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

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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 harms 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.

Keywords: Decarbonization, variable renewable energy integration, community energy, Indigenous energy, energy system modelling, participatory modelling, machine learning.

1 Introduction

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 [1]. A 2018 report by the IPCC found that this 1.5°C limit could be reached as soon as 2040 [2]. Maintaining global temperatures within this threshold requires that net-zero greenhouse gas emissions be reached by 2050 [3]. 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 [3]. In response, the Canadian government is targeting a two- to three-fold increase in national clean power production by 2050 [4].

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 [3]. Second, VRE generators are often widely spatially distributed as they must be placed wherever their powering resource is most abundant [5]. 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. 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 [6].

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 [7]. 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 [8]–[10]. For example, two of the most commonly applied tools for modelling decentralized energy systems, the Hybrid Optimization of Multiple Energy Resources (HOMER) software and EnergyPLAN, exclude most stakeholders because they require users to have prior knowledge of energy system analysis [11]–[13]. These tools are also not open source, blocking even experienced users from adapting them to reflect community priorities through model (re)development. An open source tool, called the Open Energy Modelling Framework (oemof), was developed to address this barrier, but it is still designed for users with an understanding of energy system modelling and analysis [14], [15]. oemof developers also list the communication of model results as an ongoing challenge, further limiting the ability of inexperienced users to interact with the tool in the results analysis step of the modelling process [15].

While available tools do not facilitate accessible engagement, community input into the energy system 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 [16]. For example, transdisciplinary approaches that include diverse stakeholders could help mobilize society to achieve the United Nation's sustainable development goal of affordable clean energy, which Canada has not yet achieved [17]. 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 [18]. Decarbonization presents an opportunity for reconciliation through Indigenous ownership over renewable energy production, but barriers make ownership challenging for some communities [19], [20]. One common barrier is the need for outside consultation when navigating energy technologies and modelling tools because of community capacity strains, leading to the exclusionary modelling process outlined above [20].

The Exploring Grassroots Renewable Energy Transitions (EGRET) platform introduced in this work aims to make all stages of the modelling process accessible to stakeholders. The guiding concept behind the platform is the participatory system dynamics framework described in [21], which recommends the inclusion of stakeholders at all stages of model development, use, and analysis to promote deep learning about the system in question. Designed for use in collaborative workshop settings, the EGRET platform is powered by high-speed machine learning models to support dynamic conversation and a broad exploration of the renewable energy design space. These models are packaged with a user interface and visualization suite to make the platform accessible to use and interpret. The EGRET platform was designed and developed in collaboration with Musqueam band's community energy specialist to ensure the platform would meet the needs of the community in which it would be applied.

1.1 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 [22]. 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 [23]. 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 greenhouse 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 1 shows the estimated shares of the community's top GHG emissions sources.

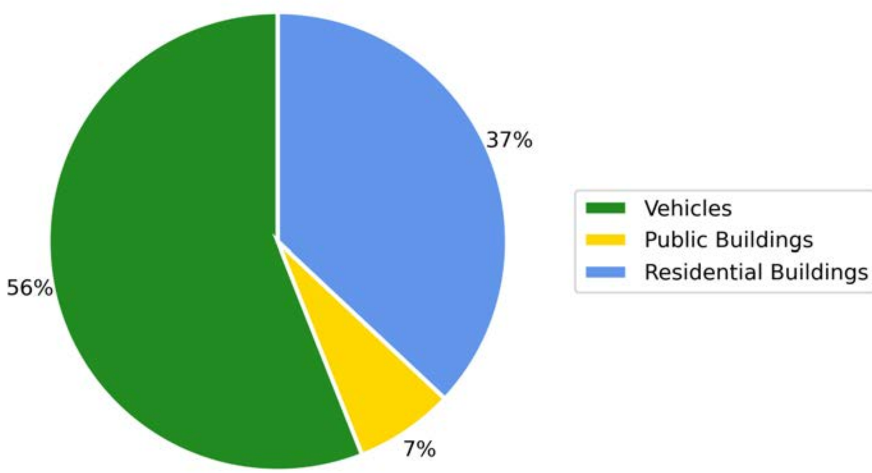

Figure 1: *The estimated share of different GHG emissions sources in the Musqueam community.*

As shown in Figure 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 energy generation capacity in the community also aligns with the self-sufficiency and self-governance goals of the Nation [23].

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.

The remaining three sections in this paper outline how the EGRET platform was constructed and evaluated, highlight the key results of the evaluation process, and discuss these results in the context of the platform's goals. The methodology section focuses on the technical development of the platform, including the machine learning approaches used and the data processing steps needed to apply them. The results section considers both community feedback and objective measures of the platform's effectiveness. Finally, the discussion section draws conclusions about the platform's ability to engage community members in the energy modelling process, addresses the limitations of this project, and makes recommendations for future work.

2 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 are shown later in figures 11 to 13. 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 [24]. 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 asset on the system 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.

2.1 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 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 model's 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

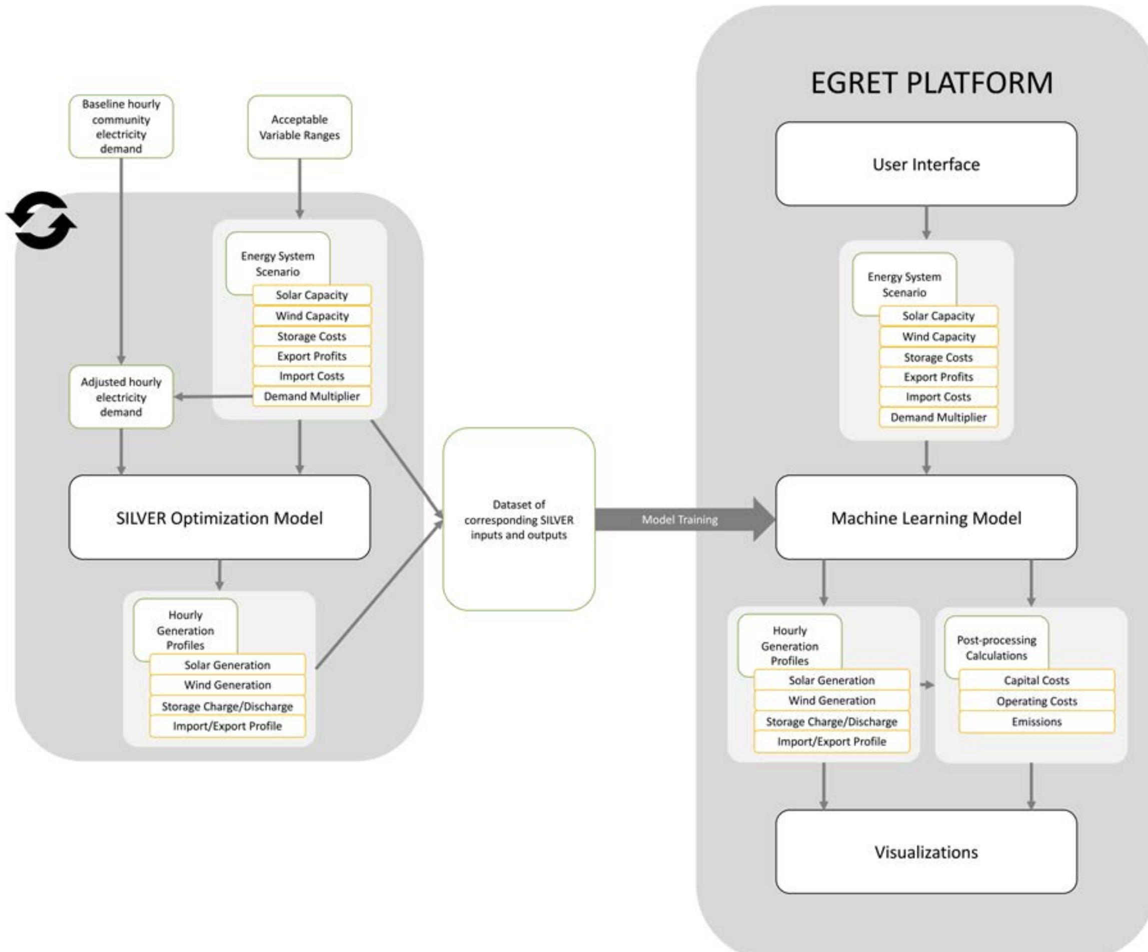

Figure 2: *The SILVER model is run repeatedly for randomly generated energy system scenarios to create a dataset of inputs and outputs. In turn, this dataset is used to train the machine learning models behind the EGRET platform.*

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 community. 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 Council of Canada (NBCC) to scale electricity demand [25]. 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 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.

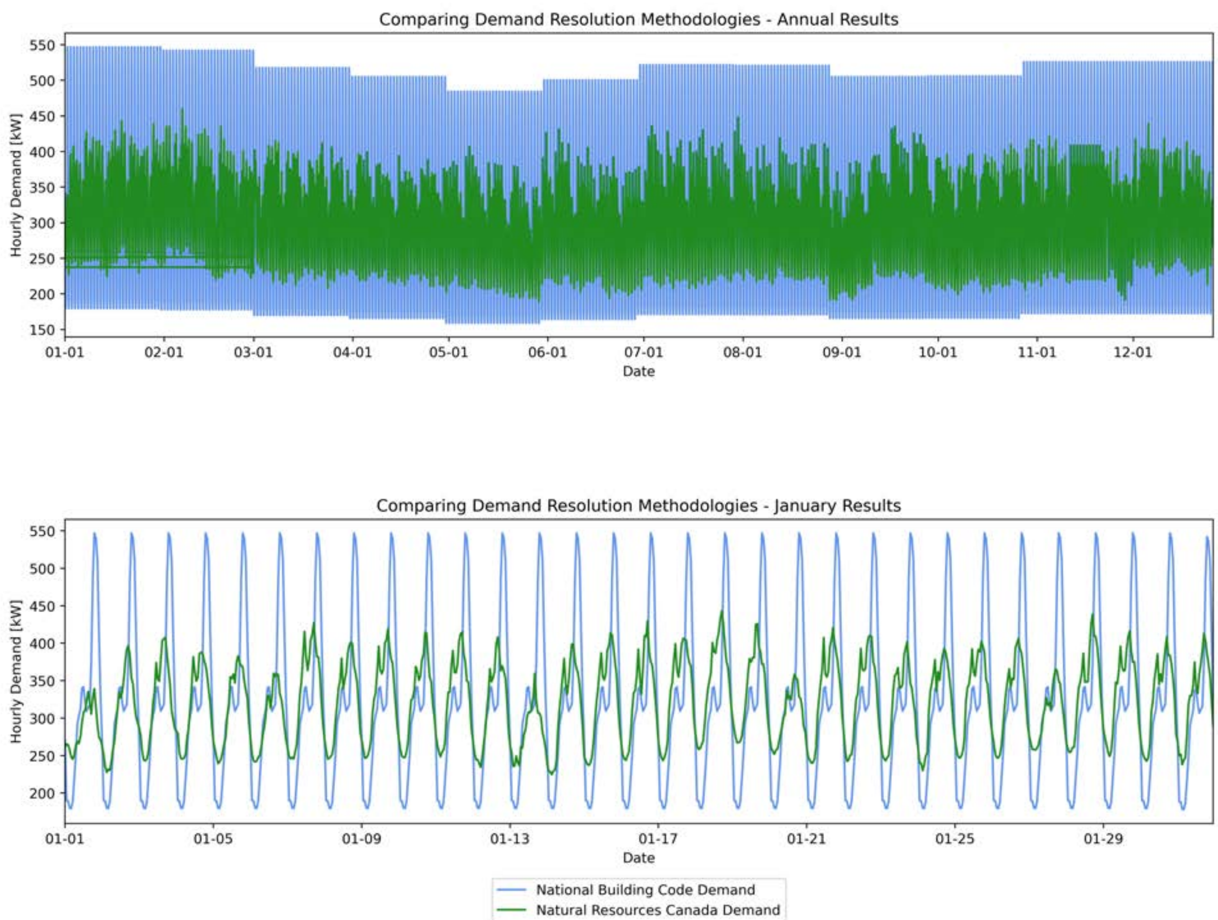

Figure 3: *These plots compare the demand curves produced by the NBCC and NRCAN demand methodologies. The top figure shows the full annual profiles, and the bottom figure zooms in to show daily fluctuations through the month of January.*

These two methods were tested by modelling the scenarios shown in table 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 1 were kept constant across all scenarios. Figure 4 compares the total generation by technology type resulting from the two demand methodologies for each scenario.

Table 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

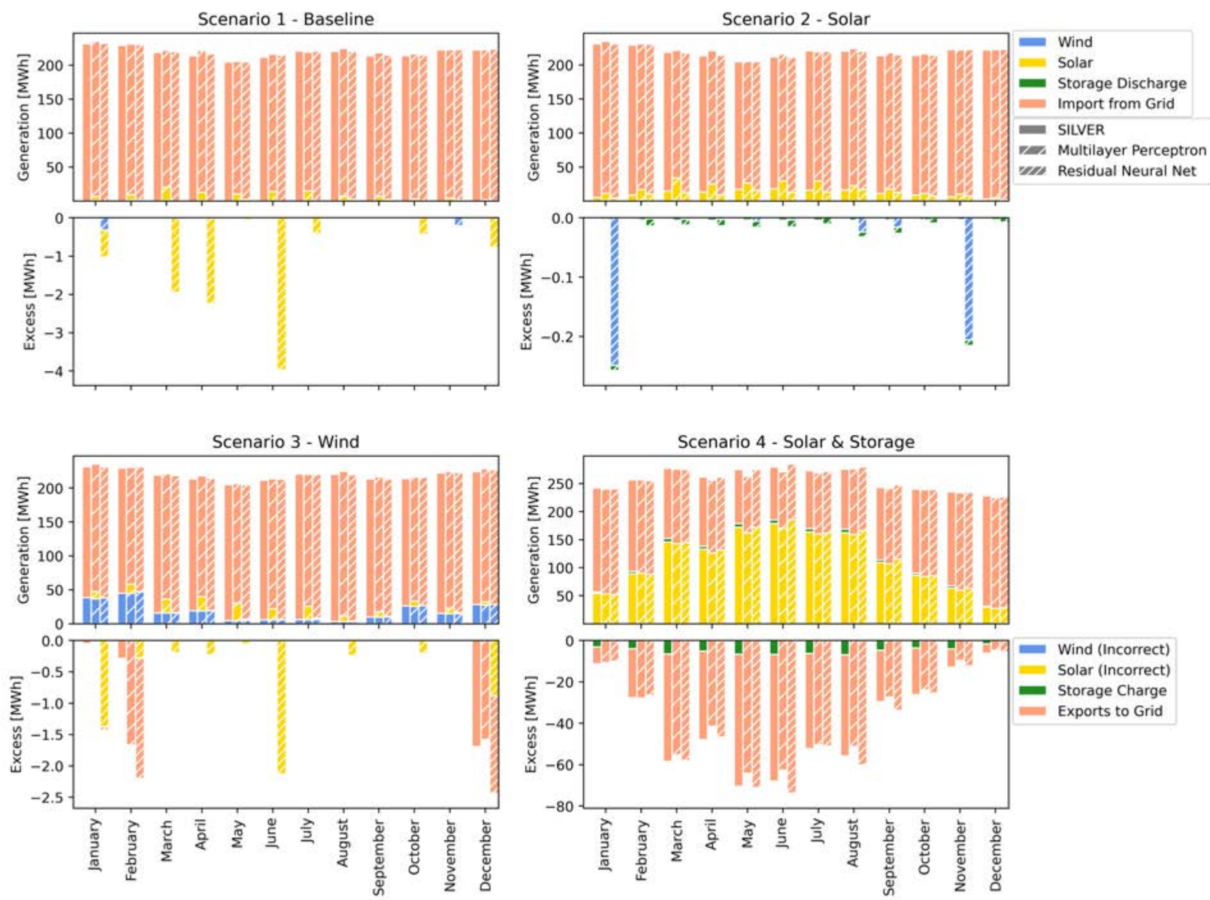

Figure 4: *Total monthly energy generation by technology type is shown for each scenario. The solid bars on the left resulted from the NBCC demand methodology, and the hatched bars on the right resulted from the NRCAN demand methodology.*

As shown in figure 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 VRE generation exceeds consumption. As the amount of generation 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.

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 [26], [27]. 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 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 Musqueam community is considering for development is converted into a solar farm [28].
Wind Capacity	10-1200kW	The minimum reflects the smallest turbine available on the market. The maximum assumes the whole area Musqueam community is considering for development is used for wind turbines [29].
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 [30].
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 [30].
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 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 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.

2.2 Surrogate Model Development

The machine learning surrogate model was developed in Python using PyTorch Lightning [31]. 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) [32]. MLP models are very flexible in terms of architecture, size, and hyperparameter selection. As such, they are good candidates for energy system model applications [33]. However, particularly complex data relationships (typically image recognition) can require neural nets that are very deep for good accuracy [34], and these additional layers can make training difficult with traditional MLPs [32]. ResNet architectures can alleviate these challenges [32]. 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 5 and 6, respectively.

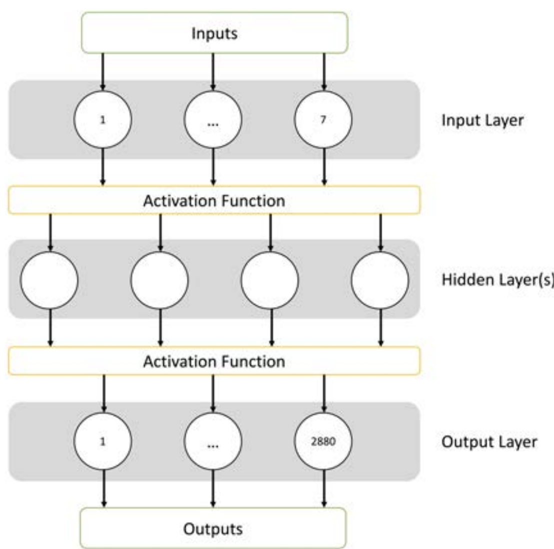

Figure 5: *Basic MLP architecture with an input layer, hidden layers, and an output layer.*

Both the MLP and ResNet architectures were tuned using the hyperparameter optimization framework Optuna [35]. 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.

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

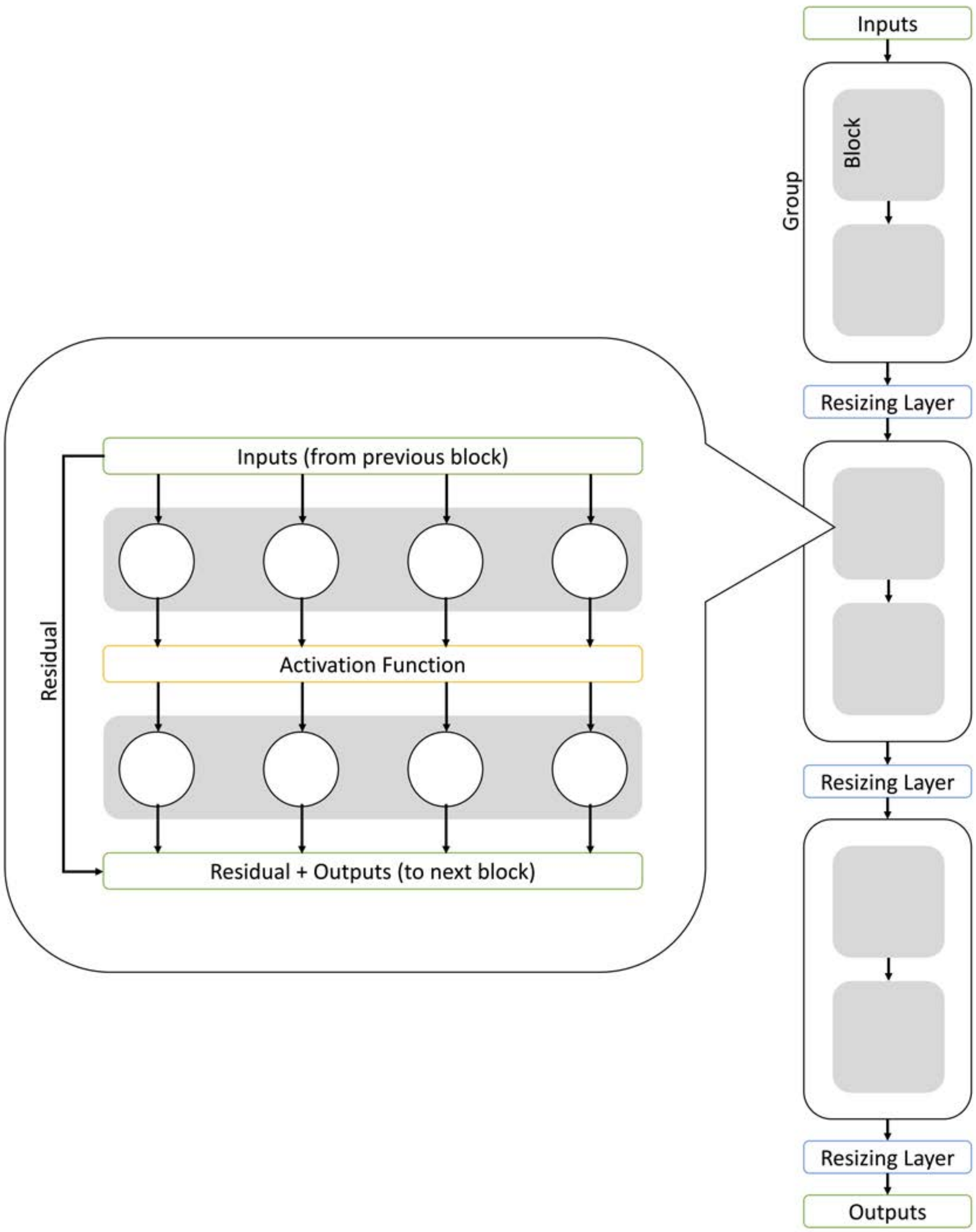

Figure 6: *Basic ResNet architecture made of groups of blocks. Each block is made of two layers, and every block in a group has the same number of neurons per layer.*

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 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.

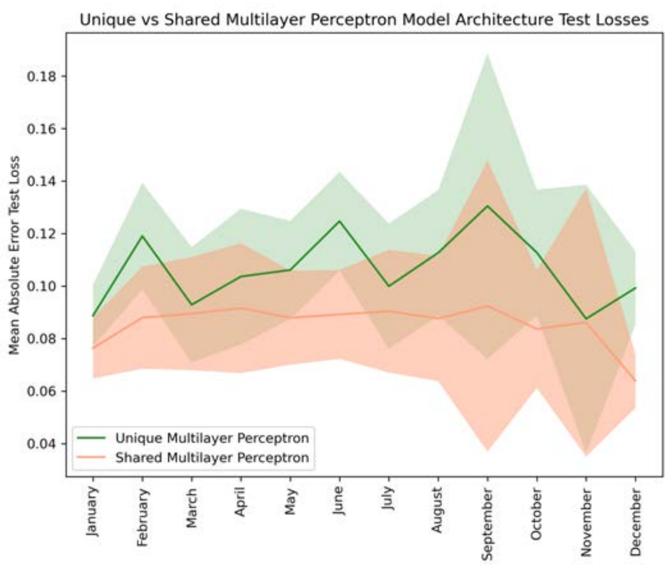

Figure 7: *Comparing the MAE losses of unique and shared monthly model architectures. The shaded areas represent the variance of the MAE loss for each architecture.*

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 and 4, respectively. The average MAE losses across all test predictions and the associated variances were recorded and visualized in Figure 8. The ResNet architecture provided consistently lower losses across all months.

Table 3: *Optimal parameter values as determined by Optuna for the MLP 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 4: *Optimal parameter values as determined by Optuna for the ResNet 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

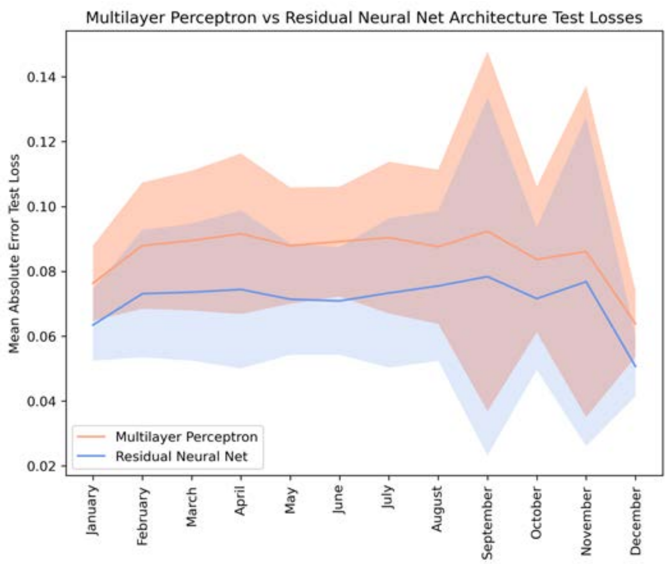

Figure 8: *Comparing the MAE losses of MLP and ResNet shared model architectures. The shaded areas represent the variance of the MAE loss for each architecture.*

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 9. The ResNet model was selected for the EGRET platform because it predicted positive generation values more accurately than the MLP model (Figure 9) and had lower average loss values in testing (figure 8).

While Figure 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 10 shows this visualization for Scenario 4. Unfortunately, a lack of community data made further benchmarking against real measured values impossible.

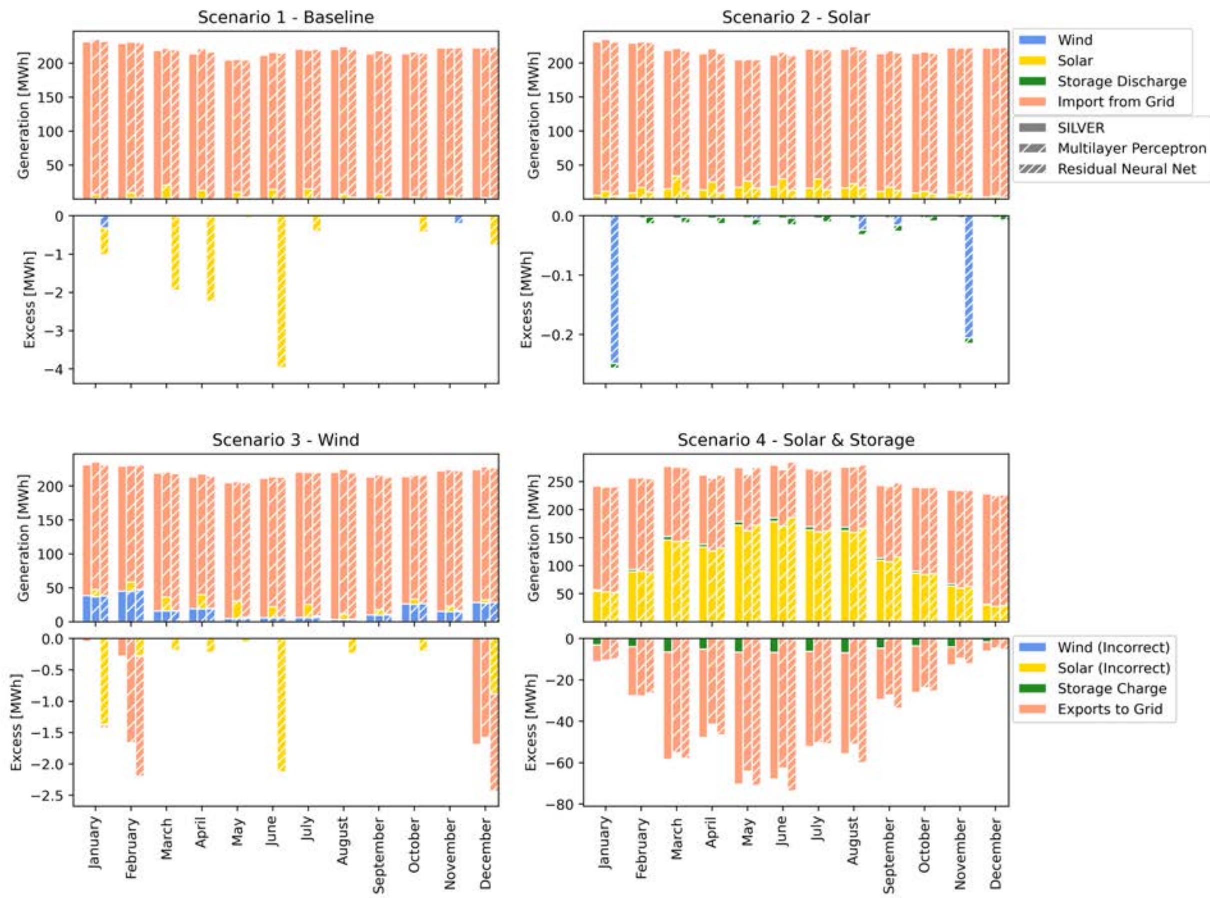

Figure 9: *Comparing MLP and ResNet monthly generation totals against the actual totals computed by SILVER for the four test scenarios.*

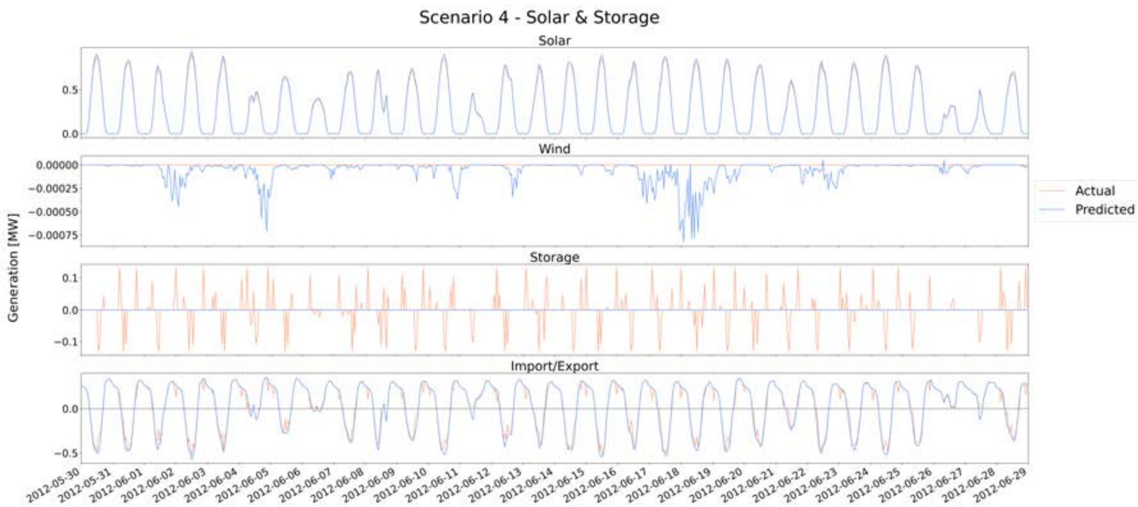

Figure 10: *June hourly generation comparison between the ResNet model and SILVER for Scenario 4 – Solar & Storage.*

2.3 User Interface and Visualizations

To make the machine learning model user friendly, it was packaged with an interface and visualization suite constructed in Bokeh [36]. 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 5.

Table 5: *Cost and emissions constants used to calculate financial and environmental impacts of each energy system.*

	Solar	Wind	Storage	Imports/Exports
Capital Costs ($/MW)	2,600,000 [37]	8,000,000 [38]	700,000 [39]	0
Operating Costs ($/MWh)	11.4 [40]	13 [40]	2.8 [40]	Variable Input
Emissions (tCO2/MWh)	0	0	0	0.04 [41]

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 11 shows the interface that users manipulate to define an energy system scenario. Figure 12 shows the scenario-specific visuals representing the generation profiles predicted by the machine learning model. Figure 13 shows the comparison visuals that illustrate the cost and emissions of each modelled scenario.

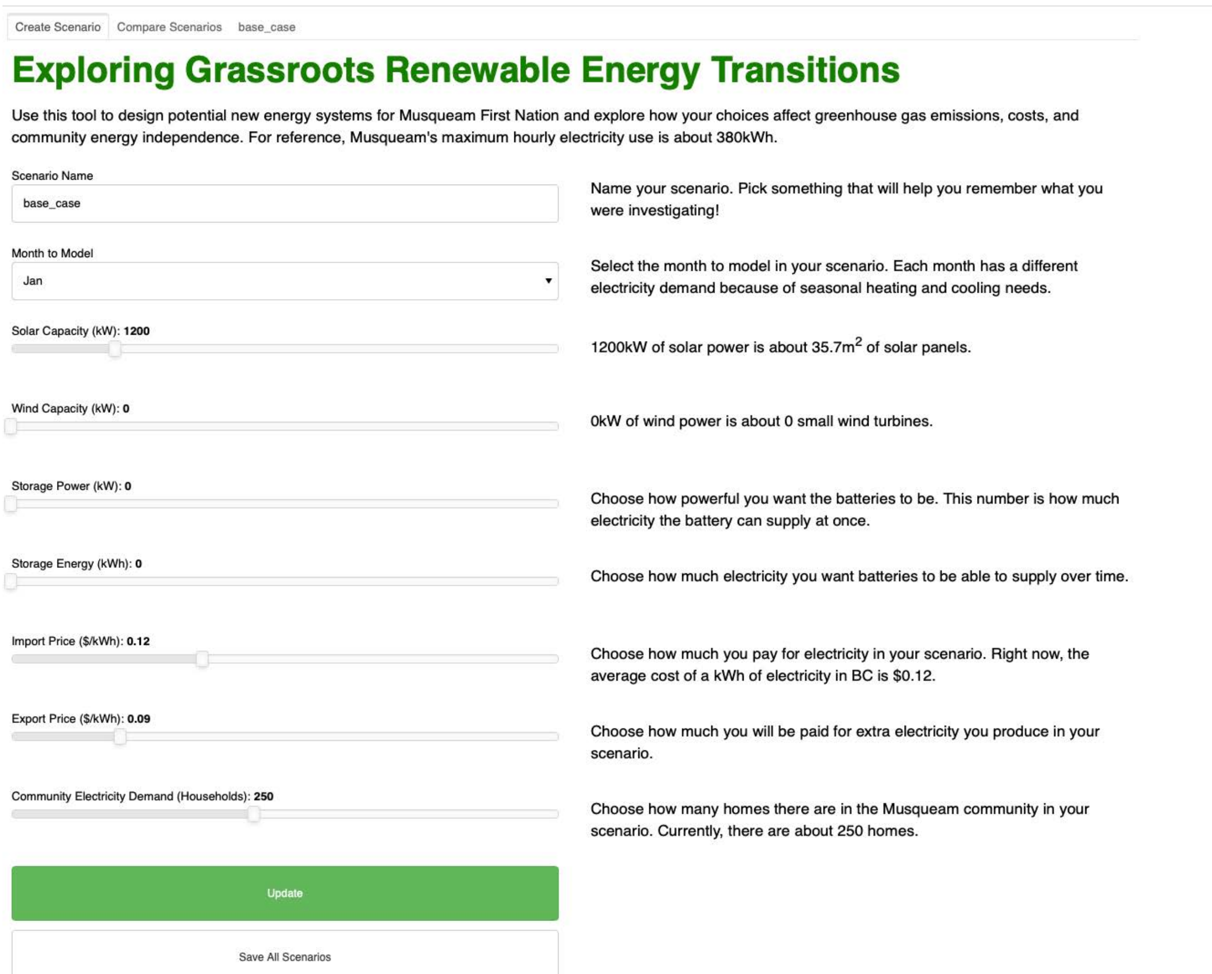

Figure 11: *EGRET user interface.*

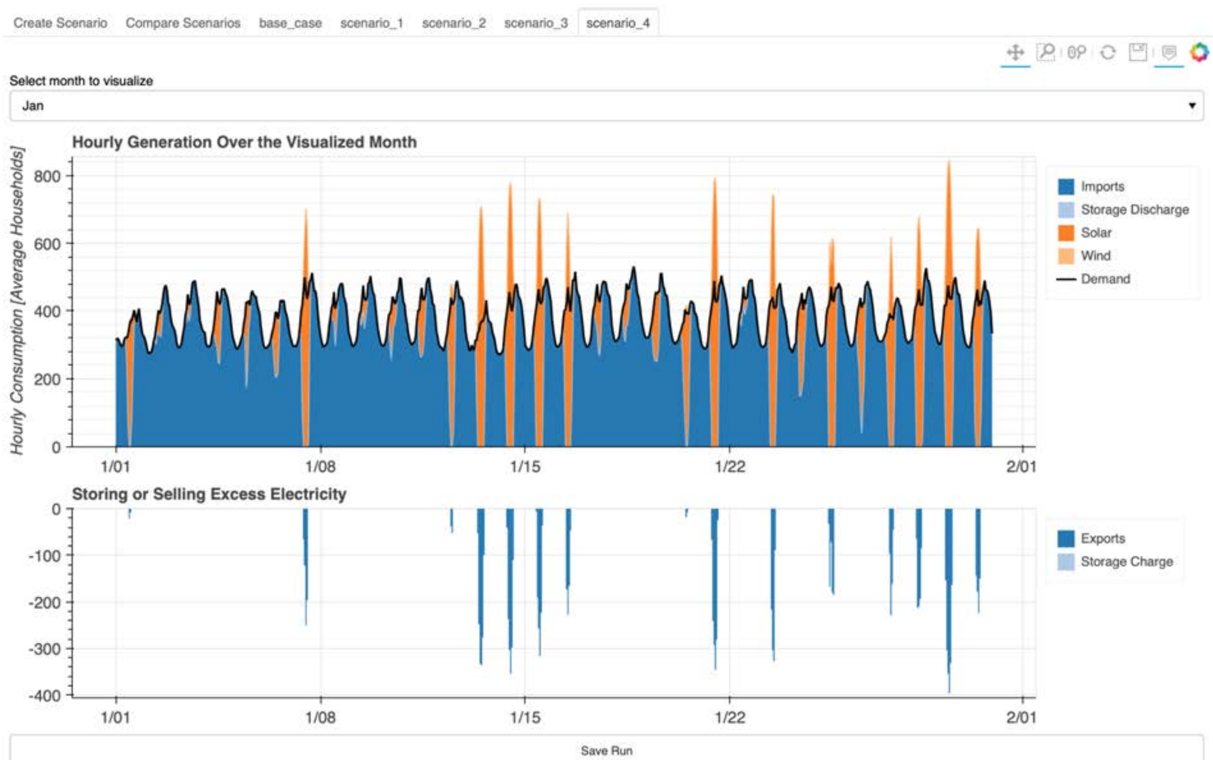

Figure 12: *EGRET visualizations showing hourly generation by technology type.*

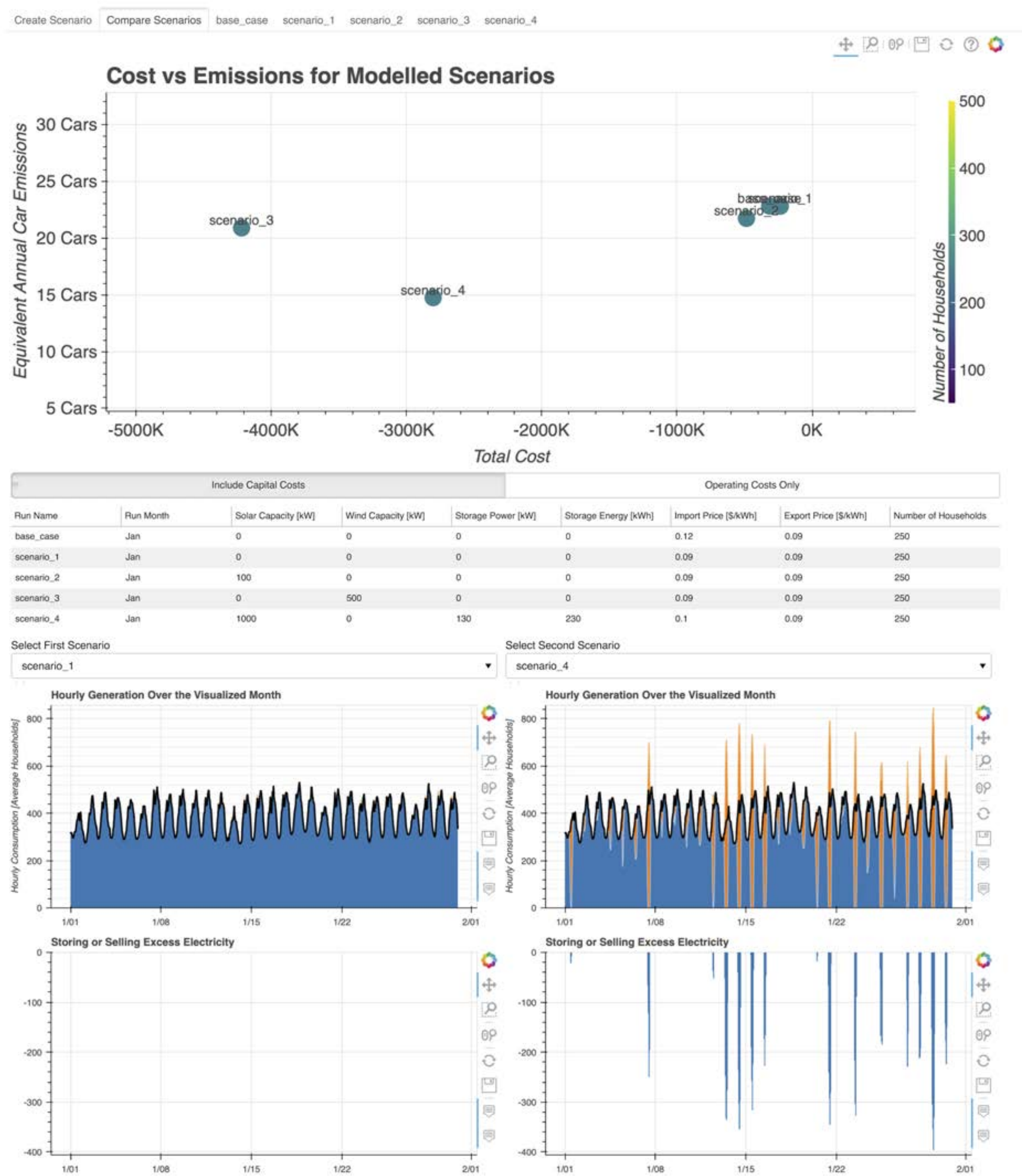

Figure 13: *EGRET visualization comparing cost and emissions across modelled scenarios.*

2.4 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. 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 [42]. 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 [42]. 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 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 [43]. 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 14. The participants' scores on the platform's usability are summarized in Figure 15.

Although the participants' usability scores were all neutral or positive —- and open-ended feedback questions were left blank — participants provided oral 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 16 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 i7CPU 3.1 GHz and 16 GB RAM memory storage.

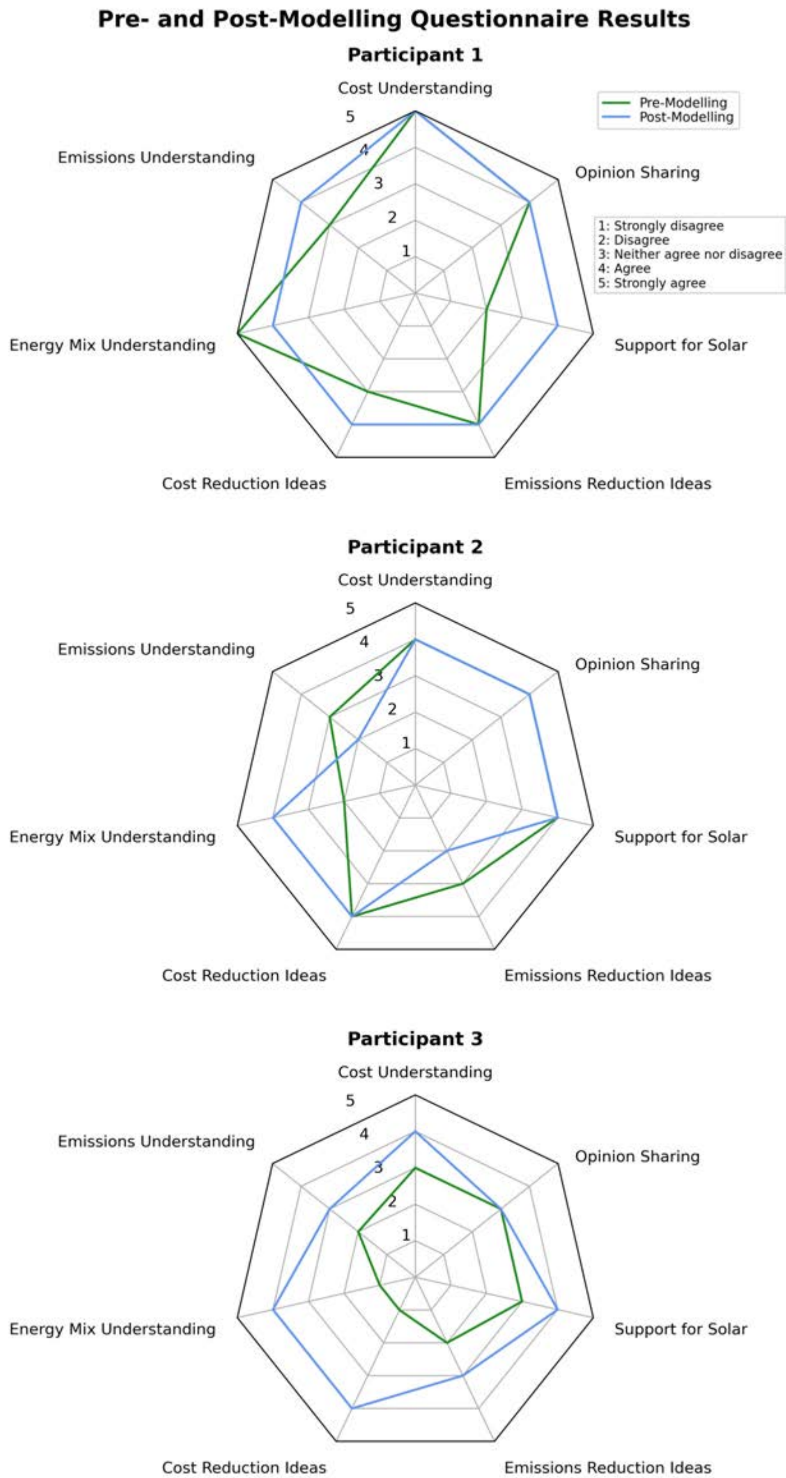

Figure 14: *Participants' pre- and post-modelling scores for their energy system understanding, ideas for the future, support for solar panels, and confidence in sharing their opinion on solar panels with others.*

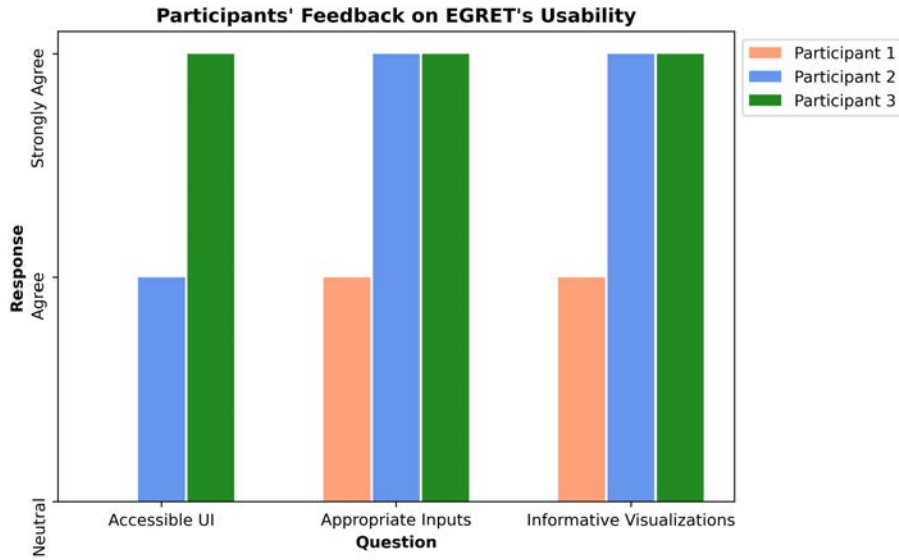

Figure 15: *Participants' feedback on whether the platform's user interface was easy to use, the available options allowed for exploration, and the visualizations provided adequate information. All participants answered neutrally or positively.*

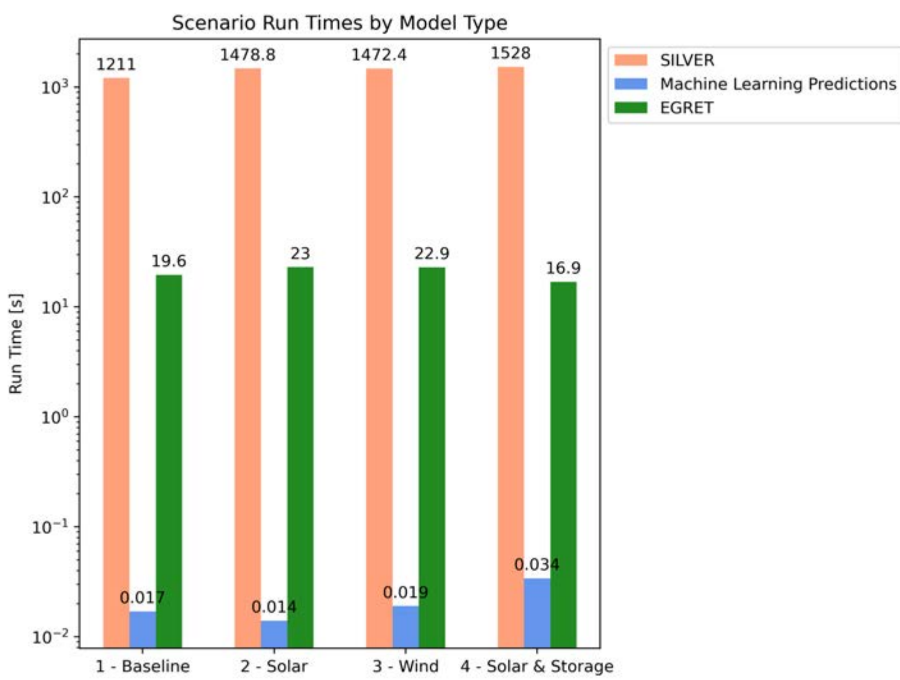

Figure 16: *Test scenario run times for each model type. The EGRET run times include the machine learning predictions, data post-processing, and visualization times.*

4 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.

4.1 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.

4.2 Usability

Participants' usability scores suggest that interacting with the EGRET platform was accessible and provided suitable flexibility and information to explore community energy questions. The 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 [7]. 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.

4.3 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.

4.4 Accuracy

Although the machine learning models provide significant run time speed benefits, these benefits come at the cost of decreased accuracy. Figure 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 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 [24].

4.5 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 community'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.

4.6 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 [44]. 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 [20]. [44]. 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 [10]. 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 [10]. 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.

4.7 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 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 [45]. Applying such an approach to the EGRET platform to create an open-source tool would further increase the accessibility of energy system modelling.

5 Conclusion

The EGRET platform looked to restructure typical energy system modelling approaches to better suit a future with decarbonized and decentralized power sources. By facilitating community-scale engagement in renewable energy development initiatives, the EGRET platform supports the decentralized governance structures needed for an equitable transition to sustainable power systems. 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 a limited number of community testers, further supporting the use of ongoing collaboration through the model development process to ensure the finished product's applicability in the community context. However, 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 and an equitable transition to sustainable energy sources at a local scale.

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Authors Contributions: Lia Codrington: Conceptualization, Methodology, Data Curation, Software, Investigation, Visualization, Writing – Original Draft. Ehsan Haghi: Conceptualization, Methodology, Project Administration, Writing – Original Draft. Kwang Moo Yi: Methodology, Writing – Review and Editing. Madeleine McPherson: Conceptualization, Funding Acquisition, Resources, Supervision, Writing – Review and Editing.

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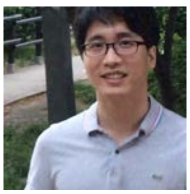

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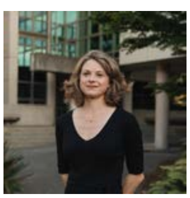

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