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Towards robust investment decisions and policies in integrated energy systems planning: Evaluating trade-offs and risk hedging strategies for remote communities

Marvin Rhey Quitoras^{a,*}, Pedro Cabrera^b, Pietro Elia Campana^c, Paul Rowley^d, Curran Crawford^a

^a*Institute for Integrated Energy Systems at University of Victoria (IESVic), Department of Mechanical Engineering, University of Victoria, PO Box 3055 STN CSC, Victoria, BC V8W 2Y2, Canada*

^b*Department of Mechanical Engineering, University of Las Palmas de Gran Canaria, Campus de Tafira s/n, 35017 Las Palmas de Gran Canaria, Canary Islands, Spain*

^c*School of Business, Society & Engineering, Mälardalen University, Box 883, SE-72123 Västerås, Sweden*

^d*Center for Renewable Energy Systems Technology (CREST), School of Electronic, Electrical & Systems Engineering, Loughborough University, Leics. LE11 3TU, UK*

Abstract

Policy and investment decisions in developing clean energy strategies for remote communities are subject to multiple uncertainties that impact overall strategy outcomes, including those related to environmental emissions and energy costs. In this context, robust modelling approaches are required that can clarify potential outcomes while subject to such uncertainties. This work introduces a novel modeling framework that enables enhanced decision making in energy systems planning for remote communities, which for the first time takes into account context-specific decision-maker attitudes towards multiple inter-related uncertainties and various energy solution philosophies. In particular, multiple energy system configurations are evaluated by simultaneously minimizing the levelised cost of energy and fuel consumption, with a test case for a specific community in the Northwest Territories, Canada. The concept of model robustness and validity together with the stochastic nature of uncertain parameters are combined in a multi-objective optimization framework that elucidates the full spectrum of energy solutions available in such a remote Arctic context. Introducing known uncertainties in renewable energy characteristics was found to reduce overall energy yields from the renewable energy technologies. Specifically, the deterministic renewable energy penetration of 69% from a specific energy system configuration reduced to a mean of 51% after the inclusion of uncertainties via probabilistic simulation. Conversely, diesel fuel consumption increased to 750,000 L/yr (mean) from its initial deterministic value of 447,470 L/yr. Holistic energy solutions which include both supply and demand-side considerations are also analysed. Specifically, a reduced community domestic heating load of 40% was achieved via retrofit of high performance building fabric enclosures evaluated in conjunction with renewable energy supply options. Ultimately, insights and real-world applications have been synthesized to provide coherent recommendations on strategies to address energy security, energy affordability and environmental sustainability, along with meaningful propositions towards Indigenous community-led energy projects in a range of contexts.

Highlights

- A robust modeling approach to handle uncertainties in energy planning is presented.
- The decision-maker risk preference towards uncertainty is considered in the model.
- Informed energy policy facilitates Indigenous community-led energy projects.

Keywords: Energy policy; Robust optimization; Uncertainty; Risk hedging strategies; Indigenous peoples; Energy sovereignty

*Corresponding author

Email address: mdquitoras@uvic.ca (Marvin Rhey Quitoras)

Nomenclature

ASHP	Air Source Heat Pump	$\varphi_{new}(t)$	New time-series of the uncertain parameter
BT	Battery	CC	Capital cost
CCOS	Cycle Charging Operation Strategy	DG_{LF}	Load factor of DG
CONV	Converter	F_0	Fuel curve intercept coefficient
DG	Diesel Generator	F_1	Fuel curve slope coefficient
DHW	Domestic Hot Water	$fuel_{cons}$	Fuel consumption
DT	Deterministic	GHI	Global Horizontal Irradiance
GA	Genetic Algorithm	LCC	Life Cycle Cost
iHOGA	improved Hybrid Optimization by Genetic Algorithms	$LCOE$	Levelised Cost of Energy
IPP	Independent Power Producer	$LPSP$	Loss of Power Supply Probability
KiBaM	Kinetic Battery Storage Model	$MTBF_i$	Mean Time Between Failure
LA	Lead Acid	$MTTR_i$	Mean Time To Repair
LFOS	Load Following Operation Strategy	n	Life of the energy system in years
LI	Lithium Ion	NPC	Net Present Cost
MINES	Multi-objective INtegrated Energy System	$O\&M$	Operations and maintenance costs
NSGA-II	Non-dominated Sorting Genetic Algorithm - II	$P_{DG,r}$	Rated capacity of DG
NTPC	Northwest Territories Power Corporation	P_{DG}	Power produced by DG
NWT	Northwest Territories	P_{excess}	Excess electricity
PPA	Power Purchase Agreement	P_{gen}	Overall power generated from the system
PV	Photovoltaic	P_{load}	Load demand
QEC	Qulliq Energy Corporation	r	Discount rate
RB	Reliability-based Optimization	RE_{pen}	RE penetration
RE	Renewable Energy	$Risk_{coeff}$	Risk coefficient
RO	Robust Optimization	S	Salvage value
URRC	Utility Rates Review Council	SOC	State of charge of the battery
WT	Wind Turbine	t	Time
$\xi_j(\mu_o, \sigma_o)$	Discrete samples of stochastic variables	T_{out}	Ambient temperature
λ_{fi}	Failure rate of the i th component	U	Overall heat transfer coefficient of the building
λ_{ri}	Repair rate of the i th component	u	Wind speed
τ_i	Outage history of the i th component	U_i	Uniformly distributed number between [0,1]
φ_μ	Mean value of the original time-series	Z	Other costs associated in building the energy system
φ_σ	Standard deviation of the original time-series		

1. Introduction

Understanding the dynamic complexities of energy systems, the long term consequences of investment decisions, and the critical role of implementing robust policy frameworks requires innovative approaches in dealing with energy systems planning uncertainties. Krey and Riahi [1]

expounded that ignorance with respect to the multitude of uncertainties can be very costly, and highlighted the significance of improved capturing of the trade-offs and risks resulting from multiple systemic uncertainties. However, despite these risks, the challenges of understanding, assessing and communicating impacts of uncertainties for energy system policy makers remain significant and are poorly evaluated in previous research [2].

This study demonstrates the application of a flexible probabilistic approach based upon robustly assessing multiple uncertainties in a holistic energy modeling framework. The case study of a remote Northern community illustrates the resulting impacts on energy policy and investment strategies from a multi-domain perspective. Holistic energy considerations and trade-offs in transitioning Arctic and more generally remote communities globally from fossil-fuel dependency is also taken into consideration, while balancing the trilemma of challenges [3] relating to energy security, energy affordability and environmental sustainability.

1.1. Literature review

The literature survey conducted for this work presents an overview of existing energy policies and initiatives in reducing diesel dependence in Northern Canada. Further, this section describes techniques in modeling uncertainties in energy systems optimization as it is critical in designing strong policies and will inform decision making across various levels in achieving energy transitions.

1.1.1. Overview of energy policies in the Canadian North

To identify existing energy policies that accelerate and support energy transitions, a cross-Canada scan of diesel reduction initiatives and clean energy policies has been conducted by the Pembina Institute [4]. The study particularly focused on policies, programs and regulations that impact energy systems in remote Indigenous communities at the federal, provincial, regulatory and utility levels. The three territories in the North¹ have various strategies to increase energy security and ensure affordable cost of energy, while transitioning to a lower-carbon economy. For example, the existing initiatives and policies designed for reducing diesel dependence in the Northwest Territories (NWT) include [5]:

- Alternative Energy Technologies Program - provides funding for communities and commercial businesses in developing RE projects such as solar, wind, wood pellet heating, and biofuel/synthetic gas, among others;
- Community Government Building Energy Retrofit Program - supports upgrades to community government-owned buildings in order to reduce electrical and heat loads;
- Commercial Energy Conservation and Efficiency Program - encourages commercial businesses to conserve energy and improve their energy efficiency in the form of rebates;
- Energy Efficiency Incentive Program - designed to provide rebates for residents and non-profit organizations after purchasing energy efficient appliances, heating appliances, LED light bulbs, and drain water heat recovery systems;
- Net Metering - allows customers of the Northwest Territories Power Corporation (NTPC) to generate their own power and then send any surplus in the electricity grid of their community.

It should be highlighted that there is no documented Independent Power Producer (IPP) policy in the NWT, and IPP project proposals are subject to government and utility negotiations (to be further discussed in Section 3.4). A community-oriented IPP policy that offers competitive Power Purchase Agreements (PPAs) would potentially facilitate Indigenous community-led energy projects. For this reason, the Pembina Institute argued that the NWT is a critical jurisdiction in Canada given the number of Indigenous remote communities (Table 1) in the Territory [4].

¹The North in Canada politically refers to the territories of Yukon, NWT and Nunavut; the use of the term Canada's Arctic for this work is inclusive of the three territories mentioned.

Table 1: Number of PPAs among Indigenous remote communities in Canada [6].

Jurisdictions	Number of communities ^a	No. of PPAs (inc. net metering)	Project types
British Columbia	25	4 current 3 developing	Micro-hydro Solar Biomass
Alberta	7	0 current	N/A
Saskatchewan	1	0 current	N/A
Manitoba	4	0 current	N/A
Ontario	25	7+ current 2 developing	Solar
Quebec	19	0 current	N/A
Newfoundland	16	0 current	N/A
Yukon	21	0 current 1 developing	Wind
NWT	26	1 current	Solar
Nunavut	25	0 current	N/A

^a Indigenous remote communities - comprised of First Nations, Metis or Inuit peoples of Canada.

1.1.2. Modeling uncertainties and scenarios in other countries

Policy frameworks to meet decarbonization targets and energy security goals must contend with multiple and overlapping uncertainties [2]. Usher and Strachan [7] emphasized that previous studies on energy systems modeling have failed to address the significant uncertainties surrounding many aspects of the transition to a low-carbon future in an integrated and systematic manner. They argued that this is the result of: (i) challenges involved in applying solely a deterministic approach to a complex and multi-faceted problem that is inherently uncertain, and (ii) the issues associated with so much effort being input by the energy modeling community on pathways and technologies rather than uncertainties. Pfenninger et al. [8] provided a comprehensive study of current challenges on energy systems modeling and efforts being taken to address them. One of the concerns they highlighted was in addressing the growing complexity of energy systems in terms of optimization approaches across various scales (spatial resolution), as shown in Fig. 1. From a modeling perspective, scale pertains to the boundary of a modeled system, so large-scale energy models cover an entire continental region with coarse temporal resolution, while small-scale energy models look at a residential or community level with a high temporal resolution. The inherent trade-offs in resolutions and simplifying assumptions influence the level of uncertainties in model outputs due to the associated computational demands in solving energy system optimization problems.

Figure 1: Optimization complexity across various spatial and temporal scales; adapted from [8].

In the majority of previous studies involving energy systems modeling, uncertainties are typically treated by performing sensitivity analyses for a given range of input parameters. This

approach provides understanding of the uncertainty space and to a certain extent, the future risks involved in understanding the complexities of an integrated energy system. However, this approach should be complemented with further analysis exploring the impact of uncertainties in a non-deterministic fashion. For example, Mavromatidis et al. [9] conducted research on designing a distributed energy system for a Swiss neighborhood by performing two-stage stochastic programming that included multiple objective functions to capture decision-maker preferences on risks resulting from uncertainties. Hamarat et al. [10] focused on multi-objective robust optimization in specifying appropriate conditions for adapting energy policies by exploring transition pathways that lead to satisfactory results across a large ensemble of scenarios in the European Union. Similarly, Majewski et al. [11] carried out a minmax robust multi-objective optimization, through a mixed-integer linear programming formulation, to identify the trade-off between economic and ecological criteria in designing sustainable energy systems.

Reliability-based optimization (RB), meanwhile, is another optimization technique suitable for use in the presence of uncertainty. This method aims at finding the best solution that satisfies the constraints with a specified probability distribution [12]. Clark and DuPont [13] applied this approach in decreasing operations and maintenance costs in designing offshore renewable energy systems. Chu et al. [14] expanded the RB optimization process by creating surrogate models with metaheuristic methods such as genetic algorithm and simulated annealing. Despite the evident advantages of RB optimization, its real-world application is quite challenging due to high numerical costs involved in its solution of the reliability constraints [15].

In previous Arctic energy system studies, Ringkjøb et al. [16] presented a stochastic long-term (2015 - 2050) energy model for a remote Arctic settlement in Longyearbyen, Svalbard. The TIMES modeling framework was employed. This model followed a linear programming approach to minimise the total system cost. The inherent trade-off of this long-term energy system analysis is its inability to track in detail the performance of each energy system component over the whole modeling horizon because of the computational expense of the energy model.

1.2. Research questions and key contributions

The literature survey indicates that various techniques for assessing uncertainties in energy systems modeling are available. However, executing such approaches and implementing them in the evaluation of a range of holistic energy solutions, especially in the Arctic region, are generally scarce. In general, previous work has taken a high-level focus on renewable energy (RE) pathways rather than looking at: (i) a wide array of energy solution initiatives (both supply and demand aspects), (ii) the technical details on the variability of the RE resources, and (iii) the types of energy storage available for both electricity and heating. Further, previous analyses on uncertainty modeling were found to be limited in terms of generating insights and recommendations from the energy model outputs, and designing adaptive and robust energy policies to accelerate energy transitions. Hence, this work builds upon the previous work of the authors in [17] wherein holistic energy solutions were introduced for the Canadian Arctic, balancing decision makers' diverse and multiple solution philosophies in addressing the energy trilemma.

With this framing in mind, the overarching research questions for this work are based on the current energy situation in the North as reflected in previous Energy Charettes², and the research gaps pointed out earlier. These research questions can be summarized as:

1. How to effectively integrate uncertainties in energy systems modeling in the Arctic given energy resource variability and future climate change impacts in the region?
2. How do extreme temperature events impact battery (BT) storage operation in the Arctic region?
3. How to advance diesel reduction initiatives in Northern latitude communities while considering risks from multiple uncertainties?
4. How can private, government and non-government entities support Indigenous-led energy projects?

²Energy Charette is a collaborative planning process where Northern communities, government and non-government organizations, industry, elders, Indigenous peoples, and energy experts come together to develop an energy strategy and plan for the future.

The main aim of this work is to bridge the gaps in previous research by establishing methods to address uncertainties in energy systems modeling, while taking into account coordinated climate and energy policies from the private sectors, Indigenous communities, governments, utilities, regulators, and other stakeholders. In particular, the four key research questions as mentioned previously are addressed by the novel contributions of this work:

1. Development of a robust Multi-objective INtegrated Energy System (MINES) model that captures decision-maker attitudes towards multiple overlapping uncertainties in designing integrated energy systems;
2. Assessment of lead acid and lithium-ion BT storage systems while taking into account impacts of BT capacity decrease from freezing temperatures in cold climate settings;
3. Adaptation of holistic energy solutions in transitioning towards robust and sustainable energy systems while addressing trade-offs and uncertainties in reducing diesel dependence;
4. Formulation of insights and recommendations on how to address barriers and opportunities in implementing strong energy policies and risk hedging strategies in remote communities.

The rest of the article is organized as follows: Section 2 describes the model developed for the study. To demonstrate functionality of the energy model developed in this work, Section 2.6 presents relevant information for the case-study community, namely Sachs Harbour in the NWT; the information presented will serve as input data for the model. Section 3 summarizes the results of the test case for the method. Section 3.4 presents insights and recommendations for policy makers and various practitioners according to the quantitative outputs generated from the model. Finally, Sections 4 and 5 discuss the conclusions and future work from this study.

2. Methods

The schematic diagram of a prototypical integrated energy system studied in this work is shown in Fig. 2. It consists of wind turbine, solar PV, battery storage, diesel generator and a bi-directional converter to facilitate power flows from the DC bus to AC bus and vice versa. Thermal (space heating and domestic hot water) and electrical loads were modeled for each 1 h timestep over a given year.

Figure 2: Schematic diagram of a prototypical integrated electrical and thermal energy system.

2.1. Robust optimization

The MINES model implements a multi-objective optimization approach to capture complex trade-offs in designing integrated energy systems. This technique provides a diversity of solutions which are critical in capturing various solution philosophies in transitioning remote communities in the Arctic towards sustainable sources of energy. In particular, the Non-dominated Sorting Genetic Algorithm - II (NSGA-II) of Deb et al. [18] was adopted for this study. It selects individuals by non-domination rank³, taking as many complete ranks as will fit in the new population. This process

³The non-domination rank is obtained by finding the near-optimal Pareto front for the whole population; these points are given a rank of 1 and then removed from the population. The near-optimal Pareto front for the remaining

Figure 3: Overall energy modeling framework of MINES.

Table 2: GA configuration parameters.

Parameter	Description
Algorithm	Variant of NSGA-II [18]
Generations	200
Population	100
Crossover function	Heuristic
Crossover rate(%)	90
Mutation function	Non-uniform
Tournament size	2

drives the population towards the near-optimal Pareto front [20] while maintaining diversity along the front [19]. Further, NSGA-II was selected as it has the generic ability to handle multi-objective trade-offs and near-optimal Pareto front pursuit, as proven in previous studies by Evins et al. [19] and Forde et al. [21]. The set of Genetic Algorithm (GA) input parameters for this work is listed in Table 2 and the approach was implemented in a MATLAB[®] platform.

For this work, the robust-based aspect was integrated into the optimization algorithm of the MINES model. There are many notions of robustness, including a good expected performance, a good worst-case performance, a low variability in performance, or a large range of disturbances still leading to acceptable performance [12]. Beyer and Sendhoff [22] conducted a comprehensive survey on robust optimization (RO), and described four types of uncertainties as related to real-world system designs; interested readers are referred to their work.

According to Gazijahani and Salehi [23], the undefined nature and poor availability of data about uncertain modeling parameters determine the most suitable approach in addressing uncertainties in a decision making framework. They argued that RO is the most suitable optimization technique in controlling the worst possible scenarios in designing microgrids due to the nature and the lack of full information of the uncertainties involved in the energy system. In this paper, a minmax principle was adapted to seek the optimal value of each decision variable under the worst-case realization of uncertainties. The mathematical representation of this concept is presented in Eq. 1 [24]:

$$\min \left[\sup_{\Xi} f_1(z, \xi), \sup_{\Xi} f_2(z, \xi), \dots, \sup_{\Xi} f_M(z, \xi) \right] \quad (1)$$

where $f_M(z, \xi)$ are the objective functions, $z \in Z$ represents a vector of decision variables, $\xi \in \Xi$ pertains to a vector of random variables, and $\sup(\cdot)$ indicates the worst-case scenario of the specific objective function. The worst-case realizations of uncertainties (robust-based optimization) was

points is found; these points are given a rank of 2 and then removed from the population, and so on until all points are ranked [19].

Table 3: The 11 discrete variables in the optimization algorithm.

Parameter	Value
WT quantity	0 - 500
WT capacity (kW)	95,95,100,100
PV quantity	0 - 500
PV capacity (kW)	15,25,20,25.025
BT quantity	0 - 500
BT capacity (kWh)	55,13.9,7.37,9.24
DG quantity	0 - 100
DG capacity (kW)	300,320,225,150
CONV quantity	0 - 10
CONV capacity (kW)	200,250,270,300
Operation strategy	LFOS and CCOS

adopted as it captures the unique considerations of decision makers in Arctic communities.

Aside from energy systems applications, RO has the generic ability to handle a wide variety of optimization problems and has been used extensively on other fields such as internet routing [25], business aircraft [26], machine scheduling [27], and intensity-modulated proton therapy [28], among others. RO has also been implemented in combination with various types of evolutionary algorithms as executed in previous studies done by Goh and Tan [29], Kuroiwa and Lee [30], and Wang et al. [31]. The algorithm behind the MINES modeling framework, NSGA-II, has also been applied in conjunction with RO as introduced by Deb and Gupta [32].

The justifications given for the RO approach and combining it with the multi-objective approach of the MINES model provides decision makers with the ability to balance and analyze trade-offs between investment decisions and environmental impacts of the energy system, while considering multiple overlapping uncertainties.

2.2. Quantifying complex trade-offs in the energy system design space

The multi-objective technique of MINES unlocks the full spectrum of energy solutions available in the Arctic. With this approach, a trade-off analysis can be done by analyzing two objective functions simultaneously. In this study, Levelised Cost of Energy (*LCOE*) (Eq. 2) [33] was formulated as the first objective function to represent energy affordability as a major concern based on the previous Energy Charettes in the NWT [34]:

$$LCOE = \frac{\sum_{t=1}^n \frac{CC_i(t) + O\&M_i(t) + Z_i(t) - S_i}{(1+r)^t}}{\sum_{t=1}^n \frac{P_{gen}}{(1+r)^t}} \quad (2)$$

where t is time (year), r is the discount rate (%), n is the total life of the energy system (year), CC is the capital cost (\$) per unit of the system component i , $O\&M$ is the operations and maintenance costs (\$/year), Z is all other costs associated with the project (\$/year), S is the salvage value (\$), and P_{gen} is the power generated from the energy system (kWh/year).

The DG's fuel consumption ($fuel_{cons}$), as shown in Eq. 3, was formulated as the second objective function in the model. This approach leads to a quantitative investigation of trade-offs between alternative sources of energy in the Arctic while observing low cost of energy (first objective function) for the community.

$$fuel_{cons} = F_0 P_{DG,r} + F_1 P_{DG} \quad (3)$$

where F_0 is the fuel curve intercept coefficient (L/h/kW_{rated}), F_1 is the fuel curve slope coefficient (L/h/kW), $P_{DG,r}$ is the rated capacity of DG, and P_{DG} is the instantaneous power coming from the DG (kW).

Table 3 shows the 11 discrete decision variables implemented in the model. The two operation strategies modeled were the Load Following Operation Strategy (LFOS) and Cycle Charging Operation Strategy (CCOS) [35]. In both strategies, the DG only operates when there is a deficit of power and the renewables or the BT storage system cannot meet the load. With LFOS, the

208 DG is dispatched to provide the exact power to meet the instantaneous load. CCOS dispatches
 209 the DG power always at its rated capacity to maximize generator efficiency; instantaneous surplus
 210 of power goes to the BT storage system. Also, the full set of constraints considered to run the
 211 optimization module in MINES are:

$$constraints \begin{cases} LPSP \leq 0\% \\ SOC_{min} \geq 30\% \\ RE_{pen} \geq 30\% \\ P_{excess} \leq 30\% \\ DG_{LF} \geq 30\% \end{cases} \quad (4)$$

212 where $LPSP$ is the Loss of Power Supply Probability (%), SOC is the state of charge of the BT (%),
 213 RE_{pen} is the RE penetration (%), P_{excess} is the excess electricity (%), and DG_{LF} is the load factor
 214 of the DG (%). The mathematical formulation of each constraint and their respective justifications
 215 to include in the model were described previously by the authors in [35]. The component sub-models
 216 including the specific technology input parameters (solar PV, WT, BT, DG, CONV) as laid out
 217 in Fig. 2 were described in detail by the authors in [35].

218 2.3. Uncertainty propagation

219 Two types of uncertainties were introduced in MINES. The first type refers to the meteorological
 220 variables relevant for the community as well its load profile. The second type of uncertainty pertains
 221 to the operational reliability of each component in the integrated energy system. The two types of
 222 uncertainty ensure robustness of the energy system being proposed for remote communities in the
 223 Arctic.

224 2.3.1. Integrating risk hedging strategies in robust optimization

225 The first type specifically relates to uncertainties from the load profile of the community (P_{load})
 226 as well as various meteorological parameters including Global Horizontal Irradiance (GHI), wind
 227 speed (u) and the ambient temperature (T_{out}). The approach is a modified version of the probabil-
 228 ity analysis being implemented through the improved Hybrid Optimization by Genetic Algorithms
 229 (iHOGA) software [36]. The iHOGA commercial software is a well-established tool in optimizing
 230 energy systems, both deterministically and probabilistically. Using iHOGA, Zubi et al. [37] con-
 231 ducted a techno-economic assessment of an off-grid PV system for developing regions to provide
 232 electricity for basic domestic needs. Dufo-Lopez et al. [38] conducted a similar study by optimiz-
 233 ing a stand-alone hybrid solar-diesel-battery energy system for an off-grid health care facility while
 234 considering uncertainties from solar irradiance and the load demand. Other applications of the
 235 iHOGA software can be found in Fulzele and Daigavane [39], Fracastoro et al. [40], Bernal-Agustin
 236 et al. [41] and Cristobal-Monreal et al. [42], among others.

237 The probability analysis in iHOGA can be performed by taking into account the Gaussian
 238 probability distribution of the mean annual values of the system load, solar irradiance, wind speed
 239 and water flow (if there is a water turbine in the system). The software performs its simulation
 240 by assigning each uncertain parameter with five possible increments/reductions from the original
 241 time-series:

- 242 • Average
- 243 • Average + Standard Deviation
- 244 • Average - Standard Deviation
- 245 • Average + 3*Standard Deviation
- 246 • Average - 3*Standard Deviation

247 For example, the user can assign Average + Standard Deviation for load, and for the solar
 248 irradiance, wind and water flow data, the Average - Standard Deviation. This combination implies
 249 that there is an increment from the original time-series of the load data while there is a reduction
 250 in the other uncertain variables in reference to the original time-series [36]. In conjunction with
 251 the second type of uncertain parameters (relating to system reliability), this paper improves the
 252 iHOGA probabilistic technique by explicitly introducing decision-maker risk preferences (captured

Table 4: Risk coefficients as introduced in the robust-based optimization of the MINES model.

Uncertain Parameter	Risk seeking	Risk neutral	Risk averse
Load	+1	+2	+3
u	-1	-2	-3
GHI	-1	-2	-3
T_{out}	+1	+2	+3

Table 5: Meteorological and load uncertainty parameters/assumptions for Sachs Harbour.

Parameter	Mean	Standard Deviation	Number of Years ^a
Average u for a year	8.075 m/s	0.290 m/s ^b	10
Average T_{out} for a year	-10.31 °C	2.4°C ^c	55
Average daily GHI for a year	2.471 kWh/m ²	0.618 kWh/m ^d	-
Average combined daily thermal and electricity load for a year	9,277 kWh	927 kWh ^e	-

^a Set of several years in reference to the standard deviation.

^b Adapted from Tuktoyaktuk, NWT [43].

^c Adapted from average temperature (1957 - 2012) increase for four communities in the NWT [44].

^d Considered 25% of interannual variation [45].

^e Considered 10% of interannual variation for P_{load} .

by a risk coefficient) towards the first types of uncertain parameters mentioned previously, and as shown in Eq. 5.

$$\varphi_{new}(t) = \overbrace{\left(\frac{\varphi_{old}(t)}{\varphi_{\mu}} \right)}^{\text{data normalization}} \underbrace{(\varphi_{\mu} \pm Risk_{coeff} \cdot \varphi_{\sigma})}_{\text{discrete samples (increment/reduction)}} \quad (5)$$

where $\varphi_{new}(t)$ is the new time-series of the uncertain parameter, obtained from its original mean value (φ_{μ}) and standard deviation (φ_{σ}). The original time-series was divided by its mean to ensure that each time-series will be proportional to the original. It can be observed that when the $Risk_{coeff}$ in Eq. 5 is zero, the algorithm reverts to a deterministic optimization (i.e old time-series is active). On the other hand, the probabilistic feature of MINES is active when the $Risk_{coeff}$ is set to a non-zero value. Specifically, this work introduces various risk attitudes of the decision maker towards uncertainty in energy system planning as presented in Table 4. The $Risk_{coeff}$ in the risk-averse column in Table 4 implies best performance of the energy system (i.e optimal value of the objective functions) against worst-case realizations of the uncertain parameters. Alternatively, the $Risk_{coeff}$ in the risk-seeking column appeals to a relatively more optimistic/risk-seeking decision-maker. An intermediate risk attitudes in the middle column (neither risk seeking nor risk averse) corresponds to a a risk-neutral decision-maker for this study.

The increment/reduction in the second term of Eq. 5 also pertains to the discrete samples $\xi_j(\mu_o, \sigma_o)$ of the stochastic variables wherein j is the number of samples (number of realization of uncertainties) and o is the uncertain variable. Through Latin Hypercube Sampling, the algorithm draws a total of j random samples from the probability distribution $\xi_j(\mu_o, \sigma_o)$ represented by its mean φ_{μ} and standard deviation φ_{σ} . Table 5 lists the respective means and standard deviations of the uncertain parameters described in this section.

2.3.2. Uncertainty on system reliability

To ensure robust operation of the energy system in the Arctic and avoid the possibility of having to fly-in emergency fuel to these remote communities (as what occurred in Paulatuk, NWT during the summer of 2019 [46]), the $LPSP$ has been set to 0% as part of the model constraints (Eq. 4). The 0% $LPSP$ implies consistent and efficient operation of the entire energy system components. However, this ideal situation has to be investigated given the operational complexity

of an integrated energy system. Hence, a sequential Monte Carlo state duration sampling has been incorporated in MINES to address uncertainty in reliability of the energy system components. This approach was adapted from the power system reliability simulation technique introduced by Billinton and Li [47], and uses component state duration distribution functions (refer to Appendix A).

Fig. 4 presents the overall uncertainty propagation process for the multiple overlapping uncertainties considered in this work. Specifically, the uncertainty formulation results in a set of input probability distribution functions that are mapped to various outputs (system reliability, economics and environmental) in the MINES model. This step involves solving the multi-objective optimization problem by repeating the uncertainty propagation process multiple times based on the number of realizations of uncertainties set by the modeler. Similar to the iHOGA software [42], the mean of each performance metric was taken into account in comparing all feasible configurations of the energy system, and this will be reflected in the non-dominated individuals (near-optimal Pareto front) of MINES.

Figure 4: Uncertainty propagation of the proposed modeling framework.

2.4. Temperature effect on battery storage systems

The World Wildlife Fund conducted a set of feasibility studies [48] for the Canadian Arctic communities using the HOMER software [49]. HOMER is a tool originally developed by the

Table 6: Battery storage thermal parameters.

Parameter	Unit	Lead Acid	Lithium Ion
Model	-	T-105 with Bayonet Cap [51]	TR 25.6-25 Li-ion [52]
Manufacturer	-	Trojan Battery	Trojan Battery
Max operating temp.	°C	55	45
Min operating temp.	°C	-20	-20
Conductance to ambient	W/K	10	10
Specific heat capacity	J/kg-K	800	800
Fixed bulk temp.	°C	20	20

National Renewable Energy Laboratory in the United States. It determines the most feasible configuration of the energy system by applying a full factorial design of experiments, and choosing the configuration with minimum Net Present Cost (*NPC*) [50]. In this paper, the HOMER modeling framework was used to evaluate lead acid (LA) and lithium ion (LI) battery storage in cold climate regions using the modified Kinetic Battery Storage Model (KiBaM). In particular, the determined optimal capacity of the battery storage system from MINES will be further investigated by incorporating temperature effect on battery storage capacity.

The thermal parameters of the battery storage used for this work are listed in Table 6. The minimum and maximum operating temperature should be observed in simulating battery performance. Outside the given temperature range, the battery shuts off, and neither charging nor discharging is allowed. Fig. 5 shows the temperature versus capacity curve of the two types of battery considered in the simulation. In Table 6, conductance to ambient refers to the rate at which heat is exchanged between the battery components and the building where the battery is located. Specific heat capacity refers to the amount of heat energy the component absorbs, per kilogram of mass, before increasing in temperature by one degree Celsius. In order to demonstrate the impact of temperature on the overall energy system performance, the mentioned parameters will be considered in simulating the hourly dispatch of the battery after getting the deterministic optimal configuration of the energy system. In theory, this demonstrates the thermal variation of the battery at each time step in the model. However, only the fixed bulk temperature will be considered in the probabilistic optimization algorithm of MINES because: (i) in real-world applications, battery storage systems are typically installed in a building with thermal management, and (ii) this approach also reduces significantly the computational requirement of the optimization algorithm. In other words, this study assumed that the fixed bulk temperature of 20°C of the battery will be maintained through the temperature regulator installed in the building where the battery is located.

Figure 5: Temperature versus capacity curve of batteries; data extracted from Trojan Battery Company (T-105 with Bayonet Cap model for lead acid [51] and TR 25.6-25 Li-ion model for lithium ion [52]).

Table 7: Scenarios implemented in the MINES model.

Scenarios	Electricity	Space Heating
Scenario 1	Home appliances including lighting and electric load for DHW	Baseboard Heater at $U = 0.5$ W/m ² -K
Scenario 2	Home appliances including lighting and electric load for DHW	Baseboard Heater at $U = 0.13$ W/m ² -K
Scenario 3 ^a	Home appliances including lighting and electric load for DHW	Baseboard Heater and ASHP at $U = 0.13$ W/m ² -K
Scenario 4 ^b	Home appliances including lighting and electric load for DHW	Baseboard Heater and ASHP at $U = 0.13$ W/m ² -K

^a Baseboard heater kicks in if ASHP shuts off when outside temperature drops below -20 °C.

^b ASHP only operates during summer and the baseboard heater runs for the rest of the seasons.

2.5. Computational expense and limitation of the proposed model

The integration of the uncertainty module in the overall modeling framework of MINES demands significant computational requirement in order to get the desired optimization output from the model. For instance, implementing parallel computing, the model implemented in MATLAB[®] converged to a solution roughly after 30 h by using 64-bit operating system, an Intel Core i7-7700HQ 2.800 GHz 4-core processor and 16 GB of RAM. For this reason, this work used state-of-the-art research parallel computing systems from Compute Canada [53] to decrease the computational requirement of the MINES model.

2.6. Case study input data

To test the methods described in this section, a case study was conducted for an Indigenous community in the Arctic. Sachs Harbour (Lat: 71.9884 N; Long: 125.23935 W), the Northernmost community in the NWT was selected for this purpose. This community has one of the most extreme winter conditions in Arctic Canada, and thus demonstrates the applicability of the modeling approach to other isolated communities in the region. All of the relevant meteorological information (GHI , u , T_{out}) and load demands (electrical and thermal) of the community have been presented in [17] and [35]. The heat load simulation conducted for this study was elaborated by the authors in [17].

3. Results and discussion

This section looks at the uncertainty modeling results generated from the MINES model. The investigation builds from the four scenarios presented in Table 7. The simulated thermal load of Sachs Harbour is assumed to be supplied by electric appliances for domestic hot water (DHW), such as instant water heating devices, and via electric baseboard heaters for space heating demand. Scenarios 3 and 4 use air-source heat pumps (ASHP) instead of the baseboard heater in the first two scenarios. Previous analysis by the authors [17] showed that the ASHP reduced space heating load by about 40% as compared to baseboard heaters. However, the simulation results indicated that load fluctuations caused by the variations of the heat pumps' coefficients of performance negatively impacted the operation of the energy system. In particular, these demand fluctuations resulted in a larger battery storage requirement, along with an increase in overall energy system costs. The authors also looked at the impact of building enclosure improvements as a function of the overall heat transfer coefficient of the building (U). The modeling results suggested that a passive house with an overall U -value of 0.13 W/m²-K reduced space heating loads by about 40% as compared to a normal building. Collectively, scenario 2 was proven to have the best system performance as compared to the other three scenarios in Table 7.

3.1. Deterministic results

Fig. 6 shows the deterministic full design space and near-optimal Pareto front of scenario 2 after minimizing simultaneously the $fuel_{cons}$ and $LCOE$ of the energy system in question for

Figure 6: Scenario 2 deterministic results: full design space with the near-optimal Pareto front and the identified solutions of interest.

Sachs Harbour. The respective configurations of the three solutions of interest as specified in the near-optimal Pareto front of Fig. 6 are listed in Table 8. Solution 1 corresponds to a solution with lowest $LCOE$ and highest $fuel_{cons}$. Solution 3, on the other hand, utilizes no back-up DG which led the algorithm to increase the WT capacity of the system. It has a RE_{pen} of 100% but also resulted in a larger BT storage capacity to handle mismatch between demand and the RE resource. Consequently, this configuration has the highest $LCOE$ and Life Cycle Cost⁴ (LCC) [54]. Solution 2, at the middle of the near-optimal Pareto curve (trade-off point), balances the two solutions mentioned, and includes all the system components of the integrated energy system. Note that the wind resource is able to meet the largest share of demand for the three solutions of interest. This reflects the viability of wind farm projects in the region. The inherent trade-off, however, is the resulting larger BT storage to handle wind's variability. This trade-off analysis is critical in the decision making process of energy system planners and stakeholders.

3.1.1. Impact of temperature on battery storage performance

This work extends the deterministic results from [17] by looking at the impact of temperature on BT storage performance considering the thermal properties (Table 6) of both LA and LI batteries. Table 9 shows the simulation performance of two deterministically optimized energy systems with different types of BT storage systems. Note that the identified deterministic optimal capacity of each system component (PV, WT, BT, DG, CONV) for both configurations (case 1 and 2) were adopted from solution 1 in Table 8. Case 1, however, uses LA as its BT storage whereas case 2 uses LI. The technical and cost parameters of these two comparable storage systems were extracted from HOMER's database.

Fig. 7 presents hourly performance of LA and LI. At this stage of the study, the simulation assumed that the BT storage systems are located in a building without thermal management. Using a modified KiBaM model, HOMER tracks the variation of BT capacity in reference to temperature. For example, Fig. 7(b) and (d) shows a decrease in available energy content due to a decrease in operating temperature of the BT (also influenced by the ambient temperature profile of Sachs Harbour). For both storage types, it can be observed that the BT is neither charging nor discharging (Fig. 7(c) and (e)) whenever the operating BT temperature is outside the temperature ranges specified in Table 9.

In general, LI performs better than LA batteries. However, this superior performance of LI has a trade-off (in comparison with LA) in reference to the other parameters listed in Table 9. For instance, LA cost less up-front than LI but the former's $O\&M$ is more expensive than the latter. Further, the power generated from the back-up DG is relatively high in case 1 (system with LA) to compensate the limited amount of battery discharge from LA. This implies higher $fuel_{cons}$ and system cost as well. Consequently, this resulted to a cheaper overall system cost, both in

⁴ LCC served as one of the model outputs to represent the sum of the cradle-to-grave economic costs of the integrated energy system for a project lifespan of 25 years.

Table 8: Deterministic configuration characteristics of the three solutions of interest determined from the near-optimal Pareto front of Scenario 2.

Parameter	Unit	Optimization results		
		Sol 1: Min. $LCOE$	Trade-off Point	Sol 3: Max. $LCOE$
PV	kW	450.45 (25.025 kW x 18)	1,725 (25 kW x 69)	0
WT	kW	570 (95 kW x 6)	1,045 (95 kW x 11)	3,325 (95 kW x 35)
BT	kWh	4,620 (9.24 kWh x 500)	7,205 (55 kWh x 131)	7,315 (55 kWh x 133)
DG	kW	675 (225 kW x 3)	675 (225 kW x 3)	0
CONV	kW	600 (200 kW x 3)	800 (200 kW x 4)	800 (200 kW x 4)
Strategy	-	LFOS	LFOS	LFOS
P_{pv}	kWh	414,407	1,405,135	0
P_w	kWh	2,456,400	4,531,567	14,418,623
$P_{BT,out}$	kWh	151,831.41	365,881	513,951
P_{DG}	kWh	1,272,995	529,758	0
$LPSP$	%	0	0	0
RE_{pen}	%	69.27	91.81	100
P_{excess}	%	15.19	4.93	1.05
$fuel_{cons}$	L/yr	447,470	183,595	0
CO_2^a	tCO	2,096	1,523	757
	2-eq/yr			
CC	CND \$	15,117,673	37,839,517	79,936,645
$LCOE$	CND	0.59387	1.06348	1.85487
	\$/kWh			
LCC	CND \$	35,756,756	64,031,794	111,681,201

^a Lifecycle CO_2 emissions of the energy system

Table 9: Performance of lead acid and lithium ion batteries as applied to integrated energy system.

Parameter	Unit	Case 1: System with LA	Case 2: System with LI
BT max temp	°C	55	45
BT min temp	°C	-20	-20
CC_{BT}	CND \$	1,345,500	1,840,916
$O\&M_{BT}$	CND \$	797,439	644,352
P_{pv}	kWh	506,195	506,195
P_w	kWh	2,475,542	2,475,542
$P_{BT,out}$	kWh	73,897	118,806
$P_{BT,in}$	kWh	87,465	127,243
P_{DG}	kWh	1,331,850	1,280,713
$LPSP$	%	0	0
RE_{pen}	%	60.7	62.2
$fuel_{cons}$	L/yr	528,472	506,491
System CC	CND \$	16,575,414	17,070,830
$LCOE$	CND	0.6659	0.6784
	\$/kWh		
LCC	CND \$	40,092,700	40,846,160

terms of $LCOE$ and LCC . Note, however, that this result is heavily influenced by the BT storage data extracted from HOMER's database, and LA might also be a better option depending on its operating temperature range.

Figure 7: Example deterministic simulation results when there is no thermal management in a building where the battery storage systems are located: (a) ambient temperature of Sachs Harbour; (b) Energy content and operating temperature of lead acid BT; (c) Charge-discharge of lead acid BT; (d) Energy content and operating temperature of lithium ion BT; (e) Charge-discharge of lithium ion BT.

This section demonstrates the negative impact of installing BT storage systems in a building without thermal management. To depict real-world situations in this study and to improve the system performance of the overall integrated energy systems in Fig. 2, the robust optimization assumes that the BT storage is located in a temperature-controlled building in Sachs Harbour. A controlled temperature environment for batteries is also recommended by BT manufacturers such as Trojan [51].

3.2. Stochastic simulation results

In comparison with the sensitivity evaluation used in the author's previous study [17], this work carries out a probabilistic analysis using the two types of uncertainty introduced in the model (Section 2.3). This approach was first applied to the deterministic solution of scenario 2-solution 1 to test statistical convergence for an individual use case.

Fig. 8 presents a series of probability distribution functions that corresponds to various technical, economic and environmental outputs that can be extracted from the MINES model for a risk-seeking stakeholder or decision maker. For example, solution 1 of scenario 2 has a mean RE_{pen} of approximately 51% after simulating 1000 times probabilistically as compared to its initial deterministic RE_{pen} of 69.27%. It can be observed that due to the uncertainties introduced in the model, the overall power generation from RE was reduced. This RE_{pen} is even lower when the risk preference shifts from risk seeking to risk averse. Consequently, the mean $fuel_{cons}$ of the DG increased to approximately 750,000 L/yr as compared to its initial deterministic value of 447,470

414 L/yr. This reflects that the DG was under-sized when multiple overlapping uncertainties were
 415 introduced in the model.

Figure 8: Risk seeking scenario 2-solution 1 series of probability distribution functions generated probabilistically using 1000 samples; dashed line refers to mean value.

416 Fig. 9 shows the mean RE_{pen} decreases to approximately 20% when the preference of the
 417 decision maker towards uncertainty shifts from being risk seeking to risk averse. The mean $fuel_{cons}$,
 418 on the other hand, were further increased from approximately 750,000 L/yr (risk seeking) to
 419 1,400,000 L/yr (risk averse). This implies increase in system costs ($LCOE$, $O\&M$, LCC) to
 420 ensure robust performance of the energy system under worst case realization of the uncertainties.
 421 Specifically, this is attributable the highest increment (in comparison with the other risk coefficients
 422 listed in Table 4) in energy demand and the reduction in the other uncertain variables (renewable
 423 resources and temperature).

Figure 9: Risk averse scenario 2-solution 1 series of probability distribution functions generated probabilistically using 1000 samples; dashed line refers to mean value.

424 A comparative analysis for the three solutions of interest in scenario 2 considering risk seeking

425 preference of the decision maker and the probabilistic results of their respective *LCOE* and *LPSP*
426 values are shown Fig. 10. In the presence of uncertainties, *LPSP* of solution 3 is approximately
427 12% (mean) as this energy system configuration has no back-up DG. Hence, this solution is not
428 resilient to extreme temperature events or any increase in energy demand in Sachs Harbour. The
429 opposite can be observed for both solutions 1 and 2 wherein 675 kW capacity of DG are available
430 (Table 8). This shows the critical role of DG to be able to maintain an *LPSP* of approximately
431 1% - 2% (mean) for both solutions. Further, this also implies that the constraint formulation
432 of 0% *LPSP* (Eq. 4) will be slightly violated (solutions 1 and 2) when multiple overlapping
433 uncertainties are considered. Note that the probabilistic simulations done so far were taken from the
434 deterministic optimization results, and hence, a separate robust optimization run will be performed
435 in MINES wherein full compliance to the constraints formulation will be strictly observed. Fig. 10
436 also shows the range of *LCOE* values with their respective probability once the *LPSP* deviates
437 from 0% (deterministic value across all solutions).

Figure 10: Risk seeking scenario 2 probabilistic simulations for the three solutions of interest generated from the deterministic optimization results; dashed line refers to mean value.

438 The hourly dispatch for solution 1 assuming risk seeking preference of the decision maker
439 towards uncertainty is shown in Fig. 11. The hourly mean values of each source of energy is illus-
440 trated together with its variations due to uncertainties. For solutions where all system components
441 are available, RE is treated as a priority dispatch before discharging available power from the BT
442 storage and DG. Hence, a significant variation in power output from the DG (solution 1) can be
443 observed as influenced by the multiple overlapping uncertainties introduced in the model. The
444 lower bound of each hourly variation of the power output coming from the DG was affected by the
445 30% DG_{LF} constraint to avoid damaging the generator by running at very low partial loads.

446 3.3. Robust optimization results

447 A comparison of the near-optimal Pareto fronts generated deterministically (DT) and through
448 the robust optimization process for scenario 2 considering risk attitudes of decision maker towards
449 uncertainty are presented in Fig. 12. The non-deterministic solution was obtained using the same
450 GA parameters listed in Table 2. Further, the last generation obtained from the deterministic
451 algorithm of the MINES model was used as the first generation of the RO optimization. Doing
452 this, along with parallel computing results in a relatively faster rate of convergence in obtaining
453 the desired robust optimal capacities of the system components and the corresponding dispatch
454 strategy for the integrated energy system.

455 It can be observed that the near-optimal Pareto front tends to shift towards higher objective
456 function values when the algorithm changed from DT to RO. This deviation implies higher *LCOE*
457 for the system when uncertainties were incorporated in the model. In comparison with the DT
458 optimal solutions, Table 10 shows an increase in the optimal capacity for majority of the system
459 components (WT, PV, DG, CONV) except the BT storage. In the presence of uncertainties,
460 this suggests that the RO algorithm assigns its preference to generate power from the DG over

Figure 11: Hourly average (ave) and variation (var) of the deterministic optimal configuration in scenario 2 that was simulated probabilistically; assumed risk seeking preference of the decision maker.

Figure 12: Scenario 2 near-optimal Pareto front comparison for deterministic and robust optimization results with specific risk preferences.

discharging the BT storage to meet load deficit. This is influenced by the charge-discharge cycles of the BT storage which is also affected by the renewables (wind and solar), treated as uncertain parameters for this work. Hence, DG offers more flexibility whenever there is load deficit in the energy system. This result is critical for consideration among remote communities like Sachs Harbour wherein fuels are being delivered via barge once a year since year-round road access is not available.

The risk attitudes of the decision maker towards uncertainty were observed to impact the optimal component capacities of the integrated energy system. As shown in Table 10, an increase in the component capacity implies higher system $LCOE$ and $fuel_{cons}$, from being risk seeking to risk averse across the three solutions of interest. This also reflects that the goal of having a robust energy system that can operate under extreme climate conditions has to be balanced with the possible implications of having an increased energy system $LCOE$ and $fuel_{cons}$. The increase in $fuel_{cons}$ is attributable to the uncertainties incorporated in the solar irradiance and wind speed of Sachs Harbour, ensuring that the load would still be met in spite of the randomness (uncertainty)

of renewable resources.

3.4. Policy recommendations

Huntington et al. [55] argued that the purpose of energy modeling is to produce insights and not just numbers. Hence, this section provides insights and recommendations based on the outputs presented in Section 3 and the overall modeling framework described in Section 2.

3.4.1. Multiple viable energy system configurations

Model insight: The results presented from the modeling work carried out for Sachs Harbour indicate that multiple energy system configurations were found to be viable in the North even in the presence of uncertainties. Specifically, Table 8 shows that wind can meet the largest share of the energy demand for the community, and this reflects that wind is a viable energy resource for remote communities in Northern Canada. Other system configurations were found to be feasible but with different levels of renewable energy penetration and capacities from back-up sources of energy such as BT storage and DG. Fig. 12 also shows that the risk preferences of decision makers towards uncertainties were also proven to impact the optimal configuration of the integrated energy system.

Policy recommendation: The first recommendation of this research is to develop a documented IPP policy in the NWT considering the feasibility of multiple renewables-based energy system in the Arctic. Note that power generation in Sachs Harbour is fully owned and operated by the Crown utility, Northwest Territories Power Corporation (NTPC). This is also the case for all Indigenous remote communities across the three territories in Northern Canada. Hence, building a renewable energy project, without a documented IPP policy in a region where there is a Crown utility, will be challenging since the majority of electric utilities worldwide, either publicly or privately owned, are regulated by utilities commission or public utilities board. For example, previous wind farm feasibility studies [56] have been conducted in Sachs Harbour but none of the projects were realized because of the lack of an explicit energy policy that supports renewable energy infrastructure development.

3.4.2. Community-specific (levelised) cost of energy

Model insight: Table 8 shows the $LCOE$ for the three solutions of interest identified in Fig. 6. Table 10, on the other hand, presents $LCOE$ for the the three solutions of interest in the presence of uncertainties while taking into account varying risk preferences of the decision maker. The modeling results show that the cost of energy varies depending on the configuration of the integrated energy system, and is influenced by the amount of energy specific for the community of Sachs Harbour. *MINES* can handle different communities to calculate community-specific levelised cost of energy in the North or remote communities in general.

Policy recommendation: The second policy recommendation of this work is to re-assess the pricing structure in determining the applicable PPA rates as outlined in a certain IPP policy. Specifically, the community-specific $LCOE$, as shown in the modeling work of this research, should be recognized in awarding PPA contracts for renewable energy developers. As of writing, for example, the Qulliq Energy Corporation (QEC) is applying to the Utility Rates Review Council (URRC) of Nunavut to have a territory-wide flat PPA rate of \$0.25 per kWh based on their proposed IPP policy [57]. The proposed rate is based on the average diesel fuel costs in the territory. This pricing structure proposed by QEC to the URRC will be a disadvantage to many renewable project proponents in areas where diesel fuel costs are higher.

3.4.3. Access to capital and transformational collaboration between stakeholders

Model insight: The modeling framework described in this work shows that trade-off analysis is critical in determining the vast range of potential energy solutions generated by the *MINES* model. In particular, it was shown in Fig. 12 that an increase in $LCOE$ is the inherent trade-off resulting from reducing diesel $fuel_{cons}$ of the integrated energy system due to the introduction of variable RE and BT storage. As shown in Table 10, this increase in $LCOE$ is significant when uncertainties and risk preferences of decision makers are introduced into the model. The other costs increases, in conjunction with the $LCOE$, is associated with the CC of the system.

Policy recommendation: Primarily, one of the main barriers for the transition of Indigenous communities towards clean and sustainable sources of energy is a lack of access to capital investments. At the moment, the First Nations Power Authority is the only North-American non-profit

Table 10: Configuration results comparison between deterministic (DT) and robust (RO) optimization with different risk preferences.

Parameter	Unit	Optimization results											
		Sol 1: Min $LCOE$				Sol 2: Trade-off				Sol 3: Max $LCOE$			
		DT	RO-RS	RO-RN	RO-RA	DT	RO-RS	RO-RN	RO-RA	DT	RO-RS	RO-RN	RO-RA
WT	kW	570	950	1,425	1,330	1,045	2,185	3,230	5,035	3,325	5,510	9,120	14,820
PV	kW	450	700	0	0	1,725	50	0	0	0	0	0	0
DG	kW	675	1,575	1,575	1,800	675	1,575	1,800	2,025	0	0	0	0
BT	kWh	4,620	4,620	4,324	4,620	7,205	7,205	7,205	7,205	7,315	7,315	7,315	7,315
CONV	kW	600	800	1,250	1000	800	1,000	1,350	1,250	800	2,000	1,750	1,500
Strategy	-	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS
$fuel_{cons}$	L/yr	447,470	553,956	675,185	1,070,200	183,595	212,878	267,474	317,622	0	0	0	0
$LCOE$	CND	0.59387	0.81333	0.87228	0.94848	1.0634	1.28017	1.42203	1.73301	1.85488	2.19247	2.86171	4.12364
	\$/kWh												

^a RS: Risk seeking; RN: Risk neutral; RA: Risk averse.

Indigenous owned and controlled organization developing power projects with Indigenous peoples [58]. Hence, this work recommends specific stipulations in the IPP policy on how to leverage capital investments for Indigenous peoples-led energy projects. Specifically, community partnerships with industry, utilities, and governments should be strengthened moving forward. These partnerships should include majority stake for Indigenous communities as this enables Indigenous stakeholders to influence distribution, re-investment and future planning [59]. This tie-up leads to mutual benefits for all parties as the respective partners have the support from the Indigenous peoples who have the land base. Ultimately, such partnerships also represent a significant step towards economic reconciliation where Indigenous peoples are not just participants but key players and partners in the mainstream economy.

3.4.4. Renewable energy integration limits

Model insight: Integrating renewables in the current electricity grid of remote communities in the North requires a grid impact study from the Crown utility. Although there is an increase in renewable energy penetration for remote communities, stability of the grid to deliver reliable power to the community, especially to those which are most isolated, should be ensured. For instance, Sachs Harbour’s solution 1 of scenario 2 has a mean RE_{pen} of approximately 51% after simulating probabilistically (considering risk seeking preference of the decision maker) while its initial deterministic RE_{pen} is 69.27%. This significant integration of intermittent renewables would be likely to cause stability and reliability issues if not properly addressed.

Policy recommendation: With the modeling results generated from MINES, this research recommends for NTPC to consider suitable BT storage systems in order to increase renewable energy integration limits in the NWT. As shown in Table 9 and Fig. 7, it is also critical to consider the impact of temperature on BT capacity given the long and cold winters in the Arctic. The BT storage system can also be integrated in the net metering systems of the territory. This would enable residents/communities to store some of the power generated locally rather than selling everything back to the Crown utility. This set-up might potentially address grid reliability issues caused by the intermittency of renewables as well.

3.4.5. Demand-side energy solutions

Model insight: This work points out that a 40% space heating load reduction can be obtained when the overall U -value of the building enclosure is $0.13 \text{ W/m}^2\text{-K}$ (equivalent to passive house performance).

Policy recommendation: According to the National Energy Board [60], energy costs are a major contributor to the high cost of living in the North, with per capita of energy use being twice the Canadian average. Hence, this work recommends that accelerating energy transitions in Arctic remote communities should be taken from a holistic perspective wherein energy solutions are not limited to the supply-side aspects but also to demand-side considerations. In particular, this work recommends evaluating building enclosure improvements especially in public housing among remote communities in the Northern territories. This does not only provide reductions in space heating loads but also offers non-energy benefits such as thermal comfort and increased resiliency in extreme temperature events. Supply-side energy solutions such as renewable energy integration is beneficial in meeting decarbonization goals, but they are generally expensive to implement. Thus, this research recommends policies that promote energy conservation and efficiency initiatives for the community. Aside from the ones in place right now in the NWT (Section 1.1.1), there should be a strict implementation of high-performance building standards in the region as prescribed by the International Passive House Institute [61].

4. Conclusions

The energy modeling framework presented in this work evaluates trade-offs and balances risk hedging strategies in integrated energy systems planning. The risk preferences of decision makers towards uncertainty was found to influence the optimal capacity of the integrated energy system. Specifically, the near-optimal Pareto front from the deterministic optimization tends towards higher optimal objective function values when the algorithm shifts to robust optimization which endogenises multiple overlapping uncertainties. This implies that the optimal capacities found deterministically were under-dimensioned considering possible increments and reductions from the load and other meteorological parameters relevant for Sachs Harbour. Uncertainties relating to

system reliability were also proven to be critical in ensuring that the energy system will operate even in extreme climate conditions.

It was observed from one of the solutions of interest that due to uncertainties incorporated in the energy model, the deterministic RE_{pen} of 69.27% dropped to around 51% (mean) after simulating probabilistically. Conversely, the deterministic $fuel_{cons}$ of 447,470 L/yr increased to 750,000 L/yr (mean) to compensate for the reduced operation of the renewables. To ensure robust performance of the energy system under worst-case realization of uncertainties, increase in component capacity and the overall system costs ($LCOE$, LCC , CC) were demonstrated as the attitude of the decision maker shifts from being risk seeking to risk averse.

The probabilistic algorithm assigns its preference to the diesel generator over the battery storage whenever there is a load deficit in the system. This is due to the latter's charge-discharge cycling behavior being influenced by the amount of excess and deficit from the renewables, while the former's power can be dispatched promptly. An inherent trade-off, however, is the increase in environmental emissions from diesel generation to compensate for the unavailability or limited power being dispatched from the renewables and battery storage.

Real-world applications of the generic modeling approaches are described, while taking into account holistic energy solutions. The method and results are applicable not just for the Canadian Arctic region, but remote communities globally that all have similar issues with diesel avoidance. In particular, achieving decarbonization targets while ensuring affordable energy costs for remote communities is possible given robust policies that can accelerate and support the energy transition towards more sustainable energy outcomes. Synergies between stakeholders (local governments, private sectors, utility corporations and Indigenous peoples) are also highlighted to be fundamental in achieving the desired energy transition for remote communities.

5. Future work

The uncertainty module of MINES will be further improved by exploring autocorrelation to examine dependencies between uncertain variables. Adding new technologies in the proposed energy system model is also valuable. For example, solar thermal and heat storage can be included in the modeling analysis done for remote Arctic communities. The thermal effects on electricity battery storage will be incorporated in the actual optimization algorithm, and higher computational resource from Compute Canada will be explored to perform this work. Finally, the quantitative outputs from the energy model will be adapted to lower latitude communities to synthesize effective policy recommendations even outside the Canadian Arctic region.

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Appendix A. Sequential Monte Carlo state duration sampling

This appendix provides an overview on relevant steps needed to generate the outage history on each component of the energy system using the sequential Monte Carlo state duration sampling method.

In a two-state component representation, the distribution functions introduced by Billinton and Li [47] refer to the operating (uptime) and repair (downtime) state of a system component i , and are usually assumed to be exponential. This can be summarized in the following steps:

- **Step 1:** Identify initial state of energy system component (i). Generally, all components are assumed to be operational at least in the first hour. Following the initial state, let τ_i denote

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the state of the i th component:

$$\tau_i(t) = \begin{cases} 0 & \text{if downstate} \\ 1 & \text{if upstate} \end{cases} \quad (\text{A.1})$$

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- **Step 2:** Sample the state duration of each component i depending on its present state. For instance, given an exponential distribution, the sampling value of the state duration can be expressed as:

$$Upstate_i = \text{round} \left(\underbrace{-\frac{1}{\lambda_{fi}}}_{\text{MTBF}} \times \ln(U_i) \right) \quad (\text{A.2})$$

$$Downstate_i = \text{ceil} \left(\underbrace{-\frac{1}{\lambda_{ri}}}_{\text{MTTR}} \times \ln(U_i) \right) \quad (\text{A.3})$$

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where U_i is a uniformly distributed number between $[0,1]$ corresponding to the i th component. If the present state is the down state, λ_{ri} will be the repair state of the i th component ($1/h$) (the annotated term in Eq. A.3 is called Mean Time To Repair ($MTTR_i$ [62])). The *round* function of MATLAB[®] was used to round $Upstate_i$ to its nearest decimal or integer. If the present state is the up state, λ_{fi} will then be the failure rate of the i th component ($1/h$) (the annotated term in Eq. A.2 is called Mean Time Between Failure ($MTBF_i$ [62])). The *ceil* function of MATLAB[®] was used to round $Downstate_i$ to its nearest integer greater than or equal to its value. Table A.11 shows the uncertainty parameters used to generate outage history for each component i of the energy system.

Figure A.13: Chronological component state transition process of each component (a and b) and the overall system (c); adapted from [47].

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- **Step 3:** Repeat Step 2 for each hour (1 - 8760) in the model, and record sampling values of each state duration for all components. A graphical representation of example chronological component state transition can be seen in Fig. A.13(a) and (b).
- **Step 4:** As shown in Fig. A.13(c), the chronological state transition of the overall system can then be obtained by combining the chronological component state transition processes for both components 1 and 2 (Eq. A.4).

$$\tau_{system}(t) = \sum \tau_i(t) \quad (\text{A.4})$$

Table A.11: Uncertainty parameters to generate outage history for each component of the energy system; approach was adapted from [47] and actual values were taken from [62].

Parameter	Value	Unit
$MTBF_{PV}$	2190	hours
$MTTR_{PV}$	80	hours
$MTBF_{WT}$	1,920	hours
$MTTR_{WT}$	80	hours
$MTBF_{DG}$	950	hours
$MTTR_{DG}$	50	hours
$MTBF_{CONV}$	87,600	hours
$MTTR_{CONV}$	80	hours

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