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

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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.

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 modeling 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 analyzed. 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.

Keywords

Energy policy
Robust optimization
Uncertainty
Risk hedging strategies
Indigenous peoples
Energy sovereignty

Nomenclature

Acronyms

ASHP
Air Source Heat Pump
BT
Battery
CCOS
Cycle Charging Operation Strategy
CONV
Converter
DG
Diesel Generator
DHW
Domestic Hot Water
DT
Deterministic
GA
Genetic Algorithm
iHOGA
improved Hybrid Optimization by Genetic Algorithms
IPP
Independent Power Producer
KiBaM
Kinetic Battery Storage Model
LA
Lead Acid
LFOS
Load Following Operation Strategy
LI

Lithium Ion
MINES
Multi-objective INtegrated Energy System
NSGA-II
Non-dominated Sorting Genetic Algorithm - II
NTPC
Northwest Territories Power Corporation
NWT
Northwest Territories
PPA
Power Purchase Agreement
PV
Photovoltaic
QEC
Qulliq Energy Corporation
RB
Reliability-based Optimization
RE
Renewable Energy
RO
Robust Optimization
URRC
Utility Rates Review Council
WT
Wind Turbine

Symbols

Discrete samples of stochastic variables
Failure rate of the th component
Repair rate of the th component
Outage history of the th component
Mean value of the original time-series
Standard deviation of the original time-series
New time-series of the uncertain parameter
Capital cost
Load factor of DG
Fuel curve intercept coefficient
Fuel curve slope coefficient
Fuel consumption
Global Horizontal Irradiance
Life Cycle Cost
Levelised Cost of Energy
Loss of Power Supply Probability
Mean Time Between Failure
Mean Time To Repair
Life of the energy system in years
Net Present Cost
Operations and maintenance costs
Rated capacity of DG

Power produced by DG
Excess electricity
Overall power generated from the system
Load demand
Discount rate
RE penetration
Risk coefficient
Salvage value
State of charge of the battery
Time
Ambient temperature
Overall heat transfer coefficient of the building
Wind speed
Uniformly distributed number between [0,1]
Other costs associated in building the energy system

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 North[1] 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 REprojects 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].

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

Jurisdictions	Number of communities[a]	No. of PPAs (inc. net metering)	Project types
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.
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.

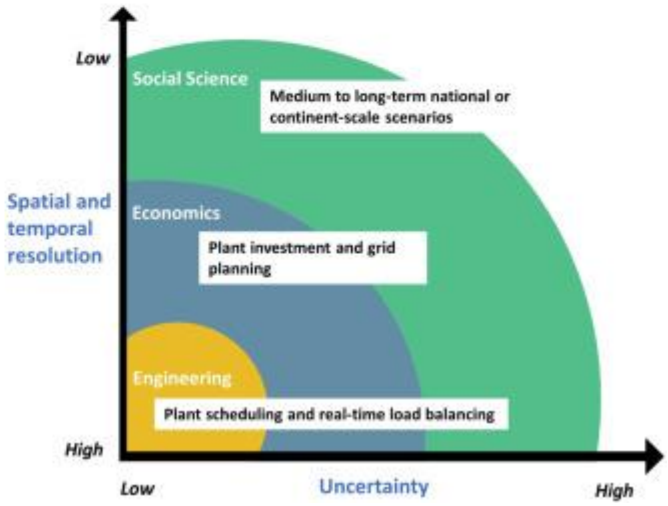

Fig. 1. Optimization complexity across various spatial and temporal scales.

Adapted from [8].

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, Ringkjob 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 minimize 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 Charettes,[2] 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?

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 Conclusions, 5 Future work 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.

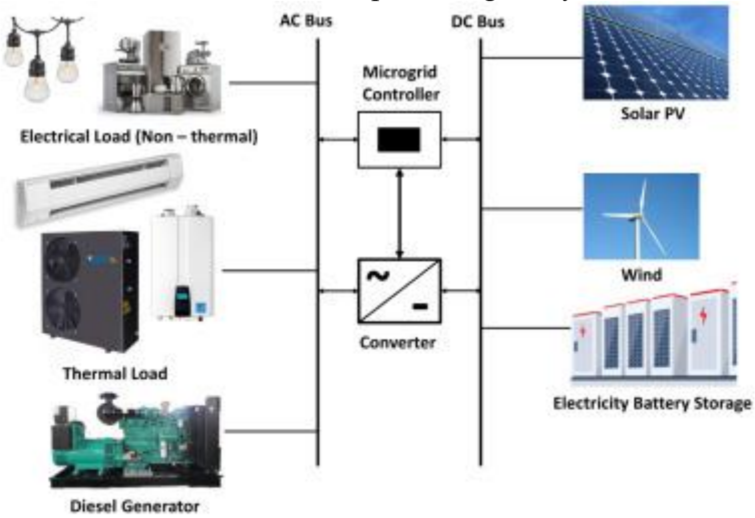

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Fig. 2. Schematic diagram of a prototypical integrated electrical and thermal energy system.

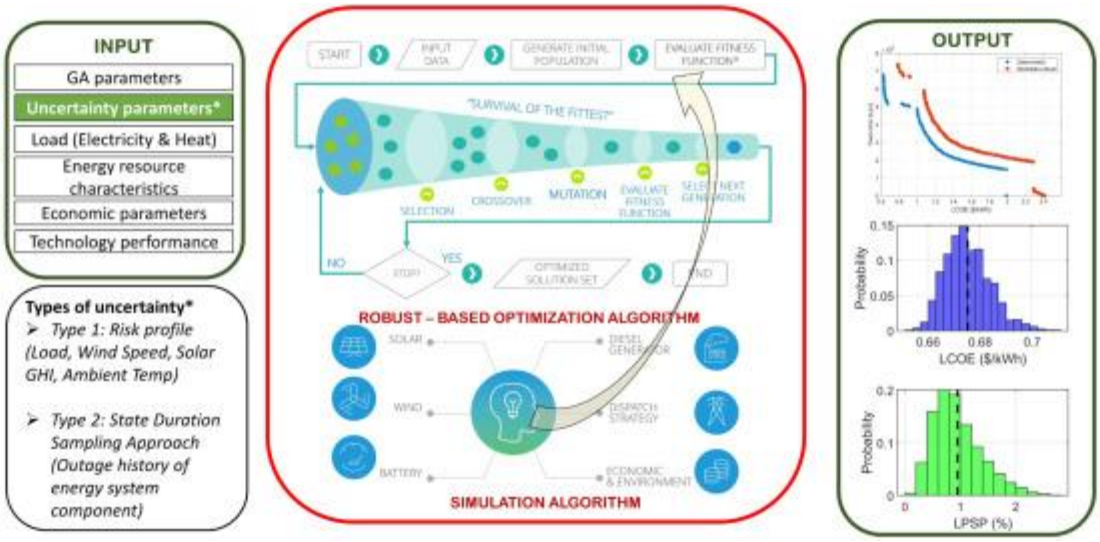

Fig. 3. Overall energy modeling framework of MINES.

2.1. Robust optimization

The MINES model, as shown in Fig. 3, 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 rank,[3] taking as many complete ranks as will fit in the new population. This process 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.

Table 2. GA configuration parameters.

Parameter	Description
Algorithm	Variant of NSGA-II [18]
Generations	200
Population	100
Crossover function	Heuristic
Crossover rate(%)	90

Parameter	Description
Mutation function	Non-uniform
Tournament size	2

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]: (1)where are the objective functions, represents a vector of decision variables, pertains to a vector of random variables, and indicates the worst-case scenario of the specific objective function. The worst-case realizations of uncertainties (robust-based optimization) was 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 () (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]: (2)where is time (year), is the discount rate (%), is the total life of the energy system (year), is the capital cost ($) per unit of the system component , is the operations and maintenance costs ($/year), is all other costs associated with the project ($/year), is the salvage value ($), and is the power generated from the energy system (kWh/year).

The DG's fuel consumption (), 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. (3)where is the fuel curve intercept coefficient (L/h/kW_{rated}), is the fuel curve slope coefficient (L/h/kW), is the rated capacity of DG, and 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 DG is dispatched to provide the exact power to meet the instantaneous load. CCOS dispatches the DG power always at its rated capacity to maximize generator efficiency; instantaneous surplus of power goes to the BT storage system. Also, the full set of constraints considered to run the optimization module in MINES are: (4)where is the Loss of Power Supply Probability (%), is the state of charge of the BT (%), is the RE penetration (%), is the excess electricity (%), and is the load factor of the DG (%). The mathematical formulation of each constraint and their respective justifications to include in the model were described previously by the authors in [35]. The component sub-models including the specific technology input parameters (solar PV, WT, BT, DG, CONV) as laid out in Fig. 2 were described in detail by the authors in [35].

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

2.3. Uncertainty propagation

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

2.3.1. Integrating risk hedging strategies in robust optimization

The first type specifically relates to uncertainties from the load profile of the community () as well as various meteorological parameters including Global Horizontal Irradiance (), wind speed () and the ambient temperature (). The approach is a modified version of the probability analysis being implemented through the improved Hybrid Optimization by Genetic Algorithms (iHOGA) software [36]. The iHOGA commercial software is a well-established tool in optimizing energy systems, both deterministically and probabilistically. Using iHOGA, Zubi et al. [37] conducted a techno-economic assessment of an off-grid PV system for developing regions to provide electricity for basic domestic needs. Dufo-Lopez et al. [38] conducted a similar study by optimizing a stand-alone hybrid solar–diesel–battery energy system for an off-grid health care facility while

considering uncertainties from solar irradiance and the load demand. Other applications of the iHOGA software can be found in Fulzele and Daigavane [39], Fracastoro et al. [40], Bernal-Agustin et al. [41] and Cristobal-Monreal et al. [42], among others.
The probability analysis in iHOGA can be performed by taking into account the Gaussian probability distribution of the mean annual values of the system load, solar irradiance, wind speed and water flow (if there is a water turbine in the system). The software performs its simulation by assigning each uncertain parameter with five possible increments/reductions from the original time-series:

Average

Average Standard Deviation

Average - Standard Deviation

Average 3*Standard Deviation

Average - 3*Standard Deviation

For example, the user can assign Average Standard Deviation for load, and for the solar irradiance, wind and water flow data, the Average - Standard Deviation. This combination implies that there is an increment from the original time-series of the load data while there is a reduction in the other uncertain variables in reference to the original time-series [36].
In conjunction with the second type of uncertain parameters (relating to system reliability), this paper improves the iHOGA probabilistic technique by explicitly introducing decision-maker risk preferences (captured by a risk coefficient) towards the first types of uncertain parameters mentioned previously, and as shown in Eq. (5).
(5)where is the new time-series of the uncertain parameter, obtained from its original mean value () and standard deviation (). 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 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 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 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 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 risk-neutral decision-maker for this study.
The increment/reduction in the second term of Eq. (5) also pertains to the discrete samples of the stochastic variables wherein is the number of samples (number of realization of uncertainties) and is the uncertain variable. Through Latin Hypercube Sampling, the algorithm draws a total of random samples from the probability distribution represented by its mean and standard deviation . Table 5 lists the respective means and standard deviations of the uncertain parameters described in this section.

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
	−1	−2	−3
	−1	−2	−3
	1	2	3

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

Parameter	Mean	Standard deviation	Number of years[a]
Average for a year	8.075 m/s	0.290 m/s[b]	10
Average for a year	−10.31 °C	2.4 °C[c]	55
Average daily for a year	2.471 kWh/m^2	0.618 kWh/m[d]	–
Average combined daily thermal and electricity load for a year	9277 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 .

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 has been set to 0% as part of the model constraints (Eq. (4)). The 0% 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).

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.

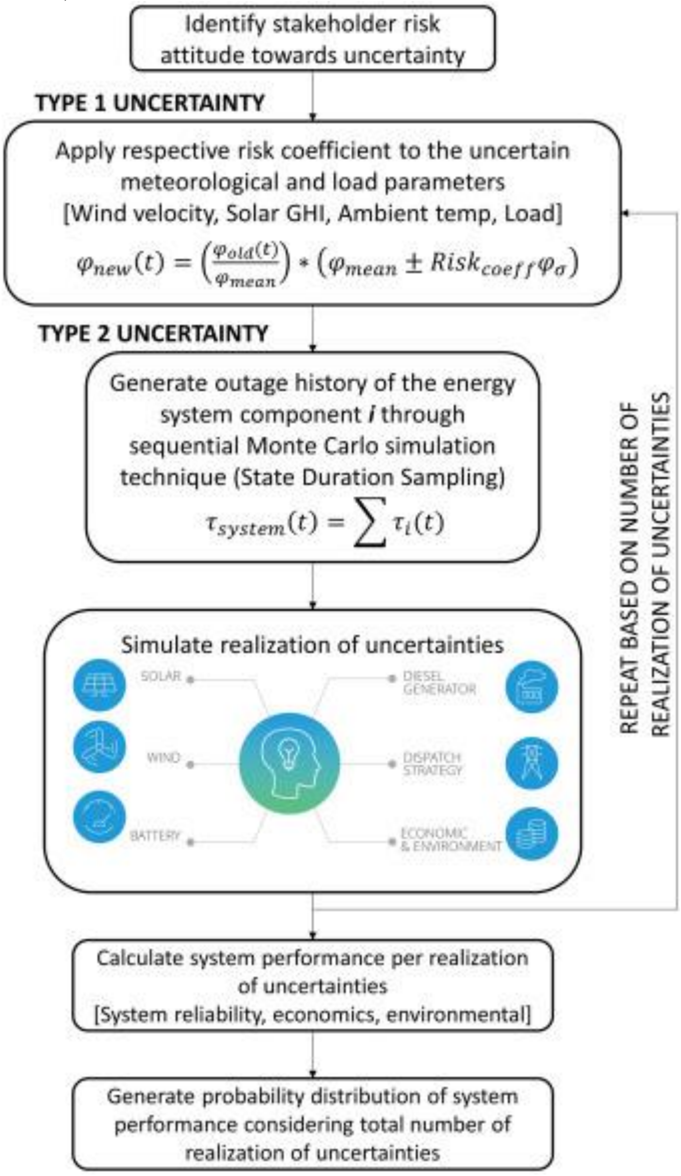

Fig. 4. Uncertainty propagation of the proposed modeling framework.

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 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 () [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.

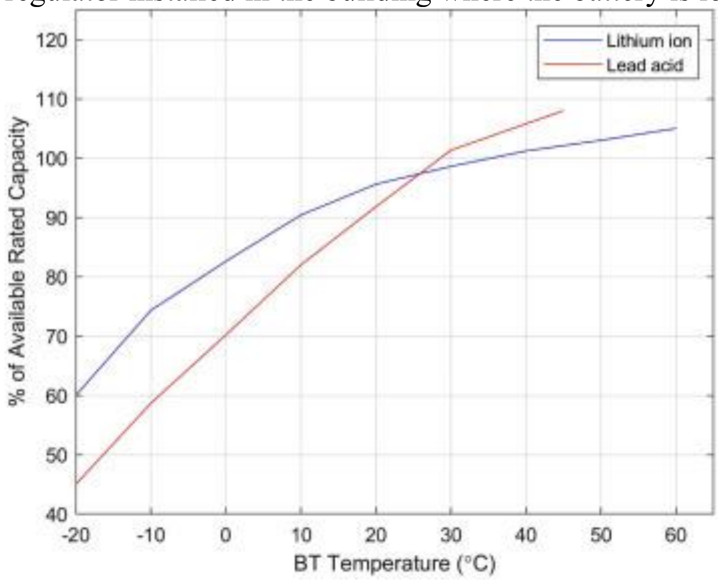

Fig. 5. Temperature versus capacity curve of batteries; data extracted from Trojan Battery Company (T-105 with Bayonet Cap model for lead acid [51] and TR 25.6-25 Li-ion model for lithium ion [52]).

Table 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

Parameter	Unit	Lead acid	Lithium ion
Fixed bulk temp.	°C	20	20

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 (, ,) 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 spaced 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 (). The modeling results suggested that a passive house with an overall -value of 0.13 W/m^2-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.

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 0.5 W/m^2-K
Scenario 2	Home appliances including lighting and electric load for DHW	Baseboard Heater at 0.13 W/m^2-K
Scenario 3[a]	Home appliances including lighting and electric load for DHW	Baseboard Heater and ASHP at 0.13 W/m^2-K
Scenario 4[b]	Home appliances including lighting and electric load for DHW	Baseboard Heater and ASHP at 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.

3.1. Deterministic results

Fig. 6 shows the deterministic full design space and near-optimal Pareto front of scenario 2 after minimizing simultaneously the and of the energy system in question for 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 and highest . 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 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 and Life Cycle Cost[4] () [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.

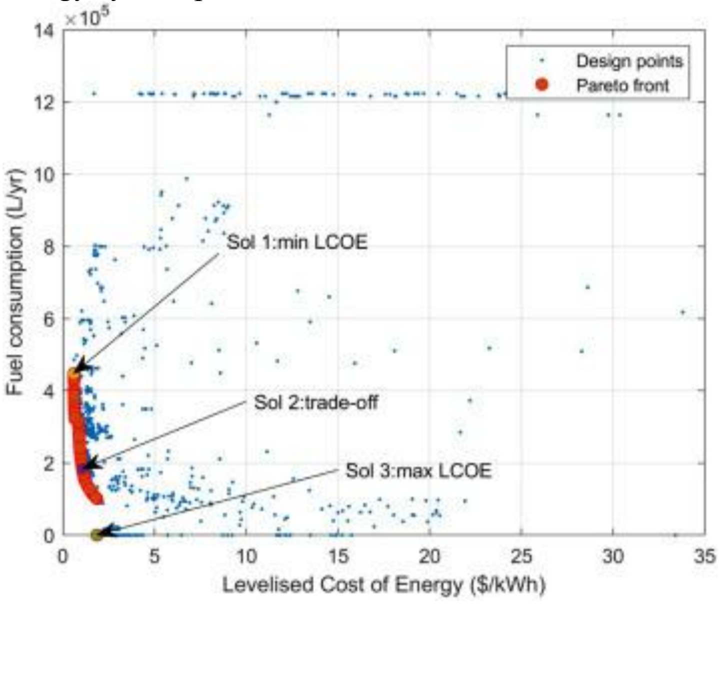

Fig. 6. Scenario 2 deterministic results: full design space with the near-optimal Pareto front and the identified solutions of interest.

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**		
Empty Cell	Empty Cell	**Sol 1: Min.**	**Trade-off Point**	**Sol 3: Max.**
PV	kW	450.45 (25.025 kW x 18)	1725 (25 kW x 69)	0
WT	kW	570 (95 kW x 6)	1045 (95 kW x 11)	3325 (95 kW x 35)
BT	kWh	4620 (9.24 kWh x 500)	7205 (55 kWh x 131)	7315 (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
	kWh	414,407	1,405,135	0
	kWh	2,456,400	4,531,567	14,418,623
	kWh	151,831.41	365,881	513,951
	kWh	1,272,995	529,758	0
	%	0	0	0
	%	69.27	91.81	100
	%	15.19	4.93	1.05
	L/yr	447,470	183,595	0
CO[a]	$tCO_{2\text{-eq}}$/yr	2096	1523	757
	CND $	15,117,673	37,839,517	79,936,645
	CND $/kWh	0.59387	1.06348	1.85487
	CND $	35,756,756	64,031,794	111,681,201

a

Lifecycle CO emissions of the energy system.

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.

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
	CND $	1,345,500	1,840,916
	CND $	797,439	644,352
	kWh	506,195	506,195
	kWh	2,475,542	2,475,542
	kWh	73,897	118,806
	kWh	87,465	127,243
	kWh	1,331,850	1,280,713
	%	0	0
	%	60.7	62.2
	L/yr	528,472	506,491
System	CND $	16,575,414	17,070,830
	CND $/kWh	0.6659	0.6784
	CND $	40,092,700	40,846,160

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 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 and system cost as well. Consequently, this resulted to a cheaper overall system cost, both in terms of and . 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.

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].

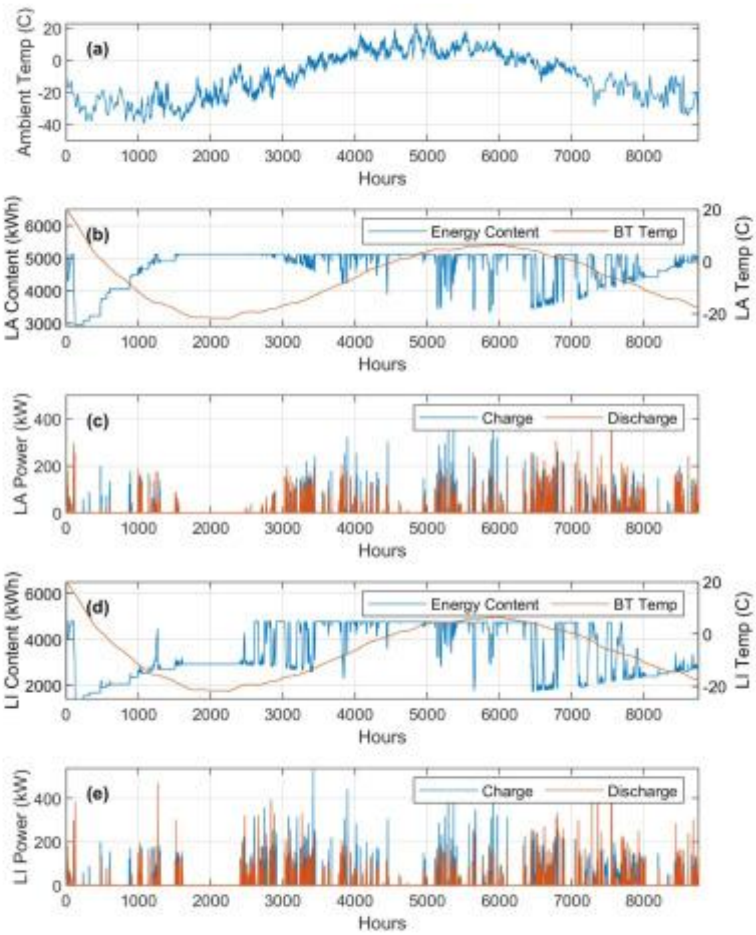

Fig. 7. Example deterministic simulation results when there is no thermal management in a building where the battery storage systems are located: (a) ambient temperature of Sachs Harbour; (b) Energy content and operating temperature of lead acid BT; (c) Charge–discharge of lead acid BT; (d) Energy content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

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 of approximately 51% after simulating 1000 times probabilistically as compared to its initial deterministic 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 is even lower when the risk preference shifts from risk seeking to risk averse. Consequently, the mean of the DG increased to approximately 750,000 L/yr as compared to its initial deterministic value of 447,470 L/yr. This reflects that the DG was under-sized when multiple overlapping uncertainties were introduced in the model.

Fig. 9 shows the mean decreases to approximately 20% when the preference of the decision maker towards uncertainty shifts from being risk seeking to risk averse. The mean , on the other hand, were further increased from approximately 750,000 L/yr (risk seeking) to 1,400,000 L/yr (risk averse). This implies increase in system costs (, ,) to ensure robust performance of the energy system under worst case realization of the uncertainties. Specifically, this is attributable the highest increment (in comparison with the other risk coefficients listed in Table 4) in energy demand and the reduction in the other uncertain variables (renewable resources and temperature).

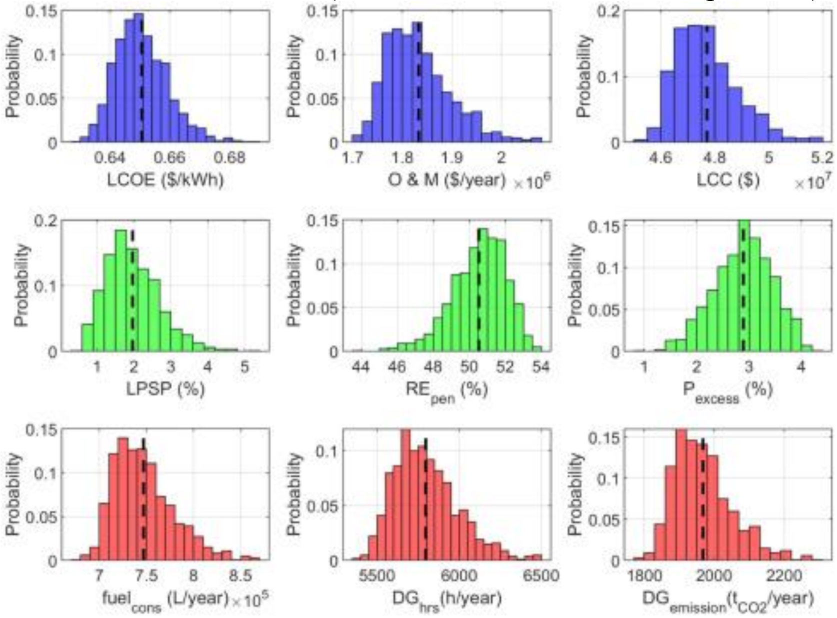

Fig. 8. Risk seeking scenario 2-solution 1 series of probability distribution functions generated probabilistically using 1000 samples; dashed line refers to mean value.

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

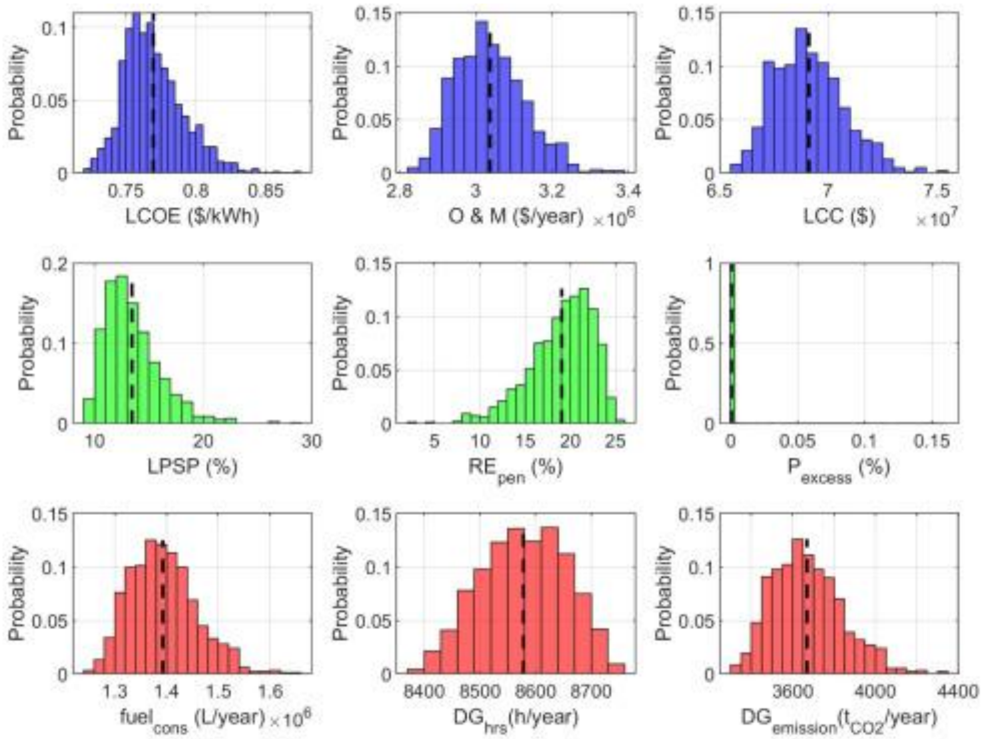

Fig. 9. Risk averse scenario 2-solution 1 series of probability distribution functions generated probabilistically using 1000 samples; dashed line refers to mean value.

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

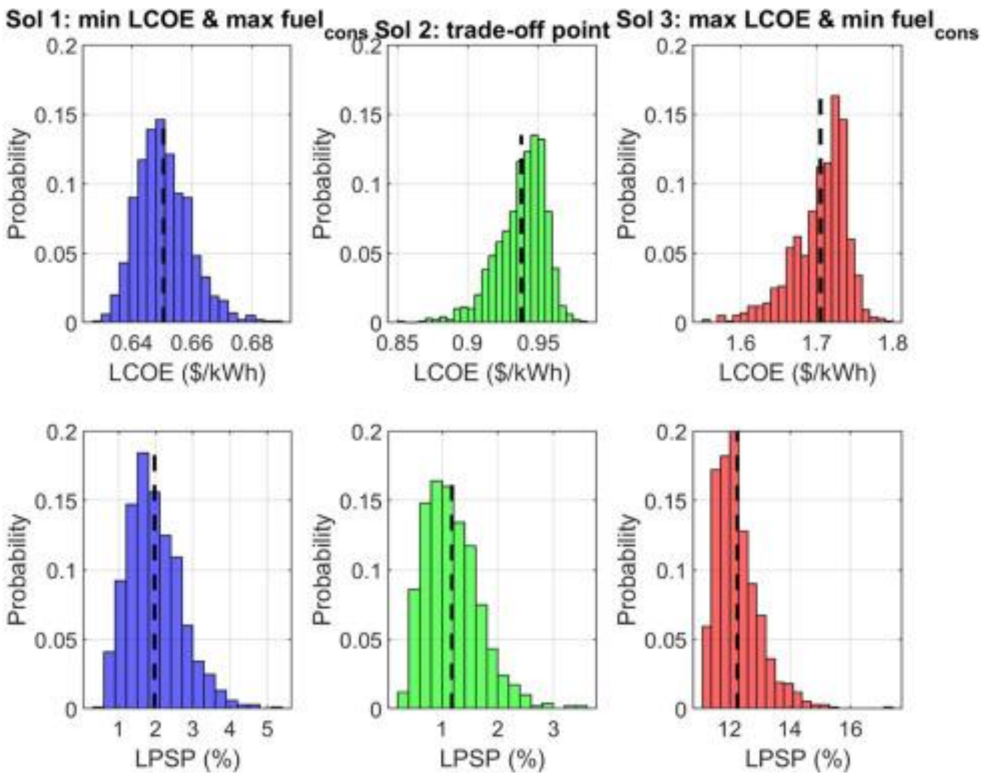

Fig. 10. Risk seeking scenario 2 probabilistic simulations for the three solutions of interest generated from the deterministic optimization results; dashed line refers to mean value.

3.3. Robust optimization results

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

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

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

Parameter	**Unit**	**Optimization results**											
Empty Cell	Empty Cell	**Sol 1: Min**				**Sol 2: Trade-off**				**Sol 3: Max**			
Empty Cell	Empty Cell	**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	1425	1330	1045	2185	3230	5035	3325	5510	9120	14,820
PV	kW	450	700	0	0	1725	50	0	0	0	0	0	0
DG	kW	675	1575	1575	1800	675	1575	1800	2025	0	0	0	0
BT	kWh	4620	4620	4324	4620	7205	7205	7205	7205	7315	7315	7315	7315
CONV	kW	600	800	1250	1000	800	1000	1350	1250	800	2000	1750	1500
Strategy	_	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS	LFOS
	L/yr	447,470	553,956	675,185	1,070,200	183,595	212,878	267,474	317,622	0	0	0	0
	CND $/kWh	0.59387	0.81333	0.87228	0.94848	1.0634	1.28017	1.42203	1.73301	1.85488	2.19247	2.86171	4.12364

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

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.

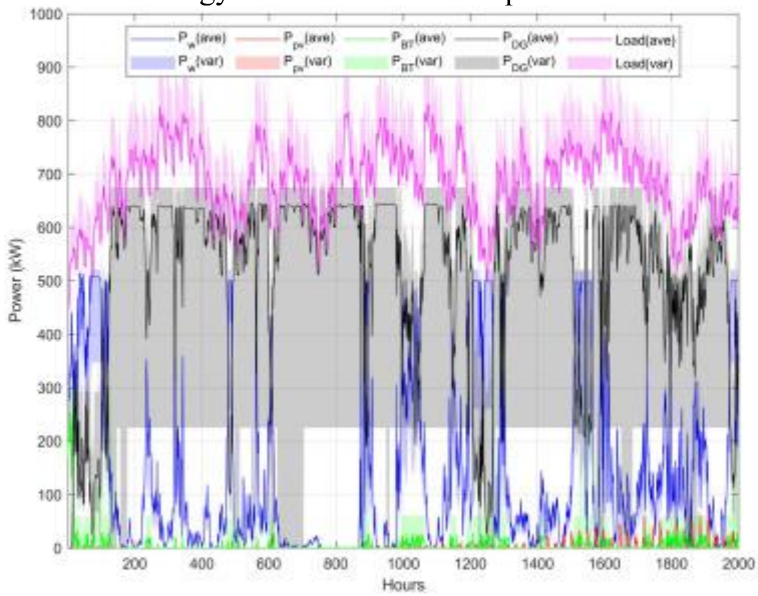

Fig. 11. Hourly average (ave) and variation (var) of the deterministic optimal configuration in scenario 2 that was simulated probabilistically; assumed risk seeking preference of the decision maker.

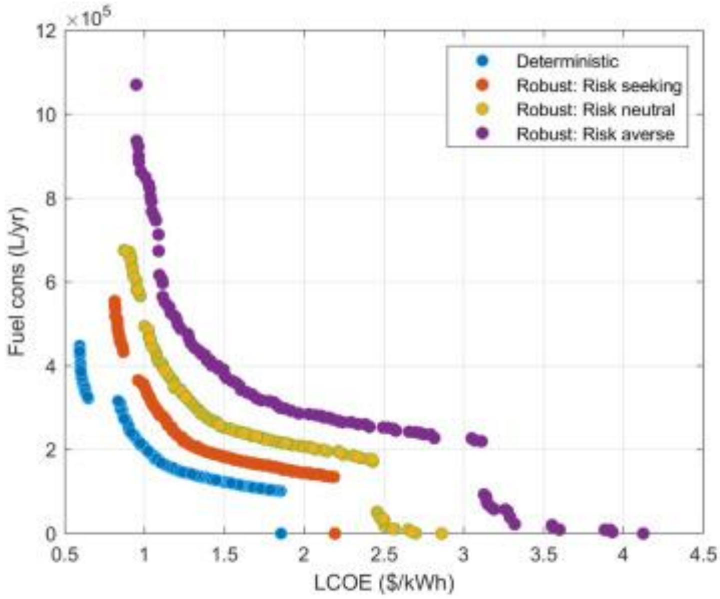

Fig. 12. Scenario 2 near-optimal Pareto front comparison for deterministic and robust optimization results with specific risk preferences.

3.4.2. Community-specific (levelised) cost of energy

Model insight: Table 8 shows the for the three solutions of interest identified in Fig. 6. Table 10, on the other hand, presents for 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. 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 , 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 is the inherent trade-off resulting from reducing diesel of the integrated energy system due to the introduction of variable RE and BT storage. As shown in Table 10, this increase in is significant when uncertainties and risk preferences of decision makers are introduced into

the model. The other costs increases, in conjunction with the , is associated with the 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 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 of approximately 51% after simulating probabilistically (considering risk seeking preference of the decision maker) while its initial deterministic 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 -value of the building enclosure is 0.13 W/m^2-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 of 69.27% dropped to around 51% (mean) after simulating probabilistically. Conversely, the deterministic 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 (, ,) 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.

CRediT authorship contribution statement

Marvin Rhey Quitoras: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Funding acquisition. **Pedro Cabrera:** Software, Writing - review & editing. **Pietro Elia Campana:** Writing - review & editing. **Paul Rowley:** Conceptualization, Writing - review & editing. **Curran Crawford:** Conceptualization, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. 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 , and are usually assumed to be exponential. This can be summarized in the following steps:

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

Step 2: Sample the state duration of each component depending on its present state. For instance, given an exponential distribution, the sampling value of the state duration can be expressed as: (A.2) (A.3)where is a uniformly distributed number between [0,1] corresponding to the th component. If the present state is the down state, will be the repair state of the th component (1/h) (the annotated term in Eq. (A.3) is called Mean Time To Repair ([62])). The *round* function of MATLAB® was used to round to its nearest decimal or integer. If the present state is the up state, will then be the failure rate of the th component (1/h) (the annotated term in Eq. (A.2) is called Mean Time Between Failure ([62])). The *ceil* function of MATLAB® was used to round 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 of the energy system.

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)). (A.4)

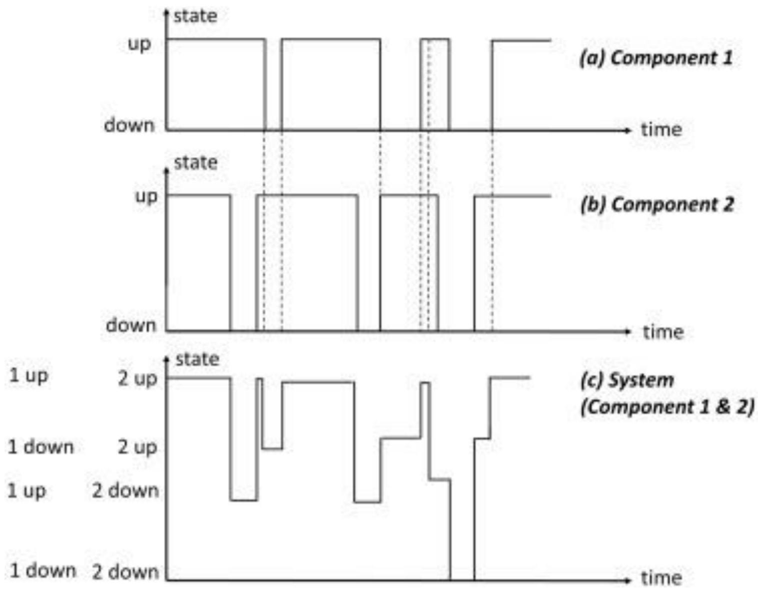

Fig. A.13. Chronological component state transition process of each component (a and b) and the overall system (c); adapted from [47].

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
	2190	h
	80	h

Parameter	Value	Unit
	1920	h
	80	h
	950	h
	50	h
	87,600	h
	80	h

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