Exploring Grassroots Renewable Energy Transitions

by

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ABSTRACT

Replacing fossil fuels with renewable energy is not a simple substitution. Variable renewable energy generators like wind turbines and solar panels must be geographically dispersed, leading to a new, decentralized energy system that requires similarly decentralized governance. However, the local stakeholders needed to run these governance structures are typically excluded from the later stages of the energy modelling process where design decisions are made. This exclusion is more prevalent in Indigenous communities in so-called Canada. The Exploring Grassroots Renewable Energy Transitions (EGRET) platform showcases an alternative energy modelling process with community participation throughout. Created in partnership with Musqueam band's energy specialist, the EGRET platform enables community members to explore renewable energy development options for their local grid through interactive workshops. These workshops are made possible by the platform's accessible user interface and visualization suite as well as the fast run times of the machine learning models that power it. Similar approaches could be applied in other communities to support renewable energy integration from the bottom up.

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List of Acronyms

ANN artificial neural net.

BC British Columbia.

CBPR community-based participatory research.

CPU central processing unit.

EGRET Exploring Grassroots Renewable Energy Transitions.

GHG green house gas.

IEA International Energy Agency.

IPCC Intergovernmental Panel on Climate Change.

MAE mean absolute error.

MERRA Modern Era Retrospective-Analysis for Research and Applications.

MLP multilayer perceptron.

MOU memorandum of understanding.

NBCC National Building Code of Canada.

NRCAN Natural Resources Canada.

OCAP ownership, control, access, and possession.

RAM random-access memory.

ReLU rectified linear unit.

ResNet residual neural net.

SILVER Strategic Integration of Large-capacity Variable Energy Resources.

VRE variable renewable energy.

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Chapter 1

Introduction

Before introducing this research, it is important that I first introduce myself. I am a white settler born on the unceded territory of the Anishinaabe Algonquin Nation, and I recently moved to the territory of the Lekwungen peoples for my studies. This research is inspired by the many Indigenous people who are empowering their communities through renewable energy. As a settler with formal engineering education, I hope to support these community-led initiatives in decolonizing and decarbonizing our energy systems.

The transition from fossil fuels to renewable energy requires a large-scale shift in energy system planning. Fossil fuel-based generators can be conveniently centralized, but renewable energy generators such as wind turbines and solar panels must be placed wherever their associated resource is most abundant [1]. Integrating renewable energy generators therefore results in a decentralized energy system that requires similarly decentralized governance structures [2], [3]. The way we approach energy modelling must also shift to accommodate the new and diverse voices leading the decentralization and decarbonization of our energy systems. Typical energy system modelling processes tend to exclude stakeholders, in part due to the inaccessibility of the modelling tools [4], [5]. The resulting absence of local knowledge leads to over-representation of modeller perspectives in the model itself [6], [7]. This exclusion is especially damaging for Indigenous peoples in so-called Canada where natural resource industries like renewable energy development harm their land and communities [8], [9]. There is a need for a renewable energy integration modelling tool that includes stakeholders at all stages of the tool's development and application.

Developing tools to support Indigenous inclusion in renewable energy decision-making is especially important given their leadership in the field and their inherent rights to their territory and resources [10]. As of 2021, there were 197 clean energy projects *involving* Indigenous communities in Canada [11]. However, the extent to which they have control over these projects is unclear, and communities can only obtain the benefits of renewable energy development when they have ownership over the initiative [12]. One way to support Indigenous ownership over renewable energy decisions and developments is through participatory, bottom-up approaches to community energy planning [13]. This approach is important in non-Indigenous communities as well. Participatory governance, particularly opportunities for local people to engage in the decision-making processes that direct the energy transition in their community, help accelerate the transition from fossil fuels to clean energy [14].

This thesis explores the development of a **community-scale energy modelling tool**, called the Exploring Grassroots Renewable Energy Transitions (EGRET) platform, that **supports a bottom-up approach to renewable energy integration**. This tool was created in partnership with Musqueam band's energy specialist to explore how solar panels could increase the community's energy sovereignty. While the EGRET platform is developed specifically for the Musqueam community, the alternative framework used to construct it could be applied in other community settings to **include stakeholder and rightsholder perspectives throughout the energy modelling process**.

Participatory modelling is not new to the energy field. However, applications to date have only caused limited improvements in community engagement [3]. For Indigenous communities, these participatory processes can be difficult to navigate if there is a lack of local experienced personnel [13], [15]. The EGRET platform aims to reduce these barriers by packaging an energy system model with an **interface and visualization suite** that make scenario definition and exploration accessible to community members. The energy system model itself uses **machine learning to drastically reduce long run times** typically experienced with community-scale energy system models [16]. As a result, the EGRET platform can be used in **interactive workshop settings**, creating opportunities for shared learning among community members [17].

Results from a workshop in the Musqueam community showed that the EGRET platform provided opportunities for participants to learn about their energy system and the effectiveness of solar panels in the local context, but due to a low number of participants these results are not statistically significant. The machine learning models behind the platform generated outputs five orders of magnitude faster than the computational model they were trained to represent. Although the increase in speed was accompanied by a reduction in accuracy, the results show that **machine learning models can be used in the exploratory stages of an inclusive energy systems modelling process**.

The remainder of this thesis will focus on both the participatory and technical processes used to build the EGRET platform, but the penultimate chapter will also discuss these results in greater detail.

Chapter 2 describes the collaborative process that was used to create the EGRET platform in partnership with Musqueam band's energy specialist.

Chapter 3 details how the machine learning models behind the EGRET platform were developed. This chapter also discusses the platform's limitations, workshop participants' feedback on their experience, and important steps to improve future versions.

Chapter 4 concludes by summarizing the findings of this project and their potential impacts on participatory energy modelling approaches.

Appendices include the questionnaires used to gather community feedback on the platform.

Chapter 2

Combining Participatory Modelling and Machine Learning for Inclusive Community-Scale Renewable Energy Integration

2.1 Abstract

Decarbonization through the integration of renewable energy technologies creates opportunities to redistribute the power of our energy system in both senses of the word. The decentralized nature of generation technologies like solar panels and wind turbines creates opportunities for communities to lead the clean energy transition. However, the three-step modelling process typically applied in renewable energy decision-making tends to exclude community actors from the later stages. Indigenous communities in so-called Canada face additional barriers to participation in renewable energy projects including capacity strains and funding restrictions. This paper proposes an alternative modelling process designed to facilitate stakeholder and rightsholder participation throughout and describes how it was applied to create an energy system modelling platform in collaboration with a local First Nation's energy specialist. This alternative process finished with an interactive workshop in which community members use the finished modelling platform to explore local energy questions. This inter-

activity is made possible by machine learning tools that accelerate scenario modelling and facilitate broad design space exploration. This paper focuses on the collaborative processes behind the development of these tools and the frameworks that guided them in hopes of inspiring future work engaging communities in renewable energy modelling and decision-making.

2.2 Introduction

As European colonizers arrived in what is now known as Canada, they displaced First Nation, Inuit and Métis peoples from their traditional territories [8], [18]. With the loss of their traditional territories came a loss of sovereignty for Indigenous peoples as they no longer had access to the land that supported their ways of life [8]. Meanwhile, the stolen land fueled Canada's growing resource economy [8]. Some of these resource projects included renewable energy developments like large-scale hydro dams, which resulted in the flooding of some Indigenous communities' remaining land [8], [9]. Most of these communities were excluded from the benefits of these projects. At the time of publication, there are still 28 Indigenous communities that do not have access to clean drinking water [19].

The extractive history of natural resource industries, including some renewable energy developments, and the potential for both community benefit and harm has forged a link between decarbonization and decolonization [12], [20]. These two movements are so deeply connected that the 2019 pact for a Canadian Green New Deal called for energy and emissions targets as well as reconciliation with Indigenous Peoples [21]. Indigenous Peoples themselves have led the way in many climate change mitigation projects, motivated by their connection to local ecosystems. The impacts of climate change are felt more keenly by Indigenous communities because, as stated by Bill Erasmus, former Assembly of First Nations regional chief, they "are most hit by what happens immediately to the land" [22].

Indigenous Peoples themselves have led the way in many climate change mitigation projects, motivated by their connection to local ecosystems. Indigenous communities are becoming particularly involved in the transition to renewable energy. As of 2021, there were 197 clean energy projects that involve Indigenous communities in Canada [11]. Cutting ties with fossil fuels provides Indigenous communities with energy autonomy, financial benefits, energy security, and decreased reliance on colonial systems [9]. A survey of Indigenous communities and economic development corporations also found that renewable energy projects contribute to reconciliation by increasing participating communities' sense of ownership over their lives, building capacity, generating revenue, renewing stewardship of the land, and developing energy resilience [23]. However, these benefits can only be realized when the community has ownership and control over the development [12]. The definition of "involvement" in the 197 projects mentioned above includes memorandums of understanding and impact and benefit agreements, which do not constitute ownership.

Participatory governance, particularly opportunities for local people to engage in the decision-making processes that direct the energy transition in their community, help accelerate the transition from fossil fuels to clean energy [14]. Collaborations between academics and non-academics in participatory governance structures bring different knowledge systems and perspectives together to generate the creative solutions needed to address complex sustainability challenges [24], [25]. However, encouraging knowledge sharing between actors from different backgrounds is not always straightforward. Conversations between community members and external experts require mutual learning and trust built through repeated interactions [26], dialogue, continuity of researchers, and cultural sensitivity [24].

Current energy system design approaches, which rely heavily on modelling, do not facilitate iterative engagement [27]. A typical three-step scenario modelling framework, as outlined by Fortes et al and shown in figure 2.1, only includes non-expert stakeholder input in the first stage to develop a qualitative understanding of the context to be modelled [4]. The exclusion of non-expert stakeholders from the later stages where the modelling occurs can lead to the overrepresentation of modeller perspectives. For example, modellers must make assumptions and simplifications to use modelling tools, and their decisions reflect their own expertise and may not represent the stakeholders' lived experience [6]. The interpretation of the model results is also dependant on the modeller's experiences and excluding stakeholders from this step leads to a loss of local insight [5], [7]. This exclusion is particularly harmful for Indigenous peoples who have the inherent right to determine appropriate development strategies for their territories and resources [10].

Participatory modelling approaches, where academics and non-academics collabora-

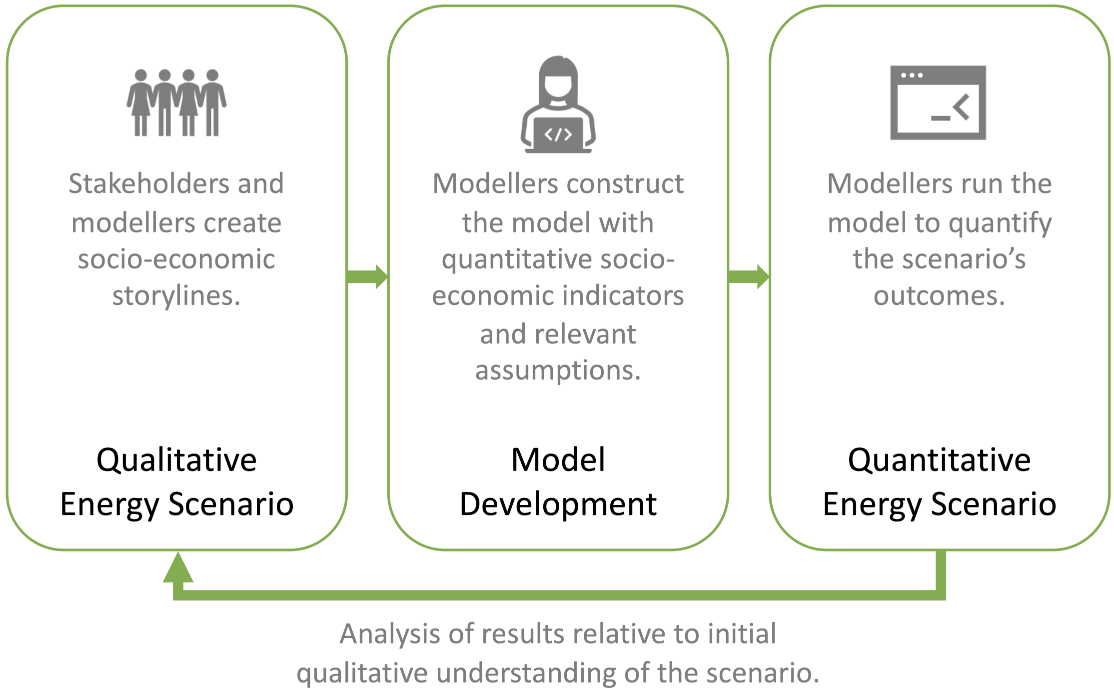


Figure 2.1: Typical scenario-based energy modelling framework, adapted from Fortes et al [4]

tively develop and apply a representative model of a problem [17], have been used in the energy field to address local stakeholder exclusion. However, a review of these attempts found limited improvements in ongoing community engagement [3]. One reason for this lack of continued participation could be that computer-based energy system models are inaccessible to community members, leading to feelings of disempowerment [5]. In First Nations communities in particular, another reason could be that navigating the engagement process is difficult without local experienced personnel [13], [15]. There is a need to convey the relationship between renewable energy options and community operations in a way that is accessible to the public [25], and in so doing involve stakeholders and Indigenous rightsholders at all stages of the modelling process [7], [27].

2.3 The Exploring Grassroots Renewable Energy Transitions Platform

The Exploring Grassroots Renewable Energy Transitions (EGRET) platform is a tool that aims to address these barriers to accessibility and engage Indigenous rightsholders at all stages of the modelling process. The EGRET platform was developed in partnership with Musqueam band's energy specialist following the alternative three-step modelling framework proposed in figure 2.2. The goal of this proposed framework, which is based on a knowledge coproduction framework by Norström et al, is to collaboratively construct a context-specific model with which community members can investigate energy questions of their choosing [24]. Engaging stakeholders in all stages of the modelling process creates opportunities for deep learning that are not possible with the typical modelling framework shown in figure 2.1 [17].

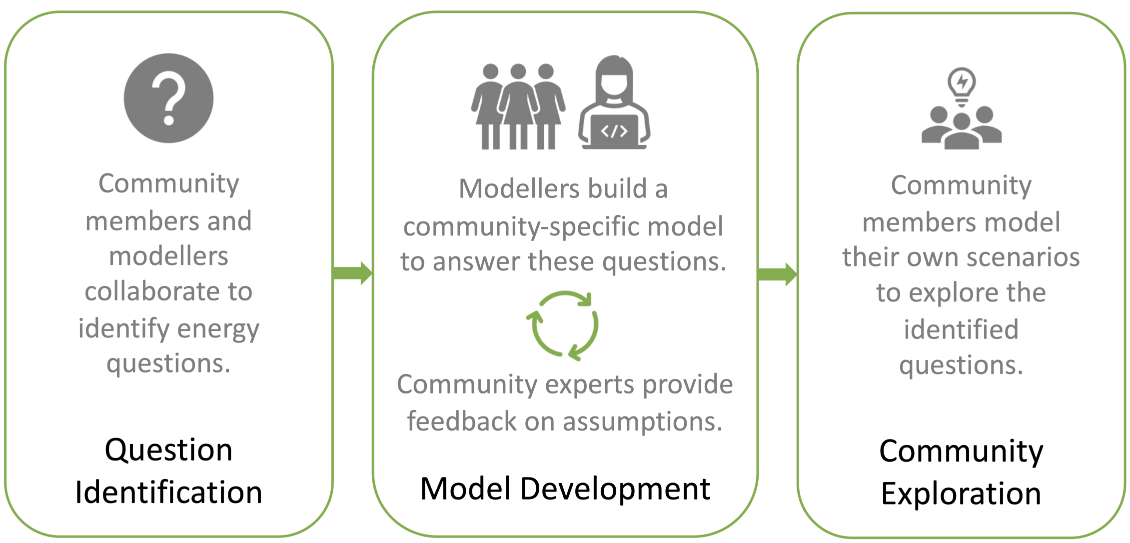


Figure 2.2: An alternative three-step modelling process adapted to include stakeholders and Indigenous rightsholders at all stages.

The EGRET platform consists of three components: a user interface, a machine learning model, and a visualization suite. Users interact with the interface to design energy system scenarios for their community. The machine learning model predicts the hourly generation of each energy technology in the system, as well as associated costs and emissions. The visualization suite presents the model's predictions to the user such that they can compare results across scenarios. Figure 2.3, figure 2.4, and figure 2.5 show the EGRET interface and two visualization options, respectively.

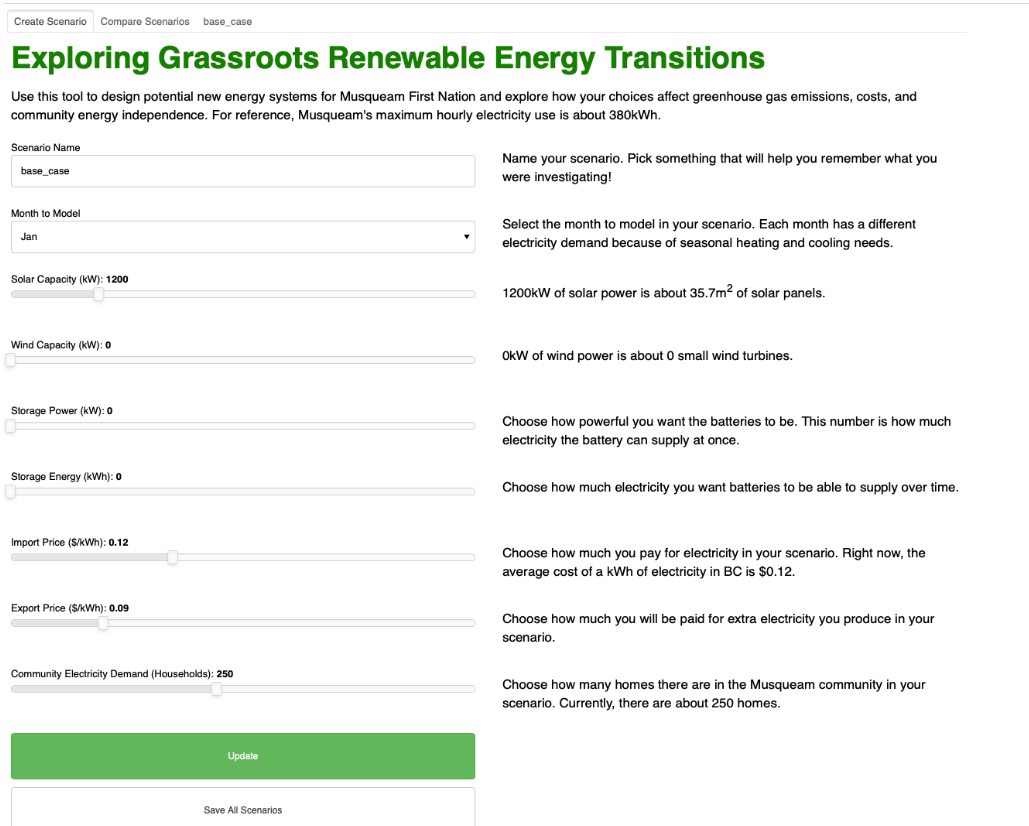


Figure 2.3: EGRET user interface.

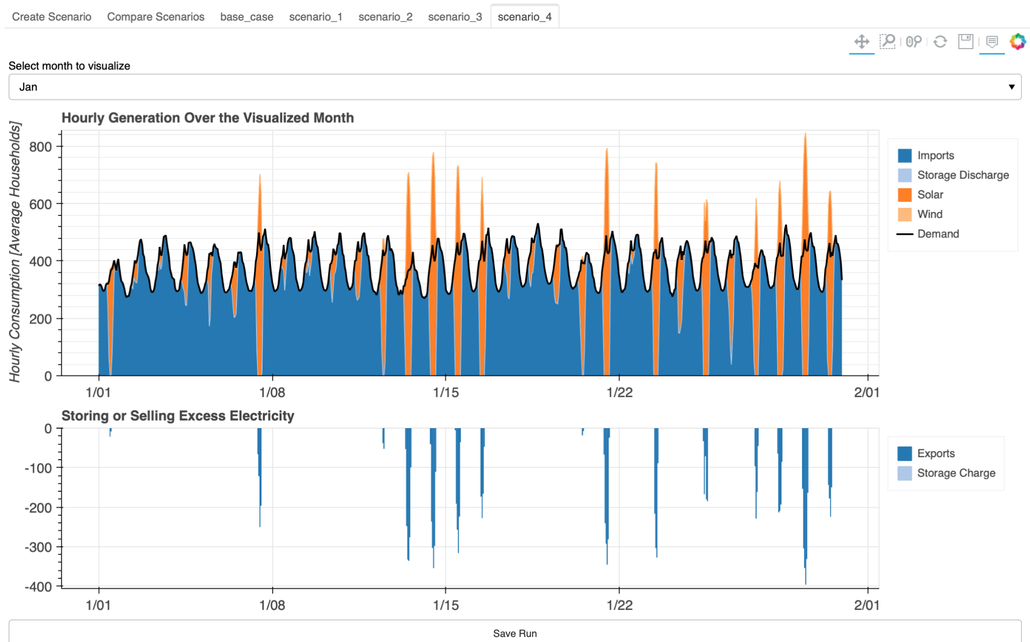


Figure 2.4: The primary EGRET visualization shows hourly generation by technology type for the modelled scenario.

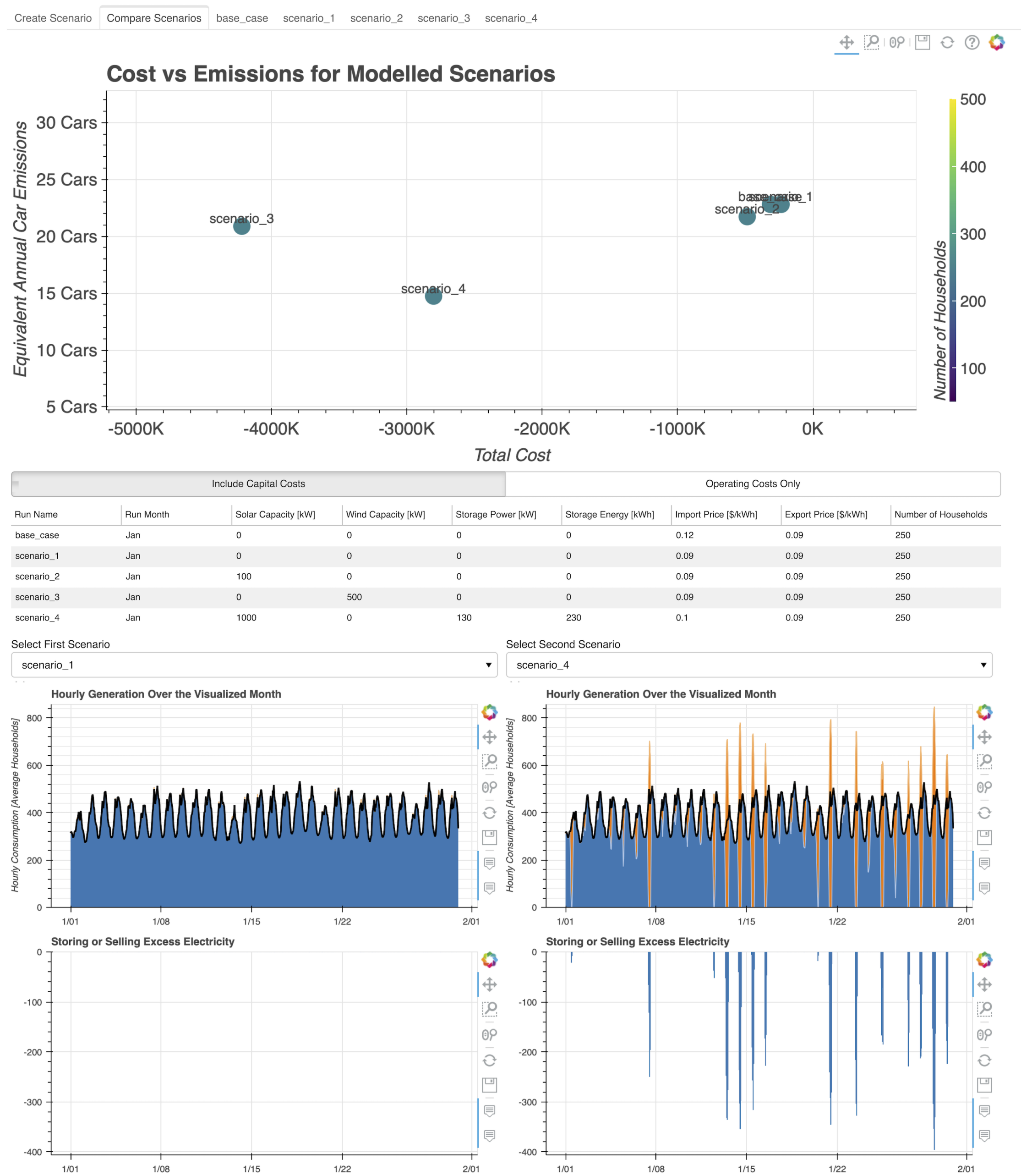


Figure 2.5: The secondary EGRET visualization compares cost and emissions across modelled scenarios.

These three components were packaged together to facilitate the Community Exploration stage of the alternative modelling process. The interface and visualization suite make the embedded energy system model and its results more accessible to those without modelling experience. Consequently, community members can be involved in the analysis stage of the modelling process from which they are typically excluded. The speed of the machine learning model, relative to typical energy system models with long run times [16], allows for broad design space exploration and dynamic interaction with the platform.

This paper focuses on the first two stages of the proposed alternative modelling process and how researchers collaborated with Musqueam's energy specialist to develop the EGRET platform for the community's interests.

2.4 Collaborative Research Design and Implementation

The goal of reconciliation is to redevelop relationships between Indigenous and non-Indigenous people based on values of respect and reciprocity, and research-based relationships are no exception. The extractive, colonial history of research has created an environment of mistrust between Indigenous people and academic institutions [28], [29]. Shaped by the principle of two-eyed seeing, a concept developed by Mi'kmaw Elders that weaves Indigenous Knowledge and Western academia together as equals, researchers are developing new processes that focus on relationship building and shared benefits [30]. One approach is called community-based participatory research (CBPR), which aims to share decision-making power between researchers and community members and prioritize changes for the community's gain [31].

The CBPR process is best initialized by Indigenous communities looking to start a research project, rather than by researchers approaching a community with a project already in mind [31]. Musqueam's energy specialist, included in this paper as a co-author, reached out to the researchers expressing interest in a collaborative modelling project. He outlined some of the community's energy priorities and how modelling might be beneficial. In turn, the researchers described the modelling tools they had available, their scopes, and areas where these models could be expanded or adapted. The three available models included an energy system operational cost optimization model called the Strategic Integration of Large-capacity Variable Energy Resources (SILVER), a transportation system model, and a building energy model which can be interconnected [32]. A summary of the available modelling capabilities is shown in figure 2.6.

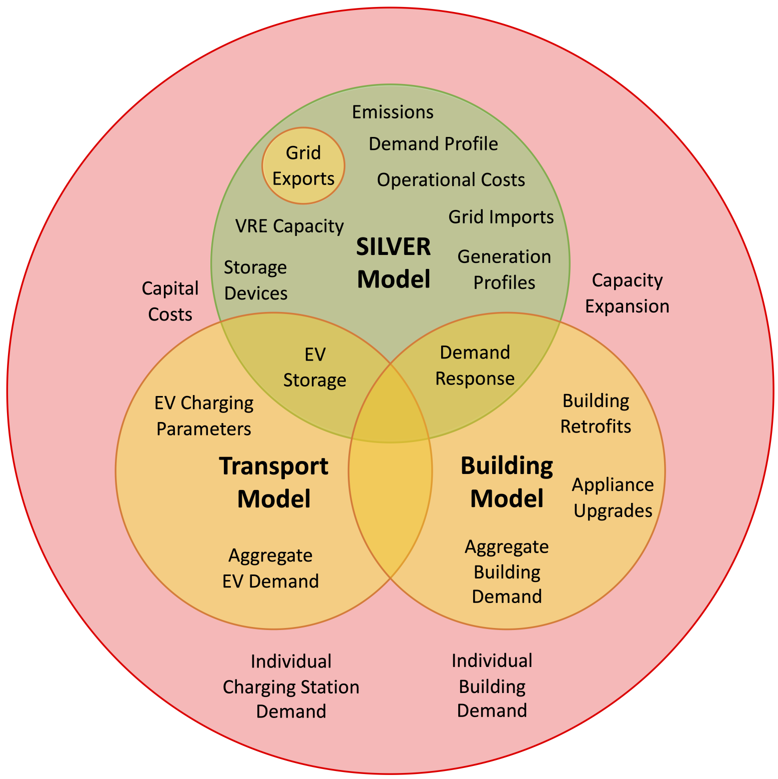


Figure 2.6: Diagram of available, potential, and out-of-scope modelling capabilities. Available capabilities are shown in green, potential additions are shown in yellow, and areas beyond the given models' scopes are shown in red.

Together, researchers and the energy specialist identified overlaps between available and potential modelling capabilities and the community's interests. The discussion resulted in several research questions, listed below in order of priority, that would guide the development of the EGRET platform. Given academic timelines, only the first question regarding solar panel effectiveness is explored in depth.

1. Are solar panel installations a cost-effective means of increasing energy self-sufficiency in the community?

2. What types of building retrofits would provide the best gains in energy efficiency?

3. How would electric vehicles affect community electricity demand?

Further, researchers and the energy specialist determined how the platform would be used to benefit both parties. To benefit the community, the researchers would hold an informal workshop in the community's administration offices where staff could experiment with the platform and explore the identified community energy questions. To benefit the researchers, these participants would provide feedback on the platform to guide future iterations. These decisions were made over a year and a half through video calls, emails, and a visit to the community. In depth discussions about community context and mutual goals were conducted approximately twice a year over video call, while progress updates and clarifying details were discussed over email on an approximately biweekly basis.

After laying out the research design and verifying modelling capabilities, the researchers worked with the energy specialist to formalize the project and partnership through a human research ethics application as well as a memorandum of understanding (MOU) between the two parties. The formalization process occurred after initial engagement to ensure the community energy specialist could participate in the research design process. The requirement for an Indigenous community's engagement in the development of research plans that affect them is present in both Canadian and University of Victoria human research ethics guidelines [29], [33]. The University of Victoria human research ethics board approved the original research project, code 21-0553-01, on April 1st, 2022, with amendments accepted on October 6th, 2022.

The University of Victoria ethics application process also requires researchers to disclose how data storage will comply with the First Nations Information Governance Centre's guidelines for the treatment of community information. These guidelines, known as OCAP (ownership, control, access, and possession), ensure the partner community maintains governance over their own data [34]. The finer details of the data sharing agreement were described in the MOU along with each party's benefits and responsibilities. The division of responsibilities in the MOU presented an opportunity for the community to specify their desired level of involvement in the project, as recommended by CBPR approaches and required by Canadian human research ethics guidelines [29], [35]. The MOU also stated publication requirements to ensure the researchers could meet degree-based obligations.

2.5 Results

Following the formalization of the project, the researchers constructed the three components of the EGRET platform with the community's questions in mind. To better explore the impacts of solar panels on community energy independence, the researchers redeveloped SILVER to include variable demand, the ability to import from and export to the electricity grid at different price points, and capital cost estimates. The researchers then used machine learning to replicate the adjusted SILVER model.

For the user interface and visualization suite, the researchers converted input and result units to be more accessible, as recommended by the community energy specialist. For example, generation units were converted from megawatt-hours to the number of average community households the electricity could supply for an hour, and emissions units were converted from tonnes of carbon dioxide to the number of cars that would produce equivalent pollution annually.

Three community members, including the energy specialist, participated in the workshop. By interacting with the EGRET platform, the participants sparked conversations that extended beyond the platform's scope. For example, participants discussed how rooftop solar panels could be connected to the grid and how financial benefits from these setups might be tracked and distributed, which they had not previously considered. The participants also suggested additions for future iterations of the platform including annual local capacity factors for wind and solar installations, the ability to model at the single-home scale, a pie chart of monthly electricity production by generator type for each scenario, and discussion of funding opportunities and generator maintenance costs.

2.6 Conclusions & Recommendations

Following the proposed alternative modelling process in partnership with Musqueam band's energy specialist resulted in a context-specific modelling platform with which community members can explore if solar panels can improve their energy sovereignty. However, applying this new framework was not without challenges.

The primary challenge faced by the researchers was the conflict between academic and community timelines. The alternative modelling process used to develop the EGRET platform took much longer than the typical three-step process would have. Particularly for junior researchers, there are expectations to produce results and publications within a short window that rush relationship building. In the case of this project, the researchers were unable to address all community questions because of the project's timelines. A potential solution would be to continue community partnerships beyond individual projects, ideally with overlap between researchers for continuous relationships. However, this challenge could also point to a need for decolonization of the university system; new methodologies like CBPR are creating space for community participation in research, but they are still ultimately limited by academic conventions.

A highlight of the collaborative development process for the researchers was a visit to the Musqueam community to meet with the energy specialist. The organic conversations that occurred in this in-person meeting had not previously been explored through email or video call. A community tour also helped researchers better understand the context in which the EGRET platform would be applied and prioritize the platform's objectives to match the community's experiences.

For other researchers looking to replicate the alternative modelling process proposed here, we recommend conducting as many engagement sessions in person as possible to ensure these valuable insights are included in the model. This is a vital step in any community project development, especially in Indigenous and First Nation communities. For decades, projects have been developed in these communities without proper consultation and engagement with community members.

An essential part of engagement with community members is providing information on different aspects of the projects. This information may include but is not limited to the cost to the community, benefits to the community, lifetime of the project, and available alternative options. In that sense, it is extremely helpful for community members to be able to explore different project development options and engage with decision makers, researchers, and contractors before and during the project development stages. The EGRET platform facilitates engagement with community members by enabling them to:

- Investigate the cost associated with renewable energy capacity development in the community;

- Compare different renewable energy generation and storage technologies (wind, solar, and battery); and
- Investigate the environmental benefits of replacing grid electricity with local renewable generation.

While EGRET was completed in partnership with Musqueam's energy specialist with a focus on Indigenous contexts, including community members or representatives early and throughout the development process is an important, but often neglected, part of small-scale renewable energy modelling projects in general. Future work applying this modelling approach more broadly could make renewable energy decision-making more accessible for communities in other contexts as well. For instance, making the platform more accessible to community Elders and youth would allow for a comprehensive engagement process.

Chapter 3

Exploring Grassroots Renewable Energy Transitions: Developing a Community-Scale Energy Model

3.1 Abstract

Decarbonizing energy systems through the integration of decentralized renewable energy generators creates opportunities for community-scale actors to participate in energy system decision-making. However, typical modelling approaches exclude community stakeholders, causing a loss of local knowledge. This exclusion is problematic for Indigenous peoples in so-called Canada where the natural resource industry can harm their land and communities. The Exploring Grassroots Renewable Energy Transitions (EGRET) platform introduced in this work presents an alternative to typical energy system modelling because it facilitates community participation throughout the model development and application process. This platform was developed in partnership with a local First Nation's energy specialist to assess whether solar panels could increase community energy sovereignty. The platform's user interface, visualization suite, and high-speed machine learning models make energy system modelling accessible to community members through interactive workshops. In the future, the EGRET approach could be generalized for stakeholder-led renewable energy exploration in other community settings.

3.2 Background & Motivation

Mitigating climate change is an urgent global issue. In 2015, the United Nations Framework Convention on Climate Change agreed upon a safe maximum global temperature increase of 2°C above pre-industrial levels, with an ideal upper limit of 1.5°C later set by the Intergovernmental Panel on Climate Change (IPCC) to further reduce the negative effects of global warming [36]. A 2018 report by the IPCC found that this 1.5°C limit could be reached as soon as 2040 [37]. Maintaining global temperatures within this threshold requires that net-zero greenhouse gas emissions be reached by 2050 [38]. The International Energy Agency (IEA) has urged the widespread, immediate deployment of every clean energy and energy efficiency technology available to make net-zero possible over the next 30 years [38]. In response, the Canadian government is targeting a two- to three-fold increase in national clean power production by 2050 [39].

Towards this effort, variable renewable energy (VRE) generators are the technologies most commonly associated with clean energy. These generators, such as wind turbines and solar photovoltaic panels, transform abundant natural resources into energy with a relatively small carbon footprint. However, there are two issues that make integrating VRE generators into electricity networks a challenge. First, as their name implies, VRE generators provide an inconsistent source of energy because operators have no control over when wind or sunlight is available. Electricity systems that incorporate VRE generators must have sources of flexibility, such as storage devices, available to provide energy when the weather is cloudy and still [38]. Second, VRE generators are often widely spatially distributed as they must be placed wherever their powering resource is most abundant [1]. Current electricity systems are designed around centralized power plants to simplify control and transmission.

The first challenge highlights the need for complex energy system modelling when integrating VRE into the grid. Every region will have different characteristics – such as the flexibility of the existing power system and the seasonal variability of wind and solar resources – that will dictate how much VRE can be reliably integrated [40]. The second challenge heralds an upcoming shift in energy system structure. The decentralization of VRE generators brings new actors and new priorities into the energy space, redistributing the power of traditional energy systems (in both senses of the word) to local actors through energy democracy [2].

Looking at these two challenges simultaneously, a third issue emerges. Communities, individuals, and other local actors in the energy democracy movement may not have the resources to design and model a VRE-integrated grid in-house. Energy system models are computationally expensive to run, and often require experience and training to operate [41]. Typical industry three-step scenario modelling frameworks only include stakeholders in the scenario development phase, leading to the overrepresentation of modeller perspectives and exclusion of local knowledge during model development and results analysis [4]–[7]. And yet, community input into that design process is crucial. Frameworks for change that bring individuals and communities into the decision-making process through participatory governance are key to ensuring an equitable transition [14]. Engaging with local communities also creates opportunities for coproduction of knowledge through both scientific and traditional bodies, building a holistic understanding of regional energy networks [42].

The exclusion of stakeholders from renewable energy decision-making is particularly damaging for Indigenous communities in so-called Canada because the natural resource industry and renewable energy developments have inflicted harm on Indigenous lands and communities [8], [9]. Further, Indigenous peoples have inherent rights to their territories and resources, and as rightsholders must be included in renewable energy decision making [10]. Decarbonization presents an opportunity for reconciliation through Indigenous ownership over renewable energy production, but barriers make ownership challenging for some communities [12], [15]. One common barrier is the need for outside consultation when navigating energy technologies because of community capacity strains, leading to the exclusionary modelling process outlined above [15].

The Exploring Grassroots Renewable Energy Transitions (EGRET) platform introduced in this work aims to make all stages of the modelling process accessible to stakeholders and particularly to Indigenous rightsholders. The guiding concept behind the platform is the participatory system dynamics framework described in [17], which recommends the inclusion of stakeholders at all stages of model development, use, and analysis to promote deep learning about the system in question. To facilitate inclusion, the EGRET platform was designed for use in a collaborative workshop setting. High-speed machine learning models power the platform to support a broad exploration of the design space and dynamic conversation. These models are packaged with a user interface and visualization suite to make the platform accessible to use and interpret. The EGRET platform was developed in partnership with Musqueam band's energy specialist to include community insight throughout the development and application process.

3.2.1 xʷməθkʷəy̓əm Energy Context

xʷməθkʷəy̓əm (Musqueam) are traditional hən̓q̓əmin̓əm̓ speaking people living in their territory (currently called Vancouver and the surrounding areas) for thousands of years [43]. Musqueam Indian Reserve number 2, located at the mouth of the Fraser River to the north of Sea Island, is a small portion of Musqueam Nation's traditional territory. Musqueam Nation has a vision of self-sufficiency and self-government as stated in the Nation's comprehensive community development plan [44]. To achieve these goals, Musqueam band and members have engaged in multiple projects focused on:

- Improving the energy efficiency of Musqueam homes and public buildings
- Reducing green house gas (GHG) emissions from energy consumption in the community
- Investigating the feasibility of renewable energy generation on Musqueam reserve

Currently, Musqueam homes, public buildings, and vehicles are the major energy consuming sectors and sources of GHG emissions in the community. Figure 3.1 shows the estimated shares of the community's top GHG emissions sources.

As shown in figure 3.1, vehicles are the most significant source of GHG emissions in the community. Residential buildings are the second largest source of GHG emissions, with a total of 37% of annual GHG emissions, while public buildings account for 7% of the annual GHG emissions.

As stewards of their land, Musqueam people are exploring options that enable their transition to a net-zero community. One of the most promising technologies that enables such a transition is solar power. Solar power is a commercially available technology that can provide clean electricity to the community and reduce energy bills for both Musqueam members and the band. The development of renewable

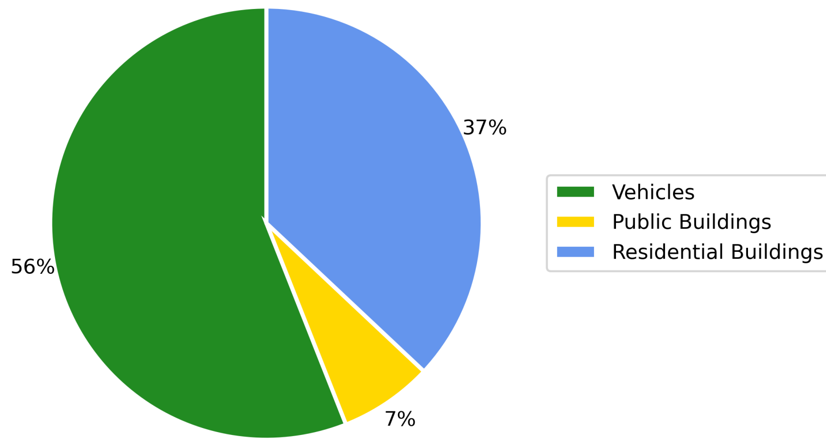


Figure 3.1: The estimated share of different green house gas emissions sources in the Musqueam community.

energy generation capacity in the community also aligns with the self-sufficiency and self-governance goals of the Nation [44].

The EGRET platform provides a tool for Musqueam departments and leadership to engage with community members regarding a renewable energy development project. The EGRET platform enables Musqueam members and staff to investigate different aspects of a renewable energy project including the cost to the community and GHG emission reduction potential. The EGRET platform also allows comparing different renewable energy technologies as well as storage system sizes. The EGRET platform eases the process of consultation with Musqueam members which is an integral step in any community-based project in Musqueam.

3.3 Methodology

The EGRET platform consists of three components: an interface where the user selects an energy system scenario, a visualization suite that compares results, and the machine learning surrogate models that transform the user's inputs into these visualized results. The user interface and two visualization views were shown previously in figures 2.3 to 2.5. In essence, surrogate models use supervised learning to understand

and replicate the connection between the inputs and outputs of an established model. The concept is applied here to maximize user interactivity; surrogate models can be evaluated much faster than the optimization-based models they replicate due to the absence of a time-consuming optimization loop.

The EGRET surrogate model replicates the results of the Strategic Integration of Large-capacity Variable Energy Resources (SILVER) model developed by the Sustainable Energy Systems Integration and Transitions group at the University of Victoria [45], [46]. SILVER takes a theoretical energy system – made of user-specified generators and their characteristics – and simulates its operation based on given demand and VRE potential data. The results are hourly generation profiles for each system asset as well as an operational cost break down over the specified period. By creating a large dataset of inputs and associated outputs from the SILVER model, EGRET can be trained to replicate these results in a fraction of the time.

This section focuses on the development and testing of the surrogate model and the data upon which it was trained, but it will also touch on the compilation of the platform and the final evaluation process. The University of Victoria human research ethics board approved the original research project, code 21-0553-01, on April 1st, 2022, with amendments accepted on October 6th, 2022.

3.3.1 Data Processing

Developing a surrogate model requires a dataset of inputs and outputs from the model being replicated; in this case, that model is SILVER. The following paragraphs outline the data processing steps taken to obtain SILVER inputs, as well as how those steps were repeated to build the full dataset. Figure 3.2 shows an overview of these inputs and the data flow through both SILVER and the EGRET surrogate model, as well as how the data is transferred from one to the other through the machine learning models' training process.

The first input needed to run SILVER is electricity demand for the region being modelled. Monthly electricity demand values for 39 residential and 6 public buildings in the community were available. The residential data came from an energy audit process previously done in the community using the building energy modelling tool HOT2000. These results were scaled up to represent the 250 total homes in the com-

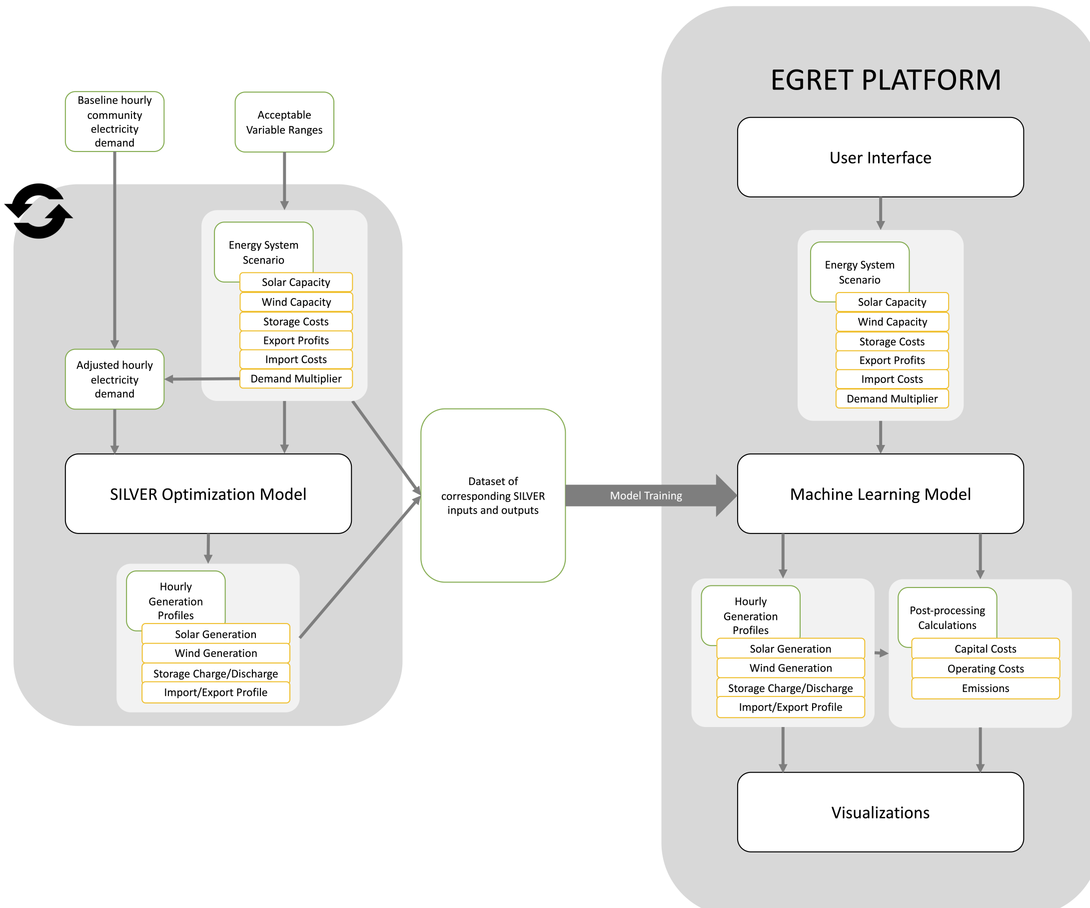
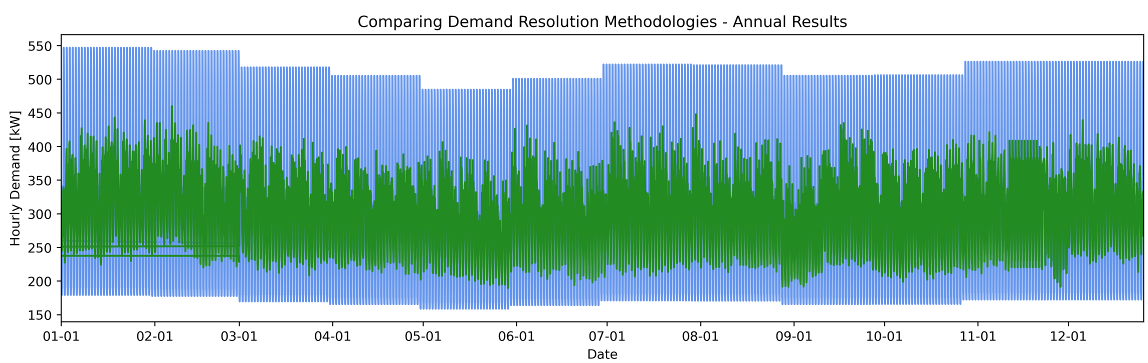


Figure 3.2: The SILVER model is run repeatedly for randomly generated energy system scenarios to create a dataset of inputs and outputs. In turn, this dataset is used to train the machine learning models behind the EGRET platform.

munity. The public building consumption data is actual electricity use measured from December 2017 to August 2021 and averaged per month. While these monthly totals are useful data points, the SILVER model requires hourly demand resolution.

Two methods of increasing resolution from monthly to hourly were explored. The first method uses hourly normalized internal gains specified by the National Building Code of Canada (NBCC) to scale electricity demand [47]. In this method, the total community electricity consumption per month is divided by the number of hours in the month to obtain an average hourly consumption value. This number is then multiplied by the NBCC's normalized hourly internal gain factor for each hour in the day. This process results in twelve 24-hour representative load profiles – one for each month – which are then repeated to build an annual curve. Because SILVER breaks the year into twelve thirty-day periods, the representative days were each repeated thirty times to create a "year" of 360 days.

The second method adjusts an annual electricity demand curve with hourly resolution from a community in Northern Quebec, Kangiqsualujjuaq, with a similar population to Musqueam Indian Reserve number 2. This publicly accessible demand curve was provided by Natural Resources Canada (NRCAN). The Kangiqsualujjuaq demand curve was scaled to match Musqueam community's monthly demand. This scaling process addressed population and climate differences between the two communities. In this method, the total demand of the reference community is summed over each thirty-day period. Each hourly demand value is then normalized by the corresponding thirty-day total to obtain hourly factors, which are in turn multiplied by Musqueam community's corresponding thirty-day demand to obtain an annual curve. Because of the normalization steps in both methods, both 360-day annual curves have the same thirty-day total demand, allowing for comparison. Figure 3.3 shows an annual comparison of the demand curves as well as a snapshot of January demand values for better understanding of day-to-day variation.



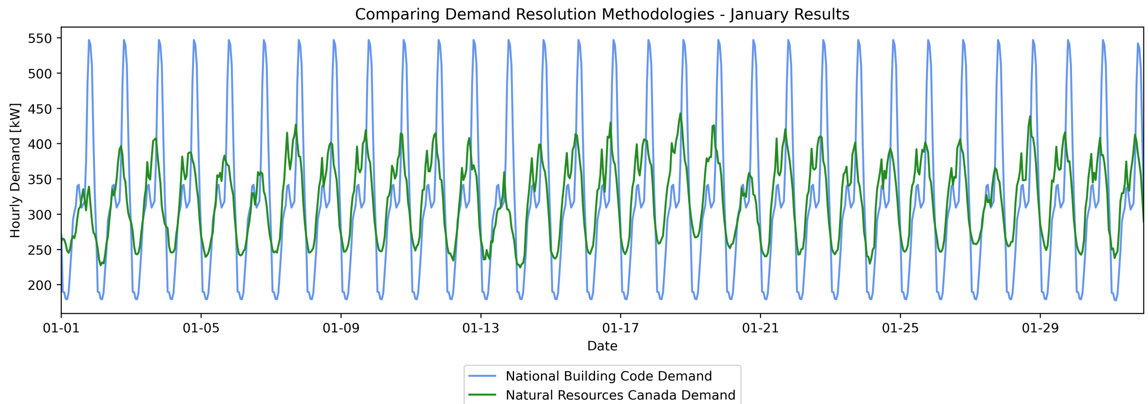


Figure 3.3: These plots compare the demand curves produced by the National Building Code of Canada and Natural Resources Canada demand methodologies. The top figure shows the full annual profiles, and the bottom figure zooms in to show daily fluctuations through the month of January.

These two methods were tested by modelling the scenarios shown in table 3.1 using SILVER over a one-year period. Each scenario was modelled twice; once with the NBCC demand, and a second time with the NRCAN demand. Variables not shown in table 3.1 were kept constant across all scenarios. Figure 3.4 compares the total generation by technology type resulting from the two demand methodologies for each scenario.

Table 3.1: SILVER scenarios used to test demand curve options.

Scenario	Solar Capacity kW	Wind Capacity kW	Storage Power kW	Storage Energy kWh	Import Cost $/kWh	Export Profit $/kWh
1 - Baseline	-	-	-	-	0.093	0.093
2 - Solar	100	-	-	-	0.093	0.093
3 - Wind	-	500	-	-	0.093	0.093
4 - Solar & Storage	1000	-	130	232	0.1	0.093

As shown in figure 3.4, Scenario 1 produced the same total monthly generation for both demand methodologies. This behaviour was expected as no variable generators were present in the scenario. The same behaviour was observed in Scenario 2, showing that temporal demand discrepancies do not have an effect when only limited VRE generation capacity is present. However, the total electricity exported per month varies between demand methodologies when modelling Scenario 3. This behaviour shows that differences in temporal demand values have an impact on SILVER's results when variable renewable energy generation exceeds consumption. As the amount of genera-

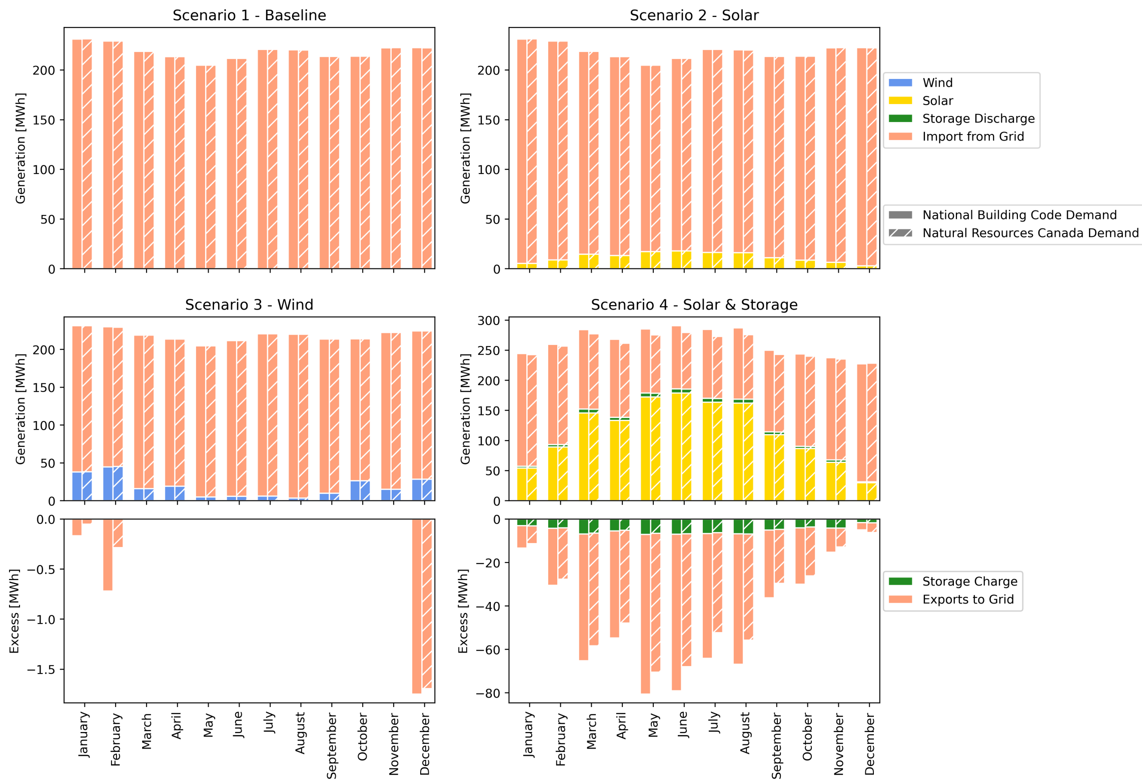


Figure 3.4: Total monthly energy generation by technology type is shown for each scenario. The solid bars on the left resulted from the National Building Code of Canada demand methodology, and the hatched bars on the right resulted from the Natural Resources Canada demand methodology.

tion increases further beyond demand, the difference in outputs from the two demand methodologies also increases, as shown in the modelled Scenario 4 results.

In the case of these two demand profiles, the first method has lower load values at midday – when solar generation is most active – than the second method. As a result, the scenarios with solar generation capabilities export more to the grid with the first demand profile. The first method also has lower demand values at night when wind resources are typically most abundant. As a result, the scenarios with wind generation capability also export more to the grid with the first demand profile. These findings highlight the importance of accurate community hourly demand data in situations where the community is looking to sell excess electricity back to the grid.

For the purposes of this study, the demand curve produced by the second method was selected for use in the EGRET training process because it is based on the demand of a real community and has more day-to-day variability, as shown in figure 3.3.

Another data component needed to run SILVER is VRE potential. VRE potential is the amount of electricity a given generator type would produce at every hour in the time series under typical weather conditions. These datasets were obtained from Renewables.ninja for Musqueam community's geographical position using the Modern Era Retrospective-Analysis for Research and Applications (MERRA) 2019 weather file [48], [49]. Solar potential was calculated assuming the South-facing, 1kW panels were oriented 35 degrees from horizontal. Wind potential was calculated assuming a Vestas V47 660 turbine.

Table 3.2: Range of acceptable inputs to the SILVER model and their justification.

Variable	Range	Justification
Solar Capacity	1-6300kW	The minimum reflects a small, one-residence installation. The maximum assumes the whole area the Musqueam community is considering for development is converted into a solar farm [50].
Wind Capacity	10-1200kW	The minimum reflects the smallest turbine available on the market. The maximum assumes the whole area the Musqueam community is considering for development is used for wind turbines [51].
Storage Power Capacity	5-130kW	This range is based on commercially available battery technologies.
Storage Energy Capacity	1-230kWh	This range is based on commercially available battery technologies.
Import Price	0.05-0.25 \$/kWh	This range is based on current BC rates of about 0.1\$/kWh and projected provincial increases with a bias towards rising energy prices [52].
Export Profit	0.05-0.25 \$/kWh	This range is based on current BC rates of about 0.1\$/kWh and projected provincial increases with a bias towards rising energy prices [52].
Number of Households	50-500 households	There are currently about 250 homes in the community. This range is biased towards growth due to the community's long housing waitlist.

SILVER also requires several inputs which together define the available electricity generation assets and the overall energy system scenario. As shown in figure 3.2, these inputs include the capacity of any solar generation assets, the capacity of any wind generation assets, the power and energy capacity of any storage assets, and the cost of importing electricity from the grid. The researchers adapted SILVER to include a separate price for electricity being exported to the grid, so Musqueam members can explore the financial impact of selling excess power generated by VRE technologies. The researchers also incorporated the number of households in the community as an extra input, which is used to adjust the baseline electricity demand curve and explore how future community growth could affect Musqueam's energy system.

To create a dataset of SILVER inputs and outputs, the above-mentioned inputs were randomly generated within a variable-specific acceptable range as defined by the researchers. These ranges and their justification are summarized in table 3.2. SILVER was run a total of 1996 times with randomly generated inputs to produce the dataset, which covered generation profiles for an entire year. However, preliminary attempts at training a machine learning model on a whole year's worth of data were less accurate than those trained on a single month. The annual dataset was divided into twelve monthly datasets to facilitate the training of separate monthly machine learning models. These twelve datasets were each split into training, validation, and testing subsets each with 1434, 281, and 281 SILVER runs, respectively. All features and labels were normalized using the mean and standard deviation of the corresponding feature or label in the training dataset.

3.3.2 Surrogate Model Development

The machine learning surrogate model was developed in Python using PyTorch Lightning [53]. PyTorch Lightning is a deep learning framework with built-in functions to simplify the machine learning process. These tools were used to construct two different machine learning model architectures: a typical artificial neural net (ANN) composed purely of fully connected layers or multilayer perceptrons (MLP), and a residual neural net (ResNet) [54]. MLP models are very flexible in terms of architecture, size, and hyperparameter selection. As such, they are good candidates for energy system model applications [55]. However, particularly complex data relationships (typically image recognition) can require neural nets that are very deep for good accuracy [56], and these additional layers can make training difficult with traditional MLPs [54]. ResNet architectures can alleviate these challenges [54]. The authors chose to investigate the use of ResNet in case a deep neural net was required to predict the large number of time series outputs produced by SILVER. Basic representation of the MLP and ResNet architectures are shown in figures 3.5 and 3.6, respectively.

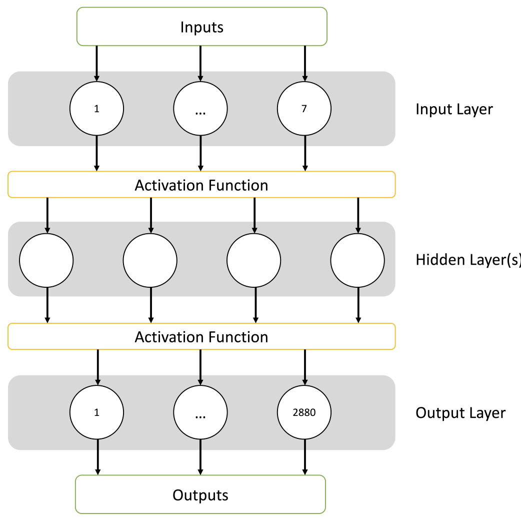


Figure 3.5: Basic multilayer perceptron architecture with an input layer, hidden layers, and an output layer.

Both the MLP and ResNet architectures were tuned using the hyperparameter optimization framework Optuna [57]. To do so, a skeleton model with optimizable parameters is trained with the provided training dataset. The trained skeleton model then predicts outputs for the inputs in the testing dataset. These predictions are compared to the actual outputs from the testing dataset using a loss function, resulting in a loss value. Optuna then repeats this process with a new set of parameter values.

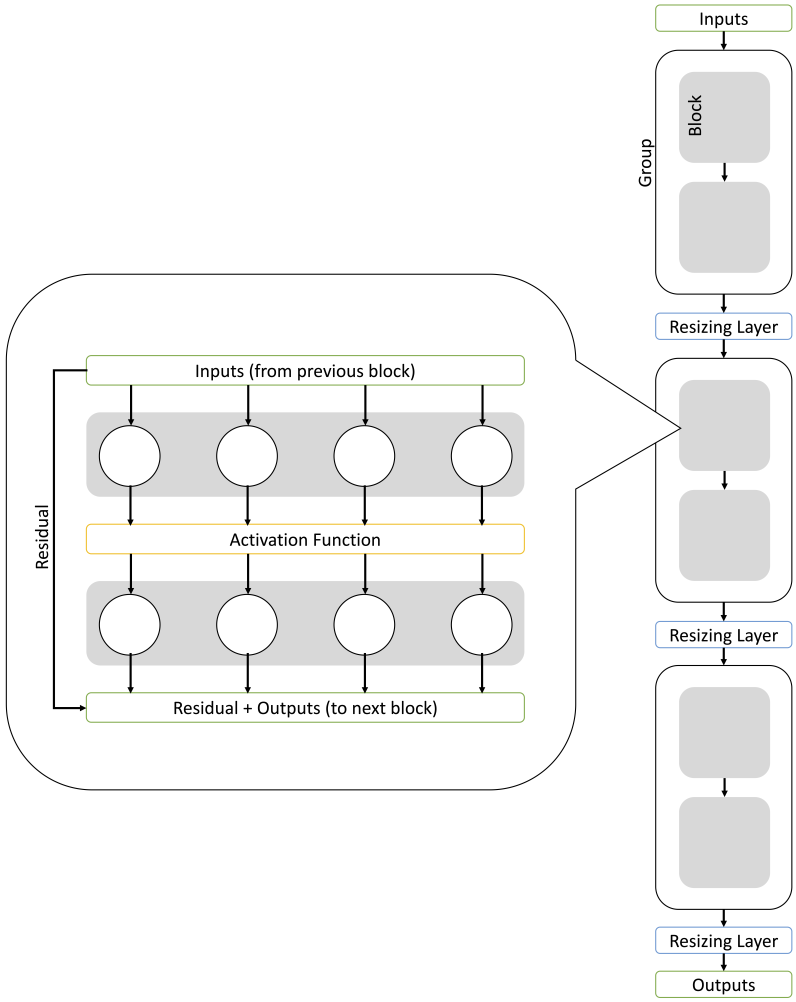


Figure 3.6: Basic residual neural net architecture made of groups of blocks. Each block is made of two layers, and every block in a group has the same number of neurons per layer.

For the MLP architecture, the number of layers, number of neurons in each hidden layer, and activation function applied to each layer, as well as hyperparameters like batch size, learning rate, and the loss function used to evaluate model performance were identified as optimizable parameters. For the ResNet architecture, the number of groups, number of blocks in a group, number of nodes in a layer in each group, activation function, batch size, learning rate, and loss function were identified as optimizable parameters.

Because of limited computational availability, the importance of having a unique model architecture for each month versus using a shared model architecture for all months was tested. Each approach has its own benefits; creating twelve unique models would optimize each architecture for the given 30-day data subset, while a single, shared model architecture would allow for broader hyperparameter space exploration and reduced optimization and training loads. Using the MLP architecture as a test, twelve Optuna hyperparameter optimizations were conducted. Each optimization was trained on the corresponding monthly data subset and consisted of 100 parameter trials. Each trial could take a maximum of 500 steps. A single optimization was conducted on the January data subset with 1000 trials of 1000 steps each. Both optimizations could prune trials with poor results after 25 steps.

To compare, the parameter values from the best trial for each optimization were used to construct MLP models. The twelve unique monthly models and twelve copies of the shared model architecture were trained and tested on their corresponding data subsets. The mean absolute error (MAE) loss and loss variance for each test were recorded and visualized in figure 3.7. The lines represent the average MAE loss across all test predictions for each architecture type, and the shaded areas represent the variance in loss across these test predictions. The shared MLP architecture performed better across all months, likely due to deeper parameter space exploration and therefore better parameter optimization.

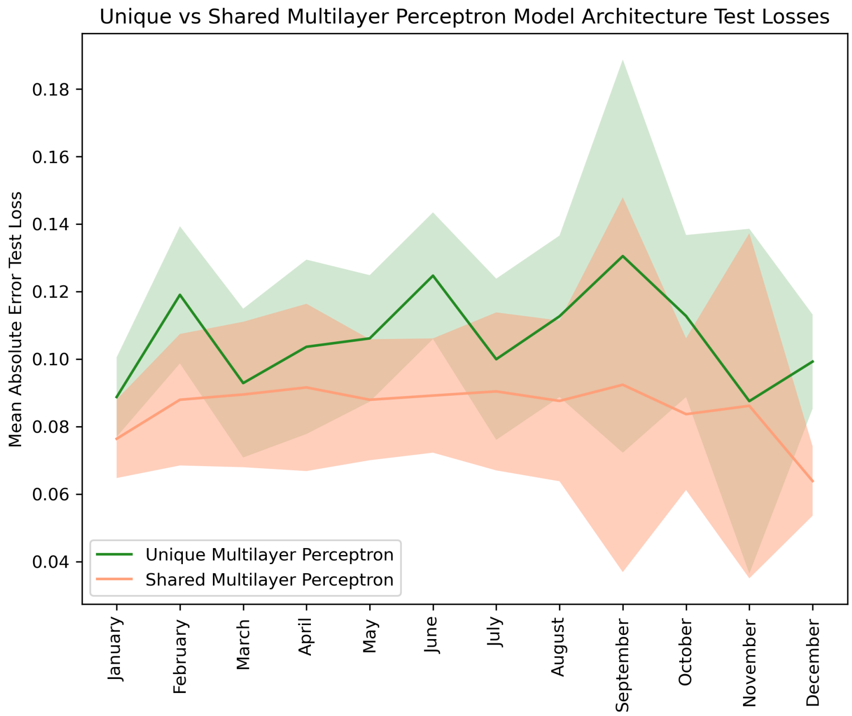


Figure 3.7: Comparing the mean absolute error losses of unique and shared monthly model architectures. The shaded areas represent the variance of the mean absolute error loss for each architecture.

The shared architecture approach was carried forward to test the MLP and ResNet architectures' ability to learn the SILVER dataset. The Optuna tuning process was repeated for an MLP and a ResNet architecture using the January data subset. A total of 1000 trials of maximum 1000 steps each were completed for each architecture. The parameters values from the best trials of the MLP and ResNet optimization processes are shown in tables 3.3 and 3.4, respectively. The average MAE losses across all test predictions and the associated variances were recorded and visualized in figure 3.8. The ResNet architecture provided consistently lower losses across all months.

Table 3.3: Optimal parameter values as determined by Optuna for the multilayer perceptron architecture.

	Number of Layers	Neurons in Hidden Layers	Dropouts	Activation Functions	Batch Size	Learning Rate	Loss Function
Optimal Value(s)	2	84, 92	0.22, 0.20	Tanh, Sigmoid	96	5.85e-4	MAE

Table 3.4: Optimal parameter values as determined by Optuna for the residual neural net architecture.

	Number of Groups	Number of Blocks	Neurons per Group Layer	Activation Functions	Batch Size	Learning Rate	Loss Function
Optimal Value(s)	2	2	56,56	ReLU	224	6.02e-2	MAE

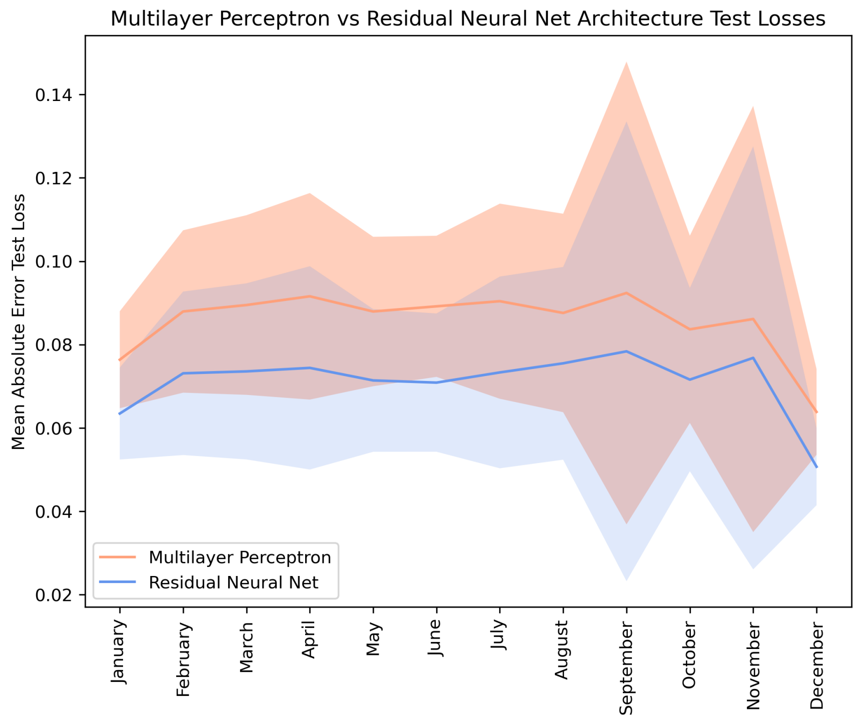


Figure 3.8: Comparing the mean absolute error losses of multilayer perceptron and residual neural net shared model architectures. The shaded areas represent the variance of the mean absolute error loss for each architecture.

To further test the MLP and ResNet architectures, each machine learning model was used to predict generation values for the four scenarios described above. The monthly by-technology generation totals for the MLP and ResNet architectures were compared against the actual generation values produced by SILVER for the same scenarios. The comparison is summarized in figure 3.9. The ResNet model was selected for the EGRET platform because it predicted positive generation values more accurately than the MLP model (figure 3.9) and had lower average loss values in testing (figure 3.8).

While figure 3.9 shows that the ResNet architecture produces similar monthly totals to the original SILVER model, further analysis was needed to assess the machine learning model's hourly performance relative to the computational model. The June hourly generation predictions from the ResNet machine learning model were visualized against the computed values from SILVER for each of the four scenarios. Figure 3.10 shows this visualization for Scenario 4. Unfortunately, a lack of community data made further benchmarking against real measured values impossible.

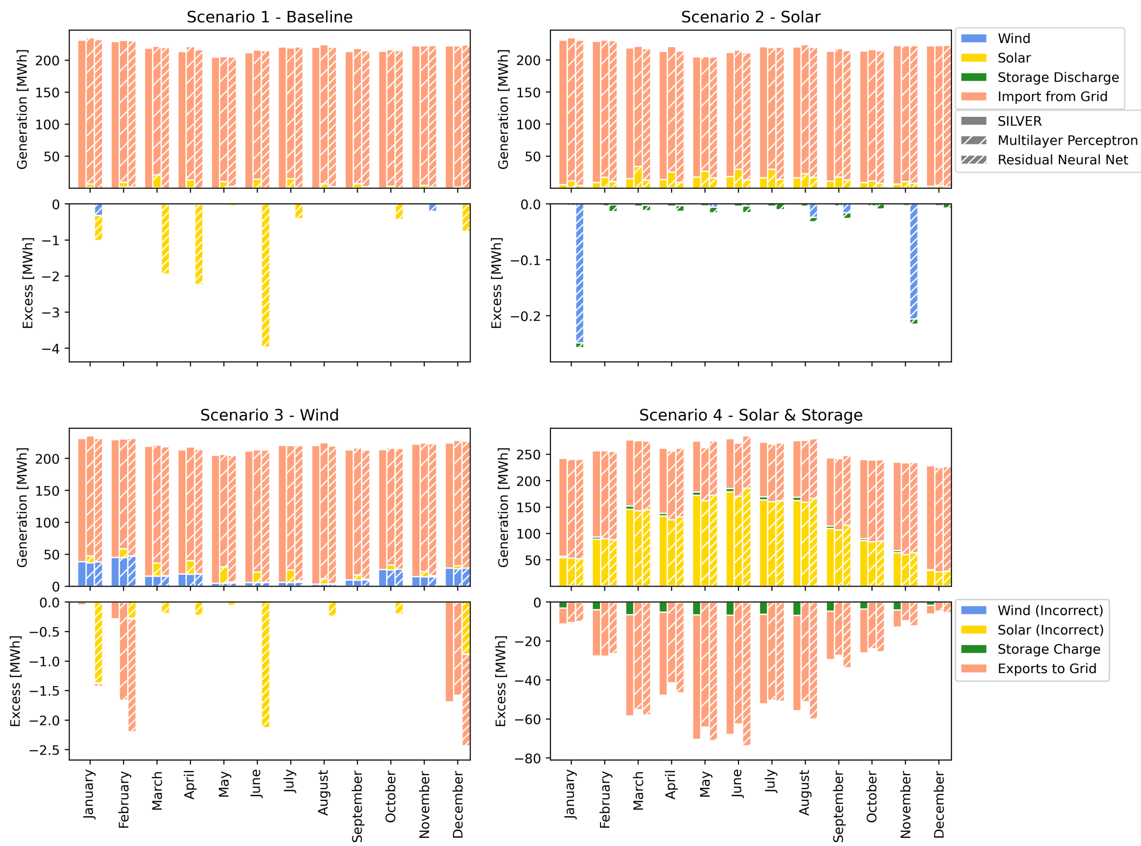


Figure 3.9: Comparing multilayer perceptron and residual neural net monthly generation totals against the actual totals computed by SILVER for the four test scenarios.

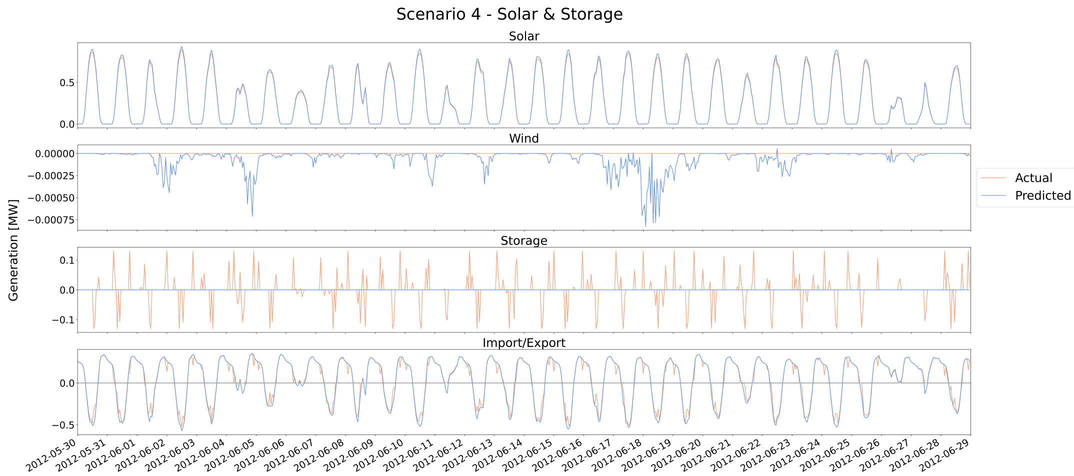


Figure 3.10: June hourly generation comparison between the residual neural net model and SILVER for Scenario 4 – Solar & Storage.

3.3.3 User Interface and Visualizations

To make the machine learning model user friendly, it was packaged with an interface and visualization suite constructed in Bokeh [58]. This package also includes post-processing scripts that calculate the costs and emissions associated with the modelled scenario. To calculate costs, the input capacity of each generator type is multiplied by an associated capital cost constant, and hourly generation values are multiplied by associated operating costs constants. Capital costs and operational costs are then summed for each generator. To calculate emissions, the hourly generation from each generator type is multiplied by an associated emissions constant and summed across the whole year. The cost and emissions constants are summarized in table 3.5.

These scripts also rescale the outputs into more familiar units – equivalent car use for emissions and equivalent household consumption for generation — at the recommendation of the community energy specialist. Figure 2.3 shows the interface that users manipulate to define an energy system scenario. Figure 2.4 shows the scenario-specific visuals representing the generation profiles predicted by the machine learning model. Figure 2.5 shows the comparison visuals that illustrate the cost and emissions of each modelled scenario.

Table 3.5: Cost and emissions constants used to calculate financial and environmental impacts of each energy system.

	Solar	Wind	Storage	Imports/Exports
Capital Costs ($/MW)	2,600,000 [59]	8,000,000 [60]	700,000 [61]	0
Operating Costs ($/MWh)	11.4 [62]	13 [62]	2.8 [62]	Variable Input
Emissions (tCO2/MWh)	0	0	0	0.04 [63]

3.3.4 Community Feedback

To gather feedback, community members were asked to participate in an informal workshop. Each participant completed a pre-interaction questionnaire, investigated the costs and benefits of community solar generation using the EGRET platform, and then completed a post-interaction questionnaire. These questionnaires evaluated EGRET for both utility and usability based on a framework proposed by Alomari et al to score computer science cyberlearning environments [64]. The utility aspect considered the platform's ability to answer the identified community energy question, while usability looked at the accessibility and ease of use of the platform.

To evaluate utility, participants were asked the same set of questions both pre- and post-modelling to assess the impacts of the platform. The questions focused on the participants' understanding of the local electricity system in terms of cost, emissions, and sources as well as whether the participants had ideas for how the electricity system's costs and emissions could be reduced. The set also included questions about the participants' opinions on solar panels and whether they felt comfortable sharing their thoughts with others. All questions used a Likert scale [65]. Through these questions, the researchers hoped to evaluate how the platform affected the participants' energy system knowledge, opinions on potential future changes, and confidence in their position.

To evaluate usability, the participants were asked whether the user interface was easy to use, whether the available inputs provided adequate flexibility, and whether the visualization suite presented the information needed to explore the community energy question. These questions also used a Likert scale and were based on the works of

Nielson and Alomari et al [64]–[66]. Participants were also given opportunities to suggest additional inputs or visualizations and provide general feedback on the platform. Through these responses, the researchers aimed to understand the platform's ease of use and accessibility.

3.4 Results

Three members of the community administration team participated in the interactive workshop. These participants were the target audience for the EGRET platform because it is important to include community decision-makers such as planners and elected officials in modelling initiatives to support policy discussions [3]. That said, it is important to note that these participants' familiarity with computer tools may not be representative of that of other members of the community. The participants' responses were coded into numeric values for visualization with Strongly Disagree corresponding to a score of 1, and Strongly Agree corresponding to a score of 5. Each participant's pre- and post-modelling responses to the utility portion of the questionnaires are summarized in figure 3.11. The participants' scores on the platform's usability are summarized in figure 3.12.

Although the participants' usability scores were all neutral or positive, participants provided suggestions to improve both the user interface and visualization suite. These suggestions included the addition of local annual capacity factors for wind and solar as reference information on the user interface page, references for potential funding options that might offset capital costs, modelling options for single home scenarios, the ability to show production from a single generator type on the hourly generation plots, and a pie chart of total monthly generation by generator type.

In addition to participant feedback, the EGRET platform was evaluated based on its speed. Figure 3.13 compares run times for the computational model (SILVER), the machine learning models, and the EGRET platform (which combines the machine learning model run times with additional data processing and visualization steps). Run times were recorded for each of the four scenarios described previously. All runs were completed on the same computer with a Dual-Core Intel Core i7 CPU 3.1 GHz and 16 GB RAM memory storage.

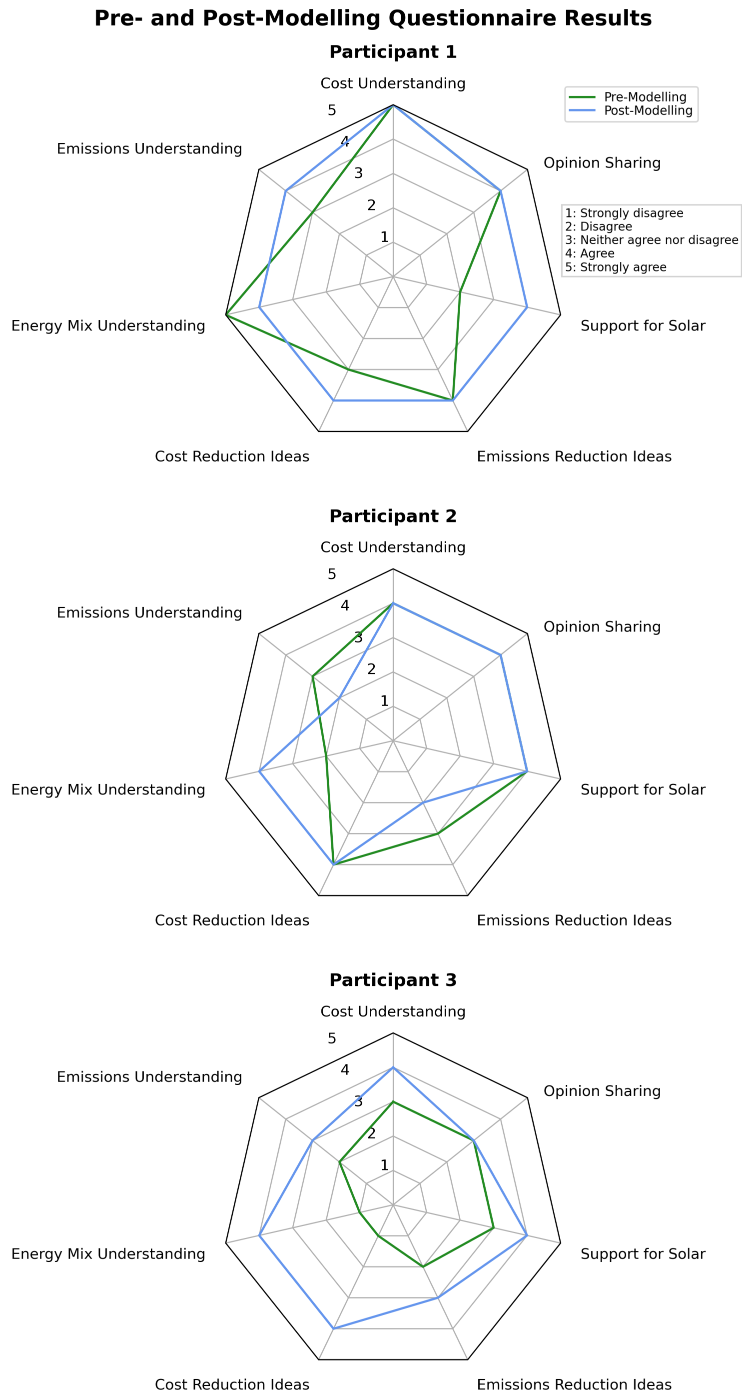


Figure 3.11: Participants' pre- and post-modelling scores for their energy system understanding, ideas for the future, support for solar panels, and confidence in sharing their opinion on solar panels with others.

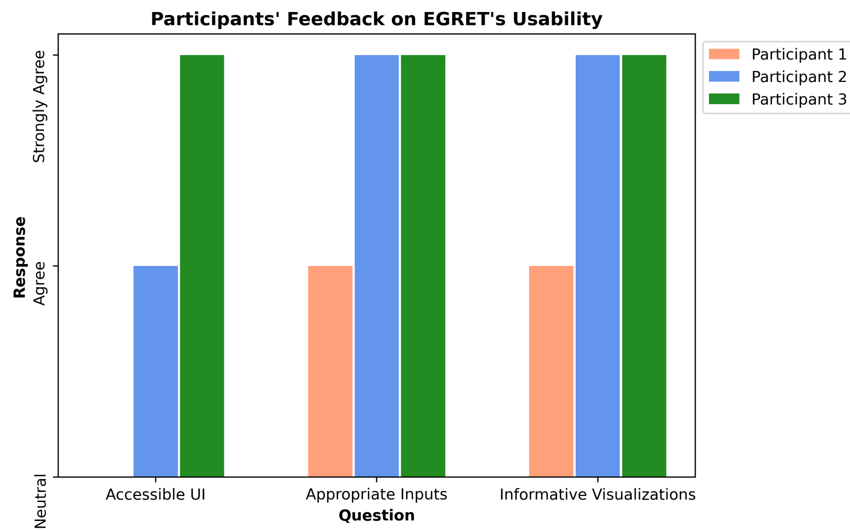


Figure 3.12: Participants' feedback on whether the platform's user interface was easy to use, the available options allowed for exploration, and the visualizations provided adequate information. All participants answered neutrally or positively.

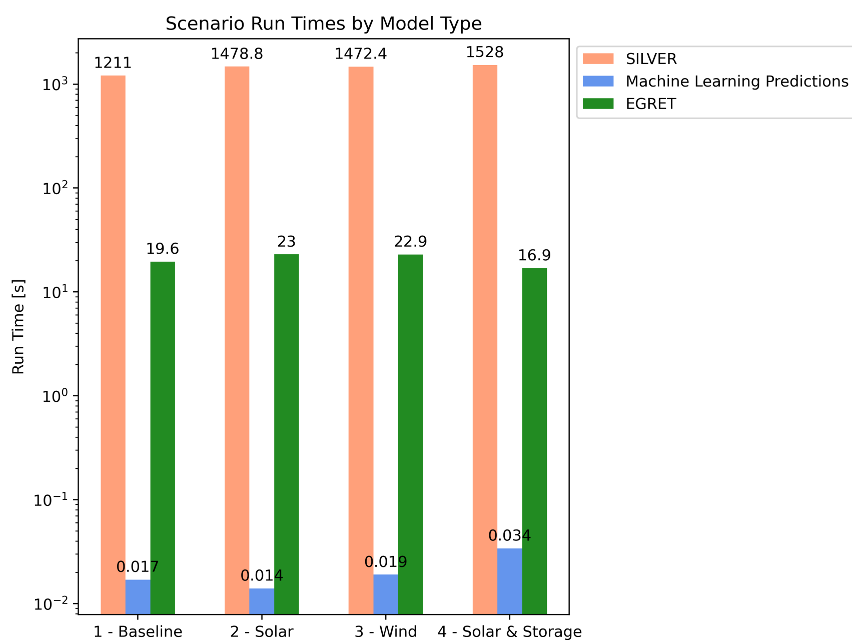


Figure 3.13: Test scenario run times for each model type. The EGRET run times include the machine learning predictions, data post-processing, and visualization times.

3.5 Discussion

The following section evaluates the EGRET platform against its goals for utility, usability, reduced computational burden, and output accuracy, and it also discusses the platform's limitations and potential next steps for improvement.

3.5.1 Utility

Responses to the utility questions varied greatly between the limited number of participants. All participants felt the same level of comfort sharing their opinions on solar panel installations before and after using the EGRET platform, suggesting that the experience did not improve self-confidence in or ownership over their energy system ideas. The overall change in ideas for energy system emissions reduction across all participants was also zero, likely because the British Columbian grid already has low emissions due to hydro integration. A different measure of environmental impact, such as land use or displacement, might be better suited to the provincial context. In general, the participants felt they had a better understanding of the local energy system's costs, emissions, and electricity sources after interacting with the platform, and supported the installation of solar panels in the community more strongly. EGRET created a positive knowledge building experience about energy system costs and the effectiveness of solar panels, but it did not facilitate learning about emissions or emissions reduction. It should be noted that these findings are not statistically significant due to the small number of participants.

3.5.2 Usability

Participants' usability scores suggest that interacting with the EGRET platform was accessible and provided suitable flexibility and information to explore community energy questions. Qualitatively speaking, participants were also able to learn how to use the platform and model and discuss three scenarios within an approximately one-and-a-half-hour workshop. Most energy system models require days or weeks of training to use [41]. However, the one neutral score for user interface accessibility and the numerous verbal suggestions for improvements highlight the need for additional work on the platform's usability. Again, the small number of participants means that the questionnaire results are not statistically significant.

3.5.3 Computational Burden

The machine learning models behind the EGRET platform are approximately five orders of magnitude faster than the original computational model. It takes some additional time to process and visualize these results on the platform. However, the overall run time of all three steps – modelling, processing, and visualization – is still short enough to facilitate live workshops and broad design space exploration that would be tedious with the original computational model.

It should be noted that although the EGRET platform is faster at run time, the machine learning model development process is extensive. Essentially, the computational burden is shifted from the actual modelling to the dataset creation, hyperparameter optimization, and model training steps needed to create the surrogate model. The accessibility of computing facilities limits who can develop platforms like EGRET. Further, communities looking to pursue ideas generated through the EGRET platform must complete additional modelling with other tools to finalize their designs due to EGRET's limitations as described below. EGRET does not reduce the computational expense needed to integrate renewable energy generators; rather, it shifts the expense such that community members can be included in the decision-making and scenario exploration phases of the process.

3.5.4 Accuracy

Although the machine learning models provide significant run time speed benefits, these benefits come at the cost of decreased accuracy. Figure 3.10 highlights two reductions in accuracy that could be improved through further experimentation with machine learning architectures. First, the EGRET models predict small outputs from generator types with zero capacity. Second, the models' predictions for storage activity do not fully capture the charge and discharge spikes in the actual results.

A third, hidden source of inaccuracy is the lack of hourly community electricity demand data. As shown in figure 3.4, the shape of the hourly demand curve impacts monthly export totals. Because exporting only occurs when generation exceeds demand, the difference between production and demand at every time step affects how much electricity is used or sold. Hourly electricity demand profiles were not available for the Musqueam community, so the predicted export quantities may not be accurate. Further, a lack of community electricity cost and supply data prevented benchmarking of the computational model against the current scenario. As a result, the researchers had to assume that the SILVER model was accurate in the community context based on previous benchmarking exercises at different scales [45].

3.5.5 Model Limitations

Several other assumptions inherent in the SILVER model introduced limitations to the EGRET platform. The first limitation is the parameters defining the VRE potential time series used to calculate hourly VRE generation. For both wind and solar, these time series are dependent on the selected technology model and its specifications. In the case of solar, the time series is also dependent on the orientation of the panel installation. Although the assumptions made for solar panel orientation reflects best practices for Musqueam's location, members might want to orient their panels differently (eg. on the roof of homes).

SILVER was also constructed with larger scale electricity applications in mind. As a result, transmission infrastructure is modelled as long distance direct current transmission. At the community scale, the transmission infrastructure would use alternating current flow. Alternating current flow produces higher losses due to capacitance. There is a need for better distribution-scale modelling to understand how these factors impact community energy planning.

3.5.6 Institutional Limitations

While the EGRET platform contains several internal limitations, the institutional context in which the platform is used can present additional challenges. One of the initial goals of the EGRET platform was to promote a sense of ownership over community energy decisions. Ideally, community members should have actual ownership over renewable energy developments to realize the development's benefits, but a simple modelling tool cannot provide that [41]. Several barriers, such as inequitable access to financing and a lack of long-term clarity on incentives, can make ownership difficult in the current energy context [15], [23]. For example, the EGRET platform assumes that Musqueam Nation could secure a power purchase agreement with BC Hydro, but these contracts are difficult to obtain. The application of the EGRET platform in this context could create feelings of "misempowerment" as community members are encouraged to engage with a system that does not value their input [5]. There is a risk that if "the tool falsely suggests free access to the machinery of plan making", it will cause a loss of trust in institutions of power [5]. There is a need to refine policies that support Indigenous ownership in renewable energy development so communities can implement and benefit from the systems they envision with tools like the EGRET platform.

3.5.7 Future Work

Focusing back on the EGRET platform itself, there are several areas of future work that would increase the scope of the tool's abilities. First, SILVER only considers the operating costs of the energy system being modelled. Capital costs were an important consideration for community decision makers, so a simplistic capital cost calculation as described in the methodology section was included in the post processing steps and optionally included in scenario comparisons. In future versions, capacity expansion modelling could be integrated into the platform to better capture capital costs.

Second, demand-side technologies will play an important role in the energy system transition alongside renewable energy generators, but SILVER does not currently include non-electric sources of energy like natural gas or gasoline. Demand-side considerations can only be integrated if they use technologies like heat pumps or electric vehicles. Expanding the suite of computational models behind the EGRET surrogate models to integrate building energy and transportation tools would expand the application of the platform into demand-side management strategies.

Third, further development of the machine learning model architecture is needed to accurately predict storage charge and discharge profiles. Although the Musqueam community is grid connected, the community energy specialist expressed an interest in having storage technology available in case of an outage. In the larger context, some

Indigenous communities in so-called Canada are off-grid, making storage a critical component of their energy systems. These off-grid communities typically use diesel generators to produce electricity, which introduce another layer of complexity when integrating renewable energy generators due to diesel generators' minimum capacities. Introducing diesel generator capacity as an input to EGRET would make the tool useful for off-grid communities.

While the above-mentioned improvements would make EGRET applicable in broader contexts, the way that EGRET is currently constructed would require the underlying machine learning models to be retrained on local data for each community that wishes to use it. Including VRE potential and demand time series as variable inputs to the machine learning models would make EGRET applicable to any location without the retraining requirement. Including time series data as inputs would necessitate restructuring of the machine learning model architectures to something more complex. This approach has already been applied by Westermann to the building energy space; the authors constructed a geographically flexible surrogate model that recreates building energy simulations using temporal convolutional neural networks [67]. Applying such an approach to the EGRET platform to create an open-source tool would further increase the accessibility of energy system modelling.

3.6 Conclusion

The EGRET platform looked to restructure typical energy system modelling approaches to better suit a future with decarbonized and decentralized power sources. The application of machine learning to create an interactive model for use in a community workshop setting was successful in that the EGRET platform provides reasonable predictions for wind and solar generation and grid connection electricity flow in a timeframe that promotes conversation. The speed at which EGRET makes these predictions relative to the original computational model shows strong potential for using machine learning in participatory system dynamics modelling approaches. The user interface and visualization suite also received positive feedback on their utility and usability from three community testers, but these results are not statistically significant due to the small sample size. In addition to more extensive testing to evaluate user experience, the EGRET platform's storage predictions could benefit from further development of the machine learning architecture, and several other factors limit its application beyond the Musqueam community. Future work to generalize the platform for use by other communities would provide additional support for Indigenous engagement in renewable energy decision making.

Chapter 4

Conclusions

The Exploring Grassroots Renewable Energy Transitions platform demonstrates how an alternative approach to energy system modelling can facilitate community engagement when integrating variable renewable energy generators. Unlike typical energy modelling approaches that exclude stakeholders from the model development process and the result analysis that follows, the construction and application of the EGRET platform invited community feedback throughout. Four aspects of the EGRET platform, two procedural and two technical, made continuous engagement possible:

1. Collaboratively identifying community energy questions at the beginning of the process – rather than specific future scenarios – creates space for community members to explore options more broadly with the finished model;

2. Using those energy questions to guide model construction, and gathering community feedback on necessary assumptions, ensures the model's results reflect the community's goals and lived experiences;

3. Replacing typical computational models with their machine learning surrogate significantly reduces run time, facilitating broad design space exploration with community members in interactive workshop settings; and

4. Packaging the machine learning surrogate with an interface and visualization suite could reduce the need for user training and make the model more accessible to community members.

Engaging community members in renewable energy decision-making processes is especially important in Indigenous communities, where natural resource projects have historically excluded those most impacted by their development. For this reason, the EGRET platform was constructed and tested in partnership with Musqueam band's energy specialist. After identifying community energy questions, we made adjustments to the SILVER model to better explore Musqueam's priorities. Next, we ran the adapted SILVER model many times with randomly generated inputs, producing a dataset of input and output pairs that was later used to train the machine learning surrogate models behind the EGRET platform. A user interface and visualization suite were also constructed to make the platform accessible to people without energy system modelling experience. Finally, we held a workshop in the Musqueam community to gather feedback on the platform and provide an opportunity for community members to explore the questions they identified at the beginning of the process. User feedback suggested that the EGRET platform provided participants with a positive knowledge building experience about local energy system costs and the effectiveness of solar panels in the community context, but these results were not statistically significant.

Although the EGRET platform was constructed specifically for Musqueam Nation, similar tools could be constructed for other communities following the same procedure. By facilitating stakeholder and rightsholder engagement in renewable energy decision-making, participatory modelling tools like the EGRET platform can support the bottom-up decentralization and decarbonization of our energy systems.

Appendix A

Additional Information

A.1 Participant Questionnaires

A.1.1 Pre-Modelling Questionnaire

1. I have an understanding of electricity costs in Musqueam First Nation.
   (a) Strongly Disagree
   (b) Disagree
   (c) Neutral
   (d) Agree
   (e) Strongly Agree
2. I have an understanding of how the Musqueam First Nation energy system impacts the environment.
   (a) Strongly Disagree
   (b) Disagree
   (c) Neutral
   (d) Agree

   (e) Strongly Agree

3. I have an understanding of Musqueam First Nations energy mix and the different kinds of electricity generators that provide our power.
   (a) Strongly Disagree
   (b) Disagree
   (c) Neutral
   (d) Agree
   (e) Strongly Agree

4. I have ideas about how Musqueam First Nation could reduce the cost of our electricity system.
   (a) Strongly Disagree
   (b) Disagree
   (c) Neutral
   (d) Agree
   (e) Strongly Agree

5. I have ideas about how Musqueam First Nation could reduce emissions from our electricity system.
   (a) Strongly Disagree
   (b) Disagree
   (c) Neutral
   (d) Agree
   (e) Strongly Agree

6. Solar energy has been identified as an area of interest for the community. I feel that solar panel installations are a cost-effective means of increasing energy self-sufficiency for Musqueam First Nation.

   (a) Strongly Disagree
   (b) Disagree
   (c) Neutral
   (d) Agree
   (e) Strongly Agree

7. I would feel comfortable sharing my opinion on solar panel installations with others in the community.
   (a) Strongly Disagree
   (b) Disagree
   (c) Neutral
   (d) Agree
   (e) Strongly Agree

8. I am curious about other aspects of the Musqueam First Nation energy system such as:
   (a) Building retrofits to improve energy efficiency
   (b) Electric vehicles
   (c) Wind turbines
   (d) Other, please specify

9. What do you expect to get out of this modelling experience?

A.1.2 Post-Modelling Questionnaire

1. I have an understanding of electricity costs in Musqueam First Nation.
   (a) Strongly Disagree
   (b) Disagree

   (c) Neutral

   (d) Agree

   (e) Strongly Agree

2. I have an understanding of how the Musqueam First Nation energy system impacts the environment.

   (a) Strongly Disagree

   (b) Disagree

   (c) Neutral

   (d) Agree

   (e) Strongly Agree

3. I have an understanding of Musqueam First Nations energy mix and the different kinds of electricity generators that provide our power.

   (a) Strongly Disagree

   (b) Disagree

   (c) Neutral

   (d) Agree

   (e) Strongly Agree

4. I have ideas about how Musqueam First Nation could reduce the cost of our electricity system.

   (a) Strongly Disagree

   (b) Disagree

   (c) Neutral

   (d) Agree

   (e) Strongly Agree

5. I have ideas about how Musqueam First Nation could reduce emissions from our electricity system.
    (a) Strongly Disagree
    (b) Disagree
    (c) Neutral
    (d) Agree
    (e) Strongly Agree
6. Solar energy has been identified as an area of interest for the community. I feel that solar panel installations are a cost-effective means of increasing energy self-sufficiency for Musqueam First Nation.
    (a) Strongly Disagree
    (b) Disagree
    (c) Neutral
    (d) Agree
    (e) Strongly Agree
7. I would feel comfortable sharing my opinion on solar panel installations with others in the community.
    (a) Strongly Disagree
    (b) Disagree
    (c) Neutral
    (d) Agree
    (e) Strongly Agree
8. The modelling experience met the expectations I described in the previous questionnaire (Question 9)
    (a) Strongly Disagree

(b) Disagree

(c) Neutral

(d) Agree

(e) Strongly Agree

9. Selecting the energy system inputs for each model run was a simple process.

(a) Strongly Disagree

(b) Disagree

(c) Neutral

(d) Agree

(e) Strongly Agree

10. The energy system inputs available allowed me to explore whether or not solar panel installations are a good fit for the community.

(a) Strongly Disagree

(b) Disagree

(c) Neutral

(d) Agree

(e) Strongly Agree

11. If you disagree, what input(s) do you feel should have been included?

12. The visualizations presented information that helped me explore whether or not solar panel installations are a good fit for the community.

(a) Strongly Disagree

(b) Disagree

(c) Neutral

(d) Agree

    (e) Strongly Agree

13. If you disagree, what information would you like to have shown in the visualizations?

14. Do you have any other suggestions for how the platform could be improved?

15. Do you have any other feedback you would like to share about the EGRET platform?

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