ELECTRIC THERMAL STORAGE FINAL REPORT

Northern Energy Innovation

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EXECUTIVE SUMMARY

Electric Thermal Storage (ETS) heating systems work by storing heat via electric coils embedded within a medium with strong heat retention properties. The ETS systems can be programmed to store heat during periods where there is lower overall demand for electricity, so-called "off-peak" hours. Thus, the energy used for heating is shifted from times when there is higher demand to times when there is lower demand. The stored heat is then released when convenient for the occupants of the building in which the ETS system is located. The Yukon's ETS demonstration project was implemented in 2020 to study the viability of ETS technology in the Yukon. The Yukon Conservation Society initiated the project with funding from Natural Resources Canada. Then, the Northern Energy Innovation research group was contracted to provide an objective and unbiased analysis of the project data. Over 40 households were participants in the demonstration project at the time the study period ended in 2023. ETS heating systems sourced from two manufacturers, Steffes and Elnur, were installed in participating homes. The ETS systems installed during the demonstration project included space heaters, centrally ducted heating systems, and hydronic heating systems sourced from two manufacturers, Steffes and Elnur.

The purpose of the ETS demonstration project was to assess the viability of ETS technology in the Yukon, specifically how effective ETS technology would be to electrify heat in the Yukon. In the Yukon, the peak loads demanded of the electricity grid occur during the winter months. Shifting when power is drawn for heat can reduce peak loads and provide benefits, such as reduced greenhouse gas emissions, cost savings from reducing the demand for rented diesel generation. ETS can also pair with intermittent renewable generation. Excess power generated by renewables can be stored as heat, encouraging higher levels of renewable power generation. To best assess the benefits and challenges of ETS technology in the Yukon, key stakeholders were consulted to formulate ten research questions to be answered through the analysis of ETS project data.

A variety of on-board ETS sensors and external sensors were placed in participating homes to monitor the performance of ETS systems and the environmental conditions around the ETS systems. The analysis of ETS project data involved modeling ETS fleet load as a function of temperature, time of day, and fleet load capacity. This ETS fleet load model was then used to create projections for ETS effects on secondary peaking, greenhouse gas emissions, and peak load reductions. The remainder of the analysis was performed through statistical analysis, data visualization, and literature review.

WINTER PEAK REDUCTION

The peak reduction effects from the ETS systems were encouraging. Steffes manufactured ETS systems drew an average of 97.7% of their total energy during off-peak hours. Elnur manufactured ETS drew an average of 88.4% of their total energy during off-peak hours. The ETS systems were observed to have more consistent load profiles when outdoor temperatures became colder. The project's total installed maximum draw was 689 kW with a total storage capacity of 4133 kWh across 45 participating homes with a total heat load of 396 kW. From this, a maximum observed peak reduction of 315 kW was achieved against a calculated winter peak of 109 MW. Generally, as temperatures decreased ETS systems were observed to have a greater capacity for peak reduction on

days of peak winter loads. Using the model for the ETS fleet load, a maximum peak reduction, while minimizing secondary peaks forming during off-peak hours, was calculated to be between 0.59 MW and 1.05 MW, representing between a 0.5% and 0.9% reduction in the that heating season's winter peak. This reduction was possible when approximately 7% of Whitehorse area homes have ETS systems installed. It was also demonstrated that when ETS penetration was below 30% any secondary peaking that did occur was within the previous range of winter peaks.

The effect of different control measures on the ETS fleet were also evaluated. The default control through the demonstration project was time of day based. On and off-peak hours were determined for the Yukon grid, then ETS systems were programmed to draw power during off-peak hours. However, an experimental period of frequency-based control was implemented for Steffes ETS systems. The ETS systems will monitor grid frequency, and based on variations in that frequency adjust charging in real time. When the frequency on an electrical grid is low, it can imply there is a lack of generation, or an excess of load demanded on the system. Conversely, when the frequency is high it can imply an excess of generation, or a lack of load demanded. Finally, ETS systems were allowed to operate independent of any external control.

The ETS systems operated independent of external control resulted in a minimal reduction of peak loads. Time of day control resulted in approximately 10 kW to 40 kW of additional daily peak shifting capacity on average than frequency-based control. However, the frequency-based control is more responsive; adjustments can be made to ETS charging in real time by the ETS system analyzing changes in the grid frequency. Frequency-based control can mitigate secondary peaking more effectively while still providing peak shifting capabilities.

GHG REDUCTIONS

The ETS fleet load model was used to create simulations of future ETS implementations in the Whitehorse area, and the resulting effects on GHG emissions. The maximum GHGs that could be reduced during a heating season are between 492 T and 580 T of GHGs, equivalent to 4.0% and 6.1% of GHGs produced from utility-power generation across a heating season.

Pairing ETS with renewable generation can reduce fossil fuel consumption at the individual and utility levels. An ETS implementation paired with renewable wind generation in remote Alaskan communities was reviewed and the results were both promising and applicable to the Yukon. The ETS systems used in the Alaskan project were manufactured by Steffes, which were also studied in the Yukon's ETS demonstration project. These Steffes systems used the same frequency-based control as was tested in the Yukon's demonstration project. The results were satisfactory, with frequency-based control still having peak-shifting capabilities in both the Alaskan and the Yukon's ETS projects. Further, the frequency-based control can determine when there is an excess of renewables in a community, and bring ETS units online to charge and absorb the excess generation.

SYSTEM PERFORMANCE

Participants in the ETS project expressed satisfaction with their ETS system's performance. Participants were provided with a survey for the 2021-2022 and 2022-2023 heating seasons where they were asked questions regarding ETS system performance. For the 2021-2022 heating season 96.4% of users responded positively when asked whether ETS systems provided adequate heat; for the 2022-2023 heating season the positive response rate increased to 100%. For the 2021-2022 heating season 89.3% of users responded positively when asked whether ETS systems delivered heat as quickly as desired; for the 2022-2023 heating season the positive response rate declined slightly to 87.7%. Empirical models for thermal comfort can use environmental data to predict the thermal comfort of an average occupant. Employing these models on ETS demonstration project data showed that a hypothetical average occupant would be comfortable a large majority of the time, which agrees with the survey responses from the actual occupants.

ETS units can retain heat during a power outage. A typical electric heater would immediately draw power to provide heat following the resumption of power after an outage. The load immediately drawn upon power being restored to a grid is referred to as "black start load" and can be challenging to manage for utilities. ETS systems can provide value for utilities by retaining heat and not drawing their full load after a power outage. If an ETS system does need to charge following a power outage, the charging can be delayed. Steffes ETS systems will recognize an outage has occurred and delay charging for an initial 30 seconds, and then slowly ramp up power draw for another 30 seconds. Some ETS project participants confirmed that heat was available during outages, especially those with baseboard-style Elnur units.

The effects of the electrification of heating on grid infrastructure were also studied in related work by Northern Energy Innovation, the Electric Vehicle and Electric Heating project. The number of transformers overloading, the number of secondary poles experiencing undervoltage, and the number of secondary poles experiencing overcurrent increased with as the penetration of electric heat increased in the Riverdale, Porter Creek, and Takhini neighbourhoods. There were two notable exceptions to this trend: in the Takhini neighbourhood the number of overloaded transformers was largely invariant to the proportion of electric heating, with only 2 transformers overloaded with 33% penetration of electric heating; in the Porter Creek neighbourhood only 3.2% of secondary poles experienced overcurrent at a 23% penetration of electric heating. However, substantial distribution system upgrades may be necessary to maintain power quality in the face of increased electrification of heating in Whitehorse.

FUTURE ETS IMPLEMENTATIONS IN THE YUKON

The paths for widespread adoption of ETS systems in the Yukon were evaluated. Several key pathways were identified: upgrades to the Yukon's electrical distribution infrastructure, creation of utility-run programs to facilitate demand response through ETS, or adjustments to existing electricity rate structures. A common variable among these paths is the Yukon Utilities Board. Measures approved by the utilities board must be economically sound since the provision of electricity in the Yukon is the responsibility of a Crown subsidiary, it is in the public's interest for any changes to be cost effective.

The utilities board has a mandate to consider the economics of any program or incentive introduced in the Yukon. Another important component for ETS adoption is user sentiment. The efficacy of optin demand response programs is dependent on public feelings regarding ETS technology. Ensuring the public is fully informed regarding the specifics of ETS, and the similarities between ETS and other demand side management programs will be crucial to the success of any ETS initiatives.

The potential for ETS in remote Yukon communities not connected to the larger Yukon grid was also investigated. The Yukon's remote communities generate their electricity largely with diesel, though many communities are exploring or have implemented renewable generation to offset diesel. ETS paired with renewable resources was identified as the most promising avenue for ETS adoption in these remote communities. The intermittent nature of renewable generation pairs well with thermal storage. Studies of ETS in remote Alaskan communities paired with wind generation showed promising results, with excess wind generation absorbed by the ETS systems and less diesel consumed.

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LIST OF ABBREVIATIONS

Abbreviation	Definition
AEY	ATCO Electric Yukon
AIC	Akaike Information Criterion
AMI	Advanced Metering Infrastructure
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BIC	Bayesian Information Criterion
CDF	Cumulative Density Function
CPR	Critical Peak Rebate
DLC	Direct Load Control
DSM	Demand Side Management
ETS	Electric Thermal Storage
EV	Electric Vehicle
EVEH	Electric Vehicle Smart Heating
GETS	Grid Interactive Electric Thermal Storage
GHG	Greenhouse Gas
HfLN	Heat for Less Now
HVAC	Heating, Ventilation, and Air Conditioning
ILM	Intelligent Load Management
KLFN	Kasabonika Lake First Nation
LNG	Liquified Natural Gas
MRT	Mean Radiant Temperature
NEI	Northern Energy Innovation
NHAC	Nicol and Humphries Adaptive Comfort
NREL	National Renewable Energy Laboratory
OCF	Our Clean Future
PMV	Predicted Mean Vote
PPD	Predicted Percentage Dissatisfied
PSA	Power Shift Atlantic
PUA	Public Utilities Act
QSTS	Quasi Static Time Series
RH	Relative Humidity
SET	Standard Effective Temperature
SSE	Summerside Electric
TOD	Time Of Day
TOU	Time Of Use
VPP	Virtual Power Plant
YCS	Yukon Conservation Society

YIS	Yukon Integrated System
YUB	Yukon Utilities Board

1 PROJECT OVERVIEW

1.1 INTRODUCTION TO THE ETS PROJECT

Electric Thermal Storage (ETS) heating systems are a technology that can shift when energy is consumed for heating through heat storage. ETS systems work using materials with good heat retention properties, such as ceramic bricks, and storing heat through heating coils. The bricks are housed within an insulated core located inside the ETS system. By storing heat with minimal losses over time, the demand for heat can be uncoupled from times of day when heat would typically be desired.

ETS systems can reduce the peak electricity demand by shifting electric heating loads from on-peak to off-peak times. In the Yukon winter peaks in electricity demand are an environmental and economic concern. Currently the excess demand is met through existing fossil fuel resources (diesel and liquified natural gas as well as rented diesel generation. Winter demand peaks continue to rise, partially driven by the popularity of non-storage based electrical heat, particularly in new home builds [1]. By reducing the Yukon's peak electricity demand, widespread adoption of ETS could result in reduced greenhouse gas emissions and cost savings by reducing the reliance on expensive rented diesel generation.

The ETS demonstration project was initiated by the Yukon Conservation Society (YCS), with funding from Natural Resources Canada, to study the viability of ETS technology in the Yukon. YCS contracted Northern Energy Innovation to provide an objective and unbiased assessment of the project data. Other project partners include Yukon Government and Yukon Energy. Seven organizations were identified as project stakeholders, and were consulted to identify which research directions to pursue for the ETS project. These organizations included Yukon Conservation Society, Yukon Government, ATCO Electric Yukon, Yukon Housing Corporation, Council of Yukon First Nations, Yukon Energy, and the Association of Yukon Communities. A document was prepared detailing 24 possible research questions. This document was circulated to the seven stakeholders.

Over 40 participating households had ETS units installed. These households are located in the city of Whitehorse, and the surrounding areas. The ETS units were comprised of three main heater types, sourced from two manufacturers. These details are outlined in Table 1.

Manufacturer	System Type	System	Max power draw	Number of units in
		Number	[kW]	project
Elnur	Space Heater	158	0.985	4
		208	1.31	27
		308	1.96	20
		408	2.62	5
Steffes		2102	3.6	3
		2103	4.5	6
		2104	7.2	2
		2105	7.5	5
		2106	9.0	2
	Central Forced Air	4120	19.2 - 24.8	8
	Furnace	4130	28.8	8
	Central Hydronic	5120	19.2 - 24.8	2
	Heater	5130	28.8	1

Table 1: Overview of ETS units in demonstration project.

The project was comprised of two periods of interest, the 2021-2022 and 2022-2023 heating seasons. For the purposes of the analyses in the later sections, a heating season for the Whitehorse areas was defined to be between September 1st and April 1st. Any distinction as to what is or is not a heating season will be subjective, but this range of time will encompass a large majority of the heater's in-use periods.

Both Elnur and Steffes ETS systems came with in-unit sensors to monitor key variables such as core temperatures and power draw. This data was accessible remotely through online dashboards. In addition to the in-unit sensors, additional sensors were ordered to capture other variables or validate data from the in-unit sensors. These include duct-temperature sensors for the central ETS heaters and temperature and humidity sensors to monitor thermal comfort throughout the dwelling.

In consultation with project partners a series of 10 research questions were developed to evaluate ETS performance and provide insight into potential future ETS implementations in the Yukon. These 10 questions are given in Table 2.

Table	2:	Research	Questions	for	FTS	project.
TUNIC	<u> </u>	incocurent	Questions	101	L13	project.

1	How effective are ETS units at reducing the Yukon's winter peak?
2	How effective are ETS units as controllable, predictable, dispatchable resources?
3	What would the Greenhouse Gas (GHG) emission reduction be from ETS implementation,
	and what would the heating fuel usage reduction be?
4	How would wide-spread ETS implementation affect residential load power factor/quality?
5	Will occupants experience a disruption in their comfort levels?
6	What is the best ETS control approach for peak reduction without producing a secondary
	peak?
7	Can ETS help mitigate the black start load of the system by delaying when it charges after a
	power outage?
8	What is the added value of controlling the ETS units in aggregate?
9	What regulatory or infrastructure changes would need to be made for adoption and wide
	implementation in the Yukon?
10	What are the value streams for integrating ETS units in diesel-powered communities?

These research questions address different aspects of ETS in the Yukon context. The research questions can be broadly categorized in terms of the potential values and challenges ETS adoption in the Yukon may have. Questions 1 and 6 investigate the effectiveness of ETS to enable peak shifting. Questions 2, 3, 7, and 10 investigate the different ways ETS can provide value to the Yukon through effective peak shifting and their ability to store energy. Questions 4 and 5 investigate potential practical challenges with ETS adoption. Question 9 focuses on the regulatory and infrastructure challenges facing ETS in the Yukon. Each of these questions will be answered in this report in the following sections.

1.2 MODELING THE ETS FLEET LOAD

1.2.1 Introduction

To effectively analyze the project data, and extract the insights required for the research questions described above, a multitude of analyses were undertaken. The most important variable in the research was the power drawn by the ETS systems. Analyzing ETS power draw with respect to time-of-day (TOD) shows how consistently ETS systems were drawing power when scheduled to do so. Knowing when and to what intensity ETS systems are consuming power will determine ETS effectiveness at reducing winter peaks. Analyzing the power consumption of ETS units together with the control strategies used in the pilot project can provide an estimate of the added value an overarching control strategy may provide, as well as ETS effectiveness as a controllable resource. To effectively calculate the GHG emissions reduced from ETS it is necessary to understand when and to what intensity ETS systems.

Using the power consumption data as is will provide insights for the limited pool of participants in the ETS project. However, by observing the patterns in the power draw data a model can be fitted to replicate those patterns with differing hypothetical pools of ETS users. As well, by relating the total

fleet power draw to outdoor temperature, a variable likely to be correlated with heating, simulations of differing ETS implementations and their total power draw can be created. Modeling the power draw of the ETS fleet allows for greater insight to be drawn from the limited selection of project data.

The fleet load model was created by analyzing power draw data from the ETS fleet across the heating seasons, and fitting a regression model to best relate the fleet load to outdoor temperature, daily fleet load capacity, and TOD. This model was used in two of the ten research questions: *"What would the GHG emission reduction be from ETS implementation, and what would the heating fuel usage reduction be?"* and *"How effective are ETS units at reducing the Yukon's winter peak?"*.

1.2.2 Exploratory Data Analysis

The maximum possible loading for the fleet, assuming all systems are charging at full power simultaneously, is 1042 kW. However, in the data this number is never approached. The reasons are twofold, the likelihood of every system charging at full power simultaneously is low, and during the 2021-2022 heating season not every ETS system was online every day, much less simultaneously.

To analyze the total load drawn by the fleet of ETS systems, multiple transformations were applied to the underlying data. The Steffes systems collected power data at a per-second resolution whereas the Elnur systems collected power data at a per-minute resolution. The maximum observed power draw within a minute was taken for the total load of the Steffes systems and then added to the Elnur data at the common resolution. The fleet load was then calculated at a per-minute resolution by adding the Elnur system's load to the Steffes system's load with respect minutely observations. This data was further aggregated by then taking the maximum observed fleet load within an hour. The maximum was taken because the highest loads are of the most interest, they represent the worst-case scenario for ETS contribution to the system-wide load. The final resolution was chosen to be hourly to better facilitate the modeling methodology while still maintaining sufficient resolution to identify peaking behaviour. In addition, the control methods employed by YCS also are at an hourly resolution. In Figure 1 the total hourly load consumed by the fleet of ETS systems is presented contrasted with the hourly outdoor temperature in Whitehorse during the 2021-2022 heating season.



Figure 1: Hourly temperature and ETS fleet load

outdoor temperature. This is not surprising, occupants will want more heat during colder days. The There appears to be a negative relationship between the load demanded by the ETS fleet and the matching positive spikes in load demand. two series in Figure 1 also appear to be closely correlated, with negative spikes in temperature

of daily load capacity respective values of 30.33% and 14.29% are used. In Figure 2 this proportion is 350 kW. Using the pure load data the change in capacity is not reflected, however using the proportion consider on another given day and hour the recorded ETS fleet load was 50 kW, but the capacity was ETS fleet load is only 50 kW, but the capacity for the ETS fleet during that day was only 150 kW. Then changes in fleet capacity. For example, consider that during a given day at a given hour the recorded to eliminate the effects of systems dropping offline for brief periods while capturing day-to-day resolution was used to calculate the effective proportion load capacity. A daily resolution was chosen the number of active ETS systems. To this end, the capacity of the online ETS systems at a daily effect of potential load capacity. This transformation will capture variability attributed to changes in It is convenient to calculate hourly load as a proportion of the potential load capacity to illustrate the given, again with the hourly outdoor temperatures in Whitehorse.



Figure 2: Hourly temperature and proportion of daily fleet load capacity.

The proportion of load capacity is negatively related to temperature, and the series appear to be correlated as before in Figure 1.

Another factor that will influence the proportion of load capacity is the control scheme YCS employed during the 2021-2022 heating season. ETS systems are supposed to charge during off-peak hours. During on-peak hours, when heat is more likely to be demanded by occupants, the stored heat will be released. Sub-daily variation in the grid load is expected, and this sub-daily variation will have correlations between days. Across the two manufacturers, the widest charging times set were from 1100-1600 hours and 2200-0600 hours. The Steffes systems can set a relative level of charging. YCS determined the relative level of charging for the Steffes ETS systems, so the peak charging occurred during the mid-point of the charging periods and tapered towards the end-points. The Elnur systems have no such capabilities, but as demonstrated in Figure 3 they can be assumed to follow a similar pattern.



Figure 3: Proportion of total load capacity for Elnur systems.

It is apparent that the Elnur systems do not have constant levels of charging during the charge periods. In Figure 4 the proportion of total load is given across the entire fleet of Ecombi systems, as well as the relative level of charging.



Figure 4: Proportion of total load capacity for ETS fleet compared with relative charging.

The pattern of desired charging is clearly reflected in the actual proportion of load capacity through the 2021-2022 heating season. The Elnur systems in Figure 3 show an increase in charging during onpeak hours in the morning, between 7 AM and 10 AM. However, when the Elnur load is combined with the Steffes load to create an ETS fleet load in Figure 4 the overall level of undesired charging is mitigated. This is due to the Steffes systems having a more consistent adherence to pre-determined charging times. The desired peaking and tapering are observed during off-peak times, in addition to lower or sometimes no charging during on-peak times.

1.2.3 Fitting the Fleet Load Model

The data in Figure 2, Figure 3, and Figure 4 identify three processes that could explain the variation in the fleet ETS load, namely the outdoor temperature when accounting for fleet load capacity, and the cyclical charging behaviour. To evaluate this, a linear model may be fit, relating fleet load to temperature, load capacity, and hour of day. A simple model could be fit where all three variables are treated as additive, shown in equation (1), where load *L* is modeled as a linear function of outdoor temperature *T*, load capacity *C*, and hour of day as a dummy vector $\mathbf{H}_{24\times 1}$.

$$L = \beta_0 + \beta_1 T + \beta_2 C + \beta_3 \mathbf{H} + \varepsilon$$
 (1)

Such that β_0 , β_1 , β_2 , are regression coefficients, β_3 is a vector of coefficients for the dummy vector, and ε is an error term, assumed to follow a Gaussian distribution. Outdoor temperature T was transformed from °C to kelvin (K). This was done to ensure 0 had a meaningful value when fitting the regression model. The coefficient of determination for (1) is 0.67, in other words the fitted model explains 67% of the variation in the data. It is important to recognize that the expected load may not be solely related to the additive effects of the explanatory variables in (1), but related to their multiplicative effects as well. Intuitively, it makes sense that fleet ETS load changes in response to joint changes in the regressors as well as individual changes. For example, modeling the multiplicative effect of $T \times C$ will capture how load changes in response to the fleet capacity increasing as the outdoor temperature drops. A series of models are fit with different multiplicative relationships. Model diagnostics are then taken, namely the coefficient of determination (R^2), adjusted coefficient of determination (R^2_{adj}), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC), and reported in Table 3.

Model Number	Interaction	R ²	R_{adj}^2	AIC	BIC
1	$T imes \mathbf{H}$	0.83	0.83	48355	48682
2	$T \times C$	0.68	0.67	51529	51712
3	$\mathbf{H} \times C$	0.80	0.79	49227	49553
4	$T \times C + \mathbf{H} \times C$	0.80	0.80	49163	49496
5	$T \times C + T \times \mathbf{H}$	0.83	0.83	48284	48617
6	$H \times C + T \times \mathbf{H}$	0.86	0.86	47288	47765
7	$\mathbf{H} \times C + T \times \mathbf{H} + T \times C$	0.86	0.86	47194	47678
8	$\mathbf{H} \times C \times T + \mathbf{H} \times C + T \times \mathbf{H} + T \times C$	0.87	0.86	47187	47821

Table 3: Diagnostics for models of differing interactions of explanatory variables

Note that the additive effects of the explanatory variables are also included in the models described Table 3, but not shown to save space. For the diagnostics, R^2 represents the proportion of variation in fleet load explained by the mode. R_{adj}^2 accounts for the number of predictors in the model,

increasing when a predictor increases the predictive ability of the model greater than would be expected from pure randomness, and vice-versa. AIC evaluates the goodness of model fit relative to model complexity, penalizing over-fitting and under-fitting. BIC works quite similarly to AIC, and the two are often used in conjunction for model selection. Larger R^2 and R^2_{adj} are desirable, while smaller AIC and BIC values indicate a better model. Analyzing the results in Table 3, it is apparent that models 6 through 8 are the clear favourites. Model complexity also increases, with 6 having the least number of predictors and 8 having the greatest. All three models have virtually the same R^2_{adj} . Model 8 has better AIC than model 6, and virtually the same AIC as model 7. However, the BIC for model 8 is the worst of the three. Model 7 has the best BIC value, giving it the edge over model 8 and model 6.

Moving forward, model 7 will be analyzed. The fitted values contrasted with the raw data, along with the resulting residuals, are shown in Figure 5.





Figure 5: Fitted values contrasted with raw data (a), residual values against time (b), and residuals versus fitted values (c).

The fit for the model is seen in Figure 5 (a), contrasted with the raw data. It is clear that the model captures much of the underlying variability in the data, as reflected in the R^2 value of 0.86. The residuals in Figure 5 (b) and Figure 5 (c) exhibit no trend in time or with the fitted values respectively, they are centered about 0. However, the variability of the residuals does change both with respect to time and with the fitted values. Inspecting Figure 5 (c) there is a clear cone-shaped pattern to the residuals, with variability steadily increasing until around a fitted value of 175 or greater, at which point the variability looks reasonably constant. Heteroscedasticity of error is problematic in statistical modeling since an important assumption is the error remain constant. Intuitively, the heteroscedasticity is due to the fitted values being much easier to predict during the hours of the day when the ETS units are set not to charge. In Figure 6 the residuals are plotted against the hourly dummy variables to confirm this intuition, with a third dimension represented by the fleet load capacity variable, coloured in shades of blue.



Figure 6: Model residuals plotted against hourly dummy variable.

It is clear the variability of the residuals is directly related to hour of day, which in turn is related to the expected fleet load for ETS. It is also clear that for days with low fleet capacity the residuals are far less variable. Modeling variability as a function of the hourly dummy variable and the fleet load capacity should improve the heteroscedasticity of the residuals. This can be accomplished through re-

estimating model 7 by weighting each observation according to the relative amount of variability expected for said observation. The weights are determined as the sample variance of the residuals at each level of the hourly dummy variable, multiplied by the variability of the residuals at each grouping of fleet load capacity, then taking the inverse square root. Observations with larger variability have smaller weights than observations with smaller variability. The variance of the residuals plotted against the fleet load capacity are shown in Figure 7.





It is clear there are three distinct groupings for fleet load capacity, demarcated by the dotted lines. Sample variances are taken from the residuals at each grouping as the weight estimate.

The re-estimated weighted model is reported in Table 4.

Model Number	Interaction	R ²	R_{adj}^2	AIC	BIC
7	$\mathbf{H} \times C + T \times \mathbf{H} + T \times C$	0.89	0.89	43477	43960

The R^2 values are improved, and the AIC and BIC are much improved. Examining the residuals in from the weighted model, there is also evidence of improvement.



Figure 8: Standardized (a) and raw (b) residuals from the weighted model plotted against the fitted values.

The standardized residuals are plotted against the fitted values from the weighted model in Figure 8 (a); standardized residuals are scaled by an estimate of the standard deviation of the residuals, and will provide a more informative picture of actual heteroscedastic behaviour than raw residuals. There is non-constant variance about the smaller fitted values, but the overall behaviour is much improved. In contrast, the raw residuals in Figure 8 (b) still exhibit heteroscedasticity.

1.2.4 Discussion

The fitted model relating fleet load to outdoor temperature, TOD, and daily fleet load capacity, provided adequate performance. It is suitable to create estimates of hypothetical ETS implementations created through estimates of future temperature and ETS capacities, or past temperature profiles. A complete parametrization of the model fit in this section is given in the Appendix in Table 31.

2 HOW EFFECTIVE ARE ETS UNITS AS CONTROLLABLE, PREDICTABLE, DISPATCHABLE, RESOURCES?

2.1 INTRODUCTION

Assessing the predictability and dispatchability of Electric Thermal Storage (ETS) systems is valuable to determine how often the systems drew power when they were supposed to, and how responsive they were to any changes in control. A predictable fleet of ETS systems indicates that the effects of future ETS implementations can be more easily accounted for. A dispatchable fleet of ETS systems indicates the chosen control strategy is effective, and changes to control can be reliably reflected in system outputs. Knowing the predictability of ETS power draw is valuable for utility operators and planners to assess ETS effects on grid electricity demand. Knowing how responsive ETS systems are to changes in control allows utility operators and planners to gauge how effective various control strategies may be.

2.2 METHODOLOGY

The ETS fleet is first subset into Steffes and Elnur systems, with the fleet power draw plotted against the time-of-day (TOD). This will illustrate the daily charging patterns of the entire ETS fleet, highlighting the consistency at which ETS systems will adhere to a charging schedule. The predictability of the ETS fleet load can be easily assessed with this visual analysis. The data is then aggregated to an hourly resolution with the maximum observed load within the hour noted. The maximum hourly load is then plotted against the hour of the day, as a smoother approximation of the fleet load for both manufacturers. Then the Steffes and Elnur loads are combined into a single fleet load profile, and plotted against the hour of day.

The proportion of load drawn during scheduled charging periods is noted for the entire heating season for both Steffes and Elnur systems. The daily proportion of charging that occurs during scheduled and non-scheduled times is then plotted against the date.

The maximum hourly load for both Steffes and Elnur ETS systems is plotted against the outdoor temperature to illustrate the effect of temperature on ETS power draw. Demonstrating a relationship between outdoor temperature and ETS load illustrates how ETS load can be modeled as a function of temperature.

2.3 ANALYSIS

2.3.1 Predictability

The predictability of ETS load can be visually assessed by plotting the daily load profile as a series of separate lines for each day in a heating season. The lines are shaded by the temperature in Whitehorse. Two plots are given in Figure 9, one for Steffes and one for Elnur ETS units.



(b) Steffes systems.

Figure 9: Minutely power draw for Elnur (a) and Steffes (b) ETS systems by day.

The Elnur load is less "peaked" than the Steffes load. It also has greater local variability. This is likely attributable to the lack of sophisticated control for the Elnur systems compared to the Steffes systems. The Steffes load appears to be more predictable than the Elnur load. The outdoor temperature is given as a greyscale gradient in Figure 9. Generally colder days correspond to higher power draw, which is expected.

The ETS load can be aggregated from the default minutely to an hourly resolution, where within the hour the maximum observed fleet load was taken. This captures the highest load the grid would experience during that hour and has a smoothing effect on the daily load plots. Figure 10 is given below illustrating the aggregated loads for Elnur and Steffes units.



(b) Steffes systems.

Figure 10: Hourly power draw for Elnur (a) and Steffes (b) ETS systems by day.

The Elnur units produce an aggregate load with greater variability than the Steffes load but still follow a reasonably consistent pattern. The overall impact of the Elnur aggregate load is also diminished, peaking at approximately 75 kW. In contrast the Steffes load is more consistent.

Combining the two load profiles into an overall fleet load and generating the same daily profiles shaded by temperature is given in Figure 11.



Figure 11: Fleet load for ETS systems by day.

The fleet load profile is still consistent and much more resembles the underlying Steffes daily loads than Elnur. This is due to the lower overall power drawn from the Elnur systems.

The maximum hourly power drawn during on-peak and off-peak times is given for Elnur and Steffes systems in Table 5 for the 2021-2022 and 2022-2023 heating seasons respectively.

Heating Season	ETS Manufacturer	On-Peak power draw [%]	Off-Peak power draw [%]
2021-2022	Elnur	11.3	88.7
	Steffes	1.47	98.5
2022-2023	Elnur	11.9	88.1
	Steffes	3.23	96.8

Table 5: Total proportion of on-peak and off-peak power drawn by ETS systems during 2021-2022and 2022-2023 heating seasons.

The Steffes systems have better performance than the Elnur systems in charging schedule adherence, corroborated by the more variable daily load profiles shown in Figure 9 and Figure 10. The proportion of power drawn during on-peak and off-peak times can be broken down by each day in the heating season to identify any trends skewing the results in Table 5. The daily proportion of power drawn during off-peak times is given in Figure 12.



(b) Steffes systems.

Figure 12: Daily proportion of on-peak and off-peak charging for Elnur (a) and Steffes (b) ETS systems.

With both the Elnur and Steffes systems there is greater variability in the adherence to the desired charging periods at the beginning of the heating season. With the Steffes systems there is also greater variability at the end of the heating season. The Elnur systems have greater variability throughout the heating season than the Steffes systems in their adherence to scheduled charging times. The Steffes systems, aside from the behaviour at the beginning and end of the heating season, maintains a steady proportion of 90% or greater of all power drawn during off-peak times. The colder the outdoor temperatures, the more regularly the ETS systems are used and the more predictable their power draw. This results in in a peak demand reduction of higher magnitude and reliability at colder outdoor temperatures. In other words, the ETS fleet load had a lower proportion of the total power draw occur during on-peak times during the colder winter weather.

Predictability can also be assessed by noting the results of the regression model fit for hourly fleet load in an earlier report. The final regression model explained over 90% of the variation in the data solely as a function between temperature, TOD, total charging capacity, and the interaction effects between the three variables. The fleet load for 2021-2022 was highly predictable evidenced by the success of this regression model.
The temperature variable is particularly important in assessing the predictability of ETS load. Heating is naturally related to outdoor temperatures and the relative effect temperature may have on ETS loads is important to demonstrate. In Figure 13 the relationship between Elnur and Steffes ETS loads, and outdoor temperature is given.



Figure 13: Relationship between outdoor temperature and ETS loads for Elnur (a) and Steffes (b) systems.

For both Elnur and Steffes systems there is a clear negative relationship between load demanded and outdoor temperature during off-peak hours. The equations for these relationships are estimated through ordinary least squares, and are provided in Table 6, where P is the load drawn by the ETS system in kW and T is the temperature in °C.

ETS Manufacturer	On-Peak	Off-Peak
Steffes	$P = 1.86 - 0.07T, R^2 = 0.03$	$P = 44.8 - 3.60T, R^2 = 0.40$
Elnur	$P = 3.19 - 0.17T, R^2 = 0.30$	$P = 13.9 - 0.83T, R^2 = 0.35$

As temperatures get colder more heat is needed. Notably during on-peak hours the Steffes system load is largely invariant to temperature whereas the Elnur systems have a stronger negative relationship. That is, the Elnur systems still draw relatively more power during colder temperatures even when they are not supposed to. Between 30% and 40% of the variation in the data is explained by the linear models for Elnur off-peak and on-peak load, as well as Steffes off-peak load, as a function of outdoor temperature. Only 3% of the data is explained for Steffes on-peak load as a function of outdoor temperature, however. There are more outliers for the Steffes systems during the on-peak period, which lowers the R^2 value.

2.3.2 Dispatchability

The Elnur systems charging control only extended to the hours of the day devices were desired to charge. Steffes systems had a more sophisticated control method wherein the relative amount of charging could be specified for certain hours. In other words, peaks, ramp-up, and ramp-down hours could be preset. This explains the pronounced peaks in Figure 10 (b) and the relatively flatter daily load profiles in Figure 10 (a) for Elnur systems. The ability of the Steffes systems to adhere to their relative-charging presets can be investigated by calculating the rate of change expected between two given hours, and comparing these to the actual data during that time period.

During the 2021-2022 heating season there was a changepoint in the charging scheduling on February 21st. In Figure 14 the normalized scheduled power draw for the Steffes systems is given before and after the changepoint.





Generally maximum power is set to be drawn overnight, with ramp-down and ramp-up periods in the early morning and evening respectively. The rate of change between the pre-set charging periods can be calculated and compared with the actual power draw data to assess adherence to the intensity of the charging schedule. A least-squares fit was calculated for the charging data between every hour and the slopes compared with the rate of change between the pre-set charging periods. In Figure 15 boxplots are given for the least-squares slopes between every hour of the day. The expected rate of change from the charging pre-sets is given by the dotted grey line.



Figure 15: Least squares estimates for rate of change of Steffes load compared with rates of change from pre-set values.

Generally, the least-squares rate of change follows the pattern expected from the pre-set charging values. An exception is between the 9-10 hours, where the expected rate of range is positive, but the actual is close to 0. The changepoint on February 21st does not affect the results, the Steffes systems were responsive to the new charging schedule.

2.4 DISCUSSION

Both Steffes and Elnur systems proved to be dispatchable and predictable. Steffes systems performed the most predictably, with over 95% of all power drawn being drawn during off-peak times for both the 2021-2022 and 2022-2023 heating seasons. The on-peak power draw for Steffes units was also correlated with outdoor temperatures, when outdoor temperatures were lower the systems drew more power. In contrast, the Elnur systems still performed predictably but less so than Steffes systems. Across the 2021-2022 and 2022-2023 heating seasons Elnur units drew over 88% of all power consumed during off-peak hours. The on-peak power draw was also correlated with temperature for Elnur systems. However, the power that Elnur systems drew during on-peak times was also correlated with outdoor temperature. The overall fleet load across both Steffes and Elnur systems was also

predictable. A regression model relating fleet load to outdoor temperature, TOD, and daily fleet load capacity, was able to explain approximately 90% of the variance in fleet load. The control method for Elnur systems was not as sophisticated as the Steffes systems, so dispatchability was only assessed for Steffes systems. During changepoints in control for Steffes systems, the Steffes fleet quickly adapted and followed the new control parameters.

3 WHAT WOULD THE GHG EMISSION REDUCTION BE FROM ETS IMPLEMENTATION, AND WHAT WOULD THE HEATING FUEL USAGE REDUCTION BE?

3.1 INTRODUCTION

A possible benefit associated with Electric Thermal Storage (ETS) adoption in the Yukon is the reduction of greenhouse gas (GHG) emissions both at the utility level and the residential level. Yukon Energy currently generates electricity with a baseline of hydro, then Liquified Natural Gas (LNG), then diesel. In other words, the greatest proportion of electricity is generated by hydro, and the associated load profile is relatively flat. Excess winter electricity demand is currently met with fixed and rented diesel generation. By shifting heating loads from times when demand is highest to times when demand is lowest, load that was previously met by diesel could be met by LNG, which emits less GHGs than diesel, or hydro, which is assumed to emit no GHGs for the purposes of this research question. Additionally, many Yukon homes are heated with fossil fuels, in particular heating oil. Transitioning homes from heating oil-based systems to electric heating systems will provide immediate local reductions in GHG emissions. However, the new electric heating loads on the grid may temper any overall change in GHG emissions.

3.2 METHODOLOGY

Generation mixture data provided from Yukon Energy was used in conjunction with ETS fleet loads derived from the regression model estimated on ETS project data. These two data sources can be used to provide an estimate of the change in GHG emissions after a simulated ETS implementation.

Yukon Energy will use hydro power as a baseline generation source, ideally meeting much of the load demanded. Then LNG based generation is used to account for any further load. If there is still load remaining, then diesel generation will be employed. Figure 16 illustrates the priority of generation sources with a random week from the winter heating season.



Figure 16: Area plot of typical winter Yukon Energy generation mix.

Both Hydro and LNG generation act as a consistent baseline, whereas diesel is more flexible to most accurately balance the system load.

In the analysis hydro power is assumed to have no direct GHG emissions. LNG is known to produce fewer emissions than diesel. The scaling factor used to calculate GHG emissions from Yukon Energy data are given in equations (2) and (3) and were adopted from figures provided in [2].

$$GHG_{diesel} = \frac{0.0703t}{1GJ} \tag{2}$$

$$GHG_{LNG} = \frac{0.0503t}{1GJ} \tag{3}$$

Where the energy associated with each generation type is multiplied by the requisite factor given above to provide GHG emissions in tons t. Then, the emission factors are scaled by the relative efficiency of each generation source. The efficiency for the diesel and LNG gensets used by Yukon Energy in Whitehorse are provided from a Pembina Institute study [3]. Then the efficiency for heating oil systems is assumed to be 78%. Since 1998 Canadian regulations required oil furnaces to be at least 78% efficient, whereas in 2010 the regulations were updated such that oil furnaces must be 84 percent efficient [4]. It is assumed that the average oil furnace in Whitehorse is likely older, since most homes built after 2010 will be electrically heated. Thus the 78% number is used. A summary of the assumed efficiencies used to calculate GHG emissions is given in Table 7.

Table 7: Efficiencies assumed in GHG calculations.

Fuel type	Efficiency [%]
Diesel	41.6
LNG	46.3
Heating Oil	78.0

In a typical Yukon heating season, a reservoir of water is maintained to ensure adequate hydro generation throughout the winter and maintain the "baseline" shown in Figure 16. The hydro

resources are "budgeted" ahead of time so consistent hydro generation is maintained through the winter, with diesel and LNG making up the remainer of the power generated.

The steps taken to estimate the effects of ETS on GHG emissions are given in Figure 17.

The overall proportion of electric-based heating systems ETS are replacing is set. It is assumed that the total energy consumed by ETS systems is equivalent to the previous electric systems total energy consumption, however the times through the day and relative amount the system load is demanded changes.

Based on a "typical" profile of when and at what intensity a non-ETS electric heating system demands load, the underlying load profile is adjusted to account for the non-ETS electric heating systems being taken offline. The generation source being adjusted proceeds from diesel, to LNG, to hydro. If on a given hour of a given day it is estimated 5 MW of non-ETS electric load is being taken offline, and the generation during that time was recorded as 1 MW of diesel, 8 MW of LNG, and 50 MW of hydro, then the adjusted generation mix would be 0 MW of diesel, 4 MW of LNG, and 50 MW of hydro. Then it would be assumed the removed non-ETS electric load on that hour of that day would be 1 MW of diesel and 4 MW of LNG

The adjusted generation mix is then added with the estimated ETS load. The ETS load is added to the adjusted generation mix data by accounting for any hydro capacity, then LNG capacity, then diesel capacity. If on a given hour of a given day the adjusted generation mix capacity results in 0 MW of hydro capacity, 8 MW of LNG capacity, and 25 MW of diesel capacity, and the ETS load is 7 MW, the ETS contribution to generation mix is 0 MW of hydro, 7 MW of LNG, and 0 MW of diesel.

The GHG emissions calculated from the sum total of the non-ETS electric heating systems being replaced are contrasted with the GHG emissions calculated from the sum total of the ETS fleet's contributions to load. If the reduction in GHGs attributable to transitioning heating-oil based systems to ETS is accounted for, then the net change in GHG emissions from YEC is added to the reduction in GHGs following a given number of Whitehorsearea homes transitioning to ETS from heating oil systems.

Figure 17: Block diagram describing GHG calculation.

A critical assumption in Figure 17 relates to the distribution of non-ETS electric heating through the day. It is assumed that the non-ETS electric heating replaced by ETS has the same heating loads as the ETS system(s), but distributed differently through the day. For example, if an ETS home uses 24 kWh of electricity in a day then it is assumed it would have used 24 kWh of electricity if fitted with non-ETS electric heating systems. To determine how the non-ETS electric heating will be distributed existing data from the National Renewable Energy Laboratory (NREL) are used [5]. The NREL data are simulated from models of energy consumption estimated for the United States building stock. This data can be subset to extract energy consumption for electric heating, and then further subset to approximate a set of building stock representative of Whitehorse. The assumptions used to subset the data were climate zone and home type. In the contiguous United States, Colorado, Maine, Michigan, Minnesota, North Dakota, Wisconsin, and Wyoming contain areas with an equivalent climate zone to the Yukon, IECC climate zone 7 [6]. Data for these states were selected and then filtered by homes in climate zone 7. In the Yukon a plurality of electrically heated homes are single-family and detached [7]. Thus, the NREL data were further filtered by single-family detached homes. The normalized electric heat demand for the subset data across all seven states is given in Figure 18.



Figure 18: Normalized curves for electric heat.

The average curve shown by the thicker black line was used to estimate the distribution of non-ETS electric heating through the day.

An electric heat curve developed from Yukon data is also considered. Yukon Government's (YG) Energy Branch has developed models which can simulate a Yukon home's various energy consumptions, including for electric heating load. Yukon Energy Branch was able to simulate a years electric heating load for an anonymized Yukon home, comprised of two storeys and a basement with an electric furnace upgrade to the home [8]. A plot comparing the normalized NREL electric heat curve with the normalized YG curve is given in Figure 19. The YG electric heat curve was created by averaging the 25 highest heating load days in the simulated dataset. Changing the exact number of days the data was subset by did not substantially change the results of the normalized electric heating curve.



Figure 19: Comparison of NREL and YG electric heating curves.

The YG electric heating curve is flatter than the NREL curve, whereas the NREL curve is smoother with less abrupt variation. The NREL curve was normalized from data that used electric heat across multiple heater types, as well as single family detached homes, which comprise many different home builds. In contrast, the YG curve is based on a specific home type (two storeys and a basement) and a specific heater type (electric furnace). The NREL curve is more generalized. However, the YG curve is informed by real-life Yukon housing data, and may capture more of the variables specific to the Yukon such as occupant behaviour, building codes, and outdoor temperature. An analysis will be conducted with both NREL and YG electric heating curve data.

When calculating the GHG emissions, it is important to consider that Yukon Energy maintains hydro reservoirs during the heating season to ensure reliable hydro generation through the winter. All the hydro resources are "budgeted" ahead of time, which must be accounted for when calculating GHG emissions. When the calculated non-ETS electric load is subtracted from the generation mix data, it can subtract from the hydro resources. When the ETS load is added back to the adjusted generation mix data it may not account for a specific hourly hydro capacity since the times when non-ETS electric heating systems draw power and ETS systems draw power do not greatly overlap. This is also more likely to occur during so-called "shoulder seasons" surrounding winter temperatures when overall electricity demand may be lower and hydro resources may be greater, resulting in greater potential for hydro capacity. To account for this unused hydro capacity in the calculations, any unused hydro is subtracted from the ETS contributions to LNG and diesel generation, at a rate proportional to the amount of LNG and diesel usage observed in shoulder seasons. This rate was calculated at 68.5% for LNG and 31.5% for diesel.

3.3 RESULTS

3.3.1 GHG reductions without heating oil

Applying the methodology described in Section 3.1 to the data, GHG emissions associated with various penetrations of ETS and proportions of electric based heating replaced by ETS are given in Figure 20 for the 2020-2021 and 2021-2022 heating seasons. The 2020-2021 and 2021-2022 heating seasons are used since they are the only seasons from which diesel generation data is available in addition to LNG and hydro generation data. The total GHGs generated through LNG and diesel generation for the

2020-2021 and 2021-2022 heating seasons are 9504 T and 12309 T respectively, calculated from Yukon Energy data for diesel and LNG generation. The GHG additions or subtractions attributable to ETS are scaled by the calculated emissions for that heating season to more effectively illustrate the GHG impact of ETS. To find the estimated tons of GHGs subtracted or added by ETS, simply multiply the percentage in each cell by the total tonnage for that heating season. For example, a 2.5% subtraction during the 2021-2022 heating season is equivalent to 12309*0.025, or 308 T of GHG emissions.



(b) GHG impact on 2020-2021 heating season.

Figure 20: Estimated GHG impact for the (a) 2021-2022 heating season and (b) 2020-2021 heating season with NREL residential electric heating curve.

With an exception in the 2021-2022 heating season, all GHG reductions occur where between 90% and 100% of the replaced heating systems are electric. When over 20% of the replaced heating systems are non-electric then GHG contributions are observed. This is expected as ETS systems replacing non-electric heating systems are new contributions to the grid. The blank spots in Figure 20's grids are a function of the number of electrically heated homes in Whitehorse. According to the Yukon Bureau of Statistics, 21.7% of homes in the Yukon are heated electrically [7]. Since Whitehorse is by far the most populous city in the Yukon it is safely assumed that 21.7% of Whitehorse homes are electrically heated, such that certain combinations of ETS penetrations and electric heating

replacements are not possible. Figure 20 is recalculated with the YG residential electric heating curve shown in Figure 19.



Figure 21: Estimated GHG impact for the (a) 2021-2022 heating season and (b) 2020-2021 heating season with YG residential electric heating curve.

The results in Figure 21 are relatively close to what was plotted in Figure 20, however, marginally more GHGs are reduced with the YG electric heating curve. This is because the YG electric heating curve is flatter than the NREL curve, illustrated in Figure 19. Using the YG curve implies more electric heat being consumed through on-peak hours, and thus more electric power available to shift through ETS. Assuming electric heating patterns follow the YG curve instead of the NREL curve will result in more GHG reductions in the resulting simulations.

Figure 20 is re-calculated with a new set of ETS penetrations to explore the maximum possible GHG reductions, shown in Figure 22 as a proportion of total emissions for the heating season.



(b) GHG impact from 2020-2021 heating season.

Figure 22: Estimated GHG impact for the (a) 2021-2022 heating season and (b) 2020-2021 heating season for maximizing electric replacement by ETS with NREL residential electric heating curve.

The greatest reduction in GHGs occurs when ETS entirely replaced electric heating. In both Figure 22(a) and (b) the maximum GHG reduction occurs when 100% electric heating is replaced and 20% of Whitehorse dwellings have ETS heating, close to the 21.7% upper bound. During the 2020-2021 heating season a maximum of 5.76% of Yukon Energy power generation emissions could be reduced; during the 2021-2022 heating season a maximum of 4.05% of Yukon Energy power generation emissions could be reduced. Focusing ETS adoption among homeowners with electrically heated homes is the best approach to reduce GHGs on the utility side. Figure 22 is re-plotted with the YG electric heating curve in Figure 23.



Figure 23: Estimated GHG impact for the (a) 2021-2022 heating season and (b) 2020-2021 heating season for maximizing electric replacement by ETS with YG residential electric heating curve.

As before, comparing Figure 22and Figure 23 shows that using the YG electric heating curve results in greater GHG reductions. The maximum GHG reduction in Yukon Energy power generation emissions increase from 4.05% to 4.22% during the 2021-2022 heating season; the maximum GHG reduction in Yukon Energy power generation emissions increase from 5.76% to 6.09% during the 2020-2021 heating season.

3.3.2 GHG reductions including heating oil

Reductions in GHGs can occur when individual fossil-fuel heating systems offline are replaced with ETS. The GHG emission factor for heating oil is the same as diesel [2], and the same scaling factor calculated in equation (2) can be applied to energy consumption from fossil-fuel heaters. Then the efficiency factor described in Table 7 is used to account for the relative difference in efficiency between home heaters and utility-side generation. A large majority of fossil-fuel based homes in the ETS pilot project were fueled by heating oil. According to the Yukon Bureau of Statistics roughly 52% of Yukon homes were heated with heating oil. To account for the GHG emissions eliminated from replacing oil-based systems with ETS, the total energy used by ETS systems replacing non-electric heating systems is multiplied by the scaling factor given in equation (2) to arrive at a figure in tons of

GHGs. Like before the energy consumed by non-electric heating systems is assumed to be equivalent to the energy consumed by the installed ETS system(s). The change in GHG emissions from replacing oil-based heating with GHG is added to the change in GHG emissions due to the ETS fleet load, and then again divided by that heating season's GHG emissions as a result of power generation from Yukon Energy. Any increase in reductions from transitioning local fossil fuel heating to electric heating is not attributable to Yukon Energy of course, but keeping the same scale for calculating GHG reductions allows for easy comparison between Section 3.3.1 and Section 3.3.2. The results for the 2020-2021 and 2021-2022 heating seasons are presented in Figure 24.



(b) GHG impact from 2020-2021 heating season.

Figure 24: Estimated GHG impact for the (a) 2021-2022 heating season and (b) 2020-2021 heating season accounting for heating oil related GHG reductions with NREL residential electric heating curve.

When accounting for GHG reductions from local oil-based heating, there are greater net reductions in GHGs across both heating seasons. For both the 2020-2021 and 2021-2022 heating seasons, a greater number of non-electric heating could be transitioned to ETS while still resulting in GHG reductions. Figure 24 is re-plotted with the YG electric heating curve in Figure 25.



(b) 2020-2021 heating season.

Figure 25: Estimated GHG impact for the (a) 2021-2022 heating season and (b) 2020-2021 heating season accounting for heating oil related GHG reductions with YG residential electric heating curve.

As in Section 3.3.1, simulating with the YG residential electric heating curve results in a greater capacity for GHG reduction. The maximum GHG reduction from Yukon Energy power generation increases from 1.75% to 1.94% of heating season emissions in the 2021-2022 heating season; the maximum GHG reduction from Yukon Energy power generation increases from 3.11% to 3.47% in the 2020-2021 heating season.

In Section 4.3.2 it was determined that the ideal penetration of ETS to most flatten (and thus avoid secondary peaking) the grid load profile exists between 30% and 40% of Whitehorse homes adopting ETS. A heatmap for GHGs associated with between 30% and 40% ETS penetrations after accounting for heating oil system replacement is given in Figure 26.



(b) GHG impact from 2020-2021 heating season.

Figure 26: Change in GHG emissions accounting for heating oil related GHG reductions. ETS adoption rates are set to when overall grid load profile is flattest for (a) 2021-2022 and (b) 2020-2021 heating seasons with NREL residential electric heating curve.

There are only two instances across both heating seasons when there are net reductions in GHG emissions across the secondary-peaking-minimizing proportions of ETS adoption. Both reductions only occur during the 2020-2021 heating season in Figure 26 (b). Re-plotting Figure 26 with the YG residential electric heating curve gives improved results, shown in Figure 27.



(a) GHG impact from 2021-2022 heating season.



(b) GHG impact from 2020-2021 heating season.

Figure 27: Change in GHG emissions accounting for heating oil related GHG reductions. ETS adoption rates are set to when overall grid load profile is flattest for (a) 2021-2022 and (b) 2020-2021 heating seasons with YG residential electric heating curve.

When using the YG residential electric heating curve, there are now minimal reductions during the 2021-2022 heating season between 30% and 31% ETS penetration, the maximum GHG reduction in Yukon Energy power generation emissions during the 2020-2021 heating season increased from 1.02% to 1.41%. However, with either the NREL or the YG residential electric heating curves, GHG reductions are minimal within the 30% to 40% range that results in the flattest grid load profiles.

3.3.3 GHG reductions given all central heating and all space heating

The previous model used to generate simulated ETS fleet loads used all ETS systems. There is value in assessing the difference between the two major heating system types, space heaters and centralbased units. The ETS fleet load was partitioned into a fleet space heater load and a fleet central heater load. Then a regression model was fit using the same process described earlier for both space heaters and central heaters. These models were used to estimate GHG reductions as in Figure 26, with the ETS penetrations that result in the flattest grid load profile. Only the NREL curve is used in the following simulations, the YG residential electric heating curve will produce similar results to what was shown previously in Figure 27. The estimated GHG reductions for the 2020-2021 and 2021-2022 heating seasons for the space heater model is given in Figure 28.



(b) GHG impact for 2021-2022 heating season.

Figure 28: Change in GHG emissions accounting for heating oil related GHG reductions for purely space heater ETS implementation. ETS adoption rates are set to when overall grid load profile is flattest for (a) 2020-2021 and (b) 2021-2022 heating seasons.

Comparing Figure 28 with Figure 26 it is evident that the model fitted purely on space heater ETS units will produce greater GHG contributions than the model fitted with both space heaters and central heater ETS units.



The results for a purely central heater ETS implementation are given in Figure 29.

(a) GHG impact for 2020-2021 heating season



- Proportion of total GHG emissions [%]
- (b) GHG impact for 2021-2022 heating season.

Addit:

Figure 29: Change in GHG emissions accounting for heating oil related GHG reductions for purely central heater ETS implementation. ETS adoption rates are set to when overall grid load profile is flattest for (a) 2020-2021 and (b) 2021-2022 heating seasons.

Comparing Figure 29 and Figure 26, the central heater ETS implementation produces similar GHG contributions to the combined space heater and central heater model. The simulated ETS penetrations imply that space heaters will contribute more GHGs than central heaters, for an equivalent heating load. It is important to qualify these results. The models used for space heating and central heating were fit with fewer datapoints than the complete fleet load model which could result in less accurate results. Further, a high proportion of the Yukon's heating load being met solely by space heating is unrealistic. Only so much demand could be met with space heaters.

3.4 DISCUSSION

GHG emissions were able to be reduced under a multitude of scenarios. To estimate the emissions reductions, two residential electric heating curves were used: a curve derived from an NREL dataset of single-family detached homes, and a curve provided by YG of a Yukon residential home with an electric furnace upgrade. When considering emissions reductions entirely on the utility side, the maximum amount of GHGs that could be reduced using the NREL curve was between 492 T and 551 T of GHG emissions, equivalent to 4.0% and 5.8% of total emissions from utility power generation across the 2020-2021 and 2021-2022 heating seasons, illustrated in Figure 22. In contrast, the YG electric heating curve resulted in marginal improvements to GHG reductions across a heating season for Yukon Energy; a maximum reduction of between 505 T and 580 T of GHG emissions, equivalent to between 4.1% and 6.1% of Yukon Energy's power generation emissions across the 2020-2021 and 2021-2022 heating curves curred when 100% of the heating systems transitioned to ETS were electric based. The maximum level of ETS penetration that could be achieved across Whitehorse area homes while not contributing to GHG emissions was approximately 20%.

Transitioning fossil-fuel based heaters to ETS represents an entirely new load on the power grid and no GHG savings on the utility side. However, by accounting for local GHG emission reductions from

transitioning fossil fuel-based heating to ETS a more complete picture of potential GHG reductions can be created. By considering local fossil fuel-based reductions in GHGs, a far greater number of fossil-fuel based heating systems can be transitioned to ETS while still reducing overall GHG emissions. Accounting for local GHG reductions from fossil fuel-based heaters, the level of ETS penetration that can be achieved while still reducing GHGs is increased to between 25% and 30%, illustrated in Figure 24, Figure 25, Figure 26, and Figure 27. Whether the residential electric heating replaced by ETS is modeled by the NREL curve or the YG provided curve, the overall trend remains constant. As was shown in Section 4.3.2 the ideal penetration of ETS for peak shifting exists between 30% and 40% of Whitehorse area homes. In Figure 26 and Figure 27 it was evidenced that only a small proportion of GHGs could possibly be reduced, between 30% and 40% ETS penetration, using both the NREL and YG provided residential electric heating curves. Thus, maximizing GHG reductions while maximizing ETS peak shifting is not possible. A new model for ETS fleet load considering ETS space heating and ETS central heating independently was evaluated at the peak-shifting optimal range of between 30% and 40% ETS penetration. In Section 3.3.3 it was shown that the space heater ETS units had less potential to reduce GHG emissions than the central heater ETS units.

4 HOW EFFECTIVE ARE ETS UNITS AT REDUCING THE YUKON'S WINTER PEAK?

4.1 INTRODUCTION

A primary motivation for Electric Thermal Storage (ETS) adoption is the "shifting" of heat load that would otherwise be drawn during peak times to off-peak times. A possible downside to ETS is the introduction of a "secondary peak", when too many ETS systems are charging at an "off-peak" time a new peak may be created. Quantifying the peak shifting and reduction accomplished by the ETS pilot project is an important factor in judging overall ETS performance. Further, project data can be used to create projections for how future ETS implementations can affect peak load. Gaining insight into ETS effectiveness at reducing winter peaking is important so the impact of future ETS adoption is understood, and the resulting economic and environmental benefits can be estimated.

4.2 METHODOLOGY

ETS system data on power draw was gathered from online dashboards. The effects of the installed ETS systems in the demonstration project are first analyzed by comparing estimating the amount of load shifted from the peak before and after the ETS systems were installed. To quantify the amount of peak load that was reduced by the ETS fleet, the equivalent heating load pre-ETS must be estimated. This is because ETS replacements of fossil fuel systems represent an entirely new load on the grid and have no effect on what a pre-ETS Yukon load would look like, whereas ETS replacements of electric heating systems represent an opportunity for peak shifting. There were heat release data available for every ETS unit studied in the ETS demonstration project. However, using this data to accurately estimate an equivalent heating load proved challenging. There were intermittent data-quality issues with some of the ETS units' heat release data, and a reliable method to handle the inaccuracy could not be determined.

To estimate the non-ETS electric load the same approach is taken as explained in Section 3.1, where electric heating data from the National Energy Research Laboratory (NREL) models is averaged and normalized to create a general profile for electric heating for a day in a heating season. This data was subset by climate zone and home type to best approximate the conditions of the typical Yukon home in this demonstration project. The total ETS load for a particular day is multiplied by the general profile to create the estimate of non-ETS heating. The ETS power draw data was subset by those participants who had ETS installed to replace pre-existing electric heating. The data was then multiplied by the NREL average load profile. This NREL-scaled load profile is an estimate of what the replaced electric heating contributions may have looked like. Using the NREL-scaled profile can more accurately determine what effects, if any, ETS contributions to the grid can have on peak shifting. As discussed before in Section 3.1, the residential electric heating curve provided by Yukon Government (YG) is used to compare with the NREL curve. The YG residential electric heating curve was developed for a detached two-story Whitehorse home with an electric furnace. See Figure 19 for a visual comparison between the NREL and YG residential electric heating curves.

The regression model described in Section 1.2.3 was used to create simulated ETS contributions to the Yukon's grid. Potential ETS contributions were simulated with respect to the proportion of electric heating replaced by said ETS systems, and the proportion of overall adoption in the Whitehorse area. Data on the Yukon grid's power consumption from Yukon Energy was used to estimate the peak reductions and secondary peaking resulting from the simulated ETS contributions. This data was only available from 2018 through 2022.

4.3 RESULTS

4.3.1 2021-2022 and 2022-2023 Heating Seasons

The load on the Yukon grid can be compared with the ETS fleet load to identify hours of the day when the two generally overlapped. The data was subset to only include days where the average temperature was less than -15 °C when winter peaking was likely to be prevalent. Two series of boxplots are given in Figure 30 for Yukon Energy load and the ETS fleet load, where every observation in a boxplot is a normalized load for that hour of day. The load is normalized by scaling by the maximum load for that data series.



Figure 30: Comparison of Yukon Energy loads and ETS fleet loads by hour of day.

It is apparent that the ETS systems charged during the lower regions of the Yukon Energy load (2100-0500 hours and 1300-1500 hours). Two series of boxplots are given in Figure 31, representing the estimated pre-ETS home electric heating load and observed ETS heating load post-ETS.



Figure 31: Comparison of replaced ETS electric load and estimated electric load by hour of day across heating season with NREL residential electric heating curve.

The estimated home electric heating load is much flatter than the ETS load which replaces it. Heating loads are being shifted from peak times to off-peak times. The resulting plot using the YG residential electric heating curve is visually extremely similar to Figure 31, however the resulting electric load boxplot series is flatter than the NREL residential electric heating curve boxplot series. This is expected, as explained in Section 3.2.

The times for the 2021-2022 and 2022-2023 heating seasons Yukon Conservation Society (YCS) programmed as off-peak and on-peak, or charging and non-charging times respectively, are given in Table 8.

2021-2022 He	eating Season	2022-2023 He	eating Season
Off-peak (charging)	On-peak (charging)	Off-peak (charging)	On-peak (charging)
1000 – 1500 hours and	0600 – 0900 hours and	1000 – 1500 hours and	0600 – 0900 hours and
2100 – 0500 hours	1600 – 2000 hours	2100 – 0500 hours	1600 – 2000 hours

Table 8: YCS Charging periods for the 2021-2022 and 2022-2023 heating seasons.

The estimated pre-ETS electric heating load and the ETS fleet load are aggregated across the 2021-2022 and 2022-2023 heating seasons to provide an estimate of the total amount of hourly power draw shifted from on-peak to off-peak times. These aggregations are given in Table 9 with respect to the larger fleet with ETS replacing electric and fossil fuel systems.

Table 9: Total hourly energy during on-peak and off-peak hours pre and post ETS installation, estimated with the NREL residential electric heating curve.

	2021-2	022 Heating Sea	ason	2022-2023 Heating Season				
	Total pre-ETS energy	Total post- ETS energy	% Change	Total pre- ETS energy	Total post- ETS energy	% Change		
Off-peak	[MWh] 78.7	[MWh] 244.5	+211%	[MWh] 105.5	[MWh] 327.6	+211%		
On-peak	52.9	33.4	-37%	62.1	55.0	-11%		

For the 2021-2022 heating season, the amount of energy drawn during off-peak times increased by approximately 166 MWh whereas the amount of energy drawn during on-peak times decreased by approximately 19 MWh. Divided by the number of days in the heating season and the length of time of an average peak, the winter peak was reduced by an average of 0.0127 MW or 12.7 kW. For the 2022-2023 heating season, the off-peak energy consumption increased by approximately 222 MWh whereas the amount of energy consumed during on-peak times decreased by approximately 7 MWh. Divided by the number of days in the heating season this resulted in the winter peak being reduced by an average of 0.0047 MW or 4.7 kW. The large discrepancy between on-peak reductions and off-peak contributions is due to the fossil fuel replaced ETS representing new load on the grid. The amount of power drawn by the electric replaced ETS systems was a smaller proportion of the overall ETS fleet's power draw. In other words, the amount of ETS systems installed replaced far more heat load that was previously met by fossil fuel systems than electric systems.

When recalculating the results in Table 9 with the YG residential electric heating curve, the post-ETS energy drawn remains the same whereas the flatter YG curve provides different results for the pre-ETS energy draw. During the 2021-2022 heating season, the pre-ETS off-peak power draw for the studied homes is estimated to decrease from 78.7 MWh to 73.8 MWh, the post-ETS on-peak power draw increases from 52.9 MWh to 57.8 MWh. During the 2022-2023 heating season, the pre-ETS off-peak power draw increases for the studied homes is estimated to decrease from 105.5 MWh to 100.6 MWh, the pre-ETS on-peak power draw increases from 62.1 MWh to 66.9 MWh. Using the YG residential electric heating curve provides marginally superior results as an additional 4.9 MWh is estimated to have been reduced from the on-peak times during the 2021-2022 heating season, and 4.8 MWh reduced from on-peak times during the 2022-2023 heating season. The average winter peak reduction for the 2021-2022 heating season increases from 12.7 kW to 16.0 kW. The average winter peak reduction for the 2022-2023 heating season increases from 4.7 kW to 8.0 kW.

The results in Table 9 are subset to only include those homes with electric heat installed that the ETS systems later replaced. This provides a clearer picture of how the load demanded by electrified heating can be shifted by ETS, without including new contributions to the grid from electrifying fossil fuel-based heating.

	2021-2	022 Heating Sea	ason	2022-2023 Heating Season				
	Total pre-ETS	Total post-	% Change	Total pre-	Total post-	% Change		
	energy	ETS energy		ETS energy	ETS energy			
	[MWh]	[MWh]		[MWh]	[MWh]			
Off-peak	78.7	115.1	+46%	105.5	142.5	+35%		
On-peak	52.9	16.5	-69%	62.1	25.1	-60%		

Table 10: Total hourly energy during on-peak and off-peak hours pre and post ETS installation with homes that had electric heat installed, estimated with the NREL residential electric heating curve.

The results for the 2021-2022 and 2022-2023 heating seasons remain unchanged from Table 9 to Table 10 in the pre-ETS column. This is because the fossil-fuel heating systems replaced by ETS had no effect on the pre-existing load, so removing them from the analysis changes nothing. The amount of energy consumed during off-peak hours increased by 46% and 35% during the 2021-2022 and 2022-2023 heating

seasons among participants with electric heat pre-ETS. In contrast, the amount of energy consumed during on-peak hours decreased by 69% and 60% during the 2021-2022 and 2022-2023 heating seasons respectively.

Employing the YG residential electric heating curve to re-calculate Table 10 gives minor changes to the results. The pre-ETS off-peak energy consumption decreases from 78.7 MWh to 73.8 MWh during the 2021-2022 heating season, and during the 2022-2023 heating season it decreases from 105.5 MWh to 100.6 MWh. The pre-ETS on-peak energy consumption increases from 52.9 MWh to 57.8 MWh during the 2021-2022 heating season, and during the 2022-2023 heating season it increases from 62.1 MWh to 66.9 MWh. Using the YG residential electric heating curve implies more energy is shifted from on-peak periods by the ETS units that replaced pre-existing electric heating.

The results in Table 9 are recalculated based on the assumption that 100% of ETS in the 2021-2022 heating season replaced pre-existing electric heating.

Table 11: Total hourly energy during on-peak and off-peak hours pre and post ETS installation assuming 100% of replaced heating systems are electric, estimated with the NREL residential electric heating curve.

	2021-2	022 Heating Seas	son	2022-2	eason	
	Total pre-ETS	Total post-ETS	% Change	Total pre-	Total post-	% Change
	energy	energy		ETS energy	ETS energy	
	[MWh]	[MWh]		[MWh]	[MWh]	
Off-peak	166.2	244.5	+47%	238.8	327.6	+37%
On-peak	111.7	33.4	-70%	140.6	55.0	-61%

Assuming that the demonstration project's installed ETS replaced 100% electric heating systems, the estimated peak reduction for the 2021-2022 heating season is approximately 78 MWh, or an average of 52.3 kW per day through the heating season. For the 2022-2023 heating season, the peak could have been reduced by approximately 85 MWh, or an average of 57.0 kW per day.

As before, using the YG residential electric heating curve provides superior results. During the 2021-2022 heating season, the pre-ETS off-peak power draw for the studied homes is estimated to decrease from 166.2 MWh to 155.8 MWh, the pre-ETS on-peak power draw increases from 111.7 MWh to 122.1 MWh. During the 2022-2023 heating season, the pre-ETS off-peak power draw for the studied homes is estimated to decrease from 238.8 MWh to 227.9 MWh, the post-ETS on-peak power draw increases from 140.6 MWh to 151.5 MWh. During the 2021-2022 heating season an additional 10.4 MWh are shifted from on-peak times, and during the 2022-2023 heating season an additional 10.9 MWh are shifted from on-peak times. This results in an increase in average peak reductions of 59.3 kW and 64.3 kW for the 2021-2022 and 2022-2023 heating seasons respectively.

The potential peak reductions for highest peak demand days of the 2020-2021 heating season were calculated in Table 12, again assuming 100% of ETS systems replaced existing electric heating. The maximum difference between pre and post-ETS grid loads for the highest peak demand days were calculated. The peak load days were determined as days when the Yukon Energy grid load exceeded 100 MW.

Date	Maximum peak	Proportion of peak	Temperature (°C)	Number
	reduction [kW] – {NREL	reduction of Yukon		of Homes
	electric heating curve,	Energy grid load [%]		
	YG electric heating			
	curve}			
2021-12-13	{133, 131}	0.12	-24.9	34
2021-12-16	{147, 145}	0.13	-27.3	34
2022-01-03	{146, 143}	0.13	-28.2	34
2022-01-04	{173, 167}	0.16	-33.8	34
2022-01-05	{198, 194}	0.18	-40.7	34
2022-01-06	{193, 191}	0.18	-40.7	34
2022-01-07	{212, 213}	0.21	-31.4	34
2022-01-08	{199 <i>,</i> 195}	0.19	-40.2	34
2022-01-09	{182, 178}	0.18	-30.3	34
2022-11-30	{143, 142}	0.14	-25.3	47
2022-12-18	{194, 191}	0.18	-32.6	47
2022-12-19	{171, 170}	0.15	-38.2	47
2022-12-20	{125, 122}	0.11	-38.4	47
2022-12-21	{315, 315}	0.29	-33.1	47
2022-12-22	{182, 182}	0.17	-28.3	47
2022-12-23	{169, 166}	0.16	-30.1	47
2022-12-24	{165, 162}	0.16	-28.5	47

Table 12: Maximum potential peak reductions for 2021-2022 and 2022-2023 heating seasons.

Overall, the results using the YG and NREL residential electric heating curves are quite similar. The maximum possible peak reduction from the ETS demonstration project on a peak load day was 315 kW, representing 0.29% of the overall Yukon Energy grid load, estimated with the YG residential electric heating curve. The average peak reduction estimated with the NREL curve on a peak demand day was 177 kW. The average peak reduction with the YG curve was also 177 kW. The project's total installed maximum draw was 689 kW with a total storage capacity of 4133 kWh across 45 participating homes with a total heat load of 396 kW. From this, a maximum observed peak reduction of 315 kW was achieved.

For the remainder of Section 4.3.1 only the NREL curve will be used in the calculation of results. The change in the results is small enough to not warrant the inclusion of additional analysis for this section.

The capacity for peak shifting can be broken down to a day-by-day resolution. Assuming that 100% of the installed ETS systems replace electric heating, the capacity of the ETS fleet for peak reduction is plotted against temperature in Figure 32.



Figure 32: Reductions in on-peak energy consumption by outdoor temperature for the 2021-2022 heating season (a) and 2022-2023 heating season (b).

There is a general negative trend in both the 2021-2022 and 2022-2023 heating seasons between outdoor temperature and the daily reductions in on-peak energy consumption. As temperatures decrease, the energy consumption during peak hours also decreases. The effect of outdoor temperature on the daily peak load can also be analyzed through boxplots capturing the variation in daily peak load reductions with respect to temperature. These results are presented in Figure 33.



Figure 33: Reductions in peak load by outdoor temperature for the 2021-2022 heating season (a) and 2022-2023 heating season (b).

As with the energy consumption shown in Figure 32, there is a broad negative relationship between outdoor temperature and reductions in peak load. As temperatures decrease, the amount of load that can be reduced from the peak increases. The relatively lower reductions seen in the coldest temperature bin are due to few data points being available for extreme cold temperatures.

The capacity for peak reduction can also be analyzed with respect to ETS unit sizing. Units with more capacity would be expected to be capable of greater peak shifting. This result is shown in Figure 34.



Figure 34: Reductions in on-peak energy consumption by storage capacity of ETS unit for 2021-2022 heating season (a) and 2022-2023 heating season (b).

The storage capacity of the ETS units is positively correlated with the amount of energy reduced from peaks, which is unsurprising. The relationship between ETS storage capacity and peak reduction is presented in Figure 35.



Figure 35: Reductions in peak load by storage capacity of ETS unit for 2021-2022 heating season (a) and 2022-2023 heating season (b).

The larger the ETS system, the greater the potential for peak reduction.

4.3.2 Simulated Loads

Using the regression model for ETS, ETS fleet loads can be simulated. These simulated ETS fleet loads can then be added to the Yukon's overall load to provide insight into how the winter peak may be affected by ETS adoptions. As was shown in Section 3.2, the NREL average electric load profile can be used to account for the proportion of electric heating ETS is replacing. The estimated non-ETS electric load is first subtracted from the Yukon Energy grid load, then the simulated ETS load is added.

A heatmap of the reduction in power draw during peak-times before and after simulated ETS contributions for the 2020-2021 heating season is given in Figure 36. The y-axis is given as the proportion of electric heating replaced, in other words what percentage of the simulated ETS contribution is replacing electric-based heating systems. A value of 80% on the y-axis would mean 80% of the simulated ETS load replaces electric heating and 20% replaces fossil fuel heating. This would mean 20% of the simulated ETS contribution are new loads on the grid.

Proportion of electric heating replaced [9 optimized 532335	0.08 0.07 0.05 0.05 0.05 0.03 0.03 0.02 0.02 0.02 0.02 0.01 0 0 0 0	8 49 0.16 0.14 0.12 0.1 0.08 0.06 0.06 0.02 0 -0.02	4 46 11.42 12.28 0.24 0.15 0.15 0.12 0.03 -0.01 -0.05	0.72 0.50 0.48 0.39 0.31 0.23 0.15 0.07 -0.01 -0.1	nn n. 10 0.90 0.76 0.57 0.37 0.17 -0.01 0.24	1 14 0 74 0.52 0.08 -0.08 -0.46
C	1.1	4.9		10	25	5()

Mean on-peak hourly power draw change [MW]

(a) Calculated with NREL residential electric heat curve.

LL				100	200	
20 01	-0.01	-0.02	-0.05	-0.1	-0.24	-0.48
0 0 10.	a	0	0	0.01	-0.02	-0.04
0 5 20.	0,01	0.02	0.04	B0.0	0,2	0,4
E CD 10	0.02	0.04	0.09	0.17	0.42	0.85
6 4 40-	0.03	0.07	0.10	0.26	0.65	1.29
E 8 501	0.04	0.09	0.19	0.35	0.87	
5 8 004	0.05	0.11	0.22	0.44	7.09	
00 /0-	D IIN	0.14	0.27	0.53	1.91	
P & 80.4	0.07	10 TH	0.37	0.62	4.54	
U	0.08	0.18	0.36	0.71		
5 8 100	0.09	0.24	0.4	0.0		

Proportion of total Whitehorse dwellings with ETS [%]

Mean on-peak hourly power draw change [MW]

(b) Calculated with YG residential electric heat curve.

Figure 36: Change in total average hourly power draw consumed during peak times before and after simulated ETS contributions for 2020-2021 heating season with NREL (a) and YG (b) residential electric heat curves.

Negative values in Figure 36 imply increased average hourly power draw during peak times after an ETS implementation, whereas positive values imply decreased average hourly power draw during peak times. Unsurprisingly the negative values occur when the proportion of electric heating ETS is replacing is lowest, between 0% and 10%. This is because between 90% and 100% of the simulated ETS load are new contributions to the grid, replacing fossil fuel systems instead of electric systems. The blank grid areas in Figure 36 represent combinations of ETS penetration and replaced electric heating which are not feasible, as there are a finite number of homes heated by electricity in the Whitehorse area and only so many can be transitioned to ETS heating. See Section 3.1 for more details. The greatest reduction in on-peak energy occurs across 25% of Whitehorse dwellings and 80% of the systems replaced are electric-based. When using the YG residential electric heating curve there is a marginally greater average decrease in hourly power draw.

However, this analysis does not account for secondary peaking. The more ETS load that is added to the grid the higher the likelihood of secondary peaking occurring. There is a threshold where the enough load is added to off-peak times and reduced from on-peak times that new peaks during the formerly "off-peak"

times are created. A heatmap with the same parameters as Figure 36 is plotted in Figure 37, where each cell represents the number of days in the heating season when off-peak times have greater mean power draw than on-peak times after the simulated ETS implementation.



Figure 37: Number of days secondary peaking occurs through 2020-2021 heating season using the NREL electric heat curve.

It is evident that secondary peaking only becomes problematic when 25% or greater of Whitehorse homes have ETS. The single day of secondary peaking that occurs at 10% or fewer Whitehorse homes with ETS is due to the underlying Yukon Energy load profile where for whatever reason a day eschewed the normal patterns for on-peak and off-peak times, which correspond to the charging and non-charging times for the ETS units. Comparing Figure 36 and Figure 37 it is apparent that the maximum reduction in on-peak power while avoiding secondary peaking occurs between 10% and 25% of Whitehorse homes having ETS installed. The YG residential electric heat curve gives the exact same results as shown in Figure 37. To identify the optimal proportion of overall ETS adoption and electric replacement Figure 36 and Figure 37 are re-plotted with adoption rates between 10% and 25% in Figure 38.

roportion of electric leating replaced [%]	1000 BOD 500 B	0.72 0.56 0.46 0.39 0.23 0.23 0.23 0.07 -0.01	D 79 D 7 D 81 0.62 0.43 0.52 0.43 0.25 0.16 0.07 0.02 -0.11	0 86 0.77 0.57 0.57 0.37 0.28 0.08 0.02 -0.12	0.93 0.72 0.62 0.51 0.3 0.09 0.09 0.02 0.13	1.01 0.66 0.55 0.44 0.02 0.09 0.02 0.02	1.08 0.83 0.71 0.59 0.47 0.34 0.22 0.1 -0.02 -0.14	1.15 0.89 0.65 0.55 0.37 0.24 0.02 0.10	1 22 1 08 0 81 0 67 0 53 0 39 0 25 0 11 -0 00 -0.16	+ 29 1 1 - 0.85 0.56 0.41 0.037 0.017	1.36 1.25 0.74 0.74 0.74 0.74 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.0	1 13 1 27 1.11 0.95 0.78 0.62 0.46 0.3 0.13 -0.03 -0.19	10-10-0085 0.48 0.03 0.48 0.03 0.48 0.03 0.48 0.03 0.42	1,22 1,04 0,86 0,5 0,5 0,5 0,5 0,5 0,5 0,5 0,5 0,5 0,5	1709 07134 000 000 000 000 000 000 000 000 000 0	1 DAT 1 134 0 54 0 55 0 16 0 04 -0.23	1.18 0.98 0.78 0.57 0.37 0.04 0.24
u.+		10.	.41	12	73	14	18	16	17	18	Ţ0	30	23	12	23	24	25
					Pro	portic	m of t	otal W	hiteho	rse du	velling	is with	ETS	[%]			
			(a)	Me: Chan	an on- ge in ł	peak nourly	powe	powe	er drav w duri	r chan ng on•	ge (M -peak	W] durinį	g on-p	eak h	ours.		
Proportion of electric heating replaced [%]	10-1-1-1-1-1-1-1-1-1-1-1-1-1-1-1-1-1-1-							000000000000	0000777777	7777772680	a mag 9 0000000	12270144444444	222222222222222	222444444444	SECONDER SECONDER	11111255555555	山南市市 · · · · · · · · · · · · · · · · · ·
ar		10	31	12	1.1	11	15	16	- 17	15	19	50	21	22	23	24	25
					Pro	portic	on of th	otal W	hiteho	irse di	velling	is with	ETS	[%]			

Number of days secondary peaking occurs

(b) Number of days secondary peaking occurs after ETS implementation.

Figure 38: Change in total average hourly power drawn during on-peak hours after simulated ETS implementations (a) and number of days secondary peaking occurs after ETS implementation (b) using the NREL residential electric heating curve.

From Figure 38(b) secondary peaking begins to occur at 14% adoption of ETS in Whitehorse. From Figure 38(a), the maximum total hourly average power reduced from on-peak times without secondary peaking is 1.01 MW. To find the change of the Yukon grid's average daily peak with an ETS implementation compared to the Yukon grid without widespread ETS implementation, the maximum total hourly average power reduction was divided by the number of days in the heating season (213).

The Yukon Energy data for the Yukon grid's load from 2018-2022 is used to show the effects of simulated ETS implementations across multiple heating seasons. The mean reduction in peaks is calculated from the simulated ETS loads as before, but then averaged across the heating season to get a daily mean reduction in peaks. A heatmap showing the effects on the average daily peak for the heating seasons between 2018-2022 is given in Figure 39, with each heating season given in a separate subplot. The NREL residential electric heating curve is used. Only cells where secondary peaking does not occur are shown, and the number of Whitehorse dwellings used to determine the proportion of ETS in Whitehorse dwellings changes to accommodate the Yukon's increasing number of dwellings from 2018-2022.

_						2	
0-	-0.01	0.02	17.07	0.07	-0.64	0.05	-0.05
10-	0	U.	0	9	0	-2	6
20 -	0.05	0.62	19.152	1710.8	13.04	0.04	0.05
30 -	0.02	0.63	0.04	0.00	0.67	0.00	1.8.8-
30 -	0.07	0.00	10.000	0.00	0.11	4.11	0.0
50-	0.03	0.00	10.476	0.14	8.15	0.10	0.45
80 -	0.04	0.00	5.0	0.45	0.10	0.21	0.20
70-	0.05	0.09	6.0	0.16	8.99	5.85	0,45
80.	9.06	0.17	D.16	024	0.2%	2.33	þ.=
90	79 C PL	0.12	0.18	0.24	-0.	0.00	60
00 -	0.07	0.44	19.4	11.27	(9340)	8.4	8.40

Proportion of total Whitehorse dwellings with ETS [%]

Mean change in daily peaks [MW]

(a) 2018-2019 heating season.

10.		0	0	U -	2	0.01	0.01	0.07
20.	0.01	0.01	0.02	0.03	0.01	0.04	0.05	0.05
30 -	0.02	0.03	0.05	10.06	0.07	0.00	6.1	0.12
40-	a (2)	0.05	70.02	0.00	. D	41.24	10.76	0.16
60-	0.00	00.00	2.09	0.42	0.16	0.10	0.21	0.24
60 -	22.04	9.09	17,97	0,15-	0.19	0.23	0.37	0,51
70	0.05	1.0	0.94	0.70	0.73	0.28	0.02	0.77
30 -	10.01	0.75	0.90	0.72	6.87	78.0	0.10	0.6%
90-	10,02	4,00	3.49	0,22	17.51	0,57	0.44	13,110
100	0.04	0.14	0.21	0.26	0.35	.0.112	0,40	0,00

Proportion of total Whitehorse dwellings with ETS [%]

Mean change in daily peaks [MW]

(b) 2019-2020 heating season.

		1.1	2	3	4	5	6	7	8	8	10	11	12	13
0 f	01	0.01	0.02	ans	-0.03	0.05	-0.04	10.07	0.08	0.09	4.0-	HB-TC	0.12	-0:10
2 3	10.	D-	0.	U.	-0.61	0.01	0.01	0,01	0.04	0.01	-0.05	10.02	0.02	0.02
8분	20 -	0.01	0.01	0.02	0.00	0.03	0.04	0.05	0.05	0.06	0.07	0.07	0.68	0.00
the Be	30 -	0.021	0.05	0.00	0.00	0.0t	0.08	0.1	0.12	0.18	0.15	-10.16	0.19	0.10
0 4	-50	0.03	0.98	w.07	0.00	30.02	8 14	6.00	0.10	871	0.23	0.26	0.28	63
E G	50-	10.03	0.07	.0.1	0.13	0.18	0.19	0.22	0.20	0.78	0.31	17.04	0.32	0.4
a of	60 -	10.04	0.06	4),32	0.05	2.0	12.23	0.20	0.22	0.95-	9.00	10.4/	U.AT.	0.65
00	70	0.05	0.1	015	0.16	534	0,79	0.55	0.56	a.+3	0.48	17.65	167	0.87
00	30 -	0.05	4.12	10.77	0.75	12.24	0.34	.0.90	-G 45	.00	0.00	10.01	0.67	0.77
50	90-	11,91	9.14	0.2	0.20	12.42	99.00	10.45	0.55	17.00	31.54	A.M.	1.977	348.8
22	100	9.05	0.10	0.22	0.20	20.56	19.0	0.01	0.4	0.05	4.12	0.17	0.08	DUD

Proportion of total Whitehorse dwellings with ETS [%]

Mean change in daily peaks [MW]

(c) 2020-2021 heating season.
	-	2	3	4	ġ.	6	7	8	0	10
0-	-0.01	-2.04	-0.04	-0.64	0.00	0.05	-0.05	-0.00	-0.00	-0.02
10-	- 49.	9.	- Ór -	0	9.401	0.01	0.01	0.01	0.01	0.01
20 -	.0.03	0.62	0(3757	0,07	0.404	42.6	0.85	0.05	0.07	10.07
30	0.02	0.63	D Del	0.00	OTH	01	10.17	0.13	0.14	0.16
40 -	0.00	-0-0E	0.07	-0.1	0.99	0.10	0.17-	0.10	.0 22	0.24
50 -	-0,04	9.02	0.3	6,53	D.7/	0.2	0.25	028	,0.29	Ú. 33
80 -	0.05	0.01	0.58	9.17	0.23	0.28	0.20	0.30	0.77	3.41
70 -	0.05	20.1	0.18	0,2	0.35	0.0	0.05	1.6	,0.75	12.40
SQ -	0.04	0.13	0.18	9.25	9,29	0.15	16.0	-9.44	11:52	0 pā
90	9.07	0.14	- 64	11,227	101	20.4	- 0.91	at and	-0.10	0,40
100 -	0.04	1.08	0.11	10.5	100	TAR.	0.84	-15	11.07	1910h

Mean change in daily peaks [MW]

(d) 2021-2022 heating season.

Figure 39: Mean change in daily peaks for (a) 2018-2019 heating season, (b) 2019-2020 heating season, (c) 2020-2021 heating season, (d) 2021-2022 heating season using the NREL residential electric heating curve. Only cells where secondary peaking does not occur are shown.

There is variability across the heating seasons in the maximum proportion of Whitehorse dwellings with ETS the grid will accept before secondary peaking starts to occur. The maximum proportion of ETS while allowing for no secondary peaking occurs in the 2020-2021 heating season (13%) whereas the minimum occurs during the 2018-2019 heating season (7%). Considering the minimum level of ETS penetration where secondary peaking does not occur across all heating seasons, an average of between of 0.47 MW and 0.53 MW can be reduced from daily peaks throughout a heating season. The maximum that could be reduced from the average daily peaks across all heating seasons was 0.93 MW. It is important to note that these peak reductions are observed when 100% of the heating systems ETS replaces are assumed to be electric. Reductions in the daily peaks across all heating seasons begin to occur when 20% or more of the heating replaced by ETS is electric.

The results in Figure 39 are re-calculated for the YG residential electric heating curve, shown in Figure 40. As before, the flatter YG residential heating curve is expected to provide marginally better results than the results calculated with the NREL curve in Figure 39.

01	-0.01	4.00	-1002		-0.04	0.05	0.05
10		100	10.00	N. Cont		A.m.	
10-	- Ö		0		11	-0	
20 -	0.05	0.62	THE:	17.644	13.04	0.05	0.50
30 .	0.02	0.63	0.68	0.07	10.08	0.7	0.15
40 •	6.03	0.00	0.08	0.0.1	10.53	0.15	0,77
50 1	0.04	0.407	0.1	0:10	0.42	-02	0.03
80 -	.0.04	0.00	0.15	0.07	02.	9329	D.mm
10.	0.05	10.1	0.05	n 9	025	11	0.10
30.	9.06	0.40	0.17	0.24	0.95	11.15	0.8
90 *	0.07	0,13	02	0.20	0.53	0.39	(DOM)
00 1	0.00	0.10	2.22	.0.0	0.60	1.14	2.27

Proportion of total Whitehorse dwellings with ETS [%]

Mean change in daily peaks [MW]

(a) 2018-2019 heating season.

	1	2	4	1	1	E.	7	
0-	-0.01	-0,052	-0.05	-0.64	-0.0+	0,05	-0.06	-0.07
10-	0	0	0	0	0	U .		Q.,
20 -	20.02	2.00	0.00	0.03	0.446	V.05	0.00	0.07
30 -	0.02	0.04	3.08	0.07	0.08	6.5	34.0	0.5%
40 -	2.03	12,000	0.09	0.4	0.13	0.40	0.10	0.2
50 -	2.94	10.07	0,0	1.94	0.57	02	0.24	380
80 -	10.05	0.00	0.15	0.47	- C211	0.2%	0.2	0.24
70-	0.05	HAC.	0.16	0.21	0,96	11,37	0.96	0,AC
80-	9.01	9.12	0,10	0.34	0.1	10.200	10.42	0.48
-90	10.07	0.14	0.21	0.20	10246	0.61	0.84	0.00
100 -	10.09	0.10	0.23	10.01	0,89	0.46	0.00	0.01

Mean change in daily peaks [MW]

(b) 2019-2020 heating season.

					in a set	in all in	I LATE SI	ali sera d	all milles		CTO IN	1.1		
		1	2	3	4.	5	6	7	8	ġ.	80	ti .	12	13
a f	01	0.01	0.02	-072	-0.04	0.05	-0.04	-D-UT	0.08	0.09	4.0-	10.11	4.42	-9/14
6 9	10-	. D-	0	U.	17	0	- 10	0	0.01	0.01	-0.01	0.01	0.01	-0.61
영물	20 -	0.01	0.07	0.53	0.03	0.04	0.05	0.00	0.07	0.07	9.06	0.00	0.1	0.15
EB	30 -	20.07	0.04	0.06	0.07	0.09	.6.1	0.12	0.14	0.16	0.17	-10 10	0.27	6.28
0 4	40	0.68	0.00	W-081	0.94	51.0	3.96	0.16	021	875	0.50	11.20	0.91	0.64
Ede	60-	20.04	0.07	.0.01	0.19	D.1E	0.21	0,23	.0.20	0032	0.33	79.507	0.42	0.45
a of	60-	11.05	0.057	436	0,10	0.23	1.27	94.0	12.26	04	10,44	10.40	0.65	6.67
ΦÖ	70 -	0.0E	0.11	0.945	0.21	0.07	0.10	0.97	0.40	0.46	0.07	0.55	0.62	0.69
a p	90 -	0.07	46.19	0.09	0.25	D'TT U	2.07	0.43	6.8	0730	30.00/6	0.08	5 / 4	0.6
35	90-	11,56	9.55	0.22	1.29	1.00	940	0.0	.8.97	0,54	0,00	0.0	1.0.85	0.02
22	100-	0.05	0.17	0.24	0.12	0.4	0.40	.0.24	106	6.72	0.0	0.00	0.90	1.92

Proportion of total Whitehorse dwellings with ETS [%]

Mean change in daily peaks [MW]

(c) 2020-2021 heating season.

100	1	ż	3	4	5	6	7	8	ġ.	ΠÔ
0-	10.01	56.0	-0.09	-0.04	0.05	-0.05	-0.07	-D @K	-0.04	0,09
10-	70	0	4	U	0	0	-0-	0	0	U.
20 -	0.01	0.62	0.03	0.04	0.255	30.0	0.02	0.07	0.08	51.09
30 -	0.01	0.04	0.00	2.07	0.09	10.31	69.55	0.18	8.56	15.10
40	3.00	-2.08	9.70	0.51	0.14	0.67.	10 119	0.2	0.90	D 27
50-	-0.04	0.000	10.11	0,10	0.19	0.22	0.20	0.29	0.35	0.17
60 -	0.45	2.1	47.94	0,10	021	0.05	6.32	0.01	10.05	0,70
70 -	0.06	0.15	0,17	0.22	0.25	6.0	0,10	0.34	DS	9.70
30 -	2.07	0 13	02	0.26	0.117	0.99	6.65	0.51	0.64	0.60
90-	0.08	0.18	0.23	(0,3	5.91	-0.46	0.52	0,58	1168	1.18
100	0.09	0.17	0.2	0.34	041	0.5	0.50	0.65	1471	0.33

Proportion of total Whitehorse dwellings with ETS [%]

Mean change in daily peaks [MW]

(d) 2021-2022 heating season.

Figure 40: Mean change in daily peaks for (a) 2018-2019 heating season, (b) 2019-2020 heating season, (c) 2020-2021 heating season, (d) 2021-2022 heating season using the YG residential electric heating curve. Only cells where secondary peaking does not occur are shown.

The results across all four heating seasons are improved when estimated with the YG residential electric heating curve. Estimating the mean change in daily peaks with the YG curve gave an increase in average

reductions of 0.048 MW. The largest average daily peak reduction estimated with the NREL curve was 0.93 MW at 13% ETS penetration and 100% of electric heating replaced during the 2020-2021 heating season; the largest reduction with the YG curve increased to 1.03 MW with the same parameters. Comparing Figure 39 and Figure 40, there are marginal improvements to the peak daily load reduction when estimated with the YG residential electric power curve across all heating seasons.

The plots in Figure 39 are re-created for the peak load day for each heating season. At the hour of peak loading on the Yukon grid, the amount of peak load that could be reduced through ETS is calculated. Once again only the penetrations of ETS in Whitehorse that do not result in secondary peaking are considered. The results for the peak load reductions are shown in Figure 41.

						14-	
0.	0.07	9 .17	-0.11	0.16	2016	-0.25	27
10-	201	0.03	0.05	70.07	0,1	-0.42	-0.14
20+	1.55	0.01	19.011		0	-12.009	30.60
30 -	0.04	0.000	12.07	0.08	10:09	0.1	0.12
30 -	6.06	0.00	10.11	07.0	17.19	0.75	03,05
50 1	0.04	0.04	0.94	0.225	11.21	11 JJ	0.77
80-	0.11	0.14	32.34	97.0	10.37	0.04	1.02
70 -	0.13	0.89	15.8	0.98	19.47	0.55	0.0.5
80	ú té	0.29	20.10	0.40	Nđã	0.46	\$C (3)
.90/4	30 TW	10.0	7.42	0.54	8.45	0.77	628
100 -	0.01	0.64	10.411	0.61	8,75	56-00	1.02

Proportion of total Whitehorse dwellings with ETS [%]

Reduction in Peak Load [MW]

(a) 2018-2019 heating season.

	1	2	3	4	5	6	7	8
0.+	10.04	-4/01	0.13	40.57	-0-25	-0.7/	22	10.3
10-	17:02	4//05	10,0%	0:12	0.15	-0:19	0(22	-2.23
20 -	.0	.0.07	10.01	-0.07	-0.08	47.11	0.93	-0.45
30 -	10.04	0	0	-0.010	-0.07	-0.05	-0.74	-070
40.	0.00	7.93	0.04	0.04	D-Alm	ALCON.	- 9.00	10.00
100 -	3.62	2.00	-17.41H	2.09	.D.AT	0.42	0.54	0.50
60	17.1 %	9.09	30.87	0,45-	11.17	0,0	0.95	0,96
70	9.06	0.42	0.10	0.7	0.76	0.205	0.00	0.36
90 -	0.7	2.05	0.7	9.05-	0.71	0.00	94.0	0.48
90-	0.12	11, 114	0.24	40,04	1.0.47	0.54	A.G.	0,60
100-	0.63	0.21	0.20	0.90	(CAL	0.51	0,60	0.6.2

Reduction in Peak Load [MW]

(b) 2019-2020 heating season.

Proportion of electric heating replaced [%]	0.55 0.55 0.5 0.05 0.05 0.05 0.05 0.05		2 = 4 1 = 1 = 1 = 1 = 1 = 1 = 1 = 1 = 1 = 1 =	0.25 0.26 0.24 0.16 0.16 0.07 0.01 -0.05 -7.11 0.16 -0.70	(c) 202	20-2021 041 0 55 0 55 0 17 0,55 0 47 0,55 0 47 0,55 0 47 0,55 0 47 0,55 0 47 0,55 0 47 0,55 0 47 0,55 0 47 0,55 0,55 0,55 0,55 0,55 0,55 0,55 0,5	heatin	g seaso	000. 0.00 0.00 0.00 0.00 0.00 0.00 0.0	0.19 9.64 9.55 0.25 0.12 0.12 0.12 0.12 0.12 0.12 0.12 0.12	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	000 000 000 000 001 001 001 001 001 001	5.1100 m 5. 他们行到领域。
roportion of electric teating replaced [%]	0.55 0.57 0.67 0.07 0.04 0.07 0.07	022 012 012 012 020 020 020 020 020 020	2 2 4 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1	0.25 0.26 0.26 0.24 0.16 0.07 0.07 0.07 0.07 0.07 0.07 0.07 0.0	(c) 202	20-2021 044 055 045 055 047 055 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	heatin	g seasc	000. 0.0000 0.0000 0.0000 0.0000 0.0000 0.000000	0.11 0.00 0.05 0.12 0.12 0.12 0.12 0.12 0.12 0.12 0.12	0 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6	000 000 000 001 001 001 001 001 001 001	0.50 0.60 0.60 0.60 0.60 0.60 0.60 0.40 0.4
portion of electric ating replaced [%]	0.15 0.15 0.17 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.0	022 012 012 012 010 010 010 010 010 010	2 4 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	0.25 0.26 0.26 0.15 0.15 0.07 0.07 0.07 0.07 0.07 0.07 0.07 0.0	(c) 202	20-2021	heatin	g seasc	0.00 0.00 0.00 0.00 0.00 0.01 0.01 0.01	10月1日 10月11日 10月111 10月111日 10月1111 10月1111 10月1111 10月1111 10月11111 10月11111 10月11111 10月111111 10月111111 10月11111111	4665565656	000 000 000 000 000 000 000 000 000 00	0.50 0.57 0.56 0.56 0.56 0.56 0.56 0.57 0.57 -0.21
nd replaced [%]	0.14 0.14 0.15 0.17 0.04 0.04 0.04 0.04	02 82 81 01 81 81 81 81 81 81 81 81 81 81 81 81 81	2 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2	0.25 0.26 0.26 0.16 0.16 0.07 0.07 0.07	(c) 202	20-2021	heatin	g seaso	0.00 0.00 0.00 0.00 0.00 0.01 0.01 0.01	0.11 944 0.55 0.35 0.12 0.12 0.12	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	000 000 000 000 000 000 000 000 000 00	0.50 118 0.56 0.56 0.56 0.56 0.56 0.57 0.77
tion of electric g replaced [%]	0.14 4.16 6.1 0.01 0.01 0.04	02 92 91 91 91 91 91 90 90	2 1 1 1	0.25 0.26 0.24 0.15 0.15 0.15 0.07 0.07	(c) 202	20-2021 050 040 055 045 045 047 055	heatin	g seaso	0.00 0.37 0.50 0.34 0.25 0.17 0	0.11 0.00 0.55 0.05 0.12 0.12 0.12	0 0 0 0 0 0 0 0 0	00 00 00 01 01 01 01	0.40 1.18 0.40 0.46 0.46 0.46 0.40 0.40
n of electric replaced [%]	0.14 0.14 0.14 0.07 0.04	02 02 01 01 0	2 2 1 1	0.25 0.29 0.24 0.15 11.2 0.07	(c) 202	20-2021	heatin	g seaso	0.00 0.37 0.55 0.35 0.17	0.00 9,60 0,55 0,00 0,00 0,00 0,00 0,00 0,00 0	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	10 10 10 10 10 10 10	0.40 8.28 0.68 0.68 0.68 0.68 0.68
of electric placed [%]	0.14 a th 3 th 0.1 0.1	02 92 81 01 01		0.25 0.29 0.24 0.16 0.16	(c) 202	20-2021	heatin	g seaso	0.00 0.a7 0.55 0.35 0.25	0.11 9,61 0.30 0.25	0 8 8 9 9	00 00 00 00 00 00 00	0.92 8.98 0.68 0.68 0.68
electric sced [%]	0.14 0.14 0.1	02 92 01 01	2	0.25 0.26 0.24 0.15	(c) 202	20-2021	heatin	g seaso	0.00 0.a7 0.55 0.35	0.11 19,61 12,51 0.31	0 11 0 0	040 04 1 040 040	0.97 0.77 0.67 0.68
ed [%]	0.14 4.16 7.24	02 92 81	9 2	0.35 0.26 0.24	(c) 202	20-2021	heatin	g seaso	on.	0.11 0,61 0,51	0 11 0	00 0 1 0 6	0.57 1 78 0.67
ctric (1%)	0.54	02 92	1 2	0.25 0.25	(c) 202	20-2021	heatin	g seaso	on. 0:00	10.11 9,64	9	0	0.97
2 2 100-	0.14	02	4	0.25	(c) 202	20-2021	heatin	g seaso	on.	an	0		0.100
					(c) 202	20-2021	heatin	g seaso	on.				
					(c) 202	20-2021	heatin		n				
			P	Reduc	tion in I	Peak Lo	ad [MV	V)	gs with	ciol%	0]		
	1	2	3	4 Iroontiu	5 of tot	Fin I Minite	7 abarna	8 durallin	g no with	10	11	12	13
IE of	-0.04	4/2	1.1	-017	-0.21	40,250	-63	-0.35	1.7%	-0.44	-0.48	0.55	-0.57
0 0 10-	0.01	0.04	0.00	0.00	0.12	41.14	-0.17	-0.10	0.22	9.25	0.27	10.1	0.33
8 = 20-	10.421		0	-0.01	0.972	-4/10	-0;03	-3.04	:0.75	-0.00	20.04	-0.67	-31 660
E 5 30 -	0.0+	0.05	0.50	0.07	0.04	0.00	0.5	0.11	0.12	0.13	0.16	0.16	0.17
0 E 4/1-	0.00	0.09	0.02	D10	0.18	3.21	0.24	24.6	6.0	0.33	0.95	0.00	041
E & 501	0.09	0.13	4.12	623	0.28	u iz	¢a1	0.42	0.47	0,54	0.50	061	000
	0.71	0.18	0.74	0.35	B.37	10.44	0.51	9.57	0.84	0.71	0.77	0.64	75.01
- 0A 22 -	D 13	0.22	6.5	40.0	6.47	3.55	0.64	11.73	0.81	20.0	80.0	1.67	615
ace ace	10.122	0.26	0.30	0.47	12.0	Gel	ii Th	0.00	9.05	1.00	1.14	1.50	3.8
aced laced	0.10		0.41	17.20	- 10 07	-12/18	0.01	1.03	T.18	1.229		152	164
aced (%	16.16	U.E	10.000			10.01	1.05	1.10	4.08	1.47.	11.81	8.55	1.85

Reduction in Peak Load [MW]

(d) 2021-2022 heating season.

Figure 41: Peak heating season load reduction for (a) 2018-2019 heating season, (b) 2019-2020 heating season, (c) 2020-2021 heating season, (d) 2021-2022 heating season, calculated with NREL residential electric heating curve. Only cells where secondary peaking does not occur are shown.

Again, using the minimum level of ETS penetration where secondary peaking does not occur across all heating seasons of 7% ETS penetration, between 0.59 MW and 1.05 MW can be reduced from the highest winter peak during a heating season. The largest calculated winter peak reduction on the highest peak day was 1.89 MW during the 2020-2021 heating season. It is important to note that these values are observed when 100% of the heating systems replaced by ETS are electric. Reductions in the largest winter peak across heating seasons begin to occur when between 30% and 50% of the heating replaced by ETS is electric. This is higher than the 20% replaced electric heating threshold to reduce the average heating season peaks in Figure 39. To reduce peaks on the highest peak days, a greater proportion of electric heating must be replaced by ETS.

Figure 41 is re-plotted using the YG residential electric heating curve.

							10.
0-	-0.01	90.00	17.07	0.09	-0.64	0.05	-0.48
10-	0	<u>u</u>	0	9	10	-2	6
20 -	0.05	0.62	の時間	17.644	9.04	0.05	0.50
30 -	0.02	0.63	0.65	0.07	10 CB	0.1	0.15
40 -	0.03	0.00	0.08	.0.1	10.52	0.15	0,17
50 1	0.04	0.407	0,1	0.15	8.42	-0.2	0.23
80 -	0.04	0.00	0.15	0.47	02*	9:25	0.24
70-	0.05	10 A	E 15	6.2	825	0.1	0,35
80	9.66	0.10	0.17	0.23	2,29	77.35	194
90	3.07	0,13	2.0	0.20	10.271	170.39	(DOM)
00 -	0.08	0.48	11.99	.0.0.	0.475	-00.A.B	39,992

Mean change in daily peaks [MW]

(a) 2018-2019 heating season.

	4	2	3	4	5	6	7	8
0-	10.04	-4.01	0.13	42.57	-0.27	-0.27	0.00	0.84
10-	0.02	47.05	12,00	0.17	0.14	0:37	-12.2	
20 -	0.01	-0.07	0.03	-0,04	-0.06	-0.07	-0.00	-15,9
30 -	17.03	0.03	0.02	163	71.005	0.00	0.05	0.00
30 -	3.06	0.06	12 006	0.09	D.a.	41.42	11 16	0.05
50 -	3.67	0.1	2.63	0.90	0.19	0.22	0.20	00210
60-	2.95	0.0	20.94	62.0	127	0.332	0.55	0.41
70	0.31	G 17	0.33	0.29	10.31	140	0.47	D.b.t.
30 -	0.69	0.81	.0.20	0.06	0.44	0.51	0.59	0.00
90-	4.15	124	3.84	0,42	1.64	8.67	0.7	19,700
100	10.12	6.0	0.10	0.47	0.0	0.71	0.97	0.04

Proportion of total Whitehorse dwellings with ETS [%]

Reduction in Peak Load [MW]

(b) 2019-2020 heating season.

					1.4	- P	0			8	10	- 11	16	20
		-		2		-	4		-		an		24	
2 5	0 -	0.04	0.08	-0.93	-0.17	-0.21	-0.25	0.9	0.35	D 39	-144	-0.40	0.66	-0.57
0 0	10 -	0,01	97/24	0.07	-100	0.12	0.15	-0.57	0.2	0.73	0.25	6.20	0.51	0.32
di	20 -	0.01		-0 D	10.60	0.02	-0.03	-0.01	-0.05	-0.00	-0.0T	+D.08	-0.09	-0.1
T B	30 -	0.05	0.05	0.00	0.00	0.07	3.98	0.99	2.0	5.11	0.12	71 12	0.65	17.14
0 -	-50-	0.06	10.0W	9.01	0.54	28.0	0.19	0.55	17.25	9.87	0.5	0.33	0.05	0.56
E a	50-	77.05	0.13	9.17	0.22	0.20	2.37	0.38	0.39	0.44	10,41	0.03	0.67	0.02
and of	60	D.Y	0.17	0,23	19.20	0.195	0,42	0.48	0.54	0.61	0.67	0.7	9.78	1088
ΦÖ	70	0.15	0.21	0.20	0.37	0.45	0.53	0.61	0.00	Q.77	0.85	10.41	3.83	1.00
0 00	30.	0.15	11.25	0.26	0.45	6.55	0.04	074	0.04	0.94	104	15.58	3.85	1.00
50	90-	0.59	9.29	0.11	0.62	per.	0.70	0.57	10,99	3.11	1.23	104	5.08	3.87
22%	100	0.5	9.32	9.47	0.0	0.71	ST.6.8	17	1.9	\$21	1.45	10	188	EAL

Proportion of total Whitehorse dwellings with ETS [%]

Reduction in Peak Load [MW]

(c) 2020-2021 heating season.

	-	2	ă.	4	6	6	ż.	8	0	10
0	-0.1	3.16	-0.22	-0,20	44.11	-0,4	-0.46	-0.62	0.51	10.64
10-	0.07	11.67	0.10	0.2	0.26	0.26	0.30	5.37	-0.41	0.40
20 -	-0.64	-0.09	-2.69	-22.51	-0,14	-0.17	-0.10	>0.22	-12.25	-D-37
2 30 4	0	10.07	-0.02	-20.03	0.04	-0.04	-0.06	-10.07	-0.68	.0.69
- 40	0.00	-0.04	0.05	0.00	0.00	0.122	0.07	0.09	0.00	0.00
501	30.02	0.6%	11.75	0.94	0.16	0.50	0.21	12.25	,0.20	4.27
80.	7.0	0.14	0.18	-12,29	0.24	2.9	0.35	0.3	0.42	.0.46
70-	9,83	0.12	15,11.0	6,3	0.00	16.00	0.37	(0.55	0.58	8.64
80.	0.14	0.24	.0.31	17.64	7840	0.64	0.0	0.64	0.70	0.62
90	0.2	0.2.0	0.286	3.9.7	-2.86	0.05	13,76	0.0	10	(3)8
100	12.20	9.84	0.44	0,65	1.00	0.97	0.07	00.00	100.1	0.50

Reduction In Peak Load [MW]

(d) 2021-2022 heating season.

Figure 42: Peak heating season load reduction for (a) 2018-2019 heating season, (b) 2019-2020 heating season, (c) 2020-2021 heating season, (d) 2021-2022 heating season, calculated with YG residential electric heating curve. Only cells where secondary peaking does not occur are shown.

The YG residential electric heating curve provides superior results during the 2021-2022 and 2019-2020 heating seasons. However, during the 2018-2019 and 2020-2021 heating seasons the NREL estimated peak load reductions are marginally superior. When considering peak heating load days, the two different electric heating curves have performed roughly equivalently.

Secondary peaking may not be undesirable if the secondary peaking is within the bounds of what the grid currently handles. If the load reduced during on-peak times roughly equals growth in load during off-peak times the overall contribution to the grid is null. What is most desirable is a load profile that is "flattened", where the distance between peaks and troughs has been minimized. Discounting secondary peaking and instead evaluating only the "flattening" effect of an ETS implementation is a more complete assessment of ETS effects on the grid load profile. To estimate the "flattening" effect of an ETS implementation the difference between the average power draw during on-peak and off-peak times is taken before and after a simulated ETS fleet load has been added to the Yukon grid's load. Then a ratio of the average difference between on-peak and off-peak power draws for post- and pre-ETS implementation is calculated. This is described in equations (4) and (5).

$$\mu_{\Delta peak} = \sum_{i \in \{1,213\}}^{n} \frac{(ONP - OFP)_i}{n}$$
(4)

Load Stability = $100 \cdot \frac{\mu_{\Delta peak \ post \ ETS}}{\mu_{\Delta peak \ pre \ ETS}}$ (5)

A negative value implies that there is secondary peaking, the post-ETS off-peak times are new on-peak times. A positive value implies that pre-ETS off-peak times are still off-peak times. Values close to 0 imply a flatter profile, values further from 0 imply a "peakier" profile.

Heatmaps are calculated for the ratio of the average difference between pre- and post-ETS during onpeak and off-peak times with respect to the proportion of electric heating replaced and the proportion of ETS adoption in Whitehorse. It was noted that there was minimal variation in the ratios between pre- and post-ETS on- and off-peak times with respect to the proportion of electric heating replaced. In other words the proportions of electric heating replaced by ETS does not have a large effect on the "peakiness" of the resulting Yukon loads. The average of the ratio of the average difference between pre- and post-ETS during on-peak and off-peak times is then taken with respect to proportion of replaced electric heating to simplify the resulting analysis. A figure showing how the ratio of the average difference between pre- and post-ETS during on-peak and off-peak times changes with respect to the proportion of Whitehorse adoption of ETS is given in Figure 43.



Figure 43: Ratio between pre and post ETS implementations average difference in on- and off-peak load, calculated with NREL residential electric heating curve.

Inspecting Figure 43 there is variability in the proportion of ETS adoption which results in the optimal "flattest" load profile. For the 2018-2019 and 2019-2020 heating seasons it occurs about 30% ETS adoption. However, for the 2020-2021 heating season it occurs between 35% and 40% ETS adoption whereas for the 2021-2022 heating season it occurs between 30% and 35% ETS adoption.

Figure 43 is re-plotted with the YG residential electric heating curve, shown in Figure 44.



Figure 44: Ratio between pre and post ETS implementations average difference in on- and off-peak load, calculated with YG residential electric heating curve.

The pattern observed in Figure 44 is identical to that calculated with the NREL curve in Figure 43, with the exception that the intercept between the 0.0 point and each heating season's ratio occurs at a slightly lower proportion of ETS penetration in Whitehorse. For the 2018-2019 and 2019-2020 heating seasons, the intercept is approximately 28% with the YG residential heating curve, compared to approximately 30% with the NREL curve. The 2020-2021 and 2021-2022 heating seasons similarly approximately intercept the 0.0 line at a 2% lower penetration of ETS in Whitehorse. Overall, the YG residential electric heating curve gives estimates of the flattest possible Yukon load profile at a lower level of ETS penetration in Whitehorse.

4.4 DISCUSSION

The amount of peak shifting attributable directly to the ETS demonstration project and broader Whitehorse ETS adoption was investigated. It was calculated that the average reduction in winter peaks from the demonstration project was 4.7 kW and 12.7 kW for the 2022-2023 and 2021-2022 heating seasons respectively, when calculated with the NREL residential electric heating curve. Using the alternative YG provided residential electric heating curve resulted in marginal increases in peak reduction during the heating season, with new peak reductions for the 2022-2023 and 2021-2022 heating seasons being 8 kW and 16 kW respectively. When assuming the demonstration project replaced 100% electric heating, such that no new loads were added to the Yukon grid, the average reduction in winter peaks increased to 52.3 kW and 57.0 kW for the respective 2021-2022 and 2022-2023 heating seasons when calculated with the NREL residential electric heating curve. Using the YG curve, these results improve to an average reduction of 59.3 kW and 64.3 kW for the 2021-2022 and 2022-2023 heating seasons.

Taking a subset of the highest peak demand days for the Yukon grid, the average peak reduction the ETS demonstration project was capable of for the highest demand days was 176 kW using the NREL residential electric heating curve. The YG residential electric heating curve did not provide notable different results to the peak demand day peak load reduction calculations. Further, outdoor temperature was used to create boxplot bins of the daily peak reductions for the 2021-2022 and 2022-2023 heating seasons. The marginal improvements to the peak load reductions from the YG residential electric heating curve were not notable enough in the boxplots to warrant inclusion in the analyses for Section 4.3.1. The series of boxplots confirmed that as temperatures dropped, the capacity for peak reduction increased. Since lower outdoor temperatures are likely to coincide with higher peak demand days on the Yukon grid, the greater the peak load reduction the ETS fleet could accomplish. Throughout the analysis of the demonstration project's ETS fleet load secondary peaking was not a concern due to the relatively small scale of the demonstration project.

The regression model relating ETS fleet load to temperature was used to simulate ETS loads with respect to proportions of ETS adoption in the Yukon and proportions of non-ETS electric heating replaced by ETS. It was determined that between 0.59 MW and 1.05 MW could be reduced from highest winter peaks and 0.47 MW and 0.93 MW could be reduced from the average daily peaks across 4 different heating seasons at the minimum level of ETS penetration before secondary peaking began to occur, when estimated with the NREL residential electric heat curve. It was determined that between 0.52 MW and 1.81 MW could be reduced from highest winter peaks and 0.47 MW and 0.93 MW could be curve. It was determined that between 0.52 MW and 1.81 MW could be reduced from the average daily could be reduced from the aver

peaks across 4 different heating seasons at the minimum level of ETS penetration before secondary peaking began to occur, when estimated with the YG residential electric heat curve. The YG residential electric heating curve in comparison with the NREL curve provides marginally better results when considering the average daily peak, and similar results when considering the highest winter peaks. Between 30% and 50% of ETS systems must replace electric heating need be replaced to reduce the average daily peaks in a heating season. The highest values of peak reduction occur when 100% of ETS systems replaced existing electric heating. The capacity for peak reduction is directly related to how many ETS systems represent new loads on the grid.

It was noted that secondary peaking by itself is not necessarily undesirable, rather the overall "peakiness" of the profile is of concern. This also implied that the overall "flatness" of the grid load profile is the most desirable state. Expanding the analysis to a greater range of ETS adoption rates revealed the flattest grid load profiles occurred between 30% and 37% adoption rates of ETS in Whitehorse, when estimated with the NREL residential electric heating curve. Applying the same analysis with the YG residential electric heating curve results in between 28% and 35% adoption rates of ETS in Whitehorse to achieve the flattest load profile. The adoption rates of ETS in Whitehorse are the proportions when the differences between the typical on-peak hours and off-peak hours are minimized. Secondary peaking is not a risk below 28% to 30% ETS penetration in Whitehorse and the surrounding area, depending on the electric heating curve used in the estimation.

5 WHAT IS THE ADDED VALUE OF CONTROLLING THE ETS UNITS IN AGGREGATE?

5.1 INTRODUCTION

It is important to understand the benefits associated with aggregate control over Electric Thermal Storage (ETS) systems. Any aggregate control strategy will require resources to be committed to create and maintain the control. Fully understanding the benefits of aggregate control can inform later decisions relating to ETS control in a future adoption of the technology in the Yukon. Throughout the ETS demonstration project, ETS units were controlled via a central dashboard. Charging schedules were predetermined and set according to utility knowledge of likely on-peak and off-peak charging hours. Aggregate control of ETS across a fleet requires homeowners to trust ETS units will still provide heat effectively and meet their needs. Aggregate control also requires costs in monitoring and maintaining control from a central point. Studying the added value aggregate control provides is essential to justify the costs associated with any aggregate control scheme.

5.2 METHODOLOGY

During the 2022-2023 heating season, ETS units from the Steffes and Elnur manufacturers were placed into charging groups that had no control for a period between 2023-02-15 and 2023-03-10. These units were allowed to operate independently from the aggregate charging schedule, and essentially draw power when it was most convenient for the unit and building occupants. A summary of these units is given in Table 13.

Manufacturer	System type	Participant	Participant power
			draw [kW]
Steffes	Central heater	OFA_01	28.8
	-	OFA_03	28.8
		OFA_06	19.2
		OFA_07	28.8
	-	OFA_08	28.8
Elnur	Room	BBO_01	7.525
	-	BBO_02	5.89
		BBO_06	6.54
	-	BBO_07	8.5
	-	BBO_08	6.54

Table 13: Participants in control/no-control experiment.

Data for participants in Table 13 were collected for the experimental period (2023-02-15 to 2023-03-10) and contrasted with a control period (2022-09-01 to 2023-02-14). Results from the experimental and control periods can be contrasted to highlight the effects of the aggregated control versus no control strategies.

To best analyze the performance differences between the two periods, a series of variables were studied. The amount of power drawn binned by hour of day illustrates can illustrate the charging patterns of ETS systems with and without a charging strategy. The amount of power drawn during on-peak hours can be calculated with respect to the date, and then plotted against average temperature for that day. As well, energy consumption can be calculated through determining the energy drawn by unit in kWh by date, and contrasting that with average daily temperatures.

To better compare the experimental and control time periods, a subsampling process is employed. The experimental period is considerably shorter than the control period, 24 days versus 22 weeks respectively. By sampling from the control period a subsample of the same length as the experimental period can be constructed. However, simply resampling dates will destroy the dependence structure inherent to the data, since it is indexed by time. The experimental period is comprised of 24 sequential days, whereas a straightforward sample from the control period will be days in a random time order. To balance between the dual goals of achieving a random sample, and a sample with a dependence structure, subsamples of a specific length can be taken. For example, subsampling from a period of 7 days with a sample length of 4 will create 2 blocks of 2 days, where the block order is random but within the blocks order is maintained. This is illustrated in Figure 45.



Figure 45: Diagram of block resampling.

The block length chosen for subsampling from the control period for the ETS data is 3, this will maintain dependence in the sample while ensuring sufficient randomness across repeated samples.

5.3 ANALYSIS

5.3.1 Effect of no aggregate control on ETS power draw

Boxplots of the ETS experiment/control group's power draw by hour are given in Figure 46.







Figure 46: ETS fleet load by hour of day across control (a) and experimental (b) time periods.

The control period is contrasted with the experimental period in Figure 46 (a) and (b) respectively. Allowing ETS units to operate independent of a central control strategy notably changed the charging characteristics of the ETS units, and thus the fleet load. In Figure 46 (a) the on-peak hours have consistently low power draw, at or close to 0 kW. In contrast Figure 46 (b) shows relatively higher power draw during on-peak hours, and lower during off-peak hours. This pattern is opposite to what is desirable to reduce Yukon winter peaks. However, the pattern is not surprising given the ETS units were allowed to operate independently, and the increased power draw during on-peak hours correlates to typical occupant hourly heat demands.

The total power draw during on-peak and off-peak hours can be broken down with respect to manufacturer as well.

Table 14: Proportion of total on-peak and off-peak power draw during time-of-day control period, by
manufacturer.

Manufacturer	On-peak [%]	Off-Peak [%]
Steffes	2.9	97.1
Elnur	11.8	88.2

manufacturer.		
Manufacturer	On-peak [%]	Off-Peak [%]
Steffes	42.7	57.3

Elnur

30.9

69.1

Table 15: Proportion of total on-peak and off-peak power draw during no control approach period, by manufacturer.

In Table 14 the Steffes units draw the majority of their power during off-peak hours in the control period.
The Elnur units draw less power during the off-peak hours, but still a large majority. In contrast, Table 15
shows that across both Steffes and Elnur systems, removing aggregate control leads to significantly
greater power draw during on-peak periods.

5.3.2 Effect of no aggregate control on ETS off-peak power draw relative to outdoor temperatures

The proportion of power drawn during off-peak periods with respect to the day is calculated during the experimental period, where ETS units were disconnected from aggregate control. The daily average temperature was also calculated. An ordinary least squares fit is computed to estimate the effect, if any, of temperature on off-peak power draw for the ETS units. The estimates of the change in off-peak power draw with respect to temperature for the experimental period are contrasted with the same estimates over the control period. As noted in Section 5.2, a distribution of likely slopes is created through block resampling periods of the same length as the experimental period from the control data. Exactly 5000 resamples are performed, and then regression slopes calculated for each sample. The results are shown in for Steffes and Elnur units in Figure 47.





Figure 47: Regression slopes for off-peak power draw proportion related to outdoor temperature for Steffes (a) and Elnur (b) systems.

In the above figure, boxplots are given of the regression estimates of slope for the resampled data during the control period. The grey targets are the value of the slope estimates for the experimental period of no-control. The numbers in grey are the p-values for the experimental regression slopes. The numbers in black are the proportion of p-values below 0.05 across all resampled regression slopes. A p-value below 0.05 is a common threshold for statistical significance. Among the Steffes units in Figure 47(a), the majority of slope estimates are close to 0, implying that proportion of off-peak charging is not related to outdoor temperature most times. The regression slopes during the experimental period of no control largely agree with the re-sampled results. Participants OFA 01 and OFA 03 have non-zero experimental slopes but only OFA_01's slope is statistically significant. Among the Elnur units in Figure 47 (b) the results are less tightly distributed about 0. BBO 06 tends to have positive slopes, whereas BBO 07 and BBO 08 tend to have negative slopes. It is important to note that only BBO 06 and BBO 08 have a majority of the resampled slopes being statistically significant. Only BBO_08 has an experimental slope that is statistically significant, and it is also clearly negative, implying as outdoor temperatures decreased the power drawn during off-peak times increased. Taking the results across both manufacturers, it is unlikely that the nocontrol strategy has an effect on the proportion of off-peak charging when related to outdoor temperature, as temperature does not appear to have a clear effect on off-peak charging when there is an aggregate control strategy in place. Most of the slopes in Figure 47 were also statistically insignificant, both in the control and experimental periods.

5.3.3 Effect of no aggregate control strategy on ETS energy consumption relative to outdoor temperatures

Daily energy consumption was calculated for each participant in the no aggregate control experiment and control period. The daily energy consumption was related to daily mean outdoor temperature through a regression to identify whether the relationship between energy and temperature was affected by the lack of aggregate control. As before, a distribution of likely regression slopes for the control period was created through block resampling, and then contrasted with the calculated slope during the no control experimental period. The results are given below in Figure 48.



Figure 48: Regression slopes for daily energy consumption related to outdoor temperature for Steffes (a) and Elnur (b) systems.

As before, the grey targets represent the calculated regression slope during the experimental period of no aggregate control. The grey text is the p-value associated with the experimental regression slope. The black text is the proportion of p-values less than 0.05 for all resampled control regression slope estimates. In Figure 48 (a) the resampled estimates of the regression slopes for Steffes units are all mostly negative. As temperature decreases, daily energy consumption increases and vice versa. This is an expected result, colder outdoor temperatures should imply greater energy consumption for heating. As well, the majority of the slopes are statistically significant for all Steffes participants. In Figure 48 (b) for Elnur units the relationship between energy consumption and outdoor temperature is still largely negative, but to a lesser degree than the Steffes units. The distribution of control period slopes for BBO_07 is close to 0, and less than half the slopes are statistically significant. This is explainable by the lower energy capacity of Elnur units relative to Steffes units, the increase in energy consumption for every per-unit decrease in temperature will be relatively lower. Every participant other than BBO_07 has a majority of the control slopes calculated as statistically significant. All of the experimental slopes fall below the majority of the control resampled slopes. As before, BBO_07 is the odd participant out as the only Elnur unit with a non-

statistically significant slope for the experimental period. Taking the results in Figure 48 as a whole, the slopes during the experimental period generally fall within the expected range of slopes shown through the resampled control periods. The only participants where this is not true are OFA_03 and OFA_06, and the results are contradictory. OFA_03 shows a rate of change between outdoor temperature and daily energy consumption close to 0, higher than the resampled control periods. OFA_06 shows a rate of change between outdoor temperature and daily energy consumption more negative than the resampled control periods. Removing aggregate control does not have a persistent effect one way or another on ETS unit's energy consumption with respect to outdoor temperatures.

5.4 DISCUSSION

Removing aggregate control of ETS units produced a marked effect on the charging patterns of the units. More power was drawn during on-peak hours than off-peak hours for the fleet of ETS units in the experiment group. In contrast, the periods of aggregate control produced a desirable load profile for the experimental fleet, with minimal or no power drawn during on-peak periods. Breaking down the ETS power draw for each manufacturer, the Steffes units under independent control drew only 57% of their power during off-peak hours. The Elnur units performed marginally better under independent control, drawing 69% of their power during off-peak hours. These figures are a stark decrease in performance relative to the same units under an aggregate control scheme. Steffes and Elnur units under aggregate control drew 97.1% and 88.2% of their power during off-peak hours respectively. The Steffes units performed better under an aggregate scheme than the Elnur units, but performed worse with no aggregate control than the Elnur units.

Assessing how ETS units performed with respect to outdoor temperatures during the aggregate control and no control periods yielded some important results. The proportion of power drawn during off-peak periods was not overly affected by outdoor temperature under aggregate control or no control strategies. The daily energy consumption was affected by outdoor temperature among both Steffes and Elnur units. Generally, as outdoor temperatures become colder ETS units consume more energy. However, whether ETS units are under an aggregate control scheme or under no control has no convincing effect on the relationship between outdoor temperature and energy consumption.

An aggregate control scheme provides considerable value as units will draw the majority of their power during off-peak hours and not on-peak hours. This ensures that ETS systems will effectively shift power demand from winter peaks, and realize all further benefits that come with peak-shifting.

6 WILL OCCUPANTS EXPERIENCE A DISRUPTION IN THEIR COMFORT LEVELS?

6.1 INTRODUCTION

Evaluating the thermal comfort Electric Thermal Storage (ETS) systems can provide users is important to establish whether ETS can satisfy users heating needs. ETS may provide excellent performance in terms of peak shifting, but if users are unsatisfied with ETS performance the adoption rates will suffer. An exploratory analysis of the temperature and relative humidity (RH) sensors placed throughout participants homes is conducted, evaluating how the data varies across different time scales and with different sample statistics applied. Models to determine thermal comfort for occupants are investigated and then applied to the participant data. Thermal comfort models are useful in providing insights into participant comfort that may not be readily apparent with the raw temperature and RH data.

6.2 METHODOLOGY

6.2.1 Handling Temperature and Relative Humidity Data

The temperature and RH data are first analyzed to identify any patterns or unusual behaviour across the participants. Multiple temperature and RH sensors were installed in different locations through participants homes. To simplify the analysis while still accounting for all information collected in homes, the data is aggregated and averaged with respect to the participant coding. In other words, for a given participant the resulting temperature and RH data will be an average across different locations in the home. To ensure sensor data was on the same time-scale, data was averaged from 5minute resolution to 1-hour. The 1-hour resolution was chosen as a balance between ensuring the averages were estimated with a moderate sample size while still being able to capture variability at a high temporal resolution. The variation in temperature and RH is first analyzed across all participants with respect to the hour of the day, to illustrate any broad trend in these variables day by day. Then boxplots are given for temperature and RH to identify any participants with data that falls outside the typical range of the entire pool of participants.

6.2.2 Fitting Thermal Comfort Models to Temperature and Relative Humidity Data

Empirical models for thermal comfort seek to quantify and predict thermal comfort as a function of environmental and human-related variables. Parsons summarizes these variables as:

...the air temperature, radiant temperature, humidity and air velocity to which a person is exposed, the metabolic heat which is produced by their activity, the clothing they wear and the adaptive opportunities afforded by the environment they occupy including their capabilities of taking advantage of them [9, p. 1].

Two common thermal comfort models will be discussed that utilize these input parameters, as well as a brief discussion on the theory and applicability of adaptive thermal comfort in the context of the ETS demonstration project.

6.2.3 PMV model

The staple model to describe thermal comfort is the Predicted Mean Vote (PMV) model, developed by Fanger [10]. Fundamentally, the model assumes that human comfort is governed by a heat-balance equation relating the human body's heat production and transfer to the surrounding indoor environment. This model will take environmental and occupant-related variables as inputs to predict responses by occupants on a thermal sensation scale in some survey. This scale is given below in Table 16.

Thermal Sensation	Numeric Value
Hot	+3
Warm	+2
Slightly warm	+1
Neutral	0
Slightly cool	-1
Cool	-2
Cold	-3

Table 16: PMV thermal sensation scale.

Acceptable thermal conditions generally will correspond to between -0.5 and +0.5 according to the ASHRAE-55 standard [11]. The PMV model is functionally related to the Predicted Percentage Dissatisfied (PPD) index, which assumes occupants will be dissatisfied scoring +2 +3, -2, or -3 on the thermal sensation scale. Acceptable thermal conditions will generally correspond to values of less than 10% within the PPD index. The PPD index can be derived from the PMV model easily, shown in Figure 49 below.



Figure 49: Relation between PMV output and PPD index

The PMV model takes four environmental and two occupant variables as inputs, described in Table 17, adapted from [11].

Table 17: PMV model input variables.

Name	Description
Air temperature	Temperature of the air measured at a single point or across
	many points [°C]
Mean radiant temperature	Temperature of a hypothetical enclosure that exchanges an
	equivalent amount of heat with the occupant as the
	surrounding environment, through heat radiation [°C]
Relative air speed	Rate of air movement at a point or across many points [m/s]
Relative humidity	Ratio of water vapour in a space over the amount of water
	vapour that space could contain [%]
Metabolic rate	The rate of transformation of chemical energy into heat and
	mechanical work by metabolic activities of an individual
	[met]
Clothing	Expresses the thermal insulation given by clothing [clo]

The PMV model as implemented in this analysis corresponds to the Analytical Comfort Zone Method in [11] which requires average metabolic rates to be within 1 and 2 mets and average air speed to be less than 0.2 m/s.

6.2.4 2-Node-model

The 2-Node-Model was developed by Gagge [12] as an attempt to improve upon the PMV model. Gagge notes that:

Since Fanger's PMV is based primarily in terms of heat load, its response by definition to changes in relative humidity or vapor pressure is minor. PMV is directly proportional to the operative temperature of the environment [12, p. 717].

That is, the PMV model is invariant to changes in RH. Given the abundance of RH data in this demonstration project, as well as the clear variability of said data described in Section 6.3, relying solely on the PMV model is likely unwise. Gagge notes that the 2-Node-Model is sensitive to changes in environmental humidity, among other factors. This model can output PMV values, denoted by Gagge as PMV*, as well as Standard Effective Temperature (SET) values. The scale and interpretation of PMV* values still correspond to Table 16. SET values can be thought of a universal temperature index (given in °C) for assessing thermal comfort, with neutral values about 24 °C [9, pp. 30-31].

The inputs for the 2-Node-Model include all the variables described in Table 17, as well as a host of others. For practical purposes, these other variables will not be investigated.

6.2.5 Critiques of the PMV approach

The PMV model in practice can misjudge occupant thermal comfort. Specifically, the PMV model has been observed to overestimate how warm occupants are during higher temperatures and

overestimate how cold occupants are during lower temperatures [13] [14, p. 595] [15, p. 673]. In a wide-ranging review of the PMV model [16] van Hoof described several critiques, including failure to validate PMV outputs in field studies, differences in PMV neutral temperatures compared with occupants preferred temperatures, and differences among building types. In a meta-analysis Humphreys and Nicol [15] found that PMV is biased with respect to all input variables and can be "seriously misleading". A key assumption of the PMV model is that model outputs are the hypothetical average of a large sample of occupants. This can lead to discrepancies between occupant's reported thermal comfort and PMV predictions with respect to individual characteristics such as gender, age, and disability [14]. In applications such as the ETS demonstration project, the large sample assumption will not hold as the number of occupants in residential homes will be minimal. Due to this, individual characteristics and preferences will be magnified and the accuracy of the PMV model may suffer. Additionally, the fact that the ETS demonstration project is comprised of individuals in homes further magnifies the role of individual preferences. This is because individuals generally have more freedom to adapt their behaviour and control their immediate environment to their own preference than in public or professional spaces. The increased adaptive capacity of residential occupants is well known in the literature and has been demonstrated in field studies [17, p. 6].

6.2.6 Adaptive thermal comfort models

The idea of individual preferences ties into the theory of adaptive comfort, summarized by Nicol and Humphreys [18, p. 564]: if a change occurs such as to produce discomfort, people react in ways tend to restore their comfort. Adaptive comfort essentially treats all the many ways in which individuals may react to maintain comfort in the face of changing conditions as a black box. Most adaptive comfort models use statistical models to correlate outdoor temperature with any number of factors within the black box (clothing, humidity, air movement, building climate controls, etc.), represented as surveys of comfort data from occupants, and then build an equation relating an ideal comfort temperature to a measure of outdoor temperature [9, pp. 56-57] [18]. In addition to correlating with factors within the adaptive black box, outdoor air temperature was also found to strongly relate to bias in the PMV model output [15, p. 680]. Instead of correlating outdoor temperatures, some adaptive models have focused on modifying the PMV index directly to reflect the black box of occupant adaption [9, pp. 57-58]. For example, Yao et al. [13] introduced the aPMV measure, where aPMV = PMV/(1+ λ PMV) and λ is coefficient estimated through regression methods for the situation of interest. It has been argued that the PMV (and thus the 2-Node-Model) model is already "partially" adaptive by virtue of the clothing, metabolic rate, and air speed parameters, which can change depending on occupant behaviour [17]

A downside to the adaptive PMV approach is that λ was estimated through a rigorous survey and environmental assessment, which may be impractical for many studies. A general criticism of adaptive models is that due to the reliance on estimating the effect of black box of occupant adaptions through statistical models, it is unclear what adaptions may have been available or undertaken by occupants, and no causal inference is really being made. Thus, in situations where it is impractical to parametrize a custom adaptive model, there is a less sound basis for applying results from other adaptive models as a generalization. The ASHRAE standard for thermal comfort [11] only recommends an adaptive model relating optimal indoor thermal comfort temperature to outdoor temperature for naturally ventilated buildings without an HVAC system. This is due to the inherent need for occupants to adapt their thermal comfort to prevailing outdoor conditions. However, it is possible that the known higher adaptive capacity of occupants in residential spaces is a compelling reason to expand the use of adaptive models beyond the strict ASHRAE standards.

It is important to note the role climactic regions will play on the adaptive characteristics of occupants due to the outlying climate norms characteristic of the Yukon. It has been observed that in different climate regions people have differing preferences for thermal conditions [19]. It is well known that indoor building temperature correlate with outdoor temperatures, and the linear model underlying the outdoor temperature adaptive models assumes locations with colder outdoor temperatures will have colder optimal thermal comfort temperatures than warmer locations. However, the relationship has not been observed to be strictly linear, rather curve-linear with a minimum about 0°C and then slowly increasing optimal thermal temperature as outdoor temperature decreases [18]. Further, Nicol and Humphreys caution that:

The relationship in buildings which are heated or cooled is more complex, and less stable. It is less precise because when a building is heated or cooled the indoor temperature is decoupled from the outdoor temperature and the indoor temperature is more directly governed by the custom of the occupants... [18, p. 569]

The functional forms for the adaptive model for heated or cooled buildings are given in equations (6) and (7), taken from analyses of two different datasets in [20].

$$T_n = 20.1 + 0.0077 (Ta_{out})^2 \tag{6}$$

$$T_n = 22.2 + 0.0030(Ta_{out})^2 \tag{7}$$

Such that T_n is the neutral temperature for thermal comfort and Ta_{out} is the monthly average temperature.

6.2.7 Selected models

A variety of thermal comfort models are investigated on the ETS demonstration project data to balance against their respective drawbacks. As was noted in Section 6.2.5, thermal comfort models are predicated on large samples, the experience of an "average" person of many. This is useful when analyzing the comfort of buildings that contain many occupants but less useful for residential homes with fewer occupants. Thus, the feedback from the actual occupants about their thermal comfort will be quite important when judging the results of these models. In Table 18 the models employed and the reasonings behind their selection are given.

Thermal Comfort Model	Reasoning for selection
PMV Model	PMV is the most well established and popular
	of all thermal comfort models. Despite the
	associated drawbacks, it is worth including.
2-Node PMV/SET model	The 2-Node method improves on the original
	PMVs invariance to humidity levels.
Nicol and Humphrey's Adaptive Comfort	The adaptive comfort approach is valuable to
(NHAC) model	(hopefully) account for the increased adaptive
	opportunities available to residential
	occupants. The NHAC model is well studied and
	has been estimated across field data in many
	conditions.

Table 18: Overview of thermal models used.

The PMV and 2-Node model outputs were generated from the *comf* R package [21].

6.2.8 PMV/2-Node Model

6.2.8.1 Air Temperature

The air temperature in participant homes is recorded by at least one and typically multiple HOBO sensors. It is averaged across multiple sensors by first being averaged to a common hourly time scale to better reflect the entire home's temperature.

6.2.8.2 Mean Radiant Temperature

The Mean Radiant Temperature (MRT) typically needs specialized equipment to measure accurately and was not directly captured in the ETS pilot project. A common assumption would be to equate MRT with the measured air temperature. However, this approach is known to underestimate MRT and introduce serious error into the output from the PMV model in certain circumstances [22]. To address this, the MRT will be assumed to be equivalent to air temperature with an added error component. To build the error interval, air temperature and MRT data from a Montreal study during the winter was extracted and analyzed [23] [24]. While not situated as far north as Whitehorse, Montreal still has cold winters and using this data is suitable for this analysis. Additionally, the data was collected from an office building and not residential homes, but it is assumed this discrepancy has a negligible effect on the distribution of the MRT less the air temperature.

A statistical visualization is given in Figure 50 below.



(c) Quantile plot with gaussian and sample quantiles

Figure 50: Statistical plots showing adequacy of gaussian fit on the distribution of MRT less Air temperature.

The histogram in Figure 50(a) shows a reasonably symmetric distribution with some outliers. However, it is assumed any outliers and non-symmetric features are conditional on latent variables present at the Montreal location and a symmetric distribution will adequately describe MRT less air temperature. A gaussian (normal) distribution is fitted to the data, shown by the grey curve. The distribution is parametrized by the maximum likelihood estimators, the sample mean and sample variance. In Figure 50(b) the empirical cumulative distribution function (in black) is contrasted with the parametrized gaussian cumulative distribution function (in grey), showing a close fit. In Figure 50(c) quantiles from the sample data are plotted against theoretical quantiles from the parametrized gaussian distribution. The grey line is set at y = x and represents the 'ideal' fit, in other words if the fitted distribution and the distribution underlying the sample data were equivalent all the points would lie upon the grey line. The plotted data shows an adequate fit, with the few outliers being explainable as mentioned above.

To generate the MRT estimates, the collected air temperature data is added to the mean of the fitted gaussian. Further quantiles from the fitted gaussian could be investigated if needed.

6.2.8.3 Relative Air Speed

This variable is not measured and must be assumed. The upper limit allowed by the PMV model used is 0.2 m/s, which is higher than what would be found in most residential environments. Unfortunately, there is a lack of good data on air speeds in residential environments to inform any assumptions. ASHRAE recommends 0.1 m/s as an assumption for analytical work, which will be used. Note that this is an average as the real-time air speed would fluctuate temporally and spatially.

6.2.8.4 Relative Humidity (RH)

The RH in participant homes is recorded by at least one and typically multiple HOBO sensors. It is averaged across multiple sensors by first being averaged to a common hourly time scale to better reflect the entire home's humidity.

6.2.8.5 Metabolic Rate

Within [11] metabolic values are given for typical tasks. For example, reading seated will consume 1.0 met while house cleaning will consume 2.0 to 3.4 met. For the purposes of this analysis, metabolic rates will be set to 1.0, the minimum metabolic activity possible while remaining awake. This is so thermal comfort can be evaluated when individuals are likely to be at rest or relaxing such that the most likely conditions in which an occupant may not feel warm enough are considered.

6.2.8.6 Clothing

Within [11] thermal insulation provided by typical pieces of clothing are given. For example, socks, undergarments, trousers, long-sleeve shirt, long-sleeve sweater, would have a thermal insulation value of 1.01 clo. This is the value clothing will be set to for this analysis.

6.2.9 NHAC Model

6.2.9.1 Monthly Mean Temperature

Monthly mean temperature values for Whitehorse are easily obtained through sensors within the ETS demonstration project, or Environment Canada. For the purposes of this analysis mean temperature were obtained from Environment Canada.

6.3 EXPLORATORY ANALYSIS OF TEMPERATURE AND HUMIDITY DATA

6.3.1 Data overview and cleaning

In the data there are 33 participant codes corresponding to 33 residential homes. There are 71 different temperature and RH sensors logging data at a time interval of 5 minutes. Temperature is measured in °C while RH is measured in %. Most participants have more than 1 sensor in a home. The date ranges the sensors were active for vary from participant to participant.

To take advantage of the multiple sensors while keeping the analysis parsimonious, data was averaged across sensors within participant codes. To ensure sensor data was on the same time-scale, data was averaged from 5-minute resolution to 1-hour. The 1-hour resolution was chosen as a balance between ensuring the averages were estimated with a moderate sample size while still being able to capture variability at a high temporal resolution.

6.3.2 Exploring the cleaned data

A typical day is calculated for temperature and RH measurements by averaging across all participants with respect to hour of day. Typical days for temperature and RH are presented in Figure 51(a) and Figure 51(b) respectively for the 2021-2022 heating season.



Figure 51: Typical temperature and RH days across all participants for 2021-2022.

The solid black line is the mean, the black dotted lines are sample standard deviations added and subtracted to show variability. The sample standard deviation computes the average difference between the mean and the data.

In Figure 51(a) the mean temperature finds a minimum about 04:00 hours and a maximum about 20:00 hours. The variability seems constant with a range of approximately 4°C. In Figure 51(b) the RH is reasonably constant in both mean and variability, although the variability is quite wide. The mean RH seems fixed at approximately 37.5% and the range of the variability at approximately 22.5%.

The same plots are calculated for the 2022-2023 heating season and shown in Figure 52.



Figure 52: Typical temperature and RH across all participants for 2022-2023.

There is not a large difference between the two heating seasons with respect to the overall dispersion of temperature and RH.

The temperature and RH are next calculated with respect to every participant across the entire period of data collected. Boxplots are given in Figure 53(a) and Figure 53(b) showing temperature and RH respectively.



Figure 53: Temperature and RH at the participant level for 2021-2022 heating season.

coding (BBO, EFA, OFA, etc.) to better illustrate any related pattern. beyond the whiskers being considered as outliers. The boxplots are also coloured by the three-letter further than 1.5 times the difference between first and third quartiles, and any individual data points third quartiles (25th and 75th percentiles), upper and lower whiskers extend to the largest value no estimate of central tendency (median), the lower and upper hinges corresponding to the first and A boxplot is a convenient way to summarize data, with the thick horizontal line representing an

temperatures. Additionally, participants HYE_01, OFA_02, and OFA_09 have moderate amounts of notable exception is SHB_07, which displays markedly colder average hourly temperatures. In Figure 53(a) we can see that most of the participant data falls within a [16°C, 24°C] interval. A norm had the BBO coding, meaning the original heat source that was replaced by ETS was baseboard. data falling above 24°C. It is notable that both participants that had a majority of data fall outside the below 16°C. Additionally, participants EFA_01, EFA_02, and OFA_03 all have a moderate amount of data falling Another exception is SHB_05, which displays markedly warmer average hourly

Moving on to Figure 53(b), the RH is less tightly distributed than the temperature, as indicated earlier in Figure 51(b). Most of the participant data falls within a [15%, 60%] interval.







Figure 54: Temperature and RH at the participant level for 2022-2023 heating season.

consistent across participants. The RH distribution in Figure 54(b) is consistent as well. of time. For HYO_01, there are many outliers around or below 0 °C. This was due to sensors being expected range. This was due to the dwelling being renovated and unoccupied for significant lengths participants colder temperatures where observed. For SHB_06, many datapoints fall outside the for data collection. Aside from these two participants, the distribution of temperatures is reasonably removed from the home and left in a mailbox for two days in April 2022 before they were delivered There is a marked change in the distribution of temperature seen in Figure 54(a), for several

given by boxplots in Figure 55(a) and Figure 55(b) for temperature and RH respectively. this, the sample standard deviation was calculated by day with respect to participant. This data is noticeable to an occupant) or within a matter of days (very noticeable to an occupant). To capture variability seen for OFA_02 in to Figure 53(a) occurs disparately across many months (not as it is useful to highlight variability on a smaller scale. For example, it is not apparent if the large Figure 53 shows how temperature and RH fluctuate across the entire period data was collected, but





SHE DI

880 0

680 02

(b) RH

Figure 55: Standard deviation of daily temperature and RH during 2021-2022 heating season.

from the mean does not exceed 3°C per day. participant exceeds more than 3°C of standard deviation for any day. That is, the average distance Once again, the data is coloured by coding to better illustrate any patterns. In Figure 55(a) no

A boxplot of the standard deviation of daily temperatures and RH are given in Figure 56



Figure 56: Standard deviation of daily temperature and RH during 2022-2023 heating season.

temperature and RH remains similar between the 2021-2022 and the 2022-2023 heating seasons. due to the home being unoccupied due to renovations. Discounting SHB_06, the variability in is explained by the abnormally low temperatures shown in Figure 54 (a) for SHB_06, which in turn was The results for SHB_06 are skewing the results in Figure 56 (a). The greater variability seen in SHB_06

variability compares to a given measure of RH variability. For example, is a typical daily standard Relative to participant comfort it is not immediately clear how a given measure of temperature Introducing empirical models for thermal comfort in Section 6.2.2 will help resolve this uncertainty. deviation in temperature of 3°C "better" than a typical daily standard deviation in RH of 7.5% In Figure 55 and Figure 56 there is much greater daily variation in the RH than the temperature.

6.4 **PROJECT DATA** APPLYING THERMAL COMFORT MODELS б ETS DEMONSTRATION

RH data for each participant. Selected models The selected thermal comfort models discussed in Section 6.2.7 are fitted with the temperature and

6.4.1 **Comparing Standard PMV Model against 2-Node PMV Model**

2-Node PMV results respectively for the 2021-2022 heating season. In Figure 57(a) and Figure 57(b) a boxplot of hourly standard PMV results is given for the PMV and the



about -1 roughly evenly. In contrast the 2-Node PMV values in Figure 57(b) are markedly higher and the outliers having PMV values well below -2 and above 0 respectively. The PMV values are distributed assess their thermal comfort somewhere between 0 (neutral) or -2 (cool), with SHB_07 and SHB_05 values more tightly dispersed, with occupants typically assessing their thermal comfort somewhere between In Figure 57(a) the standard PMV results show that occupants in participant homes would typically -0.75 and +0.5. The 2-Node PMV values are distributed about 0 (neutral) with a bias towards cooler

heating season. In Figure 58 boxplots for the PMV and 2-Node PMV model results are shown for the 2022-2023



(b) 2-Node PMV

Figure 58: Hourly PMV and 2-Node PMV across all participants for 2022-2023 heating season

as shown in the 2021-2022 heating season. the distribution of participant comfort for the 2022-2023 heating season lies within the same ranges unoccupied or sensors left outside as noted earlier in Section Exploring the cleaned data6.3.2. Overall, seems to correct this bias. The outliers in Figure 58 (a) and Figure 58 (b) are due to homes being Like in Figure 57, the standard PMV is biased towards cooler sensations, whereas the 2-Node PMV

of this analysis, the 2-Node model will be used to generate PMV (as well as SET) values and the model is more accurate and useful for the ETS demonstration project's purposes. For the remainder Given the consistent bias in the standard PMV values towards cooler occupant sensations, as well as of persistently cooler thermal sensations then this decision will be re-evaluated. standard PMV model set aside. However, if survey data of participants confirms standard PMV results invariance to humidity discussed in Section 6.2.4, it seems reasonable to conclude the 2-Node PMV

6.4.2 Analyzing 2-Node SET Values and NHAC model

values from the 2-Node model is given in Figure 59 for the 2021-2022 and 2022-2023 heating seasons occupant senses than raw temperature values. A boxplot of hourly temperature data less the SET The 2-Node model can also output temperature values that should be closer to what an average



(b) 2022-2023 heating season.

Figure 59: Difference between measured temperature and SET model for 2021-2022 and 2022-

2023 heating seasons.

data differences between the standard PMV and 2-Node PMV outputs in Figure 57 and Figure 58. The measured. The majority of the data falls within a [-1, -3] °C interval. This is not surprising given the negative difference is likely due to the 2-Node model's previously mentioned sensitivity to humidity Across both heating seasons, the SET values are warmer than what the temperature sensors have

Boxplots of hourly SET values for participants are given in Figure 60 It was noted in Section 6.2.4 that the SET model considers 24°C to be the "neutral" temperature.



(b) 2022-2023 heating season.

Figure 60: Distribution of SET for participants for 2021-2022 and 2022-2023 heating seasons.

by boxplots in Figure 61(a) and Figure 61(b) respectively for the 2021-2022 heating season. temperatures for the respective month. A value of 0°C will be the neutral point. The results are given neutral temperatures were calculated for each month, and then subtracted from the hourly SET can be set according to equations (6) and (7) from the NHAC model. Using these equations new across almost all participants in Figure 60(a) and (b). However, new neutral temperature benchmarks may be higher than the measured temperatures, they still fall below the theoretical neutral value The neutral SET temperature is illustrated in Figure 60 with the dotted grey line. While the SET values



Participant Code

(b) SET less NHAC eq.2

Figure 61: Hourly SET less NHAC equations for neutral temperature for the 2021-2022 heating

season.

equations give neutral temperatures that agree more closely with the SET values than the theoretical to be warmer or colder than what NHAC equation (7) gives as thermally neutral. Regardless, both 61(b) the SET more tightly and evenly distributed about 0°C, and there is no clear visual bias for SET In Figure 61(a) the SET is on average warmer than what NHAC equation (6) claims is neutral. In Figure neutral.

In Figure 62 the same calculations are performed for the 2022-2023 heating season.


(b) SET less NHAC eq. 2

Figure 62: Hourly SET less NHAC equations for neutral temperature for the 2022-2023 heating

season.

to the SET values than the theoretical neutral temperature. with the 2021-2022 heating season, both NHAC equations give neutral temperatures that align closer season the dispersion of the SET less NHAC values are wider than the 2021-2022 heating season, but data, and exclude the outliers for HYO_01 and SHB_06 explained earlier. For the 2022-2023 heating both Figure 62(a) and (b) are distributed reasonably symmetrically about the neutral of 0°C. As shown The plots have been cropped to provide a better illustration of the behaviour of the majority of the

factors not related to the ETS systems themselves. occupants. There were outlying datapoints in some participants, but these are explainable due to Overall, the thermal comfort models indicate no pervasive thermal discomfort observed in the

6.4.3 Survey Responses Pertaining to Thermal Comfort

of satisfaction and 5 indicates the most amount of satisfaction. performance from the 2021-2022 and 2022-2023 heating seasons are presented in Table 19 and Table To contrast the thermal comfort models, participant survey responses regarding ETS system heating 20 respectively. The survey questions were ranked on a 1-5 scale, where 1 indicates the least amount

Response	Does your ETS system provide your home with adequate heat, overall? [%]	Does your ETS system deliver heat to your home as quickly as you'd like? [%]
1	3.57	3.57
2	0	7.14
3	10.7	10.7
4	35.7	42.9
5	50	35.7

Table 19: Survey responses for heating satisfaction for 2021-2022 heating season.

The results from the 2021-2022 heating season are encouraging, a large majority of participants responded positively to both questions relating to thermal comfort.

Response	Does your ETS system provide your home with adequate heat, overall?	Does your ETS system deliver heat to your home as quickly as you'd like? [%]
1	0	0
2	0	12.2
3	7.32	14.6
4	41.5	39.0
5	51.2	34.1

 Table 20: Survey responses for heating satisfaction for 2022-2023 heating season.

The results from the 2022-2023 heating season represent an improvement, the frequency of negative responses declined, and the frequency of positive responses increased. Overall participants were highly satisfied with ETS heating performance.

Participant feelings on temperature extremes were also surveyed. Results for whether a participant's home may have felt too hot or too cold with respect to the time-of-day are given in Table 21 and Table 22 respectively.

 Table 21: Proportion of "no" responses to excessive participant warmth by time-of-day.

Are there any times of day when you feel your home is	Proportion of "no" responses [%]	
typically warmer than you'd like?	2021-2022	2022-2023
	heating season	heating season
Morning	96.4	97.6
Afternoon	92.9	82.3
Evening	92.9	92.7
Overnight	71.4	80.5

A large majority of participants did not feel excessively warm during mornings, afternoons, and evenings. The overnight period had a lower proportion of "no" responses but still represented a majority of the participants.

Are there any times of day when you feel your home is	Proportion of "no" responses [%]		
typically cooler than you'd like?	2021-2022	2022-2023	
	heating season	heating season	
Morning	60.7	46.3	
Afternoon	89.3	92.7	
Evening	67.9	75.6	
Overnight	89.3	82.9	

|--|

The results for participant coolness are less encouraging, although during the winter season this is expected. The most concerning times when participants may have felt too cool was mornings, where 60% of participants responded "no" during the 2021-2022 heating season, and only 46% of participants responded "no" during the 2022-2023 heating season. It is important to note that mornings would correspond roughly to a period of the day when ETS units would be charging, although individual perception of "morning" times is subjective. It also bears noting that 39% of participants responded "maybe/sometimes" to excessive coolness during the 2022-2023 heating season's morning period, instead of "yes". This could indicate the issue is not necessarily pervasive.

Participant's thoughts on temperature variability were assessed as well, and the results given in Figure 63.



(a) Results for 2021-2022 heating season.



Figure 63: Survey results for fluctuation in room temperatures among participants.

The majority of the responses surveyed indicated fewer fluctuations in room temperature or no difference in fluctuations. The proportion of unsure responses, or responses indicating greater fluctuations decreased from the 2021-2022 heating season to the 2022-2023 heating season.

6.5 **DISCUSSION**

The raw data analyzed in Section 6.3 showed that temperature and RH showed interesting variability across participants, and some clear outliers. However, how this raw data translated into abstract notions of thermal comfort was not necessarily clear. To this end, several models for thermal comfort that would utilize the raw temperature and RH data were discussed in Section 6.2.2. Then, in Section 6.4 the results from these models were analyzed with respect to each participant. While these models provide easy estimates of thermal comfort, it is important to emphasize that they are based upon a prediction of an average response across large samples of participants. It is crucial to validate these models on actual survey data from ETS participants on their thermal comfort to better trust model outputs.

If validated, then the usefulness of these models is readily apparent. It is not practical or feasible to expect participants to give accurate summaries of their thermal comfort every hour of every day, or every day of every week, or possibly even every week of every month. That is to say, the resolution of data to be expected from participants is low, which limits any analysis of said data. While there is high resolution temperature and RH data, making realistic claims about how exactly that data relates to thermal comfort is challenging in a vacuum. Thermal comfort models allow for very low-resolution participant feedback to be related to our high-resolution temperature and RH data in a well understood way. Through validating a model of thermal comfort, high resolution raw data can be more readily analyzed as comfort data, and more insightful conclusions can be made regarding participant comfort.

The thermal comfort models used in this analysis showed that ETS systems can readily meet the needs of a hypothetical "average" occupant. Surveys circulated to demonstration project participants revealed that there was broad satisfaction with ETS system's capability to ensure thermal comfort, agreeing with the results from the thermal comfort models. It is evident that ETS systems were

capable of meeting the thermal comfort needs of the project participants, and are capable of meeting the thermal comfort needs of future occupants of ETS heated homes.

7 HOW WOULD WIDESPREAD ETS IMPLEMENTATION AFFECT RESIDENTIAL LOAD POWER FACTOR/QUALITY?

7.1 INTRODUCTION

The introduction of new residential loads in the Yukon presents a challenge for the existing electrical infrastructure. In Whitehorse, the population center most likely to see the highest penetration of Electric Thermal Storage (ETS) systems, many neighbourhoods have electrical distribution infrastructure that cannot handle the high loads demanded by ETS. The electrical infrastructure supporting these neighbourhoods was not built with the intention of supporting modern smart heating technologies.

7.2 METHODOLOGY

The methodology supporting this analysis was developed as part of Northern Energy Innovation's (NEIs) Electric Vehicle and Electric Heating (EVEH) project. Currently, the project has explored a feeder in the Whitehorse neighbourhoods of Riverdale, Porter Creek, and Takhini, to conduct simulations studying the effects of increased electrical load from combinations of electric vehicle and smart heating adoption rates. Purely resistive electric heating has been modeled in these studies, such as an electric baseboard. These results are not optimal to draw precise conclusions, as a resistive baseboard load will not follow the load curve of a properly scheduled ETS system. The resistive heating load will be "flatter" and more evenly distributed throughout the day whereas the ETS load will have greater peaks in load during the pre-determined times of day when grid electricity demand is lowest. However, the general effect of increased electric heating on power quality is still useful as a broad assessment of increased electric heating penetration.

NEIs approach to modeling the effects of new heating on local Whitehorse feeders employs Quasi-Static Time Series (QSTS) analysis. QSTS is an approach to modeling steady-state power flow through an electrical power system at discrete time steps over the course of a pre-specified time period. QSTS is a useful approach to evaluate the effects of new loads on the local power system because it can simulate the effect of specific variables on the power flow. These variables can include but are not limited to controls associated with renewable generation, change in load demanded, generator dispatching. In the work NEI has produced so far, a typical winter peak event over the course of a day is investigated, using one-minute time steps. The power flow, voltage, and current are simulated on the local neighbourhood feeder in this analysis. A Monte Carlo iteration technique is used to introduce variability into the loads used in the QSTS analysis. For further information on the Monte Carlo process used see [25, pp. 15-16].

7.3 ANALYSIS

7.3.1 Overview of simulated variables.

Three variables are assessed: maximum power, undervoltage risk, and current. For each of the three variables, three penetration levels of electric heating are considered. The levels vary across Whitehorse neighbourhoods.

7.3.1.1 Maximum Power

If too many household loads are active at the same time, transformers servicing these homes may become overloaded, especially during times of overall peak demand on the system. Increased loads from new electric heating loads may necessitate upgraded transformers that can handle a new maximum load. The worst-case transformer loading, expressed as a per unit (pu) of rated transformer capacity is simulated. The ambient temperature surrounding the transformers are important to consider; in -30°C, temperatures regularly reached in Whitehorse during the winter, transformers can operate safely up to 160% of rated capacity [25, p. 17]. The number of transformers loaded above 160% rated capacity is calculated in the simulations.

7.3.1.2 Undervoltage-risk

Voltage can be thought of as analogous to pressure in a water piping system. The greater the pressure, the greater force with which water can be moved through the piping. Similarly, the higher the voltage, the faster electricity can be moved through the system. It is important that the voltage remains within safe tolerances to ensure the reliable flow of electricity. The addition of new loads to the electric system can cause voltages to move outside an acceptable range. The total proportion of occurrences of voltage falling below the 0.94 pu threshold is calculated through all iterations in each case study. Then the number of secondary poles with undervoltage servicing homes is reported.

7.3.1.3 Current

Using the earlier analogy where an electrical system could be thought of as a water piping system, the current can be understood as rate of flow through the system. Higher loading on an electrical system can result in higher current. The number of secondary poles with overcurrent servicing homes is reported.

7.3.2 Results

An abridged summary of key results for feeders in Riverdale, Porter Creek, and Takhini is given in Table 23: Key results for selected Whitehorse neighbourhood power quality across varying proportions of electrification of heat. Table 23, extracted from [26], [27], and [28] respectively. It is important to note that the lowest proportion of electric heat in each neighbourhood is the current baseline, in other words the current level of heating electrification in that neighbourhood.

Whitehorse	Electric Heating	Number of	Percentage of	Percentage of
Neighbourhood	Adoption Rate	Residential	secondary poles	secondary poles
	[%]	Transformers	with	with
		loaded past 1.6	undervoltage.	overcurrent.
		pu		
Riverdale	7%	3	11.6%	7.6%
	14.5%	5	24.4%	11.0%
	22%	7	37.2%	17.8%
Porter Creek	8%	3	4.0%	0.0%
	15.5%	5	8.4%	0.0%
	23%	10	10.2%	3.2%
Takhini	18%	0	21.0%	1.7%
	25.5%	0	36.5%	5.7%
	33%	2	54.2%	9.7%

Table 23: Key results for selected Whitehorse neighbourhood power quality across va	rying
proportions of electrification of heat.	

7.3.2.1 Number of Overloaded Transformers

In Riverdale and Porter Creek the number of overloaded transformers steadily increases as more heat is electrified. However, in Takhini there is a comparatively low number of transformers overloading, even at relative higher levels of electrification to Porter Creek and Riverdale. This may be due to the age of the neighbourhoods, Takhini has newer homes and electrical infrastructure than Porter Creek or Riverdale.

7.3.2.2 Undervoltage

The undervoltage measurements are lowest in Porter Creek, with only 10.2% of secondary poles experiencing undervoltage at 23% penetration of electrified heating. In contrast, at 7% penetration of electric heating in Riverdale 11.6% of secondary poles already have undervoltage problems. In Takhini the undervoltage is worse than Porter Creek, and similar to Riverdale.

7.3.2.3 Current

The proportion of secondary poles experiencing overcurrent across all three neighbourhoods is lower than the proportions experiencing undervoltage. The lowest levels of overcurrent occur in Porter Creek, while the highest occur in Riverdale. Even at 33% penetration of electric heating, only 9.7% of

secondary poles in Takhini experience overcurrent. Contrasted with Riverdale where at 22% penetration of electric heat 17.8% of poles experience overcurrent.

7.4 DISCUSSION

It is important to restate that the results from NEI's EVEH project presented above are only for conventional resistive electric heating. It is not possible to draw a direct inference from the results due to ETS consuming higher amounts of power during pre-scheduled "off-peak" times than a standard electric baseboard, and likewise consuming lower amounts of power during the "on-peak" times than a standard electric baseboard. However, there will be a deleterious effect on power quality in Whitehorse neighbourhoods if the penetration of electric heat increases through the adoption of ETS. Through all three Whitehorse neighbourhoods studied by NEI in the EVEH project, power quality decreased as the electrification of heat progressed. The best metrics were the number of overloaded transformers in Takhini, and the proportion of secondary poles with overcurrent for Porter Creek. Both these metrics were largely invariant to the penetration of electric heating; only 3.2% of poles in Port Creek experiencing overcurrent when 23% of homes had electrified heating; only 2 transformers were overloaded in Takhini when 33% of homes had electrification of heat progressed. For a more detailed analysis of the consequences of the electrification of heat in Whitehorse see [25], [26], [27], and [28].

8 WHAT IS THE BEST ETS CONTROL APPROACH FOR PEAK REDUCTION WITHOUT PRODUCING A SECONDARY PEAK?

8.1 INTRODUCTION

When too many Electric Thermal Storage (ETS) systems are drawing power during the assumed offpeak times of the day, there is a possibility of a secondary peak being created. The previous winter peak is mitigated but the growth of the secondary peak will diminish or eliminate any environmental or economic benefits. The diesel resources used during the previous on-peak times will instead be used during the new on-peak periods.

The primary control strategy used in the Yukon's ETS demonstration project was based on the timeof-day (TOD). The hours of the day which corresponded to peak times for electricity demand in the winter heating season were used to determine the ETS systems charging schedules. Generally, ETS systems would not be allowed to charge during on-peak times and were instead allowed to charge during off-peak times.

During the 2022-2023 heating season, a subset of ETS participants were selected for two alternative charging control approaches. The first approach used the Yukon's grid frequency to regulate when ETS systems would charge. When the frequency on an electrical grid is too low, it can imply there is a lack of generation, or an excess of load demanded on the system. Conversely, when the frequency is too high it can imply an excess of generation, or a lack of load demanded. ETS systems manufactured by Steffes can monitor the grid frequency and charge when it is too high, and stop charging when it is too low. The other control approach taken was an absence of control. ETS systems were allowed to operate independently and not communicate with any central control scheme. Essentially, the ETS systems operated as regular electric heating units that could store heat over time. The heat storage capability was not used strategically in any way.

8.2 METHODOLOGY

To calculate the peak reduction capabilities of an ETS system, the difference of means between offpeak and on-peak power draw is calculated at a daily resolution. This calculation provides an estimate of the ETS system's capacity for power draw during off-peak times, and thus peak reduction. This is outlined in equations (8), (9), and (10), where P_i is power draw during the i^{th} hour of the day.

$$\mu_{OffPeak} = \sum_{i \in OffPeak}^{n} \frac{P_i}{n}$$
(8)

$$\mu_{OnPeak} = \sum_{i \in OnPeak}^{n} \frac{P_i}{n}$$
(9)

Peak Reduction Capacity = PREDCAP = $\mu_{OffPeak} - \mu_{OnPeak}$ (10)

The PREDCAP can be compared between ETS systems to assess their relative capacity for peak reduction. To identify the best control approach for peak reduction, the PREDCAP was calculated for fleet load for ETS systems placed in the frequency-based control group and the standard TOD control. No control was determined to have limited peak-shifting capabilities and was not considered.

The participants in the TOD control strategy are described in Section 5.2, in Table 13. The participants in the frequency-based control experiment are described below.

Manufacturer	System type	Participant	Participant power
			draw [kW]
Steffes	Central heater	OFA_02	28.8
		OFA_05	28.8
		OFA_10	19.2
		OFA_11	28.8
		OFA_12	28.8
		EFA_01	24.8
	Hydronic heater	HYE_01	19.2
	Room heater	SHO_01	7.5
		SHO_02	9.0
		SHO_03	9.0

Table 24: ETS systems in frequency-based control experiment.

The time period for the TOD control for the units used in the frequency experiment extends from 2022-09-01 to 2023-03-21, or a length of 201 days. The period for the frequency-based control extends from 2023-03-21 to 2023-03-31, or a length of 10 days. To ensure an unbiased comparison, only the subset of ETS participants in the frequency-based control experiment will be used when comparing the performance of frequency-based control and TOD control. Due to the TOD control period lasting far longer than the frequency-based control period, subsamples are taken from the TOD period of an equivalent number of days to the frequency-based control period. A block re-sampling method is used to ensure comparisons between samples with sufficient time dependency. The block re-sampling method is similar to the one described in Section 4.2. In this block sampling strategy, blocks of length 2 are used to populate samples of a length of 10 days. The TOD control period is re-sampled 5000 times to create an appropriately random distribution. Then the PREDCAP is calculated for the fleet load across

the frequency-based control period. Then the difference between the distribution of frequency-based PREDCAP values and the TOD PREDCAP values will determine which control approach has a greater capacity for peak reduction.

To compare the differences between PREDCAP values, a t-test for difference of means is used. The ttest will determine if there is sufficient statistical evidence such that the mean difference between two samples is not due to randomness. To summarize, the PREDCAP is calculated for each of the 10 days in the frequency-based control period for the combined load of all frequency-based control ETS systems, giving PREDCAP_{frequency[10×1]}. Then the PREDCAP is calculated for each of the re-sampled time periods of 10 days from the same ETS systems under the TOD control approach. There are 5000 samples taken, giving PREDCAP_{TOD[10×5000]}. Each column in PREDCAP_{TOD[10×5000]} is compared to PREDCAP_{frequency[10×1]} through a t-test, where the mean difference between columns is determined whether to be statistically significant.

8.3 ANALYSIS

Allowing ETS units to operate under no overarching control approach was shown to produce poor results for peak shifting capability. In Section 5.3.1 the power consumption data was analyzed for those ETS participants whose ETS systems were forced to operate independently. The ETS units with no control strategy produced an aggregated load profile where units drew much of their power during on-peak hours. The mean difference between off-peak and on-peak power draw for ETS systems in the no-control and TOD control is calculated at a daily resolution and plotted in Figure 64.



Figure 64: Differences between mean off-peak and on-peak power draw for TOD control and nocontrol charging strategies. Given for Steffes (a) and Elnur (b) ETS systems.

For both Elnur and Steffes systems, the TOD control results in higher level of power being drawn during the TOD control strategy than during the no-control period. For the Steffes systems, the mean difference between off-peak and on-peak power draw is negative, implying that the average power draw was higher during on-peak hours under no aggregate control than during off-peak hours. Clearly, allowing the ETS units to operate without any control minimizes chances of peak shifting.

Allowing the ETS units to operate independently without a larger control strategy will provide minimal value for peak reduction or control over secondary peaking. The frequency-based control strategy is contrasted with the TOD control strategy by taking the mean difference in on-peak and off-peak power draw at a daily resolution in Figure 65.



Figure 65: Differences between mean off-peak and on-peak power draw for TOD control and frequency-based control strategies

The frequency-based control appears to produce a lesser differential between off-peak and on-peak power draw compared to the TOD control strategy. This means that the TOD control has a greater capacity for peak reduction. However, given the established relationship between ETS power draw and outdoor temperature, comparing the 10-day experimental period for frequency-based control in March with the entirety of the heating season will produce biased conclusions. To estimate a more accurate measure of the peak-shifting capabilities of both control strategies, the TOD control period is subset by the same outdoor temperature range which occurred during the experimental frequency-based control period in March 2023. The difference in means for the on-peak and off-peak periods is calculated for each day in the re-sampled TOD period and the frequency experiment period, and then their overall mean compared with a t-test. A distribution of results from the t-tests are given in Figure 66.



(a) P-values for mean differences between $PREDCAP_{TOD_{[10 \times 5000]}}$ and $PREDCAP_{frequency_{[10 \times 1]}}$



(b) Mean difference between $PREDCAP_{TOD_{[10\times5000]}}$ and $PREDCAP_{frequency_{[10\times1]}}$

Figure 66: Results from t-tests of $PREDCAP_{TOD_{[10 \times 5000]}}$ and $PREDCAP_{frequency_{[10 \times 1]}}$, including p-values (a) and mean differences (b).

In a histogram of the p-values associated with each comparison. A large majority of comparisons are statistically significant, meaning that any differences were likely not due to randomness. In, a histogram of the mean differences between the comparisons are given. The mean frequency contribution to peak shifting was subtracted from the mean TOD contribution to peak shifting. All the values are positive, implying that the TOD contribution resulted in an overall greater capacity for peak shifting. Looking at the range of values across the x-axis in, it clear that the TOD control results in approximately 10 kW to 40 kW of additional daily peak shifting capacity on average. This additional daily peak shifting capacity also implies TOD control has a higher potential for creating secondary peaking than frequency-based control. The responsiveness of frequency-based control to real-time changes in grid conditions will allow for fewer instances of secondary peaking.

8.4 DISCUSSION

Three ETS control approaches were assessed in their ability to reduce peaks in power demand. The no-control approach, wherein ETS units were allowed to operate independently with no central control, was ineffective at reducing peaks. ETS units under no control would often draw a significant proportion of their total power consumption during on-peak hours, and on average would draw relatively higher amounts of power during on-peak hours. The other two control approaches studied were TOD control and frequency-based control. An experimental period wherein a subset of ETS units were placed in frequency-based control for 10 days was contrasted with the conventional TOD based control over the 2022-2023 heating season. The TOD control approach was determined to result in a greater capacity for peak reduction than frequency-based control. Both control approaches still resulted in peak reduction capabilities for the ETS units. However, the greater capacity of TOD control for peak reduction also implies a greater potential for secondary peaking. TOD control is not as responsive as frequency-based control, which can handle changes in grid conditions automatically in real-time. The decreased capacity for peak-shifting is a tradeoff resulting in greater control over ETS power draw.

9 CAN ETS HELP MITIGATE THE BLACK START LOAD OF THE SYSTEM BY DELAYING WHEN IT CHARGES AFTER A POWER OUTAGE?

9.1 INTRODUCTION

When an electrical grid experiences a blackout and a subsequent restoration of power, the "black start load" of the system is the immediate power demanded by loads on the grid. Not all generation resources are suitable to provide power during a black start of the grid. The system must be energized carefully, for example loads that are important for supporting electrical infrastructure are often prioritized [29, p. 16]. Other loads on the system may be energized to help regulate the system voltage and frequency. Aside from loads which support grid infrastructure, facilities which are critical for public safety are often prioritized. The process of restoring power after a blackout is complex and must be carefully managed [29, p. 2]. Delaying when Electric Thermal Storage (ETS) loads draw power after a blackout can mitigate this black start load and reduce the challenge for operators in restoring power.

9.2 METHODOLOGY

When power is restored to Steffes ETS systems after a blackout, the system will determine the time. If the power has been restored during a scheduled on-peak time, the system will not draw power to heat the insulated core, or in other words charge. If the power has been restored during a scheduled off-peak time, then the system will charge under certain conditions. The system will first implement a 30 second delay following the restoration of power. Then after the initial 30 seconds, another 30 second period will elapse where power draw will "ramp" gradually to meet required temperatures in the insulated core and charge the ETS system. The initial 30 second delay period will stop the ETS system from drawing the maximum amount of power it normally would following a blackout, while the subsequent 30 second ramp-up period will mitigate the strain the ETS system would place on the grid following the blackout. Only after a full minute, during a scheduled off-peak period, would a Steffes ETS system be allowed to operate at full power and charge.

Outage data from ATCO Electric Yukon was used to pinpoint feeders where ETS systems were connected to. Then the periods where outages occurred were used to subset the ETS power draw data to analyze ETS behaviour surrounding the outage period.

A power quality analyzer device was also procured by Yukon Conservation Society, and used to monitor the power draw on the charging and control circuits of a handful of ETS systems, comprised of both Steffes and Elnur units. An outage was simulated on these systems by turning off all power to the system, and then restoring it shortly after. The in-rush current was captured for the system in the immediate aftermath of power being restored to the ETS system. A table describing the ETS systems tested is given in Table 25.

Manufacturer	System type	System number	Storage Capacity
			[kWh]
Steffes	Space heater	2102	13.5
	Central heater	4120	120
	Hydronic heater	5230	120
Elnur	Space heater	208	10.5

Table 25: ETS systems tested with the power quality analyzer to assess black start loading.

Participant surveys circulated to ETS demonstration project participants for the 2021-2022 and 2022-2023 heating season asked several questions regarding ETS system performance during and after power outages.

9.3 ANALYSIS

After comparing the outage data with the power draw data from the ETS systems, it became apparent that most of the outages occurred when the installed ETS systems were not online and recording data. Further, for the handful of ETS systems which were online and recording data surrounding an outage, the reported start of outage times and power restoration times were not accurate with what was observed for the power draw data for the ETS system during that day. It was impossible to use the outage data to accurately analyze the ETS power draw data around power outages.

There were also problems with the data from the power quality analyzer device, and the manual testing of ETS systems following simulated power outages. Data was not able to be fully captured for the Elnur 208 system. As well, following the tests it was clarified with a Steffes representative that the measured in-rush current would be unable to capture any changes in ETS operations due to a power outage. This was because "For inrush current [on the charging circuit], you should not expect any difference from the full load current. These are resistive heating elements so they don't change their current draw, as compared to a motor or a capacitive load such as a power supply. You can expect the elements to immediately draw their full load current at the turn-on point and never change from that point." [30]. Upon inspecting the in-rush current data for the charging circuits the Steffes representative's explanation was confirmed.

Survey responses for participants who confirmed their ETS units experienced a power outage during the 2021-2022 and 2022-2023 heating seasons are given in Table 26 and Table 27.

Heating Season	Manufacturer	Response	Number of responses
2021-2022	Elnur	Yes	3
		No	1
		Unsure	1
	Steffes	Yes	4
		No	0
		Unsure	1
	Elnur and Steffes	Yes	3
		No	0
		Unsure	1
2022-2023	Elnur	Yes	7
		No	1
		Unsure	1
	Steffes	Yes	12
		No	1
		Unsure	0
	Elnur and Steffes	Yes	6
		No	0
		Unsure	0

Table 26: Survey responses for question – "Did your ETS system return to normal operation following the blackout?"

Heating Season	Manufacturer	Response	Number of responses
2021-2022	Elnur	Yes	1
		No	0
		Unsure	4
	Steffes	Yes	2
		No	1
		Unsure	2
	Elnur and Steffes	Yes	2
		No	1
		Unsure	1
2022-2023	Elnur	Yes	6
		No	4
		Unsure	0
	Steffes	Yes	5
		No	2
		Unsure	7
	Elnur and Steffes	Yes	3
		No	2
		Unsure	1

Table 27: Survey responses for question – "Did you get any heat from your ETS system during the blackout, that you noticed?"

The majority of participants reported that their ETS systems operated as normal following the power outage, while a minority claimed they did not function normally or were unsure across both the 2021-2022 and 2022-2023 heating seasons. Whether the participant had a Steffes system, Elnur system, or both types of ETS system installed in their home did not influence the survey responses regarding the operation of the ETS system following a blackout. During the 2021-2022 heating season 5 of 14 participants observed that their ETS systems could still emit heat during an outage while 2 of 14 participants reported not noticing any heat and 7 of 14 were unsure. During the 2022-2023 heating season 14 of 30 participants reported their ETS systems releasing heat during a power outage, 8 of 30 observed no heat and 8 of 30 were unsure. Of the participants who observed heat from their ETS units during a blackout, 6 of 14 had Elnur systems installed, 5 of 14 had Steffes systems installed, and 3 of 14 had both Steffes and Elnur systems installed. The heat emissions observed by participants would be passive as fans would not have power to circulate heat themselves.

9.4 DISCUSSION

It was not possible to verify Steffes' claim regarding their system's operation surrounding power outages. The outage data was inaccurate and could not be rigorously compared to the observed power draw data for ETS systems. The power quality analyzer data for inrush current ended up being irrelevant due to a misunderstanding regarding how the Steffes ETS systems operated. Data was unable to be collected on the charging circuit for the Elnur system that was studied. Survey responses for participants indicated that ETS units did operate normally following a power outage, and some were able to keep emitting heat during a power outage. Elnur units seemed to be superior at emitting heat during a power outage. Assuming that the Steffes systems do work exactly as claimed (a 30 second delay in power draw for heat storage following the resumption of power after a blackout, then another 30 second period of "ramping" the power draw), then Steffes ETS systems would be able to mitigate the black start load on the grid following a power outage.

10 WHAT REGULATORY OR INFRASTRUCTURE CHANGES WOULD NEED TO BE MADE FOR ADOPTION AND WIDE IMPLEMENTATION IN THE YUKON?

10.1 INTRODUCTION

Electric Thermal Storage (ETS) adoption in the Yukon will be affected by the regulatory and infrastructure environment. Three major policy or infrastructure related barriers towards ETS technology in the Yukon, as well as paths towards resolving them, are explored in the following section. The three major identified barriers towards ETS implementation are: electrical distribution infrastructure, control scheme over ETS technology, and user sentiment towards ETS technology. These barriers can be categorized as issues of policy firstly, and infrastructure secondary. All infrastructural barriers are ultimately policy barriers, but not all policy barriers are infrastructural in nature. Solutions to infrastructural deficiencies are born from policy, and thus policy is the preeminent concern addressed in this section, although all barriers are investigated. Figure 67 illustrates the hierarchy.



Figure 67: Diagram illustrating hierarchy of policy barriers towards ETS in the Yukon.

Electrical distribution infrastructure refers to equipment and resources used to regulate and distribute electricity from the larger transmission network to individual consumers. The Yukon's electrical distribution infrastructure may not be robust enough to accommodate widespread usage of technology like ETS. Infrastructure deficiencies pose serious hurdles towards widespread adoption of ETS and hinder efforts to electrify key sectors within the Yukon to meet environmental targets. The control strategy used across ETS units also warrants attention. Regardless of the complexity of a control strategy, any effort to enact overarching control across multiple ETS systems will require overcoming both policy and infrastructural barriers to ensure the strategy is effective. User sentiment is the final barrier towards ETS implementation. The sentiment of Yukoners towards ETS is crucial to the overall success of a wider implementation. Encouraging results from the ETS pilot project run the

risk of being disregarded or misunderstood if not properly communicated to Yukoners. Ensuring ETS' benefits for individuals and the Yukon are effectively communicated is critical.

The next several sections discuss identified barriers towards wide ETS implementation. Sections 10.2, 10.3, 10.4, and 10.5 examine in greater detail infrastructure, control strategies, user sentiment, and government policy. Section 10.6 conducts a review of other demand response programs that utilized electric heating. Section 10.7 discusses paths towards implementing the wider use of ETS in the Yukon.

10.2 ELECTRICAL DISTRIBUTION INFRASTRUCTURE

Within the Yukon, electricity generation, transmission, and distribution fall under the responsibility of two public utilities: Yukon Energy and ATCO Electric Yukon (AEY). AEY is responsible for the distribution of electricity to over 19,000 customers across 19 communities in the Yukon [31], although Yukon Energy does sell electricity directly to some 2,200 customers [32]. AEY however, purchases electricity from Yukon Energy, and then sells it to customers. Unlike Yukon Energy, a subsidiary of Crown Corporation Yukon Development Corporation, AEY is a privately owned company within the ATCO group of companies. The distribution of electricity to consumers requires infrastructure such as poles, wires, transformers, and substations. Distribution infrastructure is responsible for moving electricity from the wider transmission systems, regulating voltage to useful levels, and then redistributing it to consumers. The operation and maintenance of this infrastructure is the responsibility of an electricity distribution company; as noted above this responsibility falls to AEY in a large majority of cases, and Yukon Energy in select communities in the Yukon (however Yukon Energy, not AEY, does operate most substations in the Yukon).

10.2.1 Infrastructure Challenges

Much of the Yukon's electrical infrastructure was implemented in the 1950s and 1960s, and requires upgrades or replacement [33, p. 3]. The capacity of electrical distribution infrastructure to handle new loads on the system is not uniform. Some areas may require more upgrades than others in the event of increased demand for power. Increased demand can arise through a greater density of people in a service area, or through changing consumer usage habits. Changes in electricity consumption may be also realized through new or larger loads within a household. Increased ETS penetration falls under this categorization; ETS heating systems will introduce new or larger loads within a consumer's household. According to a 2012 survey of the dwelling characteristics in the Canadian territories, 59.4% of Yukoner's principal heating resource were fossil fuel based (e.g. heating oil, propane), 18.2% was electricity, and 15.0% was wood [34]. It is important to note the recent trend of electrification of heating in the residential and commercial sectors within the Yukon [35]. The Yukon Government also intends to "...replace 1300 residential fossil fuel systems with smart electric heating systems...by 2030" [36, p. 44]. As well, "Electric heat is being installed in most new homes and commercial buildings [in the Yukon]" [37, p. 12]. However, fossil fuel and wood-based heating is still an important component of many residencies in the Yukon, particularly in isolated communities that rely on expensive diesel power to generate electricity. In such communities the electricity generated is too costly to use for heating when cheaper alternatives are readily available.

Replacing existing fossil fuel or wood-based fuel systems with ETS could lead to greater pressure on the distribution infrastructure servicing the home. Even replacing existing electrical heating systems with ETS can lead to larger loads within the residence. For example, electric baseboard heating has a typical range of power consumption between 0.5 kW and 2.5 kW. In contrast, a manufacturer of ETS room units, Steffes, has products that consume between 1.3 kW and 10.8 kW of power. Another manufacturer of ETS room units, Elnur, has units with a range of power draw from 0.98 kW to 26.2 kW. Steffes' line of forced air and hydronic ETS has a similarly wide range of power consumption relative to conventional electric alternatives, between 14 kW and 45.6 kW. How an ETS system draws power to store for later release often necessitates a greater peak power consumption than equivalent conventional electric systems. However, the highly controllable nature of ETS heating allows the power consumption to be managed to minimize strain to grid infrastructure. ETS can be programmed to charge during periods when overall electricity demand is known to be low. As this study has demonstrated, ETS is highly responsive to pre-determined charging schedules and the ETS load became more predictable as ETS units saw more use when outdoor temperatures fell, see Section 2.3.1. Accommodating wider ETS implementations can represent a challenge to existing electrical distribution infrastructure through increased loads, but this is offset by the controllability of ETS heating. Northern Energy Innovation is continuing the study of additional electric heating loads on the Yukon grid through the Electric Vehicle and Electric Heating project.

10.2.2 Upgrading Electrical Distribution Infrastructure

Upgrading electrical distribution infrastructure is not a uniform process. If a single customer in a service area requires upgrades, then only the infrastructure connecting that customer to the local distribution network may need to be upgraded. However, the greater load demanded on a local distribution network through a single customer can also necessitate upgrades to upstream equipment that services a wider collection of customers. ETS adoption could prove more popular among certain service areas than others, resulting in varying levels of upgrades required across multiple service areas. The scope of distributional upgrades would also be a factor in the popularity of ETS units. Currently customers are responsible for funding upgrades to their power service; this additional cost will not only affect the overall popularity of ETS in the Yukon, but it may also bias the adoption of systems towards wealthier individuals who can afford the ETS system itself in addition to the requisite upgrade costs. This may further influence the disparity of required upgrades between service areas, with wealthier service areas having higher quality electrical distribution infrastructure. The potential for ETS adoption to be constrained in this fashion would be challenging for a Yukon wide implementation, and could mitigate the overall benefits ETS may provide.

The negative effects of increased load on a distribution system due to a new technology can be managed. For example, reducing the strain on distributional equipment from domestic electric vehicle charging through smart technology has been studied in several jurisdictions [38]. However, much of the Yukon's existing electrical distribution infrastructure cannot consistently handle the additional load from ETS systems. Capacity could be exceeded even during the hours of lowest power consumption. Control of ETS system loads may be useful to facilitate less extensive and thus less costly distributional upgrades, but some baseline level of upgrades will be required once a given threshold of ETS penetration is achieved.

A critical factor in any upgrades to existing distributional systems in the Yukon is the Yukon Utilities Board (YUB). As the regulator of the Yukon's utilities, any grid upgrades conducted by Yukon Energy and/or AEY must be approved by the YUB. The work conducted within the ETS pilot study may help make a stronger case for wide-scale distributional upgrades, but larger factors are in play. The Our Clean Future (OCF) report compiled by the Yukon government describing environmental goals for the Yukon proposes projects and technologies that would necessitate distributional upgrades; with an especially important technology being electric vehicle (EV) adoption through the territory [36]. The Yukon government already offers rebates towards Yukoner's purchasing EVs meeting certain criteria [39]. Aside from the scope of distributed ETS, the inevitable increased demand for and use of electric vehicles within the Yukon is a compelling justification for electrical distribution infrastructure more robust to the adoption of new technologies.

10.3 CONTROL APPROACHES

Exerting control or influence over electric loads is an important facet of Demand Side Management (DSM), which aims to manipulate demand to suit supply of electric power. This is particularly true for loads which are distributed across many households or businesses. For example, common major appliances such as fridges, air conditioners, electric stoves, etc. Control over electric heaters is no exception to DSM strategies, and control over electric heaters in conjunction with other electric appliances is common practice in DSM initiatives [40] [41]. Controlling electric water heaters alone without considering other household loads has also been studied as a DSM strategy [42]. While utilityrun DSM programs controlling traditional electric space and water heating systems have been successfully implemented across North America, their ability to reliably shift demand away from peak times is not as strong as a utility-run program with electric thermal storage heating systems. Users are sensitive to uncontrolled changes in heating comfort. That is, people want heat quickly available and on demand. The ability of DSM programs focusing on direct load control of traditional electric resistance heating to effectively and reliability reduce peak demand is impacted by user sensitivity to changes in heat availability. The potential for participants in a utility-run thermostat-based DSM program to opt-out of a particular instance of utility control must be considered in the evaluation of the program's ability to reliably reduce peak demand. This possibility would be greatly reduced in a utility-run ETS program, as the ETS systems' on-peak draw is largely independent of the occupants' thermostat settings. In the Yukon the consequences of such a strategy will be exacerbated relative to other regions due to a longer and colder heating season than more southern jurisdictions.

ETS can bypass user concerns regarding heat availability to be an extremely reliable form of DSM. Like water heaters, heat energy is stored in a medium (an insulated core with bricks versus a tank with water) to be used on demand by the consumer. ETS units can be controlled in aggregate much like water heaters. If sufficient heat is available for the user's needs within the ETS unit, the power draw of said ETS unit is irrelevant for the user and there will be minimal chance of the user overriding any external control. While control across ETS units can be as simple as in-unit timers set to charge overnight, the efficacy of simple control is uncertain, particularly without overarching guidance or incentives. Simple control schemes still require an overarching structure, even if said structure is entirely administrative and requires no actual supplementary infrastructure. Regardless of the infrastructure required for a control strategy, implementing the simplest control strategy is still a

problem of policy, as is noted later in this section. As the complexity of control strategies increase, the need for infrastructure to support this complexity also increases. Control distributed across ETS units can be both a matter of policy and infrastructure.

The control strategy employed across ETS units will influence how distributed ETS can achieve its proposed benefits. The determination of a control strategy that is best for all stakeholders in the Yukon is not a trivial task. The interests of consumers, Yukon Energy, AEY, the Yukon Government, and any pertinent municipal and First Nations authorities will have to be accounted for.

10.3.1 Potential Control Approaches

In a review of DSM strategies across the globe, Parrish et. al classifies DSM schemes into two major categories, Demand Reduction and Demand Response, with several subcategories branching from these [43]. Demand reduction is characterized by an absolute reduction in electricity usage, whereas demand response is characterized as manipulating electricity usage at specific times, but not necessarily a reduction in total usage. Control strategies for distributed ETS in the Yukon would fall under demand response. Demand response seeks to manipulate energy usage through incentives offered to consumers. Demand response is consumer centered, relying on affecting consumer behaviour to attain energy goals. Within the umbrella of demand response, there exist dynamic and static methods; price-based and incentive-based strategies being the final classification level. Static control strategies are changes enacted across fixed time periods and dynamic control are changes enacted upon meeting a variable threshold. For example, ETS units having a timer to charge overnight would be a fixed control scheme; ETS units charging in response to real time electricity prices would be a dynamic control scheme. There are many variations to control schemes that involve some form of differential electricity pricing. Time-Of-Use (TOU) pricing is a tried-and-true method of DSM, and the associated strengths and weaknesses are well understood [44] [45]. The simplest implementations of TOU rates allow for electricity prices to be lower or higher during periods when the utility desires greater or less electricity consumption. There are more complex TOU methods that utilize real-time price data and dynamic rates.

The commonality among demand response methods is affecting consumer decisions via some sort of benefit. Among differential pricing methods, the benefit is clearly financial savings for the consumer. Across time, the price of electricity will be changed to influence consumers to modify consumption accordingly. In contrast, incentive-based methods offer a benefit conditional on consumers achieving a pre-determined goal, such as electricity reduction across a timeframe. Among incentive-based methods, financial incentives are predominant, however there are also strategies that use education and information to modify consumption habits with no financial reward.

Focusing on the price-based strategies, they range from the simplistic (static TOU) to the complex (real-time pricing). However, the viability of any price-based scheme in the Yukon is unknown. Indeed, any control scheme across ETS systems in the Yukon must take the reality of the existing regulatory structure into account. A large majority of the Yukon's electricity is generated and transmitted by public utility Yukon Energy, while managing some of the low-voltage infrastructure for distribution to individual homes and businesses. AEY manages the majority of the Yukon's power distribution through low-voltage infrastructure, as well as managing a legacy hydro plant and 11 diesel plants [35,

pp. 2-3]. As public electric utilities, Yukon Energy and AEY are bound by the public utilities act and the YUB. The YUB has sole control over approval of electricity prices set by Yukon Energy. The current rate structure offered by the utilities does not accommodate time-based electricity pricing. Any change to the rate structure will have to be accomplished through approval from the YUB, with justifications required for any changes. This process holds no guarantees and is discussed in further detail in Section 10.5.

In addition to regulatory hurdles, another challenge facing the implementation of any kind of pricing scheme is supplementary infrastructure. Ensuring real-time monitoring and collection of the requisite data for justifiable price variation require substantial upgrades to the Yukon's electrical infrastructure. This would entail upgrading existing electrical meters to monitor power flow in real time, otherwise known as Advanced Metering Infrastructure (AMI) meters, as well as revamping distribution, transmission, substation and system control centre infrastructure [46]. AEY is in the process of upgrading the Yukon's metering to AMI meters [47]. This is an important step in the Yukon's plan to modernize it's electrical grid, noted in the OCF report [36, p. 31], and is essential for any future time-based pricing of electricity in the Yukon.

10.3.2 Viable Control Approaches

Moving forward, price-based control strategies will not be considered. Instead, the viable control schemes for distributed ETS are incentive-based. Following [43], descriptions of potential incentive-based demand response strategies identified in the author's review are adopted in Table 28.

Incentive-based strategy	Description
CPR (critical peak rebate)	Customers are provided with an incentive for
	reducing usage during critical hours below a
	baseline level of consumption.
DLC (direct load control)	Customers are provided with an incentive for
	allowing an external party to directly change the
	electricity consumption of certain appliances.
	Customers can usually override control although
	they may lose some incentive.

 Table 28: Viable incentive-based control.

The control strategies listed in Table 28 were developed from a review of established trials and programs, but are by no means definitive. Any eventual control scheme adopted across ETS units in the Yukon should be informed by previous methods, but not constricted by them.

The use of CPR may be impractical for the Yukon; implementing CPR across all Yukon electricity consumers cannot be justified through the success of ETS alone as per the earlier discussion. Previous CPR schemes have involved providing incentives that were tied directly to electricity prices [48]. Due to the hurdles with dynamic and/or price-based incentives in the Yukon, any incentives would have to be provided to ETS users exclusively and not through savings in their electricity costs. Knowing this, the efficacy of CPR across ETS users alone may be underwhelming in contrast to the DLC solution.

Additionally, infrastructure to ensure peak rebates are effective, such as electrical meters with realtime monitoring, may be impractical for reasons identified above with cost and the YUB. However, if potential users are too wary of giving up nominal control of their heating or infrastructure to enable direct utility control of ETS loads is unfeasible on a large scale, CPR remains a possible option to enact demand response.

Providing a non-price-based incentive for ETS users to give direct control to the utility (which may be overridden at any time by the user) is more straightforward and effective than rewarding ETS users through an incentive conditional upon their compliance with utility information for ideal times to charge their ETS systems. It is also important to note that DLC schemes are currently in place in the Yukon through the Peak Smart Home program run by Yukon Energy [49]. The Peak Smart Home program allows utility customers to receive free controllers for their electric baseboard heaters and or electric hot water heaters. These devices work through a wireless internet connection, and allow Yukon Energy to shift loads in response to peaks in electricity demand. Despite the precedent for DLC in the Yukon, its use is not without potential hurdles. The cost and effectiveness of utility control of ETS systems and the willingness of electricity consumers to relinquish nominal control of their heating are pertinent factors to account for. However, the authors in [43] found in their review that DLC had significant potential to affect loads than CPR, varying between 10% and 80% change in reference load compared to between 0% and 30% change through CPR. The initial investment may be greater with a DLC scheme, but the outcomes likely are greater in turn. The entirety of DLC schemes reviewed by the authors were "opt-in", in other words they were recruited and their participation was voluntary. Using "opt-out" enrollment with DLC schemes likely infringes on consumer control to a degree any benefits are outweighed by negative consumer response.

In addition to a precedent of demand response with DLC via the Peak Smart Home program, TOU and DLC schemes across ETS units in the Yukon were investigated through simulation by Pinard and Wong [50]. Pinard and Wong investigated these control schemes of ETS through a smart grid infrastructure and wind generation as a balancing resource. As noted earlier, the likelihood of smart grid infrastructure being implemented solely to facilitate distributed ETS is low. However, given a wider demand response initiative in the Yukon, it may be feasible. If smart infrastructure is developed in the Yukon for demand response, and ETS is an active component, the case study by Pinard and Wong will be a valuable resource. As noted by the authors, "...every system is unique and has its own resources and load profiles. YEG [Yukon Electric Grid] ...has many opportunities for balancing loads and variable generation through its vast hydro resources". Pinard and Wong found that as ETS penetration increased, the value of TOU control diminished while DLC became essential to retain ETS usefulness. However, the authors also noted that the marginal benefits of ETS diminished as a function of overall penetration, given a large proportion of total customers are using electric heat. Another important assumption made was the use of wind resources, the capital costs and additional logistics associated with increasing wind penetration are considerable.

Regardless of whether a control scheme is selected that utilizes direct control of ETS or seeks to control ETS usage indirectly, questions regarding cost and benefit remain. Qualifying the benefits of a control scheme against the associated costs is necessary to facilitate a wider-scale ETS implementation through regulatory proposals to the YUB. Pertinent questions include the variety and

magnitude of any incentives offered to potential ETS adopters and the cost of infrastructure required to operate the selected control scheme effectively.

10.4 USER SENTIMENT

In the adoption of any new technology, how users perceive said technology is an important ingredient in its acceptance. This is particularly true for smart technology, and the smart grid as a whole. A large survey of consumer attitudes towards smart appliances in Austria, Germany, Italy, Slovenia, and the United Kingdom was conducted in [51]. The results of this survey revealed salient concerns of smart appliances common across respondents, including safety, loss of control, doubts about promised benefits, and additional costs. The relevancy of these concerns to ETS technology are apparent. Yukoner's likely will have some combination of concerns that fall within the scope of the five categories given above for their ETS systems.

10.4.1 ETS Safety Concerns

Users may have concerns with the safety of their ETS units. The nature of how ETS units operate, storing heat during off-peak hours, typically results in period of overnight charging. As many users will not be awake during these hours, Yukoners may have concerns about ETS ability to operate with no human presence safely and reliably. In addition, more dynamic charging schemes could mean ETS units are charging multiple periods during a 24-hour cycle. In this situation there will be periods where the ETS is charging with no one in the residence. Such scenarios are likely to elevate safety concerns for users, as has been noted in studies of consumer acceptance of smart appliances [51, p. 32], [41, p. 7]. However, throughout the Yukon's ETS demonstration project there were no safety concerns brought up by participants during the operation of their ETS units. Further, ETS manufacturers such as Elnur and Steffes both highlight the safety of ETS technology due to the relatively simple design, there are no fossil fuels or hydraulic circuits, so there are no risks of leaks of harmful liquids or gases [52] [53]. HVAC contractors also emphasize the safety and simplicity of ETS systems, noting that ETS systems are designed with safety features such as temperature controls and automatic shutdowns [54].

When considering smart ETS systems, one variant would involve the use of AMI meters to inform control of ETS charging. Among Canadian provinces that have implemented AMI meters there has been opposition due to concerns about privacy, health, cost to taxpayers, and environmental effects. In a 2013 survey of people in British Columbia, Alberta, and Ontario, between 10% and 25% of respondents thought AMI meters had negative health impacts for humans [55]. While individuals may have reservations regarding AMI meters, it is important to note that they are understood to be completely safe for humans [56].

10.4.2 Control of ETS Heating

Any widespread ETS implementation will require some form of over-arching control or coordination to maximize ETS benefits. The various scenarios for this have been discussed in Section 10.3, but Yukoner's sentiment will not be uniform across all options. Generally, people expect heating systems to provide heat on demand at their own convenience. Any level of external control over heating will

invariably provoke a negative response from some proportion of consumers. However, as noted earlier, control does not necessarily imply direct manipulation of devices by an outside agent, many control strategies make use of incentives and differential pricing to affect consumer behaviour. In a 2014 study [57] United Kingdom residents were surveyed about their feelings with respect to several DSM strategies; fixed TOU rates, dynamic TOU rates, direct control of load by utility, and flat rates as a baseline for no DSM. Fixed TOU rates were seen by respondents to offer greater levels of control, Dynamic TOU had a mixed reception amongst respondents, and direct load control was almost unanimously associated with negative feelings towards loss of control.

It is important to note that there was often a sense among these respondents that utilities would unexpectedly cut off electricity, which reflects a lack of information amongst the survey population about the reality of direct load control schemes. A detailed survey of Finnish consumers regarding the energy market was conducted in [41]. A salient question asked regarding third party control of room temperature had 45.9% of respondents unwilling to allow any control over thermostats even if the effect was not noticeable; 12.7% would allow given the effects were often noticeable but appropriate incentives are given; 22.5% would allow if effect is not noticeable at all; 19% would allow if effect was noticeable only occasionally. Third-party control over thermostats and third-party control over ETS systems both involve third-party control of a building's heat, the results from [41] are pertinent. A recent review of consumer engagement with DSM strategies and incentives is detailed in [58]. The authors found similar issues with consumer's perceived control across studies conducted in Australia [59], Portugal [60], and the United Kingdom [61]. In addition to the international literature discussed so far, concerns about user control over smart appliances are prevalent in Canada. A paper discussing Canadian DSM incentives noted the contribution of stakeholder trust in a British Columbia case study [62]. In a final report summarizing the PowerShift Atlantic project in the Maritimes, consumer trust was identified as a fundamentally important aspect of their smart control scheme [63]. Any negative responses to reduced user control may be magnified in the Yukon due to the colder climate and longer winters relative to other regions, heightening the stakes for consumers. Clearly any control scheme employed across ETS systems must account for possible user concerns with a lack of autonomy over their own heating.

10.4.3 Doubts Regarding ETS Technology

Potential ETS users may have doubts regarding the technology itself, or the technologies claimed benefits. The principle of storing heat within a singular unit to be released later is simple enough, but there are additional complexities involved. At the household ETS level, potential doubts may include:

- Ability to retain stored heat.
- Efficacy of stored heat to meet user needs compared to user's pre-existing system.
- Frequency of charging periods to keep up with user needs.
- Reliability and lifespan of devices.

The proposed benefits of ETS are wide-ranging, but complex. The primary benefits include:

• Ability to mitigate and shift peak loads.

- Distributed ETS' ability to increase renewable penetration through external control or differential pricing.
- Subsequent environmental benefits through increased renewable penetration and peak shifting.

Investigating and quantifying these benefits is an on-going issue in the research literature, hence effectively communicating them to potential ETS users may be a challenge. A large report on electric and non-gas heating in the United Kingdom found that 64% of storage heater users understood their systems "at least fairly well", and the remaining 36% rated their understanding as less than that [64]. The report further identified that much of the confusion that did exist among users of ETS systems resulted from interpreting the TOU differential pricing structures, and subsequent billing. It is possible a smart control scheme may result in less confusion, or it could simply confuse users in different ways. As noted by the author in [65],

"Clearly, new-generation storage heaters will need to address customer needs in order to be marketable. Can new designs and 'smart' controls alter acceptability? If it is difficult to manage basic, unsmart storage heaters, will more complex and sophisticated controls lead to a better service for customers or one that is more difficult to understand and operate?"

10.4.4 Additional Costs

Many potential ETS user's decision to adopt the technology will undoubtedly come down to cost. While there is much evidence pointing to the effectiveness of environmental and ecological benefits motivating users to adopt smart technology in conjunction with economic benefits [66] [51] [40] [67]; the potential of financial savings (or lack of savings) is a significant motivating factor for many consumers. Economic benefits were cited as being more appealing for consumers to engage in DSM programs in [41] [68]. However as [58] points out, potential environmental benefits to users may not be well communicated due to total electricity usage not necessarily decreasing under many DSM projects. That is, consumers may not have the required information to understand how load shifting under DSM can result in better environmental outcomes; in the Yukon there would be short term environmental benefits from a reduction in fossil fuels and long-term benefits through future increased renewable penetration. The task of effectively communicating this is discussed further in Section 5. Regardless, financial considerations for potential ETS users will play an important role in their decision. Some important cost related factors potential users may consider include:

- Upkeep cost for ETS unit relative to user's existing heating system.
- Upfront cost for ETS unit.
- Energy cost for ETS unit relative to user's existing heating system.
- Role (if any) differential electricity pricing or other economic incentives will play in energy cost relative to user's existing heating system.

10.5 REGULATORY AND POLICY

In addressing the problems identified in Sections 10.2, 10.3, and 10.4, there is a common factor, the necessity of regulatory and policy action through public entities in the Yukon. Public policy is a broad

term encompassing laws, programs, and other courses of action that a government may take in pursuing a goal. Regulatory and policy issues that may adversely affect the implementation of ETS technology in the Yukon have been noted in previous sections, but a deeper discussion is given here.

10.5.1 Yukon Utilities Board

The YUB is the primary government actor in the regulation of electricity generation and distribution in the Yukon. The Public Utilities Act (PUA) empowers the YUB to regulate utility operations in the Yukon, including electricity rates, service areas, equipment and infrastructure, expansion or reduction of services, operating standards, and procedures. Further, any changes with respect to these utility practices in the Yukon must be approved by the YUB. The importance of this regulating body in a wider implementation of ETS systems in the Yukon is clear. Any solutions regarding the insufficiency of existing electrical distribution infrastructure in Section 2 also must come through YUB approval. Likewise, overarching control strategies on ETS units for demand response must be approved by the YUB.

It is thus important to take stock of what the YUB is mandated to account for when considering proposed changes to existing utility practices.

10.5.1.1 Programs and Incentives for ETS Control

Any program under which a utility intends to incentivize adopters of ETS technology to accept a control scheme over their ETS units would constitute an "extension of existing services" under Section 33 of the PUA. For the YUB to approve an "extension of existing services", the following conditions must be met,

- The extension is reasonable and practical and will furnish sufficient business to justify the expense of its construction, maintenance, and operation; and
- The financial position of the public utility reasonably warrants the capital expenditure required.

As discussed in Section 3, the potential of varying control schemes across ETS units is uncertain. The above conditions imply a business case must be made for any control scheme. Control schemes involving differential pricing are unlikely to be successful for ETS implementation. A business case would have to be made for direct utility control of ETS systems, or an incentive program to reward ETS users for compliance with utility-determined usage timeframes. For such a business case to be viable, the benefits from demand response affected by users following the control scheme (decreased winter peaks leading to less fossil fuels for load following and potential increased renewable penetration) would exceed the costs of maintaining and managing the control scheme, as well as incentivizing users themselves to adopt the control scheme. The likelihood of a convincing case to be made to the YUB for a given control scheme may also be uncertain. Evaluating utility control of ETS heating is an important feature of the ETS pilot project, and the results would be useful in presenting a case to the YUB. Additionally, in a draft report detailing Yukon Energy's plans for the coming decade, a commitment was made to implement further DSM projects beyond existing programs such as Peak Smart. Yukon Energy's commitment to enabling DSM will be critical for any push to implement wider ETS within the Yukon.

10.5.1.2 2021 Direction Amending the Rate Policy Directive

An Order In Council, enacted on February 11, 2021, changed key aspects of the YUBs mandate and the Rate Policy Directive. The order allowed for DSM programs to be implemented and costs passed along to rate-payers, so long as those costs were "reasonable" and allowed to be recoverable for rate payers [69]. The definition of a DSM program in the rate policy directive was given as such:

"demand-side management program" means a measure, action or program intended to promote customer use of electricity that optimizes economy or efficiency of electricity generation or transmission by a public utility, including through the promotion of customer use of electricity that

- (a) is more efficient, or
- (b) better aligns electricity supply and demand.

This definition is broad enough to encompass differential pricing of electricity among other measures to support the adoption of ETS in the Yukon. In addition to stipulating that DSM costs are "reasonable" and recoverable, the changes to the rate policy directive further mandate that:

In determining whether costs are reasonably incurred by a public utility to provide or participate in a demand-side management program, the Board must consider the extent of any duplication between the program for which costs are incurred and a demand-side management program provided by the Government of Yukon or in which the Government of Yukon is a participant.

The amendments to the Rate Policy Directive and the YUBs mandate provide an easier path for policy changes that will facilitate ETS adoption. See Section 10.5.1.1 for information on what the PUA determines is "reasonable" for an extension of utility services.

10.5.1.3 Upgrading Electrical Distribution Infrastructure

Upgrading electrical distribution infrastructure across the Yukon to accommodate ETS systems represents a large expense to utilities Yukon Energy and AEY. As per Section 27 of the PUA, the YUB is empowered to give orders:

• Determining the areas to which a public utility shall provide service, and requiring the public utility to establish, construct, maintain, and operate any reasonable expansion of its existing services.

The key word in the above quotation is "reasonable". The potential for wider implementation of distributed ETS in the Yukon may not be sufficient or "reasonable" to motivate the large amounts of capital needed for systematic upgrades of the Yukon's electrical distribution infrastructure. However, long-term and short-term environmental goals outlined by the Yukon Government in the recently released OCF report may make a stronger case for distributional upgrades in the Yukon [36]. Within the sphere of transportation, the report lists increasing the number of zero emission vehicles on Yukon roads, installing more fast charging stations for EVs, and requiring new residences to have sufficient electrical infrastructure to support level two chargers. Increasing electrification of transportation in the Yukon will require distributional upgrades to facilitate. In addition, the report notes a goal of 1300

fossil fuel heating systems to be converted to smart electric heating by 2030 [70]. This commitment could provide further justification for infrastructure upgrades to facilitate ETS implementation.

10.5.1.4 Incentivizing ETS Purchases and Subsidizing Costs

The adoption of ETS units within the pilot project is heavily subsidized, with participants only required to pay 0% of the total costs associated with installation. However, adoption of ETS units outside the narrow confines of the research project cannot be subsidized in this way. Policy directives can make up this gap, and still provide incentives to facilitate adoption of ETS technology. Within the OCF report, two action items are providing low-interest financing to install smart electric heating in residential, commercial, and institutional spaces, as well as increasing existing rebates for smart electric heating devices in 2020. However, the Yukon Government web page currently lists no rebates for smart ETS heaters, only heat pumps. The posted rebate for heat pumps is 40% of total installation costs to a maximum of \$8000, although it is unclear if this has been increased in accordance with the OCF report. Using a rebate and/or financing incentive may prove to be essential for meeting OCF report goals as well as ensuring Yukon residents can transition to ETS heating systems with minimal costs. The Peak Smart demand response pilot program offered by Yukon Energy provided all participating utility customers with a controller for electric water or space heaters free of charge. This has undoubtedly had a positive effect towards the success of the program, which has evolved beyond a pilot into a formal program called Peak Smart Home, providing thermostats and/or hot water tank controllers for free to Yukoners who want to participate. While incentives are more likely to be effective coming from the territorial government, municipal or First Nations governments could also offer incentives to promote electrification of heating through ETS when appropriate for the community.

10.5.1.5 Educating and Informing Yukoners

The Yukon is no stranger to awareness campaigns informing citizens about energy efficiency topics and programs. Examples include the inCharge program, which offered rebates, incentives, tools, and information to promote energy efficiency, the Good Energy program, advertising for the Peak Smart pilot project and the full-scale Peak Smart Home demand response programs [49] [71] [72]. The experiences and procedures from advertising these initiatives could be applied to an ETS program. The Peak Smart program was conducted by Yukon Energy, AEY, Natural Resources Canada, and the Yukon Development Corporation. The inCharge program was conducted by AEY and Yukon Energy. The Good Energy program is ran by Yukon Government. An initiative to popularize ETS in the Yukon is likely involve the utilities that service the territory, as previous DSM initiatives were conducted by AEY and Yukon government as a stakeholder to further inform Yukoners of ETS would be useful. AEY, while being part of the private ATCO group, works closely with public entities Yukon Energy and the Yukon Government. AEY should also be involved as a stakeholder in a wider effort to "spread the message" with ETS, for example providing information on ETS to their customers.

10.6 REVIEW OF SELECT DEMAND RESPONSE INITIATIVES

A useful way to explore future larger-scale ETS implementation in the Yukon is through looking at other appropriate pilot projects, and identifying their strengths and weaknesses. Pilot projects were selected that in some way studied electric heating within a demand response paradigm [73] [63] [74].

10.6.1 Danish Demand Response Pilot Project for Direct Electric Heating

This pilot project was undertaken in 2003, seeking to affect residential consumer load curves through DLC of conventional electric heaters as well as study the effect economic incentives had on the load. Participants were selected on a basis of heating flexibility, reasoning that consumers in homes with good thermal efficiency and supplementary heat sources (wood stoves) would be less sensitive to changes in the operation of their primary heating source (conventional electric heaters). The economic incentives offered were differential electricity prices through Nord Pool, an international commodity exchange for power contracts. Utility interventions in heater control were triggered when Nord Pool hourly prices exceeded a pre-determined threshold, which typically occurred on working days between 0600-1100 and 1600-1900 hours. There were three different prices offered during interventions to assess how the magnitude of incentive affected demand response. Consumers could interrupt interventions at will through an interface; 40% of participants utilized this feature at least once. Consumers could also pre-set time intervals they did not want any utility interventions; 24% of participants used this feature at least once. Average compensation across all participants was €80 (\leq 105.25 inflation adjusted), however predicted average compensation was \leq 130. This discrepancy was due to milder than anticipated winter temperatures, reducing the potential for demand response through electric heaters. The participant response to this program was largely positive, with most "very satisfied" or "satisfied" with the financial compensation they received through the differential pricing. Nearly all participants claimed they could tolerate utility interruptions in their electric heaters for periods as long as three hours. All participants recommended that other homeowners should enroll in the system.

10.6.2 Maritimes PowerShift Atlantic (PSA) Program

This project was a large-scale evaluation of smart-grid technologies in the Canadian Maritimes to enable more effective penetration of renewable wind resources, abundant through Canada's east coast. The project involved coordination between government, utility, and academic players, as well as (most importantly) electricity customers. The project ended up comprising of over 1400 residential and commercial participants across four unique service areas. The project duration was 2010 through 2015. PSA represented a shift towards framework of "load following generation" instead of existing "generation following load" ideas. This was enabled primarily through the smart control of end-user loads. All end-use loads within the project scope were required to have the capability to store energy such that usage could be shifted. These end uses included ETS heaters and ETS central furnaces. The smart control scheme included a Virtual Power Plant (VPP) and intermediary aggregators between the VPP and the end loads; it came to be characterized as an Intelligent Load Management (ILM) system. The ILM system was claimed to be unique among demand response schemes as the VPP utilized forecasts for load demand and wind resource availability to shift participant load in near real-time. The ILM process is a more advanced demand response technique, however notable was the difference between the infrastructure envisioned in the pre-project analysis and what was needed during the actual implementation. AMI meters and associated infrastructure were not required to support the project goals to the extent initially proposed. However, it was required that significant end-use hardware be installed at the customer site to facilitate project goals and interface with the VPPs. It is interesting to note that across the entirety of the residential customers participating in PSA, no economic incentives beyond providing and installing the necessary pilot were provided. Cost savings on the consumer side was not an objective of PSA, and residential consumers were more open than expected to participating without incentives. However, the PSA team does note that a "relevant value proposition" would be required for residential participation in a long-term implementation.

10.6.3 City of Summerside's Demand Response Program

The city of Summerside in Prince Edward Island has developed a smart grid program through the municipal utility, Summerside Electric (SSE), to capture excess power from local wind sources. Previously excess wind-generated power would have been exported outside of the local system at unfavourable prices. The smart grid utilizes ETS and electric water heaters to enact demand response and capture the excess power generated from wind resources. The thermal storage devices interact with the smart grid via a VPP. The installed thermal heating also entirely serves the homes heating needs. SSE enacts demand response through DLC of thermal storage units, as well as differential TOU pricing. DLC is achieved through a network of fibre optic cables ran throughout the eastern half of the city. All customers not able to connect to the fibre optic network participate through TOU pricing. The SSE smart grid works through three primary operational areas; energy scheduling and trading, VPP managing thermal storage units, and AMI metering to capture customer-level data. Energy scheduling works through committing to purchase power from a neighbouring utility. Commitments are informed by wind potential and load forecasting. Then the VPP manages the imported and generated power in real time, dispatching commands to thermal storage devices when the power available exceeds the load demanded. Customers engage with the SSE smart grid through the Heat for Less Now (HfLN) program, which allows participants to acquire thermal storage units. Economic incentives for Summerside residents to purchase thermal storage units includes favourable TOU pricing as well as rebates and lease-to-own deals. The HfLN program has proved popular, with enrollment steadily growing over time. Interesting to note is the distribution of residential ETS systems acquired under the program: 120 room-based units, 10 central air furnaces, and 35 hydronic units have been installed through HfLN. HfLN has been well received by participants, with a 99% satisfaction reported in a 2012 survey. In general, Summerside's smart grid initiative has proven successful, with economic benefits identified for consumers and SSE, reduction of wind-generated surpluses, and reduction of greenhouse gas emissions.

10.6.4 Insights From Selected Initiatives for the Yukon

Giving further context to the positive results seen in all three selected programs is important when considering the potential of demand response through ETS in the Yukon. Roughly half of the participants in the Danish trial program had supplementary heating options in the form of wood stoves, rendering them more flexible in their heating needs. This may have biased the results towards
more positive impressions of the DLC strategy used. Further, all incentives were provided in the form of differential pricing, which as noted earlier is not currently practical to be implemented in the Yukon. However, this pilot involved DLC of conventional electric heaters, not ETS heaters. The ability of ETS to store heat and release later allows for utility interventions to be less inconvenient to consumers, and hence less likely to engender negative consumer perceptions and overriding of utility control.

There are similarities between PSA and Summerside's smart grid program, although PSA was considerably broader in scope, did not focus exclusively on thermal storage, and is not an ongoing program. Both PSA and the Summerside project's area of service are interconnected with other grids and can regularly perform balancing with outside sources. However, the Yukon grid is isolated and cannot perform load balancing with other jurisdictions. Load balancing is primarily achieved through expensive fossil-fuel based load following. Consequences of demand response underperformance in PSA and Summerside may be less costly than in the Yukon. Similarly, the impetus for demand response in Summerside is entirely different from the Yukon. Where SSE had a problem with oversupply of wind resources, the Yukon is looking to reduce peak power consumption and integrate more renewable resources such as wind. Summerside and PSA's demand response successes are qualified by the prevalence of smart infrastructure, interconnectedness with external grids, and differential pricing schemes for non-smart integrated homes; all of these enabling factors may not be practical in the Yukon within the context of wider ETS implementation, at least until the AMI metering upgrades noted in [47] are completed throughout the territory.

10.7 DISCUSSION

Throughout the preceding sections, regulatory, policy, and infrastructural barriers towards ETS implementation were discussed, as well as a variety of solutions to these barriers. There are clearly challenges inhibiting widespread ETS adoption in the Yukon, however there are also achievable steps forward that can yield a higher likelihood of a wider adoption of ETS.

A path towards wider ETS implementation involves all or some of the following steps: upgrades to the Yukon's electrical distribution infrastructure, creation of utility-run programs to facilitate demand response through ETS (and potentially other avenues), or adjustments to existing electricity rate structures. The commonality among all these steps is the YUB. The board's approval is mandatory to enact the necessary policy and infrastructure action. To justify distributional upgrades, an expansion of utility services, or changing the existing rate structures, both a business and social case must be presented. The changes approved by the YUB must be economically sound since the provision of electricity in the Yukon is the responsibility of a Crown subsidiary, it is in the public's interest for any changes to be cost effective. Any proposals to the YUB should also consider the "bigger picture" of infrastructure or policy changes to enact demand response in the Yukon. A policy change or infrastructure upgrade may be presented as economically beneficial to Yukon Energy and AEY on paper, and thus the Yukon, but a holistic approach should be taken as latent or unintended consequences are always present. This approach is also helpful in an opposing scenario; a policy or infrastructure change may be economically costly on paper, but larger-scale or longer-term benefits justify the immediate expenses for a future net positive.

An example of this approach would be the reality of increasing acceptance and use of EVs. EVs are an important way to reduce fossil fuel emissions across the Yukon territory, and fuel costs to the individual consumer. Consumers are drawn to EVs to save money and contribute to combating climate change. The Yukon government in their OCF report details plans to markedly increase the number of EVs in the territory through the coming decades [36, pp. 22-25]. The increased load represented by EVs, as well as their proclivity to all be charged during similar hours, will greatly strain existing electrical infrastructure. By noting this, a more compelling argument would be made to support upgrading the Yukon's distribution infrastructure. This example also illustrates the importance of increased DSM capabilities in the Yukon. The problems of winter peaking as well as expensive and environmentally harmful fossil fuel-based load following that were identified in the formation of the ETS pilot project will only be exacerbated by the increased use of EVs in the Yukon.

Another important facet of proposing changes to the YUB is how user sentiment would affect overall uptake of ETS in the Yukon, and thus how user sentiment may play into overall project cost effectiveness. This topic was discussed in detail with respect to heating and associated smart technologies. The potential success of opt-in demand response ETS programs is dependent on the sentiment of current and future participants. A crucial factor in fostering positive sentiment towards ETS technology is consumer awareness. This awareness can be achieved through two steps: propagating information of ETS technology and the associated program, and then ensuring the easy availability of further information. The propagation of information will ensure an initial awareness, the availability of further information will retain interested people. Propagating information on the ETS program may be done with typical advertisements through radio, print, or local television. Local media could also be incorporated, encouraging stories be produced on the ETS program. Depending on the extent Yukon Energy and AEY are involved running the program, existing customers with these utilities could be advertised to directly. Beyond popularizing ETS through the immediate stakeholders and media outlets, community organizations with environmental goals could also be involved in producing and promoting information regarding the benefits of ETS adoption. By involving a wider coalition of trusted voices, the opportunities distributed ETS presents would be more widely known. These outreach measures should all direct back to a central hub of information for interested people to find. It is important that this central hub not only provide useful information, but have a way to ensure those with further questions can contact peoples within the official program. Yukon Conservation Society's outreach efforts and website for the ETS pilot project is a good template that may be expanded upon in a larger more permanent ETS initiative. The results from the ETS pilot project will also be helpful in refining efforts to foster positive sentiment towards a larger ETS program.

Barriers to ETS adoption such as implementing differential electricity pricing or widespread smart infrastructure, which would be difficult to overcome through a demand response program utilizing a single technology, were not investigated thoroughly. However, there is the possibility a program to popularize distributed ETS in the Yukon could be part of a larger demand response initiative enabled through a comprehensive overhaul of existing utility policies and electrical infrastructure. The goals outlined in the Yukon government's OCF report [36] are ambitious, but without purposeful change may be difficult to fully realize. While the OCF report was created by the Yukon government and contains many proposed policy and infrastructure changes, including a desire to rework and

modernize the PUA, the fulfillment of these proposals is not a certainty. If steps are taken to modernize policy and upgrade infrastructure however, the scope of ETS implementation could increase while supporting other OCF objectives.

11 WHAT ARE THE VALUE STREAMS FOR INTEGRATING ETS UNITS IN DIESEL POWERED COMMUNITIES?

11.1 INTRODUCTION

Introducing Electric Thermal Storage (ETS) systems in remote diesel-powered Yukon communities represents an opportunity to create several value streams. For the purposes of this discussion, a "remote" community in the Yukon is a community that is not connected to the larger Yukon Integrated System (YIS). In other words, a community that is responsible for producing and consuming all its own power. Diesel-powered is self-explanatory, it is a community that is reliant on diesel to generate power. ETS can provide value for remote Yukon communities in multiple ways. ETS can be paired with renewable generation in a remote community, allowing for greater penetration of renewable resources. Some ETS systems can also be managed with a sophisticated control scheme to regulate grid frequency. When ETS is paired with renewables, local greenhouse gas emissions can be reduced by decreasing the demand on heating fuels, as well as the demand for diesel fuels for the local plant. Reducing heating fuel consumption can also result in cost savings for the community, provided the cost of electricity does not increase unduly.

11.2 METHODOLOGY

A literature review is conducted of previous projects that studied the pairing of ETS with renewable generation. Both theoretical studies of ETS and renewable generation, and actual practical implementations of ETS with renewables are reviewed. Grid frequency was found to be a useful way to integrate ETS with renewable generation in remote communities. The grid frequency-based control method used in this ETS demonstration project is then analyzed with respect to proportion of the maximum charge of the ETS systems. Finally, fuel prices in remote communities and potential economic savings from ETS technology are discussed.

11.3 ANALYSIS

11.3.1 Renewable Integration

The primary role of ETS in remote diesel-powered communities would be to facilitate renewable generation. These communities consume diesel fuel to generate electricity and generally heating is not electric-based to accommodate the expensive and limited supply of electricity. ETS alone will not provide value, even if ETS exclusively drew power during the optimal hours of day it still represents an increase in the overall demand for electricity in the community.

Pairing ETS with a renewable source of generation would allow ETS to draw power during optimal periods of renewable generation. The common issue with the most common renewable power solutions, solar and wind, is that generation of power is intermittent. The sun does not always shine and the wind does not always blow, and when the sun will shine or the wind blows is a random variable. Integrating renewable sources of generation into remote communities is made more

challenging from this randomness. If the local system does not have the demand to equal the electricity being produced at any given time, then the excess power generated needs to be consumed to keep the system in balance. With conventional diesel generation this is not a problem as generation can be carefully controlled to match the demand, however with renewables the random quality of the generation prohibits this. For this reason, renewable systems in remote communities must be paired with a technology that accounts for overproduction of power relative to the demand at any given time. Examples of these technologies include battery systems, load sinks, and thermal storage. ETS falls within the category of thermal storage. A major benefit of ETS is that while facilitating the adoption of renewable generation it provides value itself, in providing heat to buildings.

ETS has been studied with renewable energy before. In [75], ETS systems were modeled on the YIS and optimized with respect to various parameters, including ETS and wind penetration levels. While the YIS is remote in a sense, not being connected to the larger North American grid, it is powered by a combination of hydro and fossil fuel resources. The scope of this study does not align with the research question, but the results are notable for being Yukon-focused.

In [76], another model-centric study of ETS was conducted with the goal of evaluating ETS in northern microgrids. The model was optimized over microgrid operating costs, which was a function of generation and load curtailment costs. The model was applied to a CIGRE benchmark system and a real microgrid in Kasabonika Lake First Nation (KLFN). The CIGRE benchmark system was analyzed without renewables, but the KLFN system was analyzed with and without a planned solar plant. Three levels of ETS penetration were considered, 0%, 50%, and 100%. In both non-zero levels of ETS penetration, ETS with the solar plant resulted in lower operating costs in the KLFN microgrid. Further, the community's smaller diesel genset is used more efficiently while another less efficient genset had less operating time.

Contrary to the previous studies, in [77] results from an actual implementation of ETS were studied. Room, central air, and hydronic ETS systems were installed in the community of Summerside on Prince Edward Island. Summerside meets much of its electricity demand through wind resources. Summerside is not a remote community isolated from the larger grid, however the community wanted to avoid exporting excess wind-generated power at low prices. ETS was used to store this excess energy for later use. The control approach Summerside used was a combination of time-of-use (TOU) charging and dynamic smart charging. TOU ETS units would be forbidden to charge during on-peak times, allowed to charge during on-peak times, and allowed to charge during mid-peak times only when necessary to maintain heating requirements. ETS units under smart charging would operate under the same constraints as TOU ETS units, except when the smart grid would send a demand response request to the ETS unit. It was noted that only the smart ETS units were able to absorb excess wind energy, and the TOU ETS units performed at a level similar to electric baseboards despite being tailored to optimize wind absorption.

The best example of a practical study of physical ETS units in remote northern communities comes from Alaska. The Chaninik Wind Group is a consortium which includes four remote communities in Alaska, Kongiganak, Kwigillingok, Tuntutuliak, and Kipnuk, which all generate their own electricity. Within these communities, wind resources were paired with ETS devices in a "Wind Heat Smart Grid", to optimize diesel and wind generation, increase the amount of power sold by the utility, and reduce heating costs for community members [78]. The Wind Heat Smart Grid is designed with excess wind energy to be captured by the installed ETS systems. The ETS systems used in these remote communities were manufactured by Steffes. Lighter winds are designed to offset diesel whereas higher winds will generate the excess energy that ETS will use. An initial plan to integrate wind into these remote Alaskan communities was to employ a flywheel or battery system. However, these options were rejected due to high cost. ETS was recognized as a cheaper alternative that was able to provide ancillary benefits to community members through the reduction of heating oil in homes. A Smart Grid Controller was used to integrate ETS with the wind-diesel system and regulate excess wind energy through home metering. Every ETS device has an individual controller that has the capacity for sub-metering, radio communication, manual homeowner control, temperature monitoring, and frequency monitoring. Originally radio was used to communicate between the wind-diesel system and the ETS units, where charging set-points were given to the ETS units [79]. However, the radio communication was not fast enough to allow the ETS to perform frequency regulation on the microgrid as was originally desired. Instead, each individual ETS unit was programmed to recognize changes in grid frequency, and automatically determine their charging setpoints accordingly.

ETS as it was implemented in the Yukon demonstration project would not be feasible for remote communities. The time-of-day based charging will not necessarily correlate with times of day when renewable energy is abundant. Rather, a control scheme is needed which allows ETS units to charge when there is an overproduction of renewable power, as well as account for overall system stability.

11.3.2 Benefits of ETS and Renewable Integration in Diesel Powered Communities

11.3.2.1 Frequency Regulation

On an electrical grid, the voltage and frequency must be carefully monitored to ensure stability in the system. Frequency can change with respect to four broad factors, illustrated in Table 29.

Load Condition	Frequency Behaviour
Excess of generation	Higher frequency
Lack of load	Higher frequency
Excess of load	Lower frequency
Lack of generation	Lower frequency

Table 29: Relationship between grid frequency and electricity generation.

Higher frequency values would correspond to periods when it would be desirable for ETS units to charge. The frequency across the grid could be monitored by the ETS systems to determine the proportion of their maximum charge. As was noted in Section 11.3.2.1, originally radio was used to communicate to Steffes ETS systems their charging setpoints in response to changes in grid frequency. Radio proved to be too slow to effectively regulate frequency, and instead an electric boiler was used to regulate frequency in the community of Tuntutuliak [79]. Eventually a solution was programmed into the ETS unit's Grid-Interactive Electric Thermal Storage (GETS) controllers wherein individual ETS systems were allowed to automatically determine their charging setpoints in response to changes in the grid frequency. There was still an element of central control, where the wind-diesel plant would

radio setpoints for the ETS to activate and receive data on the proportion of maximum charge of the ETS systems. Otherwise ETS systems acted autonomously.

The GETS controller monitors the grid frequency and activates heating elements within the ETS core if needed. The heating elements activate one by one after the grid frequency increases above a certain set point threshold. All the ETS unit's heating elements will activate if the grid frequency continues to increase. Similarly heating elements will be deactivated should grid frequency decrease. An example of how the GETS controller could handle this is given in Figure 68.



Figure 68: Example of GETS controller's method for determining ETS proportion of maximum charge in response to grid frequency.

The activation set points communicated by radio to the ETS systems were staggered, they were constant across ETS systems. This was to ensure load is not demanded simultaneously by ETS systems, something that could throw the microgrid voltage and frequency out of balance. The community's electric boiler was used as a backup to regulate frequency, where ETS remained the primary tool. If the ETS systems through the community reached their maximum capacity, then the electric boiler would be used.

During the Whitehorse ETS demonstration project, 10 participant's ETS systems were placed in frequency-based charging control for a period of 10 days during the 2022-2023 heating season. The results from this experiment indicated that frequency-based charging still resulted in peak-shifting capabilities for the ETS systems, explained in detail in Section 8.3. The pre-set thresholds to determine the amount of charging as a function of grid frequency are given in Table 30.

Limit	Threshold Value [Hz]
Low Hz Limit	59.9
Low Hz Dead Band	60.1
High Hz Dead Band	59.97
High Hz Limit	61.47

Table 30: Pre-set thresholds for frequency-based charging during 2022-2023 heating season.

The grid frequency values observed by the ETS system are compared with the power draw, as a proportion of the maximum possible power draw, in Figure 69.



Figure 69: Grid frequency plotted against the input power for ETS systems during the frequencybased charging experiment. Grey dotted lines indicate the upper and lower thresholds set to determine the relative amount of charging.

The programmed range of grid frequency values did not fully encompass what was observed. Charging occurring at frequencies lower than the pre-set upper and lower limits, shown by the grey lines in Figure 69. No grid frequency values were observed anywhere close to the 61.47 Hz upper limit. A selection of the proportion of maximum charge values closely followed the lower limit for charging. Approximately 50% of the data in Figure 69 falls within the programmed frequency limits, or in other words 50% of the energy consumption occurs during the desired frequencies.

The results from the Tuntutuliak study showed that allowing the ETS units to autonomously regulate their charging in response grid frequency resulted in far greater excess wind energy converted into heat than with the pure radio control. It was observed that both radio and autonomous ETS control resulted in satisfactory variation in frequency and voltage throughout the microgrid.

11.3.2.2 Fossil Fuel Reductions

A direct benefit to remote communities with the introduction of ETS would be the reduction in heating fuel usage from transitioning fossil fuel-based heating to electric. Heating fuel is expensive and has increased in cost in recent years. Data taken from the Yukon Bureau of Statistics for remote communities (communities not connected to the YIS) and Statistics Canada for heating oil are compared in Figure 70. The remote communities for which there was available data were Beaver Creek, Burwash Landing, Destruction Bay, and Watson Lake.



Figure 70: Heating oil price comparison for remote Yukon communities and non-remote Canadian cities.

Heating oil prices in remote Yukon communities generally agree with prices across Canada. For remote communities only accessible by air in winter, such as Old Crow, there was no current data on fuel prices. However, it is reasonable to assume that the costs associated with transporting fuel by plane would be reflected in higher prices for consumers.

Any reduction in fossil fuels would have twin benefits for members of the remote community, there would be an overall reduction in greenhouse gas emissions and cost savings. In the Kongiganak community of Alaska, homeowners were reporting greater than 30% reductions in their heating oil consumption [78, p. 20] and a maximum of 50% reductions [80, p. 23]. Kongiganak's diesel consumption also was reduced approximately 40% [80, p. 23]. Combining ETS with renewable resources represents an opportunity to offset fossil fuels for both electricity generation and home heating.

11.4 DISCUSSION

The primary value stream for ETS in diesel powered communities was determined to be ETS paired with renewable resources. The intermittent nature of renewable generation pairs well with ETS' ability to store energy as heat for later use. ETS paired with renewable generation has the ability to reduce fossil fuel consumption at the individual and utility levels. An ETS implementation paired with renewable wind generation in remote Alaskan communities has already been studied and the results were promising. The ETS systems used were also manufactured by Steffes, which were also studied in the Yukon's ETS demonstration project. The original radio-based control was replaced by a more responsive frequency-based control, regulated through the Steffes GETS controllers. This same method was used in the Yukon's demonstration project for an experimental period and subset of ETS units. The results were satisfactory, with frequency-based control still having peak-shifting capabilities. However, the pre-set limits for power draw as a function of grid frequency were not closely followed, with 50% of the energy consumed by the experimental period for the evaluation of the power draw as a function of grid frequency. It is possible with a more extensive study period better results could have been observed.

12 CONCLUSIONS

An analysis of the Electric Thermal Storage (ETS) demonstration project data and results provided several useful insights for the technologies potential value in the Yukon. A summary of these insights is given below.

12.1 PEAK SHIFTING CAPABILITIES

The ETS systems were found to have effective peak shifting capabilities both for Elnur and Steffes units. Both systems followed a pre-determined control strategy and generally drew the majority of their power during the scheduled off-peak hours and drew limited power during scheduled on-peak hours. Three different control strategies were evaluated for the ETS systems with respect to peak shifting. Firstly, no control, allowing units to operate independently. Secondly, time-of-day (TOD) control, the predominant strategy used throughout the ETS demonstration project. Thirdly, grid frequency-based control where the grid frequency was used to regulate ETS power draw. Unsurprisingly the no-control strategy was identified as the worst for creating peak shifting capacity. Both grid frequency-based control and TOD control were shown to create peak shifting capacity. The TOD control was shown to provide greater peak shifting capacity than grid frequency-based control. However, frequency-based control was observed to be responsive to real time changes in grid load. Frequency-based control can more effectively change charging to address secondary peaking, as well as integrate with renewables which typically generate intermittent and variable power.

12.2 BENEFITS OF ETS TECHNOLOGY

ETS was demonstrated to follow predictable patterns of power draw through multiple heating seasons, and was responsive to the control strategies employed. As outdoor temperatures decreased ETS systems were observed to have a greater capacity for peak reduction. The ETS fleet load was also found to be more consistent and predictable at lower temperatures as ETS were used more frequently. The ETS project's total installed maximum draw was 689 kW with a total storage capacity of 4133 kWh across 45 participating homes with a total heat load of 396 kW. The ETS fleet had the capacity to reduce 315 kW from the highest peak day throughout the 2021-2022 and 2022-2023 heating seasons against a calculated winter peak of 109 MW. The average peak day reduction of 177 kW. When estimating the effect of ETS peak shifting by accounting for pre-ETS electric heat loads, the Yukon Government provided residential electric heating curve gave marginally better results than the residential electric heating curve derived from National Renewable Energy Laboratory data, though both curves were employed in the analysis. Modeling the ETS fleet load and simulating various proportions of ETS penetrations identified the optimal proportion of ETS adoption for peak shifting to be between 30% and 40% of Whitehorse area homes. This would result in the "flattest" resulting load profile; existing peaks would be diminished while previous troughs in load would be filled in. When minimizing secondary peaking, between 0.59 MW and 1.05 MW was able to be reduced from winter peaks in the ETS simulations, with approximately 7% of Whitehorse area homes having ETS systems installed.

ETS also demonstrated the potential to reduce greenhouse gas (GHG) emissions through peak shifting. When considering only utility GHG reductions from ETS, the maximum GHG reduction occurs at 20% residential penetration of ETS when replacing 100% electric heating, equivalent to a reduction of 551 T and 580 T of GHGs, or 5.8% and 6.1% of all utility power generation emissions through a heating season. Accounting for local GHG reductions from transitioning fossil fuel-based heating to ETS in addition to utility reductions from shifting diesel resources to hydro and liquified natural gas through ETS results in a greater overall reduction of GHGs, and a greater possible penetration of ETS systems while still reducing GHGs. When only considering utility GHG reductions, at 25% ETS penetration there are at a minimum net GHG contributions equivalent to between 4.2 and 4.6% of Yukon Energy GHG emissions through a heating season. When accounting for local GHG reductions, at 25% ETS penetration there is now a GHG reduction equivalent to approximately 3.0 to 3.5% of Yukon Energy power generation emissions across a heating season.

An analysis of ETS data through on-board and external sensors, as well as Whitehorse power outage data, proved inconclusive to determine whether ETS systems could provide value by delaying charging after a power outage, thereby reducing the black start load on the grid. The Steffes manufactured ETS systems are capable of delaying power draw after a power outage, but this was unable to be confirmed. Survey responses collected from demonstration project participants indicated that ETS systems operated normally following a power outage, and a subset of systems were observed to emit heat during an outage. All but one of the systems reported by participants to emit heat during an outage were from Elnur manufactured ETS units.

ETS was shown to provide value in remote communities when paired with intermittent power generation resources such as wind or solar. The TOD control strategy predominantly used in the demonstration project is less feasible for remote communities where generation resources are on a smaller scale and consequently more variable. However, a grid frequency-based control strategy is feasible when paired with renewable energy generation. The ETS system will draw power when the grid frequency crosses thresholds indicative of an excess of available renewable energy that may be "absorbed" by the ETS systems and stored as heat. The frequency-based control strategy was shown to be possible with the Steffes manufactured ETS systems and their built-in controller during an experimental period of a subset of ETS systems within the 2022-2023 heating season.

12.3 POSSIBLE CHALLENGES FOR ETS ADOPTION

If ETS systems do not provide the same standard of thermal comfort as other heating systems, individuals will be less compelled to adopt the technology regardless of the demonstrated benefits to the grid. An analysis of ETS demonstration project data comprising survey responses and temperature and humidity sensors placed in participant homes indicated that ETS systems provide a satisfactory level of thermal comfort. Survey responses for individual participants indicated a broad level of satisfaction with ETS heating performance within the demonstration project. Empirical models of thermal comfort further supported this conclusion. The empirical models employed in this research generate results that replicate what an "average" occupant would feel to be comfortable thermal conditions in a home. Results from these models show that the thermal conditions across the majority of participant homes through both the 2021-2022 and 2022-2023 heating seasons were acceptable and would meet occupant's heating needs.

The grid infrastructure through the Yukon must be robust enough to handle any significant penetration of ETS heating. It was noted in Northern Energy Innovation's work on the Electric Vehicle and Electric Heating project that the power quality in Whitehorse neighbourhoods degraded as electrification of heat increased. Ensuring that infrastructure is in place that can accommodate the increased electrification of heat through ETS will be critical. Another factor in shaping the future of ETS in the Yukon is the regulatory environment surrounding ETS technology and electricity pricing. Given ETS' primary function of energy storage through heat, differential pricing of electricity is a natural policy to incentivize ETS users to store heat with their units during cheaper off-peak hours. Offering a direct rebate or subsidy for installing ETS units is a policy that has been demonstrated to work with consumer technology before, and has also been implemented in the city of Whitehorse. Another important variable in the adoption of ETS technology within the context of the Yukon is essential to ensure support for any policy designed to facilitate ETS adoption.

13 APPENDIX

13.1 DETAILED PARAMETERS FOR ETS FLEET LOAD MODEL

The full parametrization of the model described in Section 1.2 is given below in Table 31.

Table 31: Full parametrization of fleet load model for ETS systems in Whitehorse.

Model Term	Estimate	Std.error	t-statistic	P.value
(Intercept)	1207.1852779129008	57.53476576948849	20.981840488400643	9.369576344121751e-
				94
hour1	-180.10250537050973	75.351012542557	-2.390180294774285	0.01687684602645037
				8
hour2	-418.28089651484095	71.87627171775156	-5.819457332975946	6.271024146801673e-
				9
hour3	-680.0508877089569	68.53363004914524	-9.922878552052396	5.390129326002565e-
				23
hour4	-794.2146556925826	67.9286140408767	-11.691901371852756	3.552413202885334e-
				31
hour5	-951.0698397442794	65.99216911175738	-14.411859051543644	3.6166402857121535e
				-46
hour6	-1318.4523731348102	61.9156442555599	-21.294333427151827	2.1484063793969656e
				-96
hour7	-1331.3137126765803	60.14682637163688	-22.134396658780002	1.1928411195306253e
				-103
hour8	-1315.807441877635	59.130663540048054	-22.252539767061197	1.0907688619122881e
				-104
hour9	-1294.2791813252954	58.52431028226517	-22.115240232357007	1.7563132554797699e
				-103
hour10	-971.9143907559688	65.72835914174344	-14.786834837304124	1.8504436514980586e
				-48
hour11	-508.3656975622501	71.3220764721012	-7.127746732964311	1.1653708794399602e
				-12
hour12	-390.6739224011319	73.32759367259442	-5.3277886650076045	1.0376906279725193e
				-7
hour13	-238.7449080054244	75.18746352402012	-3.1753286627251716	0.00150574636257853
				72
hour14	-377.2141761071766	72.33382975042632	-5.214906737396321	1.913111925066335e-
				7
hour15	-774.0992504093317	66.74946247348996	-11.597085904875579	1.0489884346326866e
				-30

Huu 10 1,288,15304,10203633 38,303934,18310203 1,21303160,50000444 1,00040303793339344 hour17 -1273,1141321725613 58,117601112208064 -21.905827284828064 1,184597500150938e- 101 hour18 -1285,8052849259295 58,353826882801094 -22.03463514926561 8.918209145013842e- 103 hour19 -1279,520058736184 58,25627927466372 -21.963641939842542 3,71582566121212e- 102 hour20 -1196,1650292556362 59,6280557856851 -20.060439896864782 3,6654090913343044e -86 hour21 -632,5390036986101 70,63135351971101 -8,955498828464163 4,683674512671015e- 19 hour22 61,77346707562186 80,57379646817945 0,7666694357639918 0,44331421809443494 hour23 8,096152632576405 79,45479863775098 0,1018963315274325 0,91843039920203 loadCap 0,32222937214242275 0,0229397112350852 14,050308618908165 5,20587741071569e- 44 temp_adj -4,452118949192317 0,21052350582900664 -21.147847275583842 3,7455405883002151e- 55 hour1;loadCap - 0,0084776000642173991 -1.6922426219033482	hour16	1299 1550/10205902	E8 90E0E119E10202	21 005190502060944	1 2000/500705002/10
hour17 -1273.1141321725613 58.117601112208064 -21.905827284828064 1.184597500150938e- 101 hour18 -1285.8052849259295 58.353826882801094 -22.03463514926561 8.918209145013842e- 103 hour19 -1279.520058736184 58.25627927466372 -21.963641939842542 3.71582566121212e- 102 hour20 -1196.1650292556362 59.6280557856851 -20.060439896864782 3.6654090913343044e -86 hour21 -632.5390036986101 70.63135351971101 -8.955498828464163 4.683674512671015e- 19 hour22 61.77346707562186 80.57379646817945 0.7666694357639918 0.44331421809443494 hour23 8.096152632576405 79.45479863775098 0.10189633315274325 0.918843039920203 loadCap 0.32222937214242275 0.02293397112350852 14.050308618908165 5.20587741071569e- 44 temp_adj -4.452118949192317 0.21052350582900664 -21.147847275583842 3.745540583002151e- 95 hour1:loadCap - 0.008072339373472237 -6.5331650245571167 7.078544877409762e- 11 hour2:loadCap - 0.007702510273336851 -10.100077964383832	1100110	-1288.1330410203803	38.80393418310203	-21.903180302000844	-101
Init Init hour18 1285.8052849259295 58.353826882801094 -22.03463514926561 8.918209145013842e- 103 hour19 -1279.520058736184 58.25627927466372 -21.963641939842542 3.6554090913343044e hour20 -1196.1650292556362 59.6280557856851 -20.060439896864782 3.6654090913343044e hour21 -632.5390036986101 70.63135351971101 -8.955498828464163 4.683674512671015e- 19 hour22 61.77346707562186 80.57379646817945 0.7666694357639918 0.44331421809443494 hour23 8.096152632576405 79.45479863775098 0.10189633315274325 0.918843039920203 loadCap 0.32222937214242275 0.02293397112350852 14.050308618908165 5.20587741071569e- 44 temp_adj -4.452118949192317 0.21052350582900664 -21.147847275583842 0.09066192932702331 hour1:loadCap - 0.008072339373472237 -6.533165024571167 7.078544877409762e- 95 hour3:loadCap -0.0779595428216961 0.007702510273336851 -10.100077964383832 9.308439716657055e- 24 hour4:loadCap -0.08553741828564158	hour17	-1273.1141321725613	58.117601112208064	-21.905827284828064	1.184597500150938e-
hour18 -1285.8052849259295 58.353826882801094 -22.03463514926561 8.918209145013842e- 103 hour19 -1279.520058736184 58.25627927466372 -21.963641939842542 3.71582566121212e- 102 hour20 -1196.1650292556362 59.6280557856851 -20.060439896864782 3.6654090913343044e -86 hour21 -632.5390036986101 70.63135351971101 -8.955498828464163 4.683674512671015e- 19 hour22 61.77346707552186 80.57379646817945 0.76666694357639918 0.44331421809443494 hour23 8.096152632576405 79.45479863775098 0.10189633315274325 0.918843039902023 loadCap 0.32222937214242275 0.02293397112350852 14.050308618908165 5.20587741071569e- 44 temp_adj -4.452118949192317 0.21052350582900664 -21.147847275583842 0.09066192932702331 hour21:loadCap - 0.008072339373472237 -6.533165024571167 7.078544877409762e- 11 hour3:loadCap -0.007779595428216961 0.007702510273336851 -10.100077964383832 9.308439716657055e- 24 hour4:loadCap -0.08653741828564158 0.0067627702518976373 -11.					101
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loadCap 0.32222937214242275 0.02293397112350852 14.050308618908165 5.20587741071569e- 44 temp_adj -4.452118949192317 0.21052350582900664 -21.147847275583842 3.745540583002151e- 95 hour1:loadCap - 0.008477600642173991 -1.6922426219033482 0.09066192932702331 hour2:loadCap - 0.008072339373472237 -6.533165024571167 7.078544877409762e- 11 hour3:loadCap - 0.007702510273336851 -10.100077964383832 9.308439716657055e- 24 hour4:loadCap -0.08653741828564158 0.007622702518976373 -11.352590248695998 1.6476616640799914e -29 hour5:loadCap -0.0993290320467802 0.007417333134470985 -13.39147510918215 3.311269867099155e- 40 hour6:loadCap -0.13909055733851605 0.006955873106325314 -19.996132076077444 1.2113953771334365e -85 hour7:loadCap -0.14591656886401508 0.006761741009741244 -21.579733481924496 7.818245852660388e- 99 hour8:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e	hour23	8.096152632576405	79.45479863775098	0.10189633315274325	0.918843039920203
image: second	loadCap	0.32222937214242275	0.02293397112350852	14.050308618908165	5.20587741071569e-
temp_adj -4.452118949192317 0.21052350582900664 -21.147847275583842 3.745540583002151e- 95 hour1:loadCap - 0.008477600642173991 -1.6922426219033482 0.09066192932702331 hour2:loadCap - 0.008072339373472237 -6.533165024571167 7.078544877409762e- 11 hour3:loadCap - 0.007702510273336851 -10.100077964383832 9.308439716657055e- 24 hour4:loadCap -0.08653741828564158 0.007622702518976373 -11.352590248695998 1.6476616640799914e -29 hour5:loadCap -0.0993290320467802 0.007417333134470985 -13.39147510918215 3.311269867099155e- 40 hour6:loadCap -0.13909055733851605 0.006955873106325314 -19.996132076077444 1.2113953771334365e -85 hour7:loadCap -0.14591656886401508 0.006761741009741244 -21.579733481924496 7.818245852660388e- 99 hour8:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e					44
bour1:loadCap - 0.008477600642173991 -1.6922426219033482 0.09066192932702331 hour2:loadCap - 0.008072339373472237 -6.533165024571167 7.078544877409762e- hour2:loadCap - 0.0052737925261237543 - 11 hour3:loadCap -0.07779595428216961 0.007702510273336851 -10.100077964383832 9.308439716657055e- 24 - - - 24 hour4:loadCap -0.08653741828564158 0.007622702518976373 -11.352590248695998 1.6476616640799914e -29 - - - -29 - hour5:loadCap -0.0993290320467802 0.0076174733134470985 -13.39147510918215 3.311269867099155e- 40 - - - - -29 - hour6:loadCap -0.13909055733851605 0.006955873106325314 -19.996132076077444 1.2113953771334365e -85 hour7:loadCap -0.14591656886401508 0.006761741009741244 -21.579733481924496 7.818245852660388e- 99 hour8:loadCap -0.1469475673929025 <td< td=""><td>temp_adj</td><td>-4.452118949192317</td><td>0.21052350582900664</td><td>-21.147847275583842</td><td>3.745540583002151e-</td></td<>	temp_adj	-4.452118949192317	0.21052350582900664	-21.147847275583842	3.745540583002151e-
hour1:loadCap - 0.008477600642173991 -1.6922426219033482 0.09066192932702331 hour2:loadCap - 0.008072339373472237 -6.533165024571167 7.078544877409762e- hour3:loadCap -0.07779595428216961 0.00770251027336851 -10.100077964383832 9.308439716657055e- hour3:loadCap -0.08653741828564158 0.007622702518976373 -11.352590248695998 1.6476616640799914e hour4:loadCap -0.0993290320467802 0.007417333134470985 -13.39147510918215 3.311269867099155e- hour5:loadCap -0.13909055733851605 0.006955873106325314 -19.996132076077444 1.2113953771334365e hour7:loadCap -0.14591656886401508 0.006761741009741244 -21.579733481924496 7.818245852660388e- 99 hour8:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e					95
0.014346157138162023 hour2:loadCap - 0.008072339373472237 -6.533165024571167 7.078544877409762e- 0.052737925261237543 11 11 hour3:loadCap -0.07779595428216961 0.007702510273336851 -10.100077964383832 9.308439716657055e- 24 - - -29 16476616640799914e -29 hour4:loadCap -0.0993290320467802 0.007417333134470985 -13.39147510918215 3.311269867099155e- 40 - - - 40 - hour6:loadCap -0.14591656886401508 0.006761741009741244 -19.996132076077444 1.2113953771334365e -85 - -85 - - - hour7:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e	hour1:loadCap	-	0.008477600642173991	-1.6922426219033482	0.09066192932702331
hour2:loadCap - 0.008072339373472237 -6.533165024571167 7.078544877409762e- 0.052737925261237543 -10.00077964383832 9.308439716657055e- hour3:loadCap -0.07779595428216961 0.007702510273336851 -10.100077964383832 9.308439716657055e- hour4:loadCap -0.08653741828564158 0.007622702518976373 -11.352590248695998 1.6476616640799914e hour5:loadCap -0.0993290320467802 0.007417333134470985 -13.39147510918215 3.311269867099155e- hour5:loadCap -0.13909055733851605 0.006955873106325314 -19.996132076077444 1.2113953771334365e hour7:loadCap -0.14591656886401508 0.006761741009741244 -21.579733481924496 7.818245852660388e- 99 - - - - - hour8:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e		0.014346157138162023			
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hour4:loadCap -0.08653741828564158 0.007622702518976373 -11.352590248695998 1.6476616640799914e hour5:loadCap -0.0993290320467802 0.007417333134470985 -13.39147510918215 3.311269867099155e- hour6:loadCap -0.13909055733851605 0.006955873106325314 -19.996132076077444 1.2113953771334365e hour7:loadCap -0.14591656886401508 0.006761741009741244 -21.579733481924496 7.818245852660388e- hour8:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e	hour3:loadCap	-0.07779595428216961	0.007702510273336851	-10.100077964383832	9.308439716657055e-
hour4:loadCap -0.08653741828564158 0.007622702518976373 -11.352590248695998 1.6476616640799914e hour5:loadCap -0.0993290320467802 0.007417333134470985 -13.39147510918215 3.311269867099155e- hour6:loadCap -0.13909055733851605 0.006955873106325314 -19.996132076077444 1.2113953771334365e hour7:loadCap -0.14591656886401508 0.006761741009741244 -21.579733481924496 7.818245852660388e- hour8:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e					24
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hour5:loadCap -0.0993290320467802 0.007417333134470985 -13.39147510918215 3.311269867099155e-40 hour6:loadCap -0.13909055733851605 0.006955873106325314 -19.996132076077444 1.2113953771334365e-85 hour7:loadCap -0.14591656886401508 0.006761741009741244 -21.579733481924496 7.818245852660388e-99 hour8:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e					-29
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hour7:loadCap -0.14591656886401508 0.006761741009741244 -21.579733481924496 -85 hour8:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e	hour6:loadCap	-0.13909055733851605	0.006955873106325314	-19.996132076077444	1.2113953771334365e
hour7:loadCap -0.14591656886401508 0.006761741009741244 -21.579733481924496 7.818245852660388e- 99 hour8:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e	_				-85
hour8:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e	hour7:loadCap	-0.14591656886401508	0.006761741009741244	-21.579733481924496	7.818245852660388e-
hour8:loadCap -0.1469475673929025 0.006656542589426717 -22.075659461161518 3.9028735880084644e	_				99
	hour8:loadCap	-0.1469475673929025	0.006656542589426717	-22.075659461161518	3.9028735880084644e
-103					-103
hour9:loadCap -0.14621111186792074 0.00660005414365693 -22.153017033722197 8.187491824550343e-	hour9:loadCap	-0.14621111186792074	0.00660005414365693	-22.153017033722197	8.187491824550343e-
104					104
hour10:loadCap -0.08926316823039927 0.007501293164755552 -11.899703993679086 3.216791436001056e-	hour10:loadCap	-0.08926316823039927	0.007501293164755552	-11.899703993679086	3.216791436001056e-
32					32
hour11:loadCap - 0.008218859213864569 -5.7729964027332 8.256387907628715e-	hour11:loadCap	-	0.008218859213864569	-5.7729964027332	8.256387907628715e-
		0.047447444676210766			9
0.047447444676310766		0.04/44/4446/6210/66			3

hour12:loadCap	-	0.008476520201439634	-3.353355864570342	8.043065532854225e-
	0.028424788728646573			4
hour13:loadCap	-	0.008735215584090584	-2.05490884138663	0.03993957287920552
	0.017950071735166016			
hour14:loadCap	-0.04106996787354951	0.008373445394574974	-4.904787209833375	9.64886405595014e-7
hour15:loadCap	-0.08265556645122214	0.007673632825043612	-10.771373655182984	9.213014039885864e-
				27
hour16:loadCap	-0.14431626433418354	0.006679333774718309	-21.606386086053902	4.612837335250936e-
				99
hour17:loadCap	-0.14503206343544742	0.006597773210513741	-21.981971614958614	2.571535281765567e-
				102
hour18:loadCap	-0.14525148056397635	0.006622502159672888	-21.93302124512269	6.868638589133543e-
				102
hour19:loadCap	-0.14597203550363452	0.006592832236011531	-22.141020775002048	1.0434108873193234e
				-103
hour20:loadCap	-0.14278273678944337	0.006737690967868122	-21.19164228077106	1.596318105629067e-
				95
hour21:loadCap	-0.06952162576076452	0.008022828077165468	-8.665476200173929	5.985539757781331e-
				18
hour22:loadCap	0.01540088973201384	0.009151403719648017	1.6828991708614283	0.09245694513138973
hour23:loadCap	0.003562587773817361	0.008985682752829726	0.3964737985764576	0.691772425607005
	6			
hour1:temp_adj	0.6526530563092804	0.27559952322079956	2.3681211370833912	0.01791644520866842
hour2:temp_adj	1.554723690865833	0.26289782300448844	5.913794466222298	3.5648696412040317e
				-9
hour3:temp_adj	2.523586242391397	0.250770416422202	10.063333141109586	1.3430211645708578e
				-23
hour4:temp_adj	2.938568366529396	0.2486182328356854	11.819601213526157	8.157194569621834e-
				32
hour5:temp_adj	3.5178615278365184	0.2415250590548554	14.565203054303108	4.244925824146195e-
				47
hour6:temp_adj	4.882506076229498	0.2265517165612416	21.55139740426401	1.3692027233263422e
				-98
hour7:temp_adj	4.9232560815484	0.22000004112633764	22.37843255093376	8.42897949734398e-
				106
hour8:temp_adj	4.864384360395194	0.2162192773463723	22.49745915394351	7.409143691897952e-
				107
hour9:temp_adj	4.782449588504893	0.2138865788992344	22.35974605380914	1.2335250461135944e
				-105

hour10:temp_adj	3.580518433258804	0.23994100245870006	14.922495099082125	2.6623349536806874e
				-49
hour11:temp_adj	1.876899685672596	0.2597621497777503	7.2254548527506834	5.746309025920626e-
				13
hour12:temp_adj	1.4632778908322475	0.2664738161221017	5.491263314823228	4.187630624786107e-
				8
hour13:temp_adj	0.9154282357455591	0.2726655063168352	3.3573305553429207	7.928575944947752e-
				4
hour14:temp_adj	1.4297800082466705	0.2622888566988441	5.451165658510309	5.2439576423059e-8
hour15:temp_adj	2.8777953504043254	0.24243258122503938	11.870497504347387	4.519224984110511e-
				32
hour16:temp_adj	4.753321260873696	0.2144189342648445	22.16838394972396	6.00053919670021e-
				104
hour17:temp_adj	4.6980175336115195	0.21200669841983688	22.159759897340766	7.143989496141963e-
				104
hour18:temp_adj	4.7459223869829685	0.21288810959364796	22.293036450188737	4.7929250542733966e
				-105
hour19:temp_adj	4.7241271377568355	0.21261800030425262	22.218848502933394	2.159958264318754e-
_				104
hour20:temp_adj	4.428947246423505	0.21763474083915046	20.350368830575867	1.6069927337281332e
				-88
hour21:temp_adj	2.3433777359930765	0.25759758027059504	9.097048712691556	1.3123262254847646e
				-19
hour22:temp_adj	-0.22723836761565078	0.2938322330488795	-0.7733609252387544	0.4393453095749563
hour23:temp_adj	-	0.29004289820885776	-0.05325033438978431	0.957534575365725
	0.015444881317003849			
loadCap:temp_adj	-6.39355940331858e-4	8.267767820557531e-5	-7.733114356962476	1.2602246918407133e
				-14

13.2 TABLE OF PARTICIPANTS

		System			Maximum	Heat
Participant	System	Manufacturer	Installed	Maximum	Storage	Load
ID	Type(s)		Devices	Draw (kW)	(kWh)	(kW)
		Elnur	1 x E158			
			2 x E208			
	Space					
BBO_01	Heating		2 x E308	7.525	60.3	3.77
		Elnur	3 x E208			
	Space					
BBO_02	Heating		1 x E308	5.89	47.2	2.95
BBO_04	Space	Elnur				
	Heating		2 x E308	3.92	31.4	1.96
		Elnur	2 x E208			
			1 x E308			
BBO_05	Space					
	Heating		1 x E408	7.2	57.7	3.61
		Elnur	2 x E208			
BBO_06	Space					
	Heating		2 x E308	6.54	52.4	3.28
		Elnur	1 x E408			
BBO_07	Space					
	Heating		3 x E308	8.5	68.1	4.26
		Elnur	2 x E208			
	Space					
BBO_08	Heating		2 x E308	6.54	52.4	3.28
		Elnur	1 x E208			
	Space					
BBO_09	Heating		1 x E308	3.27	26.2	1.64
		Elnur	1 x E208			
			3 x E308			
	Space					
BBO_10	Heating		1 x E408	9.81	78.6	4.91

		Elnur	1 x E158			
	Space					
BBO_11	Heating		2 x E208	3.605	28.9	1.81
		Elnur	1 x E158			
			1 x E308			
	Space					
BBO_12	Heating		2 x E408	8.185	65.6	4.1
		Elnur	1 x E308			
	Space					
BBO_13	Heating		1 x E408	4.58	36.7	2.29
		Steffes	24.8 kW			
EFA_01	Forced Air		4120	24.8	120	13.4
		Steffes	19.2 kW			
EFA_02	Forced Air		4120	19.2	120	12.3
		Steffes	19.2 kW			
HYE_01	Hydronic		5120	19.2	120	12.3
		Steffes	24.8 kW			
HYE_02	Hydronic		5120	24.8	120	13.4
HYO_01	Hydronic	Steffes	28.8kW 5130	28.8	180	18.5
		Steffes	28.8 kW			
OFA_01	Forced Air		4130	28.8	180	18.5
		Steffes	28.8 kW			
OFA_02	Forced Air		4130	28.8	180	18.5
		Steffes	28.8 kW			
OFA_03	Forced Air		4130	28.8	180	18.5
		Steffes	24.8 kW			
OFA_04	Forced Air		4120	24.8	120	13.4
		Steffes	24.8 kW			
OFA_05	Forced Air		4120	24.8	120	13.4
		Steffes	19.2 kW			
OFA_06	Forced Air		4120	19.2	120	12.3
		Steffes	28.8 kW			
OFA_07	Forced Air		4130	28.8	180	18.5
		Steffes	28.8 kW			
OFA_08	Forced Air		4130	28.8	180	18.5
		Steffes	19.2 kW			
OFA_09	Forced Air		4120	19.2	120	12.3
OFA_10	Forced Air	Steffes	28.8kW 4130	28.8	180	18.5

		Steffes	19.2 kW			
OFA_11	Forced Air		4120	19.2	120	12.3
		Steffes	28.8 kW			
OFA_12	Forced Air		4130	28.8	180	18.5
		Steffes	28.8 kW			
OFA_13	Forced Air		4130	28.8	180	18.5
		Steffes	24.8 kW			
OFA_14	Forced Air		4120	24.8	120	13.4
		Steffes & Elnur	1 x 4.5 kW			
			2103			
	Space		1 x E408			
	Heater +					
SHB_01	Forced Air		1 x E208	8.43	51.75	4.13
		Steffes & Elnur	1 x 3.6 kW			
			2102			
			4 5450			
			1 X E158			
			1 ~ 5000			
			1 X E208			
			1 v E308			
			(ungraded:			
			2102 to 6.0			
SHB 02	Snace		kW 2104			
0110_02	Heater +		F158 to			
Yukon 8	Forced Air		E100 (0	7 855	47.6	5 17
	1010007.01	Steffes & Flnur	$1 \times 6.0 \text{kW}$	7.000	47.0	0.17
SHB 03	Snace		2105			
0110_00	Heater +		2100			
Yukon 2	Forced Air		1 x F208	7.31	44.25	4.27
		Steffes & Elnur	1x E208			
			1 x 3.6 kW			
			2102			
	Space					
	Heater +		1 x 4.5 kW			
SHB_04	Forced Air		2103	10.31	44.25	4.26

		Steffes & Elnur	2 x E208			
SHB_05	Space					
	Heater +		1 x 7.2 kW			
Yukon 13	Forced Air		2104	9.82	48	4.19
		Steffes & Elnur	1 x E208			
			1 x E308			
SHB_06	Space					
_	Heater +		1 x 9.0 kW			
Yukon 17	Forced Air		2106	12.27	66.2	5.97
		Steffes & Elnur	1 x E308			
	Space					
	Heater +		1 x 5.4 kW			
SHB 07	Forced Air		2103	7.36	35.95	3.14
		Steffes & Elnur	1 x 6.0 kW			
			2104			
			-			
	Space		3 x E208			
	Heater +					
SHB 08	Forced Air		1 x E308	11.89	74.2	5.83
		Steffes & Elnur	3 x E208			
			1x E408			
SHB 09	Space					
	Heater +		1x 4.5 kW			
Yukon 10	Forced Air		2103	11.05	72.75	5.44
		Steffes & Elnur	2 x E308		-	-
	Space					
	Heater +		1 x 7.5 kW			
SHB 10	Forced Air		2105	11.42	65.15	5.57
		Steffes & Elnur	1 x 9.0 kW			
	Space		2106			
	Heater +					
SHB 11	Forced Air		1x E308	10.96	55.7	5.31
	Space	Steffes				
	Heater +		1x 7.5 kW			
SHO 01	Forced Air		2105	7.5	33.75	3.61
	Space	Steffes		-		
	Heater +		1 x 9.0 kW			
SHO 02	Forced Air		2105	9	33.75	3.61
SHO_02	Forced Air		2105	9	33.75	3.61

	Space	Steffes				
	Heater +		1 x 9.0 kW			
SHO_03	Forced Air		2105	9	33.75	3.61

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