However, even though the framework is developed to be applicable to a large variety of microgrid designs, there is no one-size-fits-all solution to all of Canada's rural remote communities. There always exist new technical challenges, specific concerns, or collaboration issues, all of which make the decision-making harder. Consequently, a Python-based application has been developed by the UNB team for deployment of the proposed microgrid design framework. This toolkit provides an open-source microgrid design and planning platform, which allows modelers and researchers to integrate with their models, algorithms, analysis tools, or any related information, and thereby making a substantial contribution to providing a clean, efficient, reliable and affordable solution for supplying energy to off- and weak-grid communities across Canada.

The economic sustainability of renewable energy integrated microgrids aimed at rural and remote communities may require policy intervention, which means allocating public funds for covering both the initial investment and the operation and maintenance (O&M) expenses (specific to some particular equipment, such as lead-acid batteries). With the proposed framework, policy makers and system planners not only understand the optimal microgrid solution, but also have a detail expense estimation of the solution. In addition, policy makers and system planners should fully consider specific challenges and limitation of the investigated community and add them into the proposed AHP-based MCDM model. Lack of the knowledge of that could cause considerable difficulties in practice.

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