Reliability, Availability and Resilience Assessment of Heating Systems using Sequential Monte-Carlo Simulation and Critical Load Analysis

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Abstract

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Ambitious sustainable development goals lead cities to invest in renewable energy infrastructure as the primary energy source. With an increasing number of people moving to urban areas, providing reliable heating energy, especially in cold regions needs more investigation. A resilient and reliable energy system is able to provide the intended demand in day-to-day operation under a wide range of failure modes, as well as extreme situations. The focus of this research is to provide a framework to investigate reliability indices, availability, and resilience of electric heating systems.

The availability and reliability indices such as Energy Not Served (ENS) and Loss Of Load Expectation (LOLE) are evaluated using sequential Monte Carlo (SMC) simulation. SMC is a probabilistic approach that is able to capture the random failures and behaviour of the systems over a defined sequence of time. To evaluate the energy system resilience under a major power outage, a method considering the resilience in terms of system robustness, ENS, and Average Energy Not Served (AENS) is proposed. During the power outage, resilience metrics are analyzed considering critical loads instead of business-as-usual demand. The critical load is the minimum demand that needs to be provided to customers and it is defined based on the ranking and assigning weights to user types.

The method is applied to a district to compare the performance of centralized and decentralized ground source heat pump systems. In terms of system resilience, the two energy systems have similar performance, however, results of the reliability simulation indicate that the centralized scenario is more reliable than the decentralized design in terms of the number of hours where energy is available to the area, and the amount of energy served to the consumers.

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List of abbreviation

DHN	District Heating Network
MC	monte Carlo
SMC	Sequential Monte Carlo
R(t)	Reliability Function
f(t)	Failure Density Function
λ(t)	Hazard Function
MTBF	Mean Time Between Failure
MTTR	Mean Time To Repair
λ	Exponential Failure Rate
α	Weibull Scale Parameter
β	Weibull Shape Parameter
μ	Repair Rate
SAIFI	System Average Interruption Frequency Index
SAIDI	System Average Interruption Duration Index
CAIFI	Customer Average Interruption Frequency Index
CAIDI	Customer Average Interruption Duration Index
ASAI	Average Service Availability Index
ENS	Energy Not Supplied
EENS	Expected Energy Not Supplied
AENS	Average Energy Not Supplied
LOLE	Loss of Load Expectation

Chapter 1: Introduction

1.1 General overview

With 81% electricity production from non-emitting resources, Canada has one of the cleanest electricity production systems in the world [1]. Some ongoing projects in the electricity sector aim to modernize the electricity grid and storage in order to incorporate renewable energy sources and invest in innovative renewable technologies [1].

As the second-largest municipality in Canada, Montreal has provided an action plan that includes goals, challenges, and requirements needed to become more sustainable. In the pathway toward sustainability and carbon mitigation goals, the city has three main sustainable development challenges, which are [2]:

- Reduction of GHG emissions by 80% (3,003 kilotons CO2 equivalent) by the year 2050 compared to the year 1990 baseline.
- Enhancing access to services and facilities among different neighbourhoods in the city and ethical distribution of resources for every dwelling.
- Becoming an exemplary model for other cities by integrating sustainable plans into all aspects of the city.

In the sustainable development of cities toward sustainability, resiliency, and carbon neutrality, the role of municipalities, efficient energy system design, and buildings' energy consumption should be considered [3]. Municipalities' plans and goals define the scope of changes and enhancements in different sectors. Hukkalainen et al. discussed a methodology to design an energy-efficient and sustainable urban area by considering the municipality's plans and investigated the effects on carbon reduction goals [4]. Their results show 2% to 79% carbon mitigation by considering different urban design options. Fenton et al. discussed the influential role of municipalities and urban planners on climate impacts and energy consumption [5]. It has been found that a wide range of drivers could enhance the planning process; some of these drivers are ageing infrastructures, growing demand, and economic crises.

One of the sustainable development drivers in the cities is to incorporate more renewable energy resources [6]. A sustainable system has four dimensions, availability, accessibility, affordability, and acceptability [7]. In the context of urban energy, availability means having an adequate amount of energy supply units, storage, and transmission lines in service. Accessibility refers to all end users' uniformly distributed energy (in terms of quality and quantity). Affordability denotes the share of income a household should spend on energy needs. In sustainable and resilient system, energy should be affordable for all the members. Acceptability ensures that the energy generation, transmission, and distribution are well-suited in the area [7]. In conclusion, providing clean, reliable, and affordable energy is one of the issues in city-scale sustainable development [6], [7].

Countries aim to tackle sustainable development with different strategies while keeping the mutual goal of reduction in emissions and improvements in efficiency [8]. Based on [8], the Austin campus project in the USA is investing in improving energy efficiency by implementing thermal storage, microgrid and emergency power generation. Another example is the University of British

Colombia, Canada where because of aging infrastructure and carbon tax, new advancements through increasing the share of renewables are taken [8].

Due to the increasing number of people moving to urban areas pressure on infrastructure, especially local renewable energy infrastructure is increasing [9]. On the other hand, the cold climate in Canada results in an average of 61.6% of space heating demand in residential buildings' total energy demand [10]. Based on studies, renewable energy systems that could participate in sustainable development are supposed to be more resilient and flexible than the current examples [6]. Based on these points, providing reliable energy that could fit in sustainability goals and endure extreme events needs to be investigated more precisely.

Different disruptive events could threaten the normal operation of renewable energy systems. Some of them might cause a minor defect in some parts of the system, for example, failure of a heat pump compressor and corrosion of a distribution network. Other disruptive events could cause more significant effects on the system; for example, high wind may cause significant disruption in overhead electricity lines, flooding could decrease the working capacity of many parts of an energy system, and an earthquake could cause the failure of distribution pipelines. The first type of event is studied under the reliability evaluation, and the second type refers to the resilience of a system [11].

Reliability is defined [12] as the "probability that the element is capable of performing its required function in the established time interval, under established conditions" [12]. And Availability refers to the ability of an item to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval, assuming that the required external resources are provided [12]. Different approaches have been defined to evaluate a system's availability or reliability. Based on the system operation, failure modes, and available information about the system operation, appropriate assessment approaches are selected [13].

The National Infrastructure Advisory Council (NIAC) defines infrastructure resilience as the ability to reduce the magnitude, impact, or duration of a disruption. Resilience is the ability to absorb, adapt to, and recover from a potentially disruptive event [14]. Resilience has three capacities, absorptive, adaptive, and recovery capacity [14], [15]. The resilience assessment approaches are divided into qualitative and quantitative assessment methods, each applicable to different domains and fields [16].

1.2 Problem statement

The difference between reliability-focused planning and resilience-focused planning of energy systems is in the type of the event (hazard) and the methods to evaluate the effects of events on the system [17]. In the study of systems' reliability, high probability events with low impacts are under study [18]. On the other hand, the subject of resilience-focused planning is low probability events with destructive consequences [18]. While resilience addresses the flexibility and survivability against extremes, reliability addresses the issues of service interruption and energy supply loss [18].

In the literature, a lack of studies in integration of thermal energy system reliability and resilience has been found. Carbon mitigation goals of cities and communities, on the one hand, and progress

in the 4th generation of district heating and cooling systems, on the other hand, raise questions regarding the reliability and resilience of these systems.

1.3 Research objectives

This research aims to provide a framework to assess the generation system reliability indices, availability, and resilience considering the end-users hourly energy demand and intends to combine a realistic simulation method with algorithms developed in Python programming language to improve the estimated outputs. The review of the literature in this perspective reveals that the studies of large-scale heating systems, for instance, district heating networks, are scarce. The scope of this study is to simulate the real-world condition of heating energy systems. The objectives of this research are as follow:

- In the literature, energy systems have been studied either under normal operation (blue sky condition), or in time of hazardous events (black sky condition). One of the objectives of the current work is to integrate the reliability and resilience indicators to investigate the performance of different energy system designs in both day-to-day operation and in time of a disruption.
- Another objective of this work is defining the critical load for resilience assessment. As shown in the literature review chapter, in different studies a wide range of quantitative indicators to assess the resilience are defined. In the proposed method, the same reliability indices are used to assess the system resiliency. The difference between the indices in resilience study and reliability study is the type of the demand which in reliability evaluation is the business-as-usual demand, and in resilience assessment is the critical load.
- Due to lack of data regarding the thermal energy system failure and repair times, using a simulation- based probabilistic approach (also known as MCS) a synthetic dataset of failure time and repair duration of each component is developed. A model to evaluate the system level reliability and availability considering the interdependency of components and hourly demand is developed.

1.4 Thesis outline

This thesis is comprised of five chapters. Chapter one, the current chapter is the introduction of the thesis. Chapter two summarizes the state of the literature regarding the reliability assessment and resilience studies of the energy systems. The literature review contains an overview to the reliability, availability, and resilience concepts and their assessment methods. In chapter three the proposed method to evaluate the energy system reliability and availability using the Monte Carlo Simulation (MCS) is discussed. The focus is on electric heating systems that provide space heating. In the rest of the chapter, the resilience assessment method, considering the critical load in time of the disruption is presented. In chapter four, the case study which is a district in Montreal is introduced, and in chapter five, the proposed method is implemented on the case study in three steps and the results are given. The last chapter presents the conclusion of reliability indices outputs and resilience results, and future steps are discussed.

Chapter 2: Literature review

This section discusses concepts of reliability, availability, and resilience in energy infrastructure, especially space heating production systems. The connection between sustainable development, urbanization, and the importance of providing reliable and resilient energy sources are argued, and the state of the literature on this matter is provided.

2.1 Reliability and availability in the energy system

2.1.1 Reliability concept

Before further investigation into reliability assessment approaches, defining some of the ground definitions is needed. The Institute of Electrical and Electronics Engineers (IEEE) defines reliability as "the ability of a system or component to perform its required functions under stated conditions for a specified period" [19]. Four key elements of this definition are 1) ability: which refers to the probability that a component will work properly. 2) Required function: each system must work based on a predefined standard. If the system works correctly without failure, it is providing its required function. 3) Special period of time: each system will fail eventually fail; a realistic time period should be considered on time. 4) Stated condition: design factors, e.g., humidity, air pressure, shock, etc., needed to be considered [20]. The mathematical form of reliability is [21]:

$$R(t) = P(t_f \geq t) \qquad 2.1$$

Where $R(t)$ is the reliability of the component, $P(t_f \geq t)$ is the probability that a component will fail after its service time, t_f is time to failure, and t is continuous random variable[21]. In fact, $R(t)$ is the probability that a system will work failure free during [0, t], and it is formulated as [22]:

$$R(t) = \int_t^{\infty} f(t)\, dt \qquad 2.2$$

A system has two states, either working or malfunctioning. Therefore, based on equation 2.2, the function of unreliability is [22]:

$$F(t) = 1 - R(t) = P(t_f < t) = \int_0^t f(t)\, dt \qquad 2.3$$

Based on the equation 2.3, the failure probability density function is [22]:

$$\int_0^{\infty} f(t)\, dt = 1 \qquad 2.4$$

2.2.1.1 Failure rate

"The failure rate can be defined as the anticipated number of times that an item fails in a specified period of time" [23]. This value is normally expressed as failures per hour, year, or million hours [23]. The failure rate in repairable systems with a constant failure rate is equal to the inverse of the mean time between failure (MTBF) [23]. Based on the conditional probability the failure rate is defined as the limit of the probability that a failure occurs per unit time interval Δt given that no failure has occurred before time t [24].

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{p(t<T\leq t+\Delta t|T>t)}{\Delta t} = \frac{\lim_{\Delta t \to 0}\{F(t+\Delta t)-F(t)\}/\Delta t}{R(t)} = \frac{f(t)}{R(t)} \qquad 2.5$$

Where $\lambda(t)$ is the failure rate, $f(t)$ is failure density function, and $R(t)$ is reliability function. In reliability engineering, different statistical distributions are used, and based on the distribution type, formulas for $f(t)$ and $R(t)$ are defined. Commonly used distributions in energy system components are exponential and Weibull distributions [25], [26], [27].

2.2.1.2 Mean Time Between Failure (MTBF), and Mean Time To Repair (MTTR)

In case of repairable components, the time duration between the moment failure happens until the moment that repair is completed, and system is back to work, is know as Mean Time To Repair (MTTR) [22]. Another concept in repairable systems is Mean Time Between Failure (MTBF) that refers to the period start with working state and failure of a component [22].

Having the probability distribution of the component known, enables to calculate the relative life data analysis functions, namely reliability function, failure rate function, MTTR, etc. Two most common functions in reliability engineering are discussed and their statistical formulations are mentioned.

2.2.1.3 Exponential and Weibull distribution

The exponential distribution is probably known and used more than other types of distributions [13]. It considers a constant hazard rate and is a good measure to evaluate the reliability during the useful life of components. This distribution is effective in complex systems because the constant failure rate reduces the complexity among the component and subsystems [13]. From the equation 2.5, the failure density function in exponential distribution is [13]:

$$f(t) = \lambda \times e^{[-\int_0^t \lambda dt]} = \lambda \times e^{-\lambda t} \qquad 2.6$$

$$R(t) = e^{[-\int_0^t \lambda dt]} = e^{-\lambda t} \qquad 2.7$$

The mean time between failure (MTBF) in repairable components or mean time to failure (MTTF) in non-repairable components is [13]:

$$MTBF = \frac{1}{\lambda} \qquad 2.8$$

The Weibull distribution has been widely used in reliability analysis as a result of its capability to represent different stages (burn in, useful life, and wear out) of life of a component. It has two parameters: shape (β) and scale (α) parameters. Hazard function, reliability function, and failure density function are defined based on these parameters [13].

$$\lambda(t) = \frac{\beta t^{\beta-1}}{\alpha^{\beta}} \qquad 2.9$$

$$f(t) = \frac{\beta t^{\beta-1}}{\alpha^{\beta}} exp[-(\frac{t}{a})^{\beta}] \qquad 2.10$$

$$R(t) = exp[-(\frac{t}{a})^{\beta}] \qquad 2.11$$

2.2.2 Availability concept

"Availability is the probability that a product or system is in operation at a specified time" [20]. Another definition of availability is "the percentage of time that a system is available to perform its required function(s); It is measured in a variety of ways, but it is principally a function of downtime" [28]. Availability is a concept that discussed in boundaries of repairable systems, and considers any scheduled maintenance, repair time and reliability aspects of the repairable components [29]. Two types of availability are defined [28]:

1) Inherent availability which is the percent of time a system would be available if delays regarding supply, maintenance, etc. are not considered; and

$$A_i = \frac{MTBF}{MTBF+MTTR} \times 100 \qquad 2.12$$

Where A_i is inherent availability, MTBF is mean time between failure, and MTTR is mean time to repair.

2) Operational availability that includes maintenance and logistics delays and it could be calculated using two equations. One is related to times between maintenance and the other one is related to time duration in which the system is available (uptime), and the time duration in which system is not available for use (downtime) [28].

$$A_O = \frac{MTBM}{MTBM+MDT} \qquad 2.13$$

Where A_O is Operational availability, MTBM is the mean time between all maintenance, and MDT is the mean downtime for each maintenance action.

$$A = \frac{Uptime}{Uptime+Downtime} \qquad 2.14$$

2.2.3 Reliability configuration (parallel and series)

To evaluate a system's availability or reliability, different approaches have been defined. Based on the system operation, failure modes, and available information about the system operation, appropriate assessment approaches should be selected [13]. Reliability evaluation techniques fall into two categories: analytical and simulation [13]. Techniques in the former category evaluates the system reliability by a mathematical model, and the simulation technique mostly refers to the Monte Carlo (MC) where the reliability is assessed by simulating the actual process considering the random behaviour of the components [13].

Before starting either approach, a simple block diagram of the system is needed to show the relation between subsystems and their components. This visualization tool is denoted as reliability block diagram (RBD). Each component could be connected either in series or parallel to other components. The same logic is true in connection between two subsystems. But a system might include several subsystems and components connecting in both ways, this is called a complex system and most of the engineering systems are of this kind [22]. Equations and illustrations regarding each connection type is provided below.

Block diagram of a series configuration is represented in figure 2.1. In a series configuration, the system operates if and only if all the components are working correctly [22]. Equation 2.15 shows the reliability of a system that contains N independent components at time t [22]:

$$R_s(t) = R_A(t) \times R_B(t) \times R_C(t) \times \ldots . R_N(t) \qquad 2.15$$

The failure rate of such a system is the summation of each components failure rate [22]:

$$\lambda_s(t) = \sum_{i=1}^{N} \lambda_i(t) \qquad 2.16$$

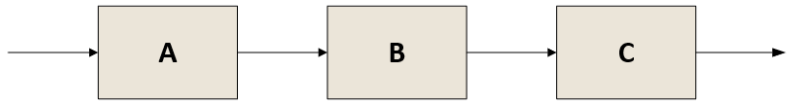

Figure 2. 1: Series structure

A system with parallel components fails whenever all the components stop functioning, therefore, the operation of the system depends on working of at least one component [22]. Figure 2.2 illustrates a parallel system, and equation 2.17 shows the reliability function of a parallel system [22].

$$R_s(t) = 1 - [1 - R_A(t)] \times [1 - R_B(t)] \times [1 - R_C(t)] \times \ldots [1 - R_N(t)] \qquad 2.17$$

Failure rate in parallel configuration is assessed by equation [22]:

$$\lambda_s(t) = -\frac{d}{dt}[Ln\, R_s(t)] \qquad 2.18$$

$$\lambda_s(t) = -\frac{d}{dt}[Ln\, \{1 - \prod_{i=1}^{N}[1 - R_i(t)]\}] \qquad 2.19$$

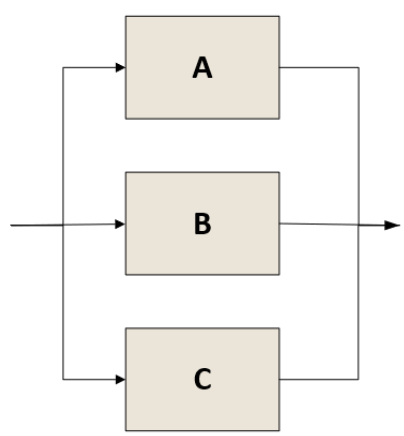

Figure 2. 2: Parallel structure

Most of the engineering systems are a combination of parallel and series configurations, therefore, the system should be divided into smaller series or parallel connections and using the appropriate equations, the reliability of each part is calculated. This process is repeated until the reliability of each section and at the end the system is estimated [29]. The configuration rules are applicable for both reliability and availability assessment [28].

2.2.4 Reliability assessment approaches

Reliability evaluation methods in terms of generation system adequacy assessment falls into deterministic and probabilistic approaches [30], [31]. Deterministic approach considers constant failure and repair rate to evaluate failure probability of components and could provide limited insights [32]. Probabilistic approaches contain analytical methods and MCS [30], [31], [33]. The analytical methods measure reliability using mathematical models and direct analytical solutions [30]. On the other hand, MCS simulate the actual process and randomness of the system with respect to the simulation time and number of occurrences of an event [30]. A wide range of outputs are calculatable in simulation techniques, e.g., probability density function, but the outputs of the analytical methods are limited [13].

2.2.4.1 Monte Carlo Simulation

The behaviour of n number of identical systems, e.g., HPs, will be different in terms of number of failures, repair time, time to failure, etc. [33]. System simulation can capture the randomness and real behaviour pattern of components [33]. MCS is capable of modelling stochastic systems [34]. MCS methods are classified into two categories of sequential and non-sequential (or state sampling) techniques [35], [33]. A non-sequential method simulates the components time independently, whereas in the sequential method the state of the component depends on the previous time step and the system is simulated in a chronological order [33]. Figure 2.3 shows a simple parallel system where the heat generation part of an energy system including a heat pump and a boiler is shown. Table 2.1 shows the system's performance that could be either up or down. Since the boiler and HP are connected in parallel, system is up if either boiler or HP is up, and system is down only if both HP and boiler are down.

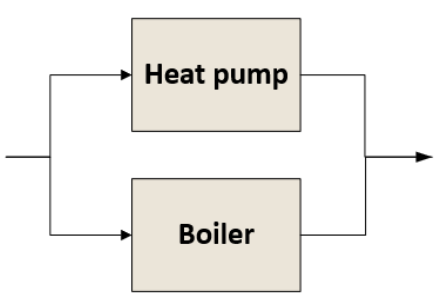

Figure 2. 3: A system containing two parallel components

Table 2. 1:Ups and downs of a system with two parallel components

HP	Boiler	System
Up	Up	Up
Up	Down	Up
Down	Up	Up
Down	Down	Down

In the sequential monte Carlo (SMC) method, a synthetic history of the components' ups, and downs based on probability distributions, failure and repair times are generated (an example is shown in table 2.1) [33]. Based on the failure and repair rate data available for components, appropriate probability distribution, e.g., exponential, Weibull, etc. is chosen and at the end of the process, a variety of reliability indices are evaluated. The detailed process simulating a system using SMC method discussed in the methodology section, a summary of the method is given in [13], [33]:

The first step of SMC simulation is generating a random number (between zero and one) for each component. This random number needs to be converted to MTBF using the relative equations considering the distribution type of the component and appropriate conversion method. The same process needs to be repeated to generate the MTTR of each component. A sequence of MTBF and MTTR that starts at time zero and ends with the specific time (for example after one year) for each component is generated. This process is repeated for desired number of iterations, and in each iteration, reliability and a variety of indices are calculated. To improve the accuracy of the method, the whole process needs to repeat for a desired number of times [13], [33].

In each iteration, if there are no overlapping repairs among the components, that trial is considered as a success, in contrary, if there is any overlapping system downtime, the trial is called a failed trial. In this context, reliability refers to the number of successes over the number of trials. Based on the objective of the study, a variety of reliability indices could be determined.

SMC method is further discussed in methodology section. MCS is capable of modelling stochastic systems, for example in [34], stochastic behavior of wind speed, irradiance, and load electricity rate are modeled using this approach. In [36], energy systems' availability by predicting failure and repair moment of components using the MC method is discussed.

To assess the reliability and availability of a complex cogeneration plant a model to capture the real behavior of the system using MC approach were developed [37]. Based on the proposed method, at first, subsystem's configuration is investigated. Then, MTTR, and MTBF, etc. of each subsystem is assessed and based on those, the system is modeled in VENSIM tool. At the next step, the system simulation is done using MC with constant time intervals, and different scenarios are generated. At the end, the results of scenarios in terms of system's availability are discussed [37].

Real world condition availability assessment of energy systems is discussed in this publication [36]. Using MCS, real behavior of the system is predicted in terms of failure moment and repair moment of system's components. Based on the available data, the underlying function of MCS was Weibull distribution. The proposed method was implemented on a combined cycle gas turbine, and based on the simplified configuration among the subsystems, three sets of subsystems were presented using RBD. Results of the simulation indicates that the MC method could reduce nominal fuel consumption and nominal power generation by 4.4% and 5.05%, respectively.

In [38] the risks and economic analysis of two different power generation PV systems is discussed. The benefit of using MCS in this study is that modifying the model is not time consuming, and there is possibility to add other sources to this model.

2.2.4.2 Reliability indicators in energy system adequacy

Energy system reliability indicators could be categorized in two groups: 1) distribution system reliability which measures the reliability in perspective of end-users and considers barriers like number and duration of interruptions. And 2) generation system reliability that evaluates the adequacy of power system to fully supply the customer demands [39].

Some of the widely used metrics in distribution system reliability are the System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), Customer Average Interruption Frequency Index (CAIFI), Customer Average Interruption Duration Index (CAIDI), and Average Service Availability/Unavailability Index (ASAI/ASUI) [39]. The formulations of these metrics are [40]:

$$SAIFI = \frac{CI}{N_T}(interruption/customer) \qquad 2.20$$

$$SAIDI = \frac{CMI}{N_T}(hour/customer) \qquad 2.21$$

$$CAIFI = \frac{CI}{CN}(interruption/customer\ affected) \qquad 2.22$$

$$CAIDI = \frac{SAIDI}{SAIFI}(hour/interruption) \qquad 2.23$$

$$ASAI = \frac{8760N_T - CMI}{8760N_T} \qquad 2.24$$

Where CI is the total number of customers interrupted, NT is the total number of customers served, CMI represents the total time of customers' interruption, and CN represents the total number of distinct customers who have experienced a sustained interruption during the reporting period. In ASAI, customer hours demanded are determined as the average number of customers served during 8760 hours [39] [40].

The second set of indices is generation system reliability which evaluates the adequacy of the power system to fully supply the customer demands [39]. In the distribution metrics, the performance of the overall generation system to fulfil the demand is not considered [39]. Therefore, metrics including Energy Not Supplied (ENS), Expected Energy Not Supplied (EENS), Average Energy Not Supplied (AENS), and Loss of Load Expectation (LOLE) are defined [40]. The equations of these metrics are [40]:

$$ENS = \sum_j L_{a(j)}\, U_j\ (kWh) \qquad 2.25$$

$$AENS = \frac{ENS}{N_T}\ (kWh/customer) \qquad 2.26$$

$$EENS = \sum_k ENS_k p_k\ (kWh) \qquad 2.27$$

$$LOLE = \sum_i Pr(C < L_i)\ (hour/year) \qquad 2.28$$

Where $L_{a(j)}$ is the average load connected to load point j ,Uj is the annual outage time, p_k is the probability of system state k, and $Pr(C < L_i)$ is the probability of loss of load on day I or during hour i, in which C is the capacity and Li represents the load on day i or during hour i [40].

In [41], a comparison between MC and Markov cut-set approach indicates the ability of MCS in estimating the probability distribution function of emergency and standby power system components. In [35], distribution system reliability is investigated by implementing MCS and analytical methods. The calculated indices in this study are failure rate, outage time, and annual unavailability. Besides those indices, other end-user reliability indicators, e.g., SAIFI, CAIFI, CAIDI, ENS, and AENS are evaluated. Using the SMC, an artificial history of the system is generated, and reliability indices and probability distributions are measured. A comparison between the results of analytical and SMC simulation shows the capabilities of MC to evaluate complex renewable systems [35].

In [42], reliability of an active distribution system in two scenarios using the MCS are evaluated. A variety of metrics, for instance, LOLE, LOEE, SAIFI, SAIDI, and EENS were calculated by implementing sequential MC to model a distribution system that includes wind and solar energy. The problem of integrating low and high distributed generation in system which actively operates was formulated in two low and high distributed generation cases. and the results indicated that in both cases, the reliability of the system was improved.

2.2 Resilience concept

Due to the increasing number of people moving to urban areas pressure on infrastructure, especially local renewable energy infrastructure is increasing [9]. On the other hand, moving towards sustainability goals in energy infrastructures increases the number of multidisciplinary challenges. In recent discussions, resilience concepts bridge different aspects of energy systems, for instance, social, ecological, and technical [43].

The US department of homeland security defines resilience as the ability to resist, absorb, recover from, or successfully adapt to adversity or a change in condition [44]. International Energy Agency (IEA, Annex 73) [11], defines resilience energy system as: “A resilient energy system (electric or thermal) is one that can prepare for and adapt to changing conditions, and that can recover rapidly from such disruptions as deliberate attacks, accidents, and naturally occurring threats” [11]. Mutual resilience properties in different definitions are absorptive, adaptive, and recovery capacity [14], [15]. Absorptive capacity is the ability of the system to endure a disruption without significant deviation from normal operation performance. Adaptive capacity is the ability of the system to adapt to a shock to normal operation condition, and recovery capacity is the ability of the system to recover quickly from disruptive events [14].

In this study [11] a framework to integrate the resilience goals in energy master planning is developed. This framework has six general steps and could be applied to both electrical and thermal energy systems. Based on this framework, the critical assets and demands are identified. Different hazards should be studied and the top ones with the higher risks and higher impact on critical assets is assessed. Based on the resilience metrics defined in the study, the resilience gap

between the current energy system, and the required energy system is calculated. In the end, based on the resilience gap, system improvements, e.g., backup generators, low-temperature district heating networks, and thermal and electrical storage, are suggested.

In this study [9] a resilience framework which is comprised of three layers of energy resilience at community-level energy master planning is introduced. These layers are 1) engineering resilience which refers to Physical assets and engineering-designed measures. 2) Operational resilience is defined as a set of technological and organizational measures. And 3) community resilience which denotes cooperation and contributions of customers and other community stakeholders.

Traditionally, electrical systems are designed based on reliability requirements, this is the reason why in case of a low-probability, high-impact event they are not predictable [45]. In this study, a framework using the Monte-Carlo simulation approach is developed to assess the impact of weather-related events on both the short-term and long-term resiliency of electrical infrastructures [45]. Short-term resilience refers to the features that a resilient electrical network must have before, during and after an electrical event, i.e., robustness/ resistance, resourcefulness/redundancy, and recovery respectively. Long-term resilience refers to the adaptability of critical infrastructure to changing conditions and new threats [45].

2.2.1 Energy system resilience indicators

Resilience is an emerging concept and is defined based on the performance of a system under specific conditions and time frames. Many researchers have proposed indicators to quantify the energy resilience. Zhivov et al. have divided these energy resilience metrics into two categories; attribute-based, which describe the characteristics that make a system resilient, such as robustness or reliability; and performance-based, e.g. cost-effectiveness and sustainability [46]. In this study [46] three resilience metrics, which are energy system robustness, energy system recovery and energy availability are introduced. Then, methods to evaluate each of them are discussed.

Energy robustness is one of the discussed energy resiliency metrics in IEA [11]. Figure 2.4 [11] demonstrates the performance of two system under a mutual disruption. The baseline shows the business-as-usual condition of the systems, and when the event occurs each system degraded to a different level. In black sky condition (when the hazard has happened), system two is able to recover to baseline faster than the system one, therefore, it is able to absorb the impact of the disruption better and it has higher robustness. Resilience could be assessed in terms of the area between baseline and degraded level of the system. With this definition, the system two is more resilient than the system one [11].

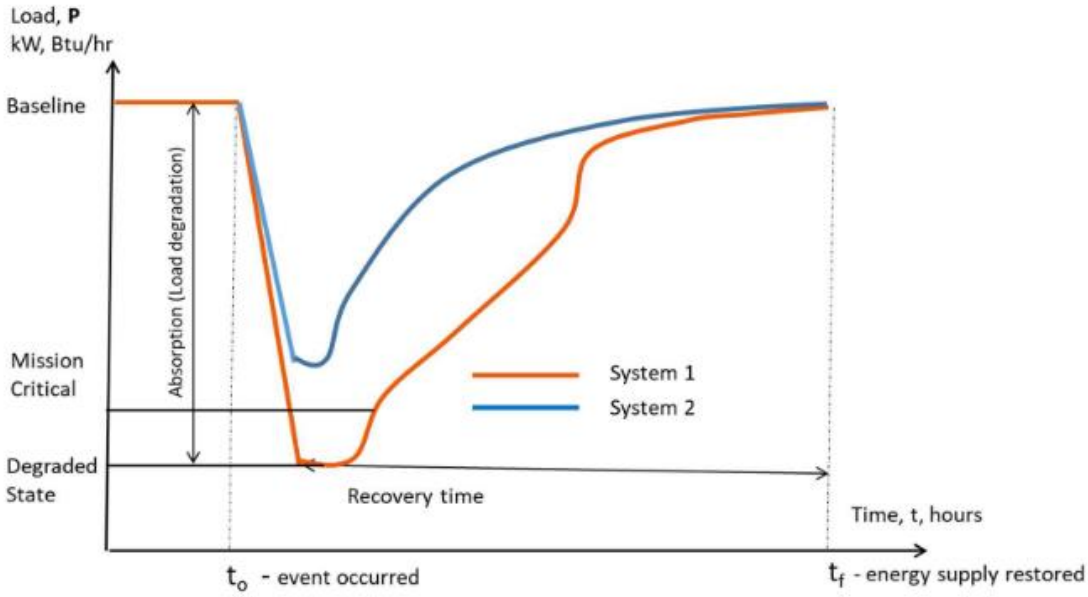

Figure 2. 4:Comparison of resilience in two systems, [11]

A quantitative resilience metric that is based on three resilience capacities, absorptive, adaptive, and restorative capacity, is suggested in [15]. The resilience is defined as a probabilistic concept combining the proposed metric with experts' knowledge [15]. Another study related to energy resilience metrics is Roege et al work [47] In this research, metrics are defined based on the implementation of energy-related planning, design, investment, and operation of the system's resilience. This method is developed using a matrix which connects the abilities of a resilient system (prepare, absorb, recover, and adapt) to dimensions that correspond to situational awareness and decentralized decision-making, which are physical, information, cognitive, and social. In table 2.2 some of the resilience indicators are gathered.

In the resilience assessment of an area, distinguishing between critical and non-critical infrastructures is important. For example, in a district, that has a hospital, a fire station, a residential complex, and a university campus, the hospital and fire station are the most critical infrastructures (CI) and providing their energy has higher priority. This method has been used in a recent publication [48], where the authors came up with an availability-based resilience metric by considering CIs. The next step after defining the CIs is defining weights for each CI which reflects the level of importance of each CI in the resilience metric [48].

In the energy master planning guide [11], the benefits of using the critical function instead of CI have been discussed. Some examples of critical functions are shelter, security, food, water, communication, medication, safety, etc. The advantage of using the critical functions is that maybe a campus building will not be considered a CI, but it might have a critical function, for instance, a small clinic inside the campus. Therefore, instead of considering the whole campus as non-CI, only the functions that are critical (medical services and medications) would be

considered. After ranking the critical functions, the next step is giving weight coefficients to the functions based on their ability to provide the intended level of service.

Table 2. 2:Suggested resilience indicators in literature

Reference	Resilience Indicator	Descriptions
Defining, Measuring and Assigning Resilience Requirements to Electric and Thermal Energy Systems [46]	$R_{m.c} = \frac{E_{event}}{E_{m.c}}$ $R_{baseline} = \frac{E_{event}}{E_{baseline}}$	Resilience in terms of robustness of the system. $R_{m.c}$ and $R_{baseline}$ evaluate the amount of energy that has been supplied during a specific period.
Metrics for energy resilience [47]	4*4 dimension energy resilience matrix	First dimension: plan, absorb, recover, and adapt Second dimension: physical, information, cognitive, social
Power system resilience [48]	$R_B^{aug} = \sum w_c \frac{\sum_{i=1}^{N_c} T_{U,i}}{\sum_{i=1}^{N_c} T_{U,i} + T_{D,i}}$	Where, W_c : weight of customer type N: total number of customers $T_{U,i}$: uptime of the ith costumer $T_{D,i}$: downtime of the ith costumer
Energy master planning for resilient public communities [11]	Energy system robustness (ER) Energy availability (EA)	ER: the percentage of mission energy served, the ability to absorb the impact EA: The percentage of time mission served, a measure of readiness of the system to perform its required function
Resilience of critical infrastructures: probabilistic case study of a district heating pipeline network in municipality of Latvia [49]	$R = \frac{S_\alpha}{S_\beta}$	R: Probabilistic resilience S_α: Number of scenarios in the resilience limits S_β: Total number of scenarios

While research about the resilience of electric energy systems has been an ever-growing trend, the resilience of thermal networks has been addressed less [46]. Thermal energy systems share some features, i.e. robustness, energy availability, and redundancy with electrical systems. The challenge of thermal systems' resilience is due to a lack of data since these systems are mostly in cold regions [50]. In studying the resilience of thermal energy systems besides the energy supply side, the demand side is important [51]. Supply-side is comprised of energy conversion, transmission lines, storage and distribution network. Demand-side refers to the type of occupants, the demand, and the material of the buildings [50].

Thermal energy infrastructures are one of the critical infrastructure systems, and in this study [49] a probabilistic method to assess the resilience of such a system is discussed. In this work [49], the

district heating network is considered an asset and using simplified analytical methods, the failure probability of network's nodes is estimated. Different scenarios are generated to analyse the system performance under cold temperature, and based on these scenarios and failure probabilities, system resilience is evaluated.

Thermal comfort especially in a cold climate and under extreme conditions an essential parameter. The comfortable temperature is vary based on the user type of the building or room. In Zhivov et. al.'s work [51] the comfortable temperature and relative humidity based on use type are identified. In this study [51] thermal requirements are defined as "criteria for thermal comfort and health, process needs, and criteria for preventing the freezing of water pipes, growth of mould and mildew, and other damage to the building materials or furnishings." Using the thermal requirements would help to identify how long it takes for a building, after a disruption in energy supply, to reach habitable temperature toeholds for both people, and buildings' assets.

Chapter 3: Methodology

The methodology is divided into reliability assessment and resilience assessment parts. The first part includes the sequential Monte Carlo (SMC) method and its application in evaluating reliability and availability of thermal energy systems. In the resilience assessment part, the proposed method and indicators are discussed. In both parts, the hourly demand of the end user is taken into account. The Venn diagram represents the system boundary of the current study and as it shows, the interdependency of thermal energy system's adequacy to provide the load curve in case of common failures and extreme events are under study.

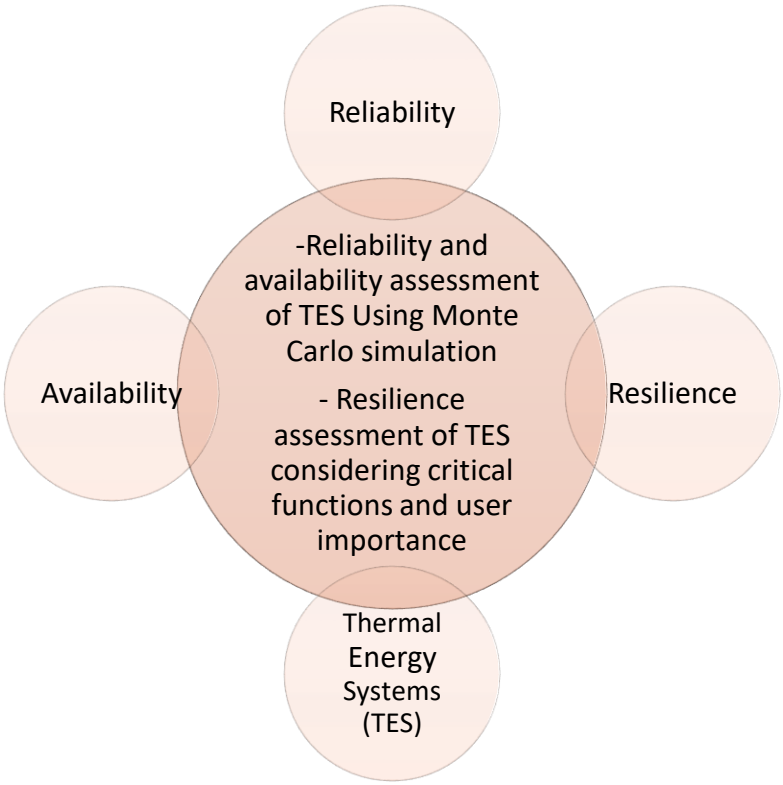

Figure 3. 1:Scope of current work

3.1 Reliability evaluation method

The reliability assessment of a system needs ~~censoring~~ measured, historical data. On one hand, data regarding the performance of the low temperature renewable urban thermal energy systems are not available and on the other hand, using the statistical methods which do not require data does not consider the real-world condition. One of the approaches to solve this problem is MCS which can generate the synthetic dataset with respect to the randomness and stochastic behaviour of the system. The MCS method generates random variables based on a defined statistical distribution of components over a sequence of time and converts those random variables to components' up or down states (An example is shown in table 2.1). Based on the availability of failure and repair data, it has been assumed that the probabilistic distribution of components'

failure and repair times are matched with exponential distribution. The exponential distribution has been widely used in reliability and availability assessment [25], [26], [27].

Considering the connection between components and subsystems, different outputs, for instance, availability, reliability, ENS, etc., are assessed. The flowchart of the proposed method using the SMC is presented in Fig. 3.3 and the steps are explained in the following parts. The SMC has been repeated ten thousand times and each run has 100,000 iterations. After generating the up and down sequences for each component in each iteration, the systems-level indices are calculated. The bottom-up process of evaluating the system-level reliability by having the component's data is illustrated in the Fig. 3.2.

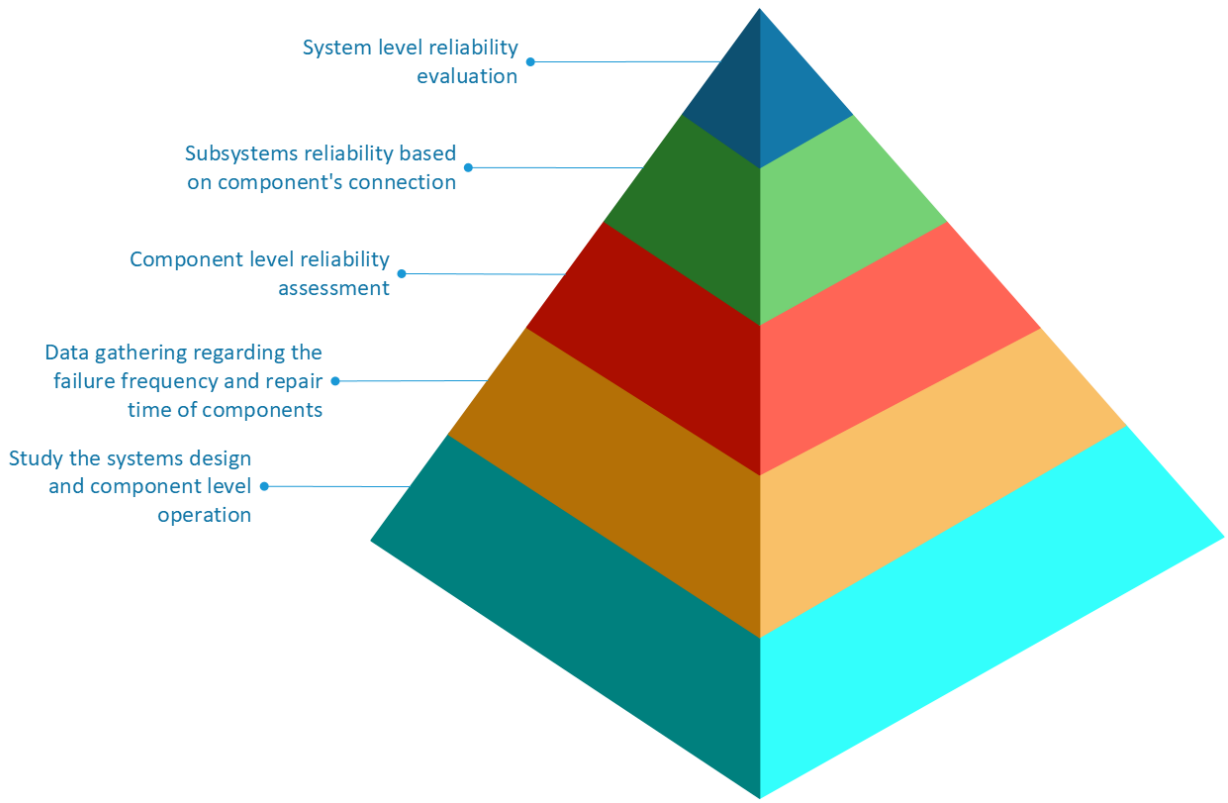

Figure 3. 2: Proposed reliability assessment process

3.1.1 Sequential Monte-Carlo Simulation

The sequential Monte-Carlo method generates random variables based on a defined statistical distribution over a sequence of time and converts those data to specific measures and indicators to assess the intended output. By employing the MC method and running the simulation for a large number of iterations, the output will converge to a specific number. In the current work, the SMC method has been proposed as a part of the framework to assess the reliability, availability, and other indicators (ENS, etc.) of an electric heating energy system.

In this method, reliability is defined in terms of the ability of the system to work failure-free for a specific period, for example, one year. If there is an overlapping failure among the components within the time horizon, that trial is a failure, but if there are no overlapping failures, the trial is considered a success. Other indices are defined to measure the generation system reliability in terms of quantitative amount of the gap between supply and demand.

Figure 3.3 shows the flowchart of the proposed method using the SMC. The outputs of this flowchart are system level reliability, ENS, AENS, and LOLE. Reason for choosing this metrics was the purpose of the study which is measuring the reliability of the generation system to fulfill the demand. These set of metrics (ENS, AENS, and LOLE) are able to evaluate the adequacy of the system to supply the customer's demand.

Inputs of the SMC simulation are statistical parameters of failure frequency and repair time distributions at the component level. A data gathering process needs to be done before starting the simulation. The needed data are components' failure rate, repair rate, parallel or series connections of components in a subsystem, and relation between subsystems of the system. For example, a heat pump has five components that are connected in series, therefore, malfunctioning of each of them, causes failure in the heat pump. An example in a subsystem level is a system that contains two identical parallel connected heat pumps. Failure of one of the heat pump's components, will cause 50% reduction in supply.

The details of SMC simulation are discussed in the following steps, and it starts with generating a random number considering uniform distribution. To assess the reliability of a repairable system including two parallel components:

Step 1, Generate a uniformly distributed random number between zero and one.

In the uniform distribution, an infinite number of points exist between 0 and 1, where they all have an equal opportunity to be seen. the probability density function of uniform distribution is [22]:

$$p(x) = \frac{1}{b-a} \qquad 3.1$$

Step 2, Convert this random number into the corresponding time to failure (TTF) using the appropriate conversion method. The cumulative density function (CDF) of exponential distribution with a failure rate (λ) > 0 is:

$$F(x) = 1 - e^{-\lambda x}, x \geq 0 \qquad 3.2$$

Solving $u = F(x)$ in terms of x gives:

$$F^{-1}(u) = -\frac{1}{\lambda} ln(1-u) \qquad 3.3$$

Since U ~ U (0,1), then 1-U ~ U(0,1), then by generating random number U, the TTF is:

$$TTF = -\frac{1}{\lambda}U \qquad 3.4$$

Step 3, Generate another uniformly distributed random number between zero and one

Step 4, Like step 2, using the conversion method convert the number in step 3 to repair time (MTTR). Similar to equations 3.2 to 3.4, the TTR having repair rate μ is:

$$TTR = -\frac{1}{\mu}U \qquad 3.5$$

Step 5, Repeat steps 1 to 4 until the summation of the MTBF and MTTR is equal to or greater than the time horizon (one year)

Step 6, Repeat all the steps for the second component

Step 7, Compare the sequences of two components. If there is an overlapping downtime during the mission time, the mission is a failed trial. Since the two components are connected in parallel, if at least one component is running, the trial is a success.

Step 8, Repeat steps 1 to 7 for any specific iterations.

Step 9, Reliability of the system is the number of the success over the number of iterations

Step 10, Other reliability metrics, ENS, LOLE, etc. are calculated based on the data generated for the components.

3.1.2 Reliability method validation

In order to validate the accuracy of the suggested method, example below that was found in one of the reliability engineering reference books [13] were solved using the current method and results were compared. The problem is: "Assess the reliability of a system with two parallel components after 1000 hours. The failure rate and repair rate of the components are: λ_1= 0.001 f/hr, λ_2= 0.0024 f/hr, μ_1= 0.003 r/hr, and μ_2= 0.005 r/hr [13]." In figure 3.4, the book's result and current method's result are illustrated. The figure in the left is the book's result and as it is shown in the right figure, the behaviour of the system in terms of randomness is repeated and final outputs converge to a constant number.

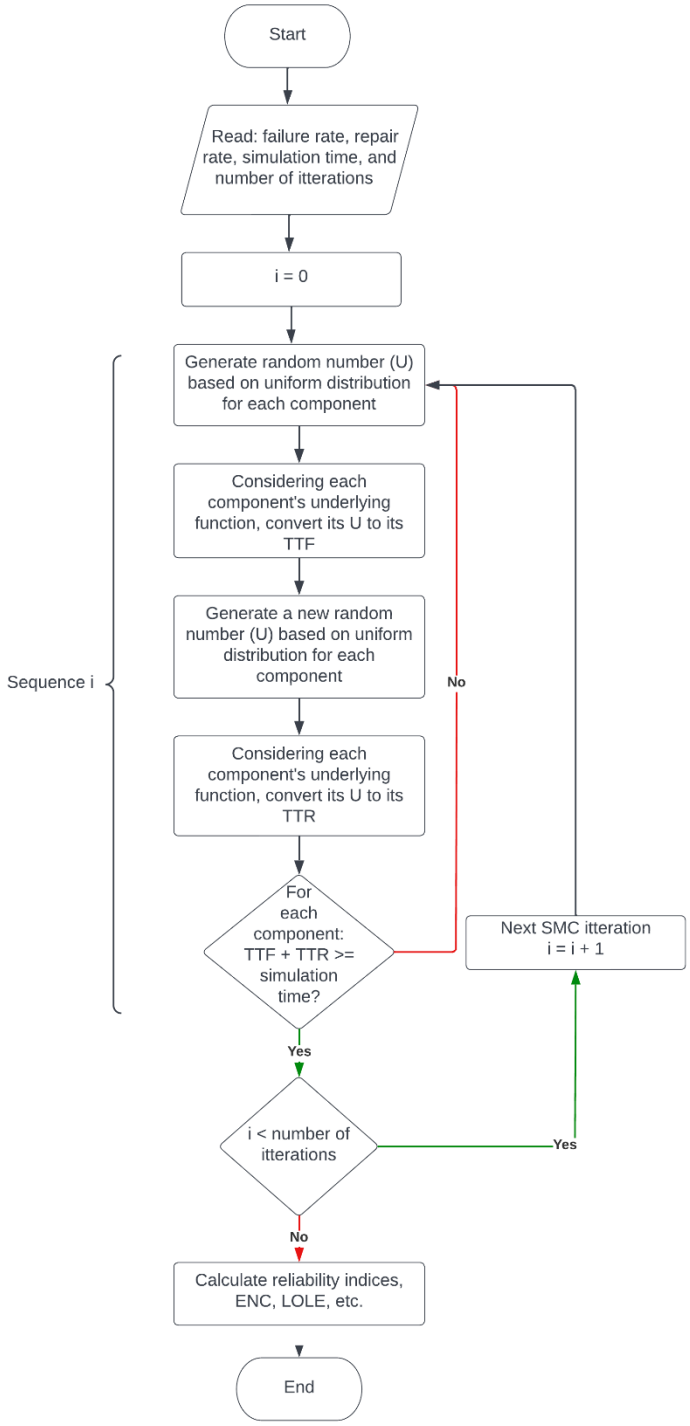

Figure 3. 3: Suggested SMC flowchart

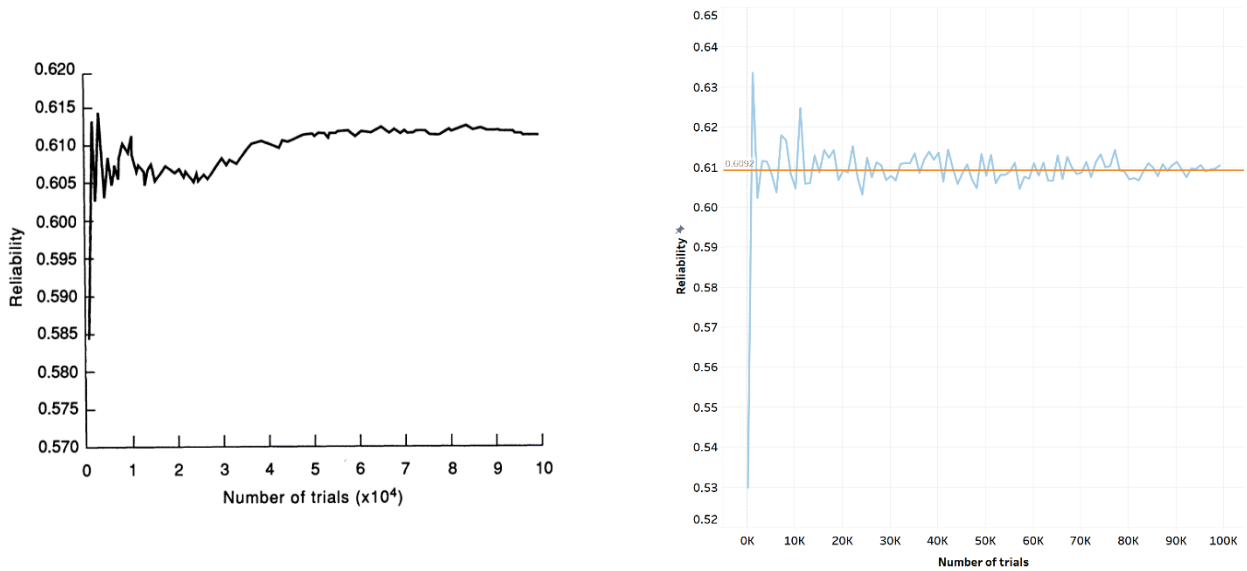

Figure 3. 4: Left, reliability result of the method in [13]. Right, reliability result of the proposed method

3.2 Availability evaluation method

While the reliability evaluates the probability of the system working failure free, availability measures the percentage of time a system is operating, with respect to the total considered operational time. Availability is concerned with the operational and repair periods of a system, over the defined total time. In the current method, the availability process is similar to the reliability assessment mentioned previously. The ups and downs are randomly generated and different parameters, for instance, system unavailability and availability, system total downtime, and system failure frequency are evaluated. Availability evaluation process of a repairable system including two parallel components using SMC is:

Step 1, Generate a uniformly distributed random number between zero and one (equation 3.1)

Step 2, Convert this random number into the corresponding time to failure (TTF) based on the distribution type, using the appropriate conversion method (equations 3.2 to 3.4)

Step 3, Generate another uniformly distributed random number between zero and one

Step 4, Like step 2, using the conversion method convert this number to repair time (MTTR) (equation 3.5)

Step 5, Repeat steps 1 to 4 for specific operational time

Step 6, Repeat all the steps for the second component

Step 7, Compare the sequences of two components and find the system failure frequency, system downtime, and system availability.

Step 8, Repeat steps 1 to 7 for the preferred number of simulations

Step 9, Evaluate system level indices including availability, system total downtime, and system failure frequency.

3.2.1 Availability method validation

The accuracy of the proposed method is evaluated by comparing it with an example in the same reference book that used for reliability method validation [13]. "Assess the availability of a system with two parallel components. The failure rate and repair rate of the components are: λ_1= 0.001 f/hr, λ_2= 0.0024 f/hr, μ_1= 0.003 r/hr, and μ_2= 0.005 r/hr [13]."

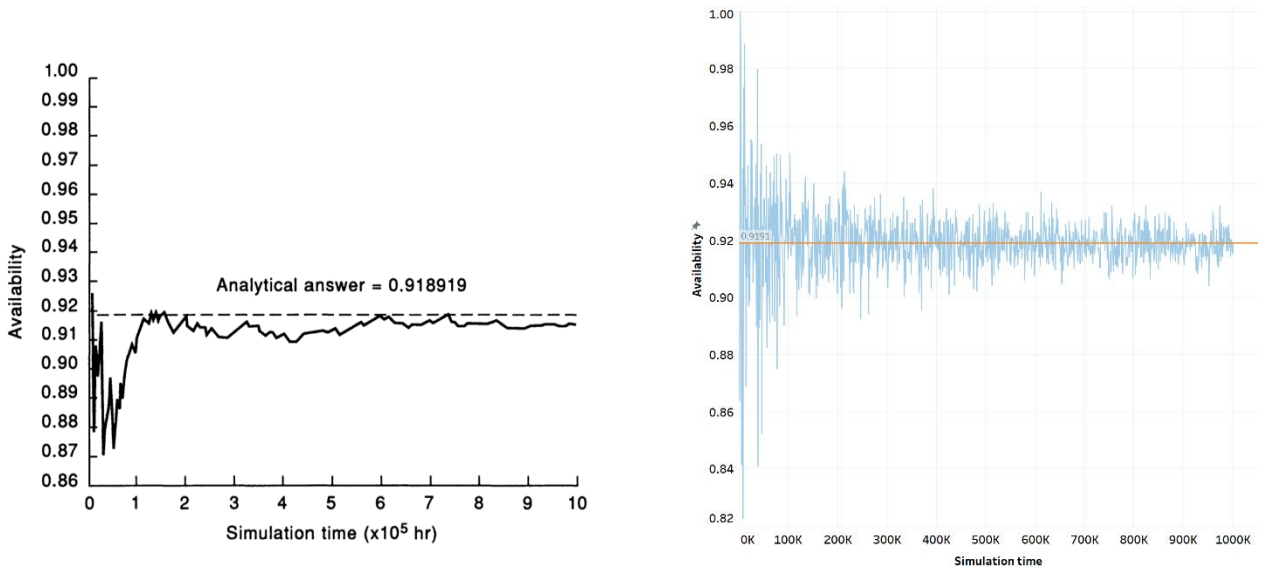

Figure 3. 5: Left, availability result of the method in [13]. Right, availability result of the proposed method

3.3 Resilience assessment method

In this part, a method to evaluate renewable energy systems resilience is suggested. In reliability-focus planning, the focus is on high probability events with relatively low impact. On the other hand, in resilience-focused planning, low probability events with destructive impacts are objectives [18]. Resilience is contextual and needs specific formulations and quantitative approaches to identify the resiliency of each system under predefined hazards. In the current work, resilience of the central and decentral heating systems with electricity sources are under study.

In Quebec, Canada, Hydro Quebec is the electricity provider. Different hazards might have effects on an energy system. However, the main concern threatening a DHN in Quebec region would be an off-site power outage caused by different reasons such as extreme weather fluctuations, floods, major failures, etc. In this work, the resilience assessment aims to evaluate the ability of the heating system to provide the space heating demand during a disruption. It is assumed that the hazard is a major power outage that lasts for a certain number of hours. Since the coldest months in Montreal are January and February [52], the space heating demand is the highest in this period. Therefore, the start time of the power outage is set to February 2nd at 06:00 A.M. to evaluate the system resiliency under the extreme condition

Resilience refers to the ability of the system to provide its intended level of service in time of disruption. Based on this definition, effective factors in resilience assessment are the duration of time, service level, decreased level of service, the type of disruptive event, and business as usual condition. In the current method, normal condition operation and disrupted condition will be called blue sky and black sky conditions, respectively; the time horizon is equal to the duration of the power outage; service level is the blue-sky condition's hourly demand; and the decreased load curve refers to the critical load of the district during the event.

In this method, the resilience of heating energy systems is measured by three indicators which are energy not served (ENS) during the black sky condition, average energy not served (AENS), and Energy Robustness (ER). Based on the provided definition in IEA annex 73 [18], ER is the ratio of the demand in each hour that is provided by the energy system. The value of ER is between zero to one, zero means no energy is available to supply the load curve and one means that the energy system is able to provide the critical demand. ENS evaluates the amount of energy (kWh) not served during the mission and AENS is the ratio of the not served energy to the number of the customers. These indicators together reveal the ability of a specific design to meet the critical demand in black sky condition.

The flowchart below illustrates the proposed resilience assessment methodology. This method aims to analyse resilience through quantitative indicators such as ENS, AENS and ER. Hourly demand of the area and list of the occupant types are the important inputs of this method.

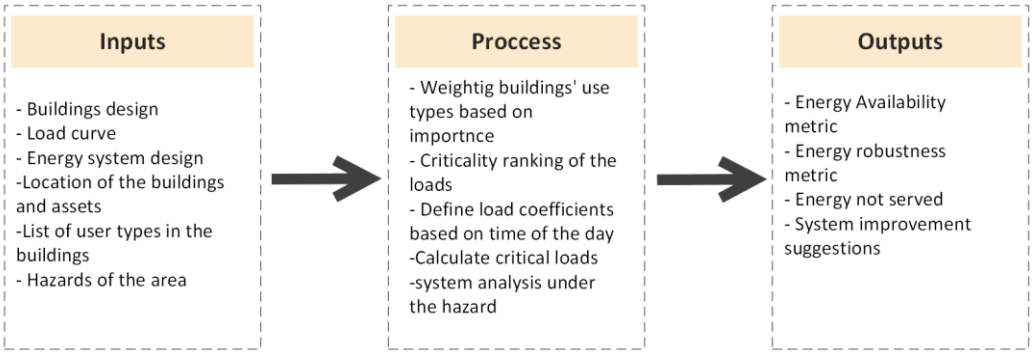

Figure 3. 6: Proposed resilience assessment process

3.3.1 Critical Load

In order to evaluate mentioned resilience metrics, critical load needs to be defined. The critical load, or black sky condition demand, refers to the minimum load that needs to be supplied to provide the minimum habitable temperature for the dwellings and prevent serious damage to buildings. In the black sky, a part of the heat production unit that works with electricity will stop working. However, by providing backups and redundancy, other part of the heat production unit might be able to provide a part of the business-as-usual demand or critical load.

Step 1: To find the critical loads, the first step is listing all the user types of the area. On a district scale, buildings might have different user types from residential to commercial, schools, educational institutes, and medical centers. In time of a disruption, the level of importance of these user types, therefore, their loads, are different.

Step 2: In the second step, after having all the user types known, they need to be ranked based on the level of the criticality. On a DOD document [53], three levels of loads are defined; 1) uninterruptable loads which need to be supplied without a momentary disconnection, 2) essential loads, for instance, HVAC loads that can suffer short de-energized, and 3) non-essential loads, which can be de-energized for noticeable periods of times. Similar to the mentioned document, criticality levels of thermal load in buildings with different occupants are defined in three categories. For an urban district with multiple types of buildings and functions, table 3.1 shows the load importance levels.

Table 3. 1: Criticality level of different use types, [53]

Low	**Significant**	**High**
Offices, housing, administrative, etc.	Medical centers, warehouses, educational institute, etc.	Hospitals, critical communication facilities, etc.

Loads within high level of importance need to be prioritize to other categories. In time of a disaster, the demand of buildings in this category, for instance, hospitals, can not be delivered by any disconnection.

Step 3: In third step, time-dependant coefficients are defined in two categories; if the disruptions happen a) between 08:00 and 16:59 and b) between 17:00 and 07:59. For instance, in a two-story building where the first and second floors are commercial and residential if the disruptive event happens during the day, most residential occupants would be elsewhere, i.e., at work, school, etc. At the same time, the commercial floor is open to the inhabitants. Therefore, the commercial floor's share of critical demand during the day is higher than the residential.

Step 4: Based on time of the day, two coefficients for each use type are estimated. The critical load in each building is a portion of the day-to-day demand, therefore, the coefficients are a number between 0 to 1. Having the coefficients and normal hourly demand, the critical load is evaluated.

Output of the process unit in the figure 3.6 is the critical load of the area during the power outage. Using this load curve, interested resilience indicators such as ENS, AENS, and ER are estimated.

Chapter 4: Case study

4.1 Overview of the project

As the second-largest municipality in Canada, Montreal has provided an action plan that includes goals, challenges, and requirements needed to become more sustainable. In the pathway toward sustainability and carbon mitigation goals, the city has three main sustainable development challenges, which are [2]:

- Reduction of GHG emissions by 80% (3,003 kilo tonnes of equivalent CO2 equivalents) by the year 2050 compared to the year 1990 baseline.
- Enhancing access to services and facilities among different neighbourhoods in the city and ethical distribution of resources for every dwelling.
- Becoming an exemplary model for other cities by integrating sustainable plans into all aspects of the city.

The case study of the current paper is a district located in Montreal and named "Lachine-Est." Figure 4.1 shows the location of the case study. Lachine-Est is a former industrial hub bordered by the Lachine Canal on its southern part, 6th Avenue to the west, Victoria Street to the north, and the east's Canadian Pacific Railway line. This project's area is 63.8 hectares and includes two heritage buildings that are going to be saved. The final design includes six building complexes, that two of them are heritage buildings, with different user types, i.e., healthcare facilities, commercial, residential, and offices. The estimated number of residences are 10,000 people, and number of people in each building is calculated based on total floor area. To achieve the sustainability goals of the Lachine-Est, high-efficiency materials are considered in the building design stage. Table 4.1 shows the considered parameters in buildings' design. After creating the 3D model of the buildings, their hourly space heating demand were calculated in EnergyPlus [54]. Table 4.2 shows the buildings' specification and heating demand.

Figure 4. 1: Lachine-Est location

Table 4. 1: Assumed parameters in buildings' design and modelling

Parameters	Settings	
Window to wall ratio	0.35	
Constant heating set point	22 ℃	
Constant cooling set point	25 ℃	
HVAC Templates	Ideal loads air system	
Solar distribution	Full interior and exterior	
Shading calculation	Calculation method	Average over days in frequency
	Calculation frequency	20
	Maximum figures in shadow overlap calculations	15000
	Polygon clipping algorithm	Suther land Hodgman
	Sky diffuse modeling algorithm	Simple sky diffuse modeling
	External shading calculation method	Internal calculation
Surface convection algorithm: inside	TARP	
Surface convection algorithm: outside	DOE-2	
Heat balance algorithm	Conduction transfer function	
Sizing period: design day	Winter design day Summer design day	
Solar model indicator	ASHRAE clear sky	
Occupancy	Number of the people calculation method	People/Area
	People per zone floor area	0.05 people/m3
Lighting	Design level calculation method	Watts/Area
	Watts per zone floor area	10
Equipment	Design level calculation method	Watts/Area
	Watts per zone floor area	5
Infiltration	Design flow rate calculation method	Residential: Flow/ExteriorArea and Commercial: Flow/ExteriorWall Area
	Flow per exterior surface area	Residential: 0.0002 Commercial: 0.0005
HVAC	Outdoor air method	Flow/Area
	Outdoor airflow rate per zone floor area	0.00043

Table 4. 2: Buildings' specification and heating demand

Specifications \Building ID	**Building_ A**	**Building_ B**	**Building_ C**	**Building_ D**	**Building_ E**	**Building_ F**
Number of Floors	9	6	2	6	2	9
Total Floor Area (sq m)	122,737	31,044	49,224	47,292	11,782	15210
total space heating load (kWh/year)	8,249,180	1,460,777	3,785,383	4,113,954	930,336	1,300,850
Peak Space Heating Demand (kW)	5161	999	2331	2411	516	785
Specific Heating (kWh/sqm/year)	67	47	77	87	79	86

4.2 Energy system design and scenarios

Two energy system designs are defined to compare the energy efficiency of centralized and decentralized designs in terms of providing the space heating demand of the area. Based on the project's goals and consultation with a company which is focused on ground source heat pump (GSHP) installation in Montreal, Canada, the GSHP was chosen as the most suitable choice for this project. The GSHP known as a reliable energy production unit and pairing it with gas boiler, which is connected to Montreal's gas distribution pipeline, makes it more efficient. Designing the energy system is not in the scope of this study; however, the details regarding the energy system design of this case study are available in a previously published paper [54].

The Lachine-Est project has six building complexes, and two thermal energy system designs are proposed; a district heating network (DHN) that benefits from central energy production unit and a decentralized scenario where each building complex relies on its own energy system. The details of these two designs are:

1) DHN: This design is a district heating network that consists of a heat production unit and a distribution network that delivers thermal energy to the buildings. The heat production unit consists of 14 ground source heat pumps, a gas boiler with 4000 kW capacity, and thermal energy storage that has 190 m^3 capacity. GSHP is sized to provide 60% of the heating demand, and boiler and storage together will cover the rest of the load curve. Electricity input of the energy system is provided by Hydro-Quebec, and the boiler is connected to the natural gas network of the city.

2) Decentralized design: This design has a decentral ground source heat pump with a gas boiler as backup for each building block. The number of needed heat pumps in buildings varies, since the

size and demand in each building is different than each other. The GSHP unit and the gas boiler are designed to cover %60 and %40 of the load curves, respectively. Unlike the baseline, no thermal energy storage (TES) is considered in this design. The details of buildings' demand, number of heat pumps and other specifications are mentioned in the table 4.3.

Figure 4.2 shows the COP curve of the selected water to water heat pump from Climate Master company and this heat pump could be used in ground loops and surface water loops. The variation of COP is shown against the variations of the source temperature.

Table 4. 3: Energy systems design details

Specifications \Building ID	**Building_A**	**Building_B**	**Building_C**	**Building_D**	**Building_E**	**Building_F**	**Central**
total space heating load (kWh/year)	8,249,180	1,460,777	3,785,384	4,113,954	930,337	1,300,851	19,840,483
Peak Space Heating Demand (kW)	5,162	1,000	2,331	2,411	516	786	12,082
Number of Heat Pumps in Operation	6	1	3	4	1	1	14
Heat pump SCOP	2.07	2.05	2.07	2.08	2.08	2.09	2.07
Thermal Energy Storage Capacity (m3)	80	15	37	40	10	13	195

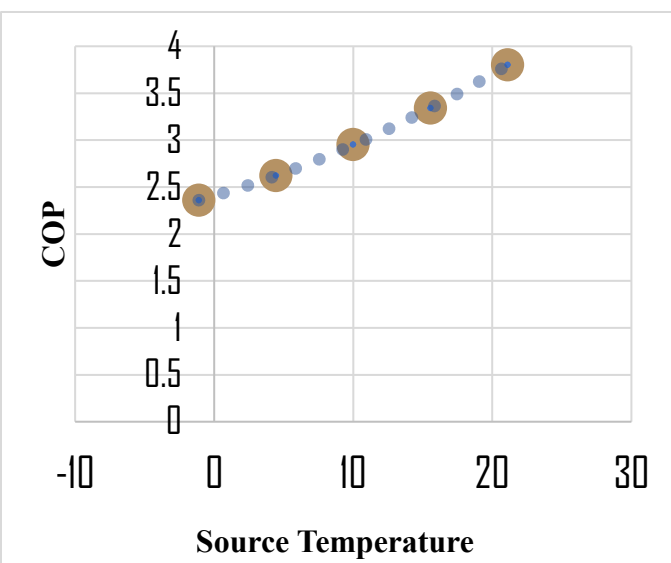

Figure 4. 2: COP vs source temperature curve in water-to-water heat pumps

Chapter 5: Implementation of the method to the case study

5.1 Reliability and availability assessment

The details of the reliability and availability model using the SMC simulation is discussed in chapter 3. To assess the reliability indices and availability of energy system designs of the Lachine case study, two models are integrated in a workflow (figure 5.1) to calculate the objectives. The workflow is discussed in four steps which are:

1) Investigating the components of subsystems and physical connections between them; and finding failure frequency and repair time of components.

2) Using the availability model, calculate the availability and working condition of subsystems.

3) In system level, using the reliability model calculate the mechanical reliability of the system, and generation system reliability indices including ENS, LOLE, etc. Using the availability model, calculate the unavailability of each design.

4) Gathering results and outputs of previous steps regarding each system design

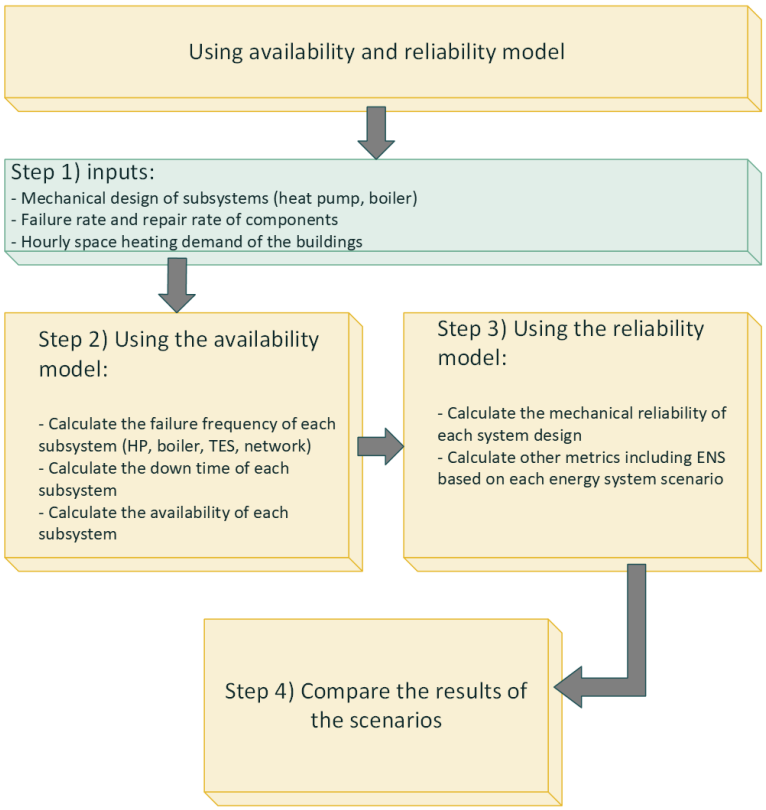

Figure 5. 1: System-level reliability and availability evaluation process

5.1.2 Step one: inputs

Previously discussed in methodology chapter that most of the inputs for reliability and availability models are similar. For example, components failure frequency, repair time, physical connection between components in subsystems, etc. In the first step, the input information of the models needs to be identified. Subsystems components are investigated through manufacturer's information pamphlet and other web-based resources. The information regarding the failure and repair rate of components are gathered from different resources; the main reference for mechanical parts failure and repair rates is the OREDA reliability handbook [55].

OREDA is a project organization, which supported by major oil and gas companies, for instance, Eni/Agip, British Petrolium, Chevron, ExxonMobil, Norsk Hydro, Conocophilips, Statoil/Hydro, Shell, Texaco, and Total. Main purpose of the project is to communicate the latest developments of oil and gas exploration and production companies with participating in collection and analysis of operational data, investigating and providing high quality reliability dataset, and sharing the latest technologies in maintenance and reliability with the joined companies.

Regarding the network's failure frequency, the following assumptions were considered: 1) the width of pipes is constant and equal to 12 inches, 2) the total length of the network is 445 meters, and 3) the network's mean time to repair is fifteen hours. The length of the network is discussed in a separate publication with the same case study [54]. Gilski et al have discussed the failure probability in the district heating networks from different perspectives [56]. In [56], one of the projects aims is to contribute to a software development workflow that is going to lead to the increased reliability of DHNs. The project is focused on investigating the failure rate and repair duration of DHN [56]. The mentioned reasons make this study a good reference to extract the network's failure data. Based on this reference [56], the failure rate of 0.12 failure/km/year or 1.3698e-5 failure/km/hour was considered. The length of the network is 445 meters, therefore, for the total network, the failure rate equals to 1.3698e-8 failures/h. Failure rate and repair rate of all the components are mentioned in the table 5.1.

Table 5. 1: Component's failure rate and repair rate

Component	**Failure rate (per hour)**	**Repair rate (per hour)**
Compressor	0.000212842	0.11765
Condenser	2.1254E-05	0.02857
Pump	7.0159E-06	0.02342
Valve	4.13993E-06	0.14286
Evaporator	4.34783E-05	0.05780
Burner	0.000323288	0.06250
Heat exchanger	6.85244E-06	0.05556
Safety valve	1.86544E-06	0.04166
Storage	2.38927E-06	0.31290
Network	1.3698E-5	0.0667

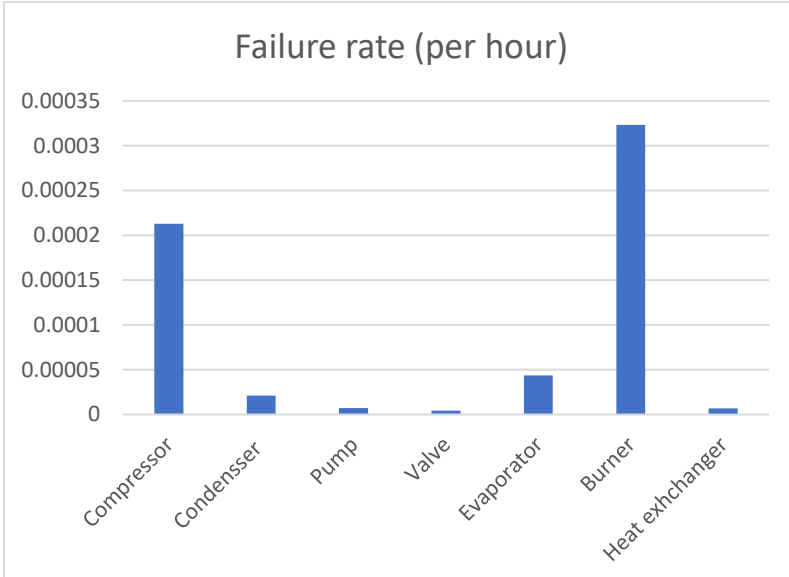

Figure 5. 2: Components' failure rate

Subsystems refer to the elements of energy systems, for example, heat pumps, boilers, thermal energy storage, and network. Each subsystem contains different components and the physical connection among these components defines the complexity of the system in terms of series and parallel connections. As mentioned in the methodology chapter, the type of connection is one of the inputs of the reliability and availability models.

Figures 5.3 and 5.4 illustrates the components of a heat pump and boiler, respectively. A heat pump includes five components, compressor, condenser, evaporator, pump, and valve, which all are connected in series. Similar to heat pump, three components of a boiler, burner, heat exchanger, and safety valve, are connected in series. Based on the characteristics of a series system, failure of one component will lead to the system failure. As an example, among the components of the HP, compressor has the highest failure rate at 0.000212842 (f/h), it is illustrated in components' failure rate figure 5.2. Improving the quality of this one component will have a great impact on the heat pump reliability. For example, changing the failure rate of the compressor to 0.0000212842 (f/h) which is ten times smaller than the original rate, will result in improving the heat pump's reliability after 1000 hours from 0.74% to 0.90%.

Figure 5. 3: Components of a heat pump

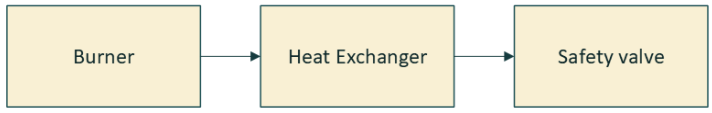

Figure 5. 4: Components of a boiler

5.1.3 Step two: availability model

Having all the inputs of the availability model ready, the downtime and failure frequency of each subsystem is evaluated. For example, the central scenario consists of heat pumps, a boiler, thermal energy storage and the network. The failure data has been gathered in step 1 and based on the available data, it's been assumed that the failure and repair rates are exponentially distributed. According to the flowchart and methodology, for each component two random numbers are generated then these are converted to times to failure and repair. The conversion has been done using the inverse-transform method. The process for exponential distribution is shown in the formulation below:

The cumulative density function (CDF) of exponential distribution with a failure rate (λ) > 0 is:

$$F(x) = 1 - e^{-\lambda x}, x \geq 0 \qquad 5.1$$

Solving $u = F(x)$ in terms of x gives:

$$F^{-1}(u) = -\frac{1}{\lambda} ln(1-u) \qquad 5.2$$

Since U ~ U (0,1), then 1-U ~ U(0,1), then by generating random number U, the TTF is:

$$TTF = -\frac{1}{\lambda} U \qquad 5.1$$

Similarly, the TTR having repair rate μ is:

$$TTR = -\frac{1}{\mu} U \qquad 5.2$$

For the availability model, the total simulation time was 500,000 hours, time steps were 100 hours, and process repeated for 5000 iterations. The availability, failure frequency, and system downtime of a heat pump are shown in the figures 5.5. Based on the simulation results, the HP's availability

is 99.6% which is equal to 50 minutes of unavailability per week. The average downtime of the HP is 13 hours, and its failure frequency is 0.000261 failures/hour or 2.28 failures/year. Since the connection between the five components of the HP is series, it has been expected that the failure frequency of the HP was more than the failures of the component with the most failures. Figure 5.6 illustrate the boiler's metrics. For a boiler, the availability is 99.48%, the failure frequency is 2.74 per year and the average downtime after each failure equals to 16.2 hours.

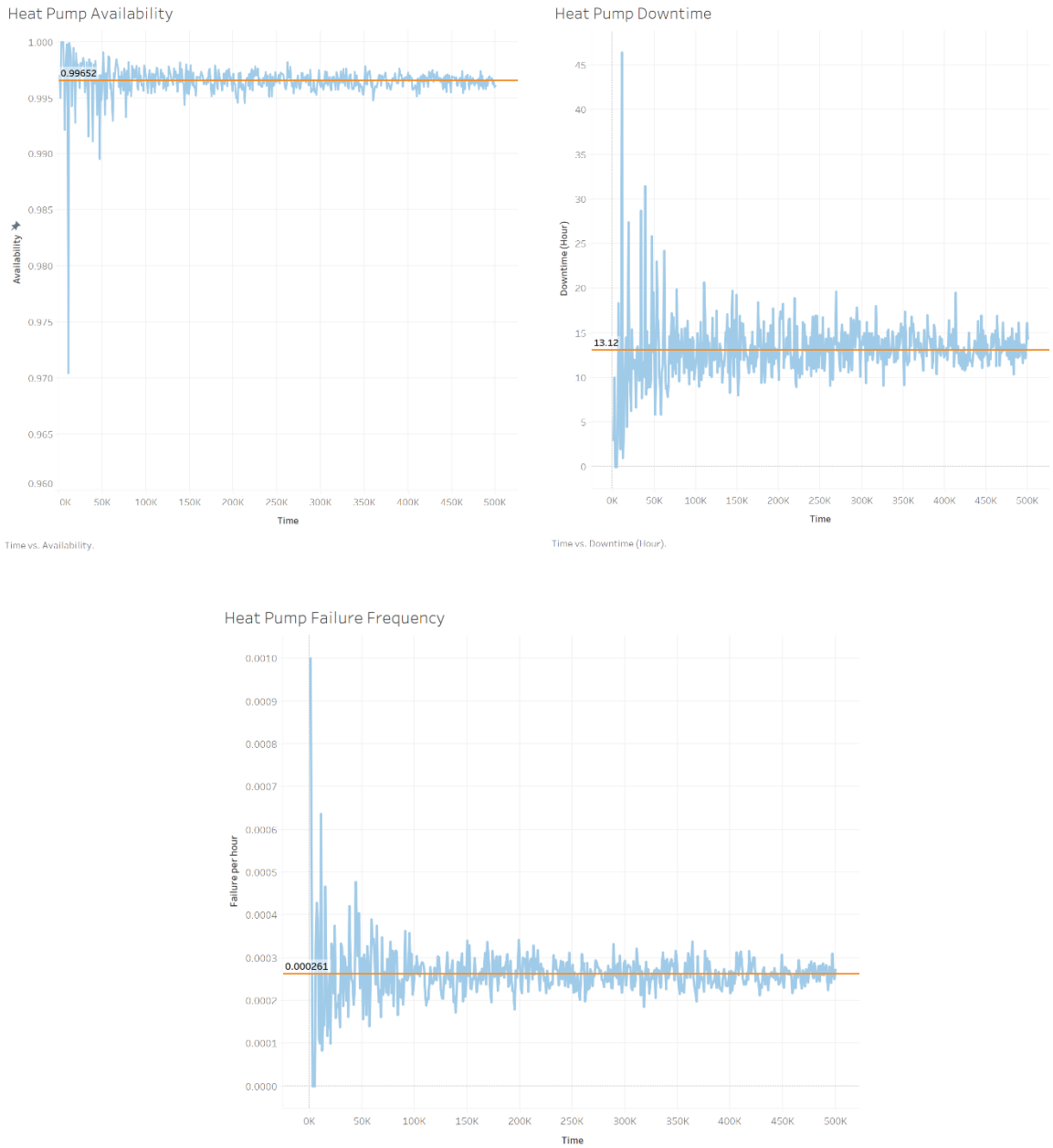

Figure 5. 5: Result of availability, downtime, and failure frequency of a heat pump

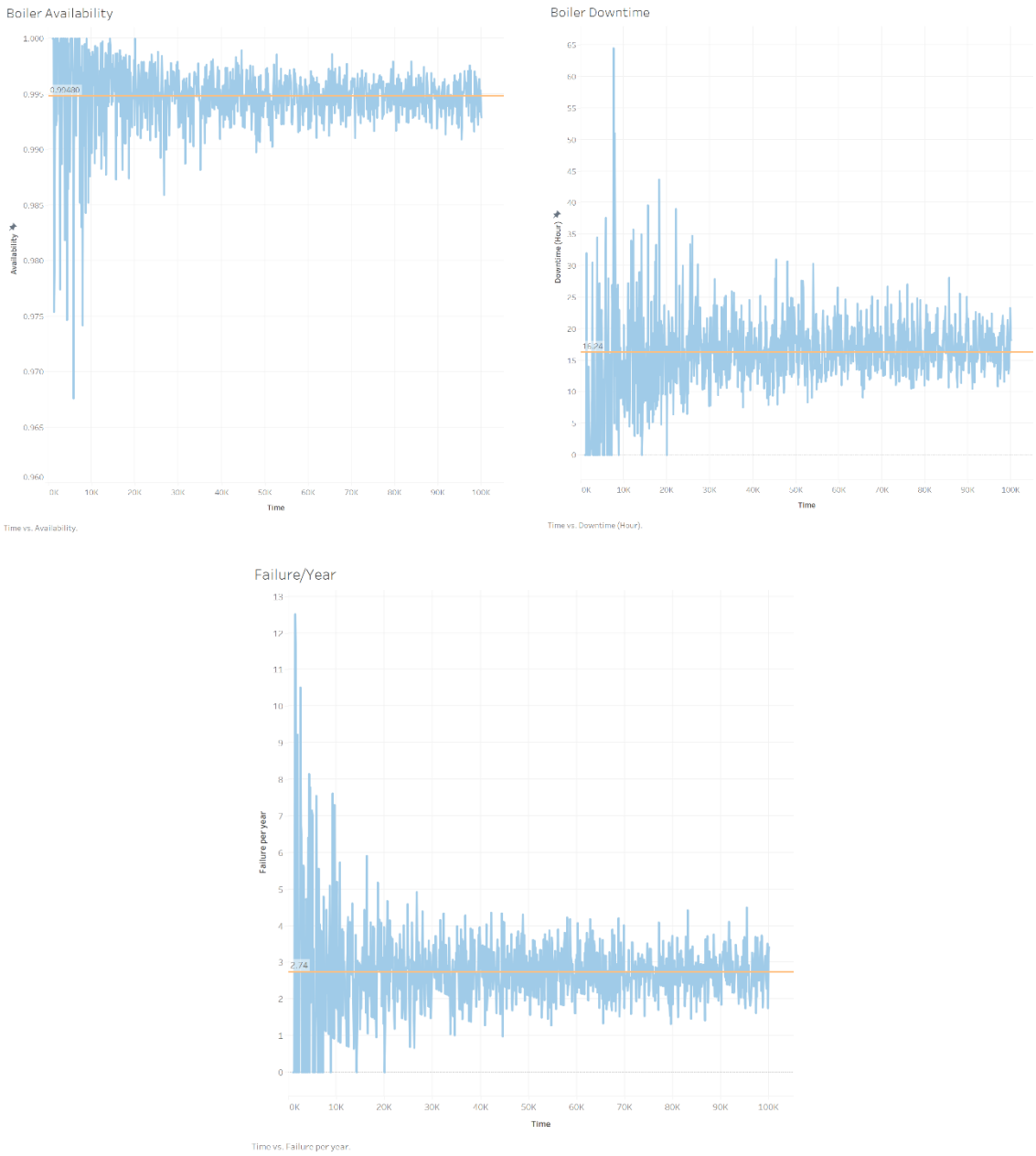

Figure 5. 6: Result of availability, downtime, and failure frequency of a boiler

5.1.4 Step three: reliability model

Outputs of the previous step and the hourly heating demand of the area are the inputs of the reliability model. In the context of this research, reliability is defined as the ability of the thermal energy system to provide the heating demand of the district without failure for one year (8760 hours). Similar to the availability mentioned in step 2, the reliability section follows the exponential distribution as well. Therefore, the random generation and inverse-transformed methods are identical (equations 5.1 to 5.3). At each step of the SMC simulation, TTF and TTR are generated and considering the connections between the components and their capacities the reliability metrics are evaluated. The schematic energy system design of both scenarios is shown in the figures 5.7 and 5.8.

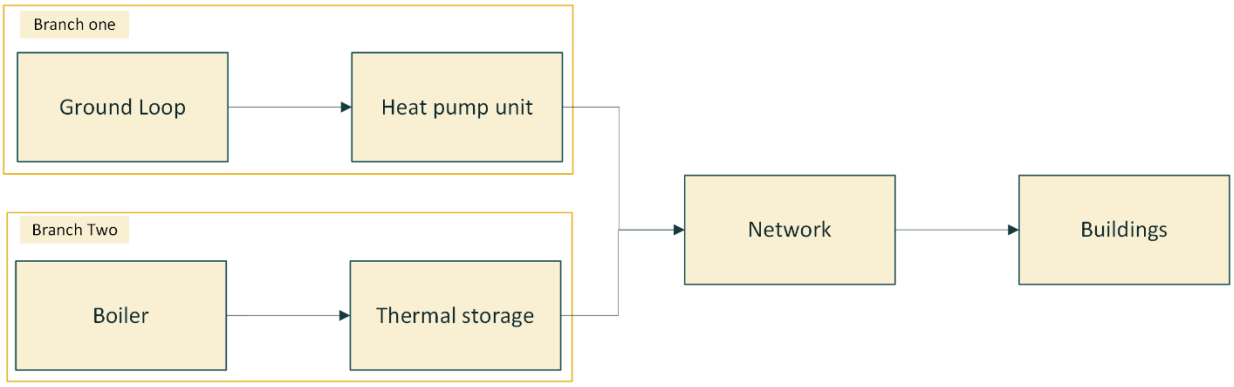

Figure 5. 7: Centralized scenario

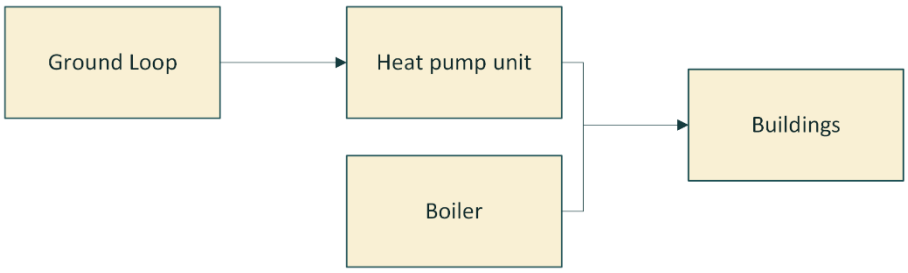

Figure 5. 8: Decentralized scenario

5.1.5 Step four: results

The subsystems of the first design (DHN) are illustrated in the figure 5.7, and as shown in branch one, the ground loop and HP unit are connected in series which means malfunctioning of each of them results in the failure of that branch. It is worth to mention that the failure in geothermal is rare and in current work, it has been assumed that it is 100% reliable. Similarly, the boiler and TES

are connected in series and the failure of the boiler will enable the TES to store energy. If branches one and two work properly, then the energy is transferred into the network to be delivered to the buildings. If the network fails due to corrosion, or any other failure mode, no energy will deliver to the buildings. Based on the same logic, if either branch one or two stops working, the share of the produced energy of that branch will not be transferred into the network.

Details of energy system designs were shown in Table 4.3. The DHN has 14 similar HPs, and If at least one HP is working, the HP unit is partially available means that it is not working with its full capacity, but a part of the unit is functioning. The HP unit is assigned to provide 60% of the demand, so based on the number of HPs working at each hour, and the hourly demand the reliability and other metrics are evaluated.

In the decentral scenario, each building has an individual energy system and the difference between the energy systems is in the number of needed HPs. The number of HPs needed to meet the demand in each building is mentioned in table 4.3. Similar to the central design, HP and the boiler are working in parallel. Although the failures of one of them will not affect the working of the other one but will reduce the delivered energy to the end-user. For example, building B has one HP and one boiler; if the HP stops working, only 40% of the demand will be provided by the boiler. Similarly, if the boiler fails, the HP is able to meet the 60% of the load curve. On the other hands, buildings A, C, and D have more than one HP and at each time step, one or more HP might not be operational. Reliability and availability are assessed based on the degraded capacity of the HPs and working condition of boiler at each hour.

Table 5.2 shows the availability, unavailability, and reliability of scenarios after one year of operation (8760 hours). Failure rate and unavailability have a linear relation and this point is reflected in figure 5.9. As the number of failures increases, the unavailability of the system increases, too. The fact that during the failures system is out of operation results in system unavailability.

Table 5. 2: Results of reliability and availability simulation

Scenario	**ID**	**Reliability**	**Availability**	**Unavailability**
Central design	DHN	0.984921197	99.9970%	0.003050%
Decentral design	Building A	0.981763209	99.9984%	0.001567%
	Building B	0.97468658	99.9966%	0.003360%
	Building C	0.982690128	99.9987%	0.001290%
	Building D	0.984468493	99.9985%	0.001546%
	Building E	0.980708602	99.9982%	0.001818%
	Building F	0.982027821	99.9985%	0.001469%

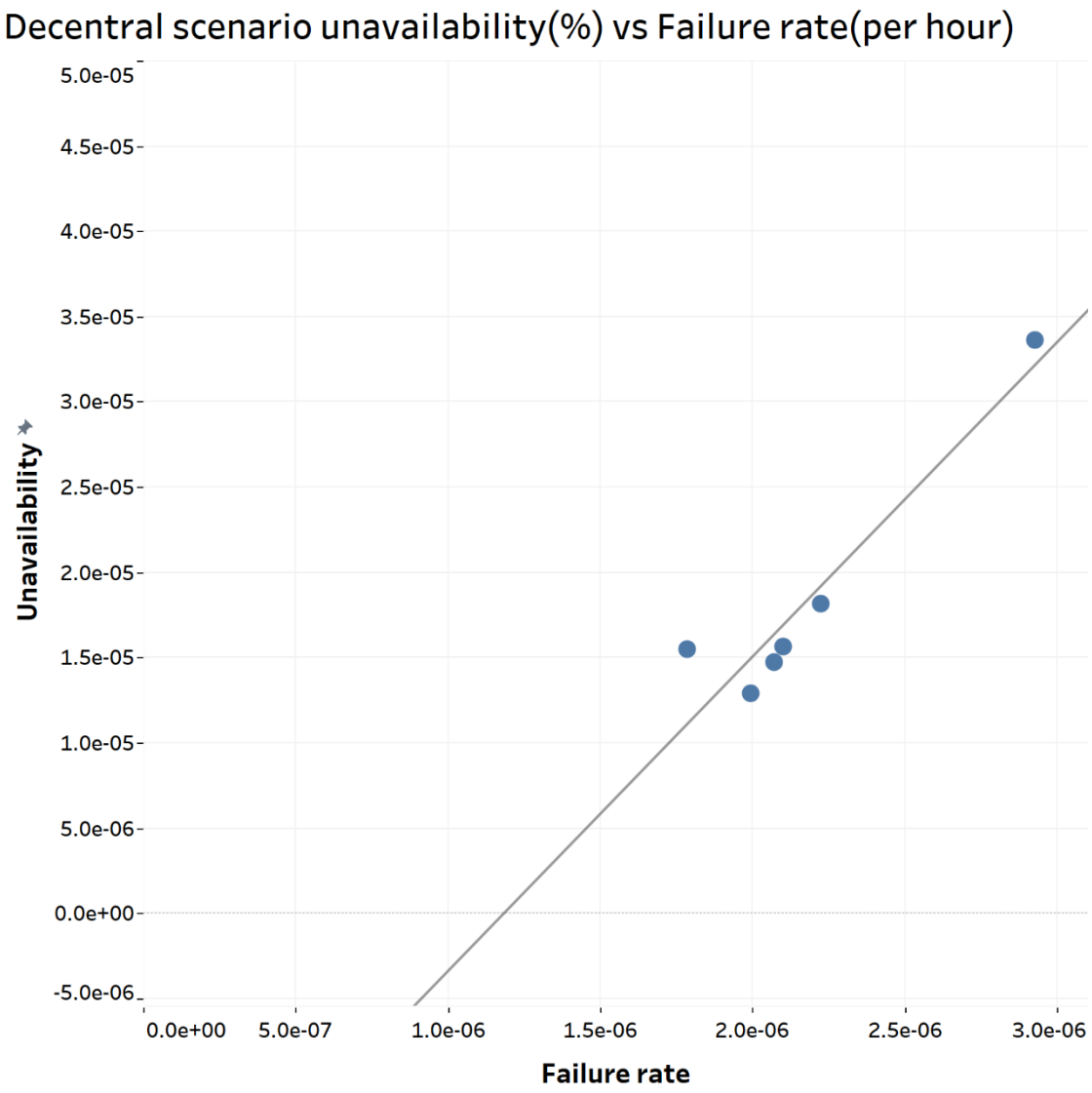

Figure 5. 9 Linear relation between unavailability and failure rate in decentralized design of each building

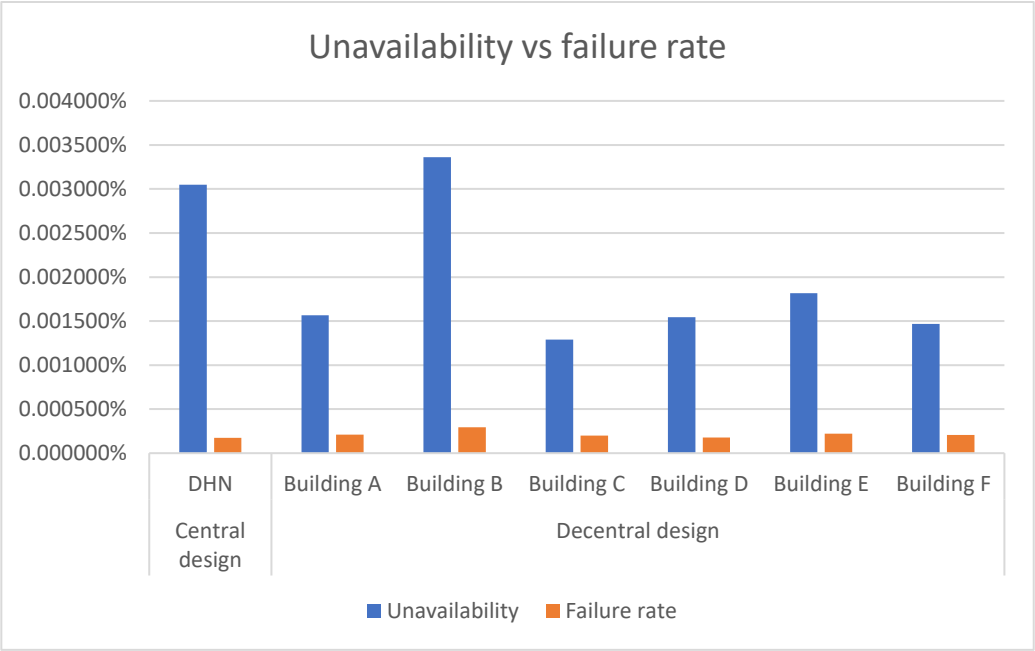

Figure 5. 10: Unavailability, and failure rate in centralized vs decentralized scenarios

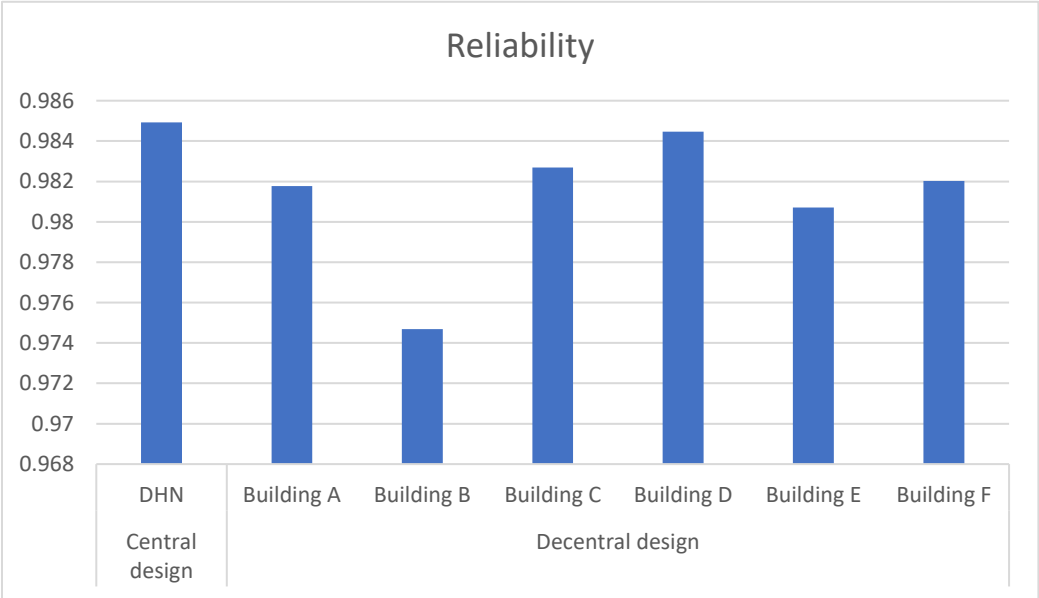

Figure 5. 11: Reliability results of centralized vs decentralized scenarios

5.2 Reliability discussion

Among all the buildings, building B has the lowest availability and reliability. Buildings B, E, and F have only one HP that is identical and among these three buildings, building B has the higher floor area, peak demand, and total demand. Therefore, the HP in building B has higher operational hours during a year in comparison to two other buildings and this point results in higher failures and lower operational availability. One of the benefits of the current simulation methods is considering the demand side in the calculation. The deigned energy systems in buildings B, E, and F have the same number of HPs, but because the consumers' specifications and hourly demand have been considered, the results are realistic and different.

Results indicate that overall the DHN has higher reliability than the decentralized scenario. One of the reasons is in this scenario the number of HPs is more than in individual buildings, therefore, in case of failure of one HP, others will continue their operation and supply the load curve.

Figure 5.12 illustrates the ENS in both scenarios, and table 5.3 shows the reliability indices including ENS (kWh), AENS (kWh/consumer), and LOLE (hour/year). The total row in the decentral design section shows the scenario's performance in general. In terms of the amount of energy not served, DHN has less amount of kWh energy not served. Regarding AENS results are similar to ENS, AENS in DHN is 7.3 while the total AENS in the decentralized scenario is 8.6 (kWh/consumer). The total hours of energy unavailability during a year in DHN is lower than in the second design. As mentioned before, the DHN design has more working subsystems in parallel, and this point is an effective factor in increasing the system's reliability. The second design does not benefit from the thermal energy storage. Adding this subsystem to the design will create more redundancy and increase the reliability of the energy systems in individual buildings.

Table 5. 3: Simulation results of reliability indices

Scenario	**ID**	**ENS (kWh)**	**AENS (kWh/consumer)**	**LOLE (hour/year)**
Central design	DHN	72812	7.3	345.00
Decentral design	Building A	37628	8.5	214.35
	Building B	6114	5.4	73.92
	Building C	13980	7.9	135.56
	Building D	18470	10.8	161.31
	Building E	4119	10	69.08
	Building F	5658	10.3	76.09
	Total	85971	8.6	730.31

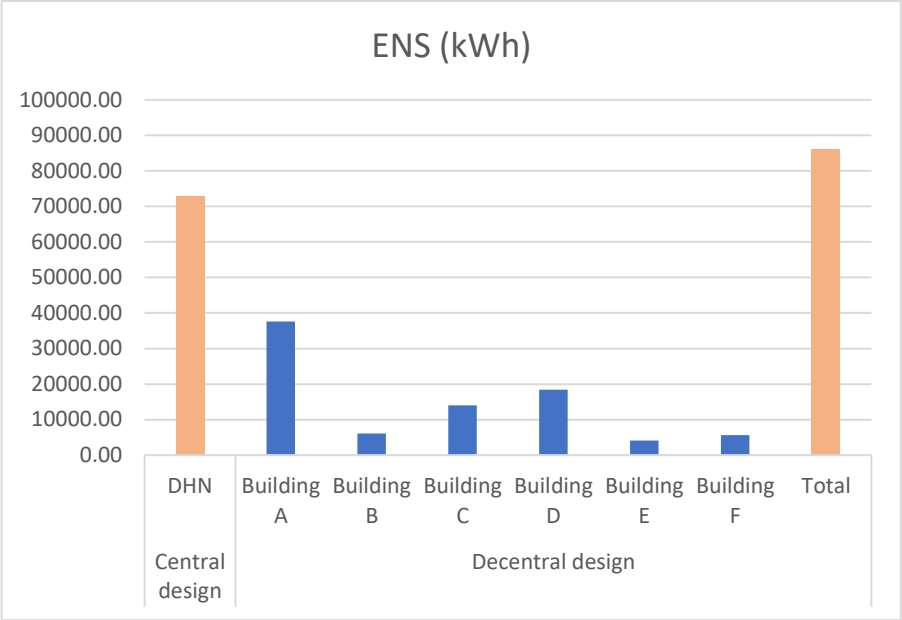

Figure 5. 12: ENS in central and decentral scenarios

5.3 Resilience assessment

Renewable energy systems that could participate in sustainable development are supposed to be more resilient and flexible than the current examples [6]. Different events could lower the resiliency of a system. Some examples are extreme weather temperatures, earthquakes, floods, power outage, manmade errors, etc.

In Quebec, more than 80% of households use electricity for heating [57]. One of the concerns is providing reliable space heating for the buildings. The resilience assessment of this project aims to evaluate the robustness of the energy system to provide the critical demand in case of a major power outage. In the black sky scenario of this research an off-site major power outage that lasts thirty hours is considered. Critical demand needs to be provided instead of day-to-day demand in the black sky scenario.

The load curve in an emergency condition differs from the business-as-usual demand. In a time of disruption, the goal is to keep the spaces temperature above the habitable thresholds. Based on the energy master planning guide [58], the maximum allowable downtime for the buildings like the Lachine area is 29 hours (High-efficiency mass buildings, -17.8^{o} C). It means in case of a blackout in -17.8^{o} C ambient temperature, buildings with high-efficiency material are able to stay habitable for 29 hours.

Following the method, critical loads are evaluated in four steps. Step one is listing all the functions in the Lachine area. Table 5.5 illustrates the details of occupants in floors of each building.

In second step, the user types are ranked based on their importance. Building complexes in the Lachine area have multiple user types, and in case of a disruption, the level of criticality of these use types plays an important role in resilience assessment. An example of an essential load in the Lachine area is the medical center and healthcare facilities in building B. Other types of occupants in the Lachine are residential, commercial, and civic center. Considering the level of importance of providing essential loads as high, other loads in this area are defined in the tables 5.4.

Table 5. 4: User importance ranking in Lachine-Est

Low	**Significant**	**High**
Offices, housing, commercial	Warehouses, educational institute, civic center	Medical centers

The critical load in each building is a portion of the day-to-day demand. In third step coefficients are defined based on the hour of the day and main occupants' type. For instance, building E's first and second floors are commercial and residential. If the disruptive event happens during the day, most residential occupants would be elsewhere, i.e., at work, school, etc. At the same time, the commercial floor is open to the inhabitants. Therefore, the commercial floor's share of critical demand during the day is higher than the residential. This point is reflected in the critical demand calculation by assigning coefficients based on time categories: a) between 08:00 and 16:59 and b) between 17:00 and 07:59.

Table 5. 5: Buildings' use type in the case study

Building ID	No. of floor	Floor area (sqm)	Use type
Building A	9	13,637	First floor Commercial / 2 to 9 residential
Building B	6	5,174	First floor health care facilities / 2 to 6 residential
Building C	9	5,469	First floor offices and commercial / 2 to 9 residential
Building D	6	7,882	First three floors civic center / 3 to 6 educational & cultural institute
Building E	2	5,890	First floor Commercial / second floor residential
Building F	9	1,690	First floor offices / 2 to 9 residential

A 30-hour long off-site power outage has been considered to investigate the system's resilience. Two random days, April 8th and December 28th, and the coldest day of the year, February 4th, were chosen to investigate the resilience. It has been assumed that the power outage starts at the midnight of each chosen day and continues for thirty hours.

In the last step, using normal demand and coefficients, the critical load is estimated. The critical load in each hour (CL_i) is the multiplication of critical coefficient C_i and actual demand. The assumed C_i for available use types in Lachine-est are represented in table 5.6.

$$CL_i = C_i \times demand_i$$

Table 5. 6: Critical Coefficients of the buildings in Lachine-est

C_i	Residential	Commercial	Offices	Health care	Civic Center	Educational institution
$C_{i,\,Day}$	0.5	0.5	0.5	1	0.75	1
$C_{i,\,Night}$	0.75	0.25	0.25	0.5	0.25	0.25

Different metrics are evaluated based on the duration of the power outage and critical load. Energy Robustness is the ratio of the demand that is provided by the supply during the power outage, Energy Not Served (ENS) refers to the amount of the energy that is not served during the power outage, and Average Energy Not Served (AENS) refers to the average amount of energy not served

to each consumer. The amount of day-to-day demand and critical demand for the same buildings are distinguished by the coefficients. The only critical load in this study is the space heating load. In the day-to-day operation of both scenarios, the heat pump, boiler, and TES supply the demand simultaneously. The needed electricity of the heat pumps is provided from the grid therefore, in case of a power outage, the heat pumps will not be functional, but boilers are available to provide the demand. In table 5.7, calculated ER, ENS, and AENS of February 4th, which is the coldest day of the year, are shown. In two other random days, both of the energy systems were able to cover the critical demand.

In both scenarios, a gas boiler is sized to provide 40% of the space heating demand. In case of a power outage, the critical demand is less than the day-to-day demand. Therefore, boilers can cover more than 50% of the demand in each building. In figure 5.14, ER shows the amount of critical load which is covered by the TES and boiler.

Table 5. 7: Resilience indices results in central and decentral designs

Date	**Scenario**	**ID**	**ENS (kWh)**	**AENS (kWh/ Consumer)**	**ER**
February 4th	Central	DHN	58667	5.8667	0.681
	Decentral	Building A	30755	7.0	0.641
		Building B	6664	6.0	0.605
		Building C	13661	7.7	0.642
		Building D	1639	1.0	0.939
		Building E	1351	3.2	0.798
		Building F	4633	8.4	0.641
		Total	58703	5.8	0.71

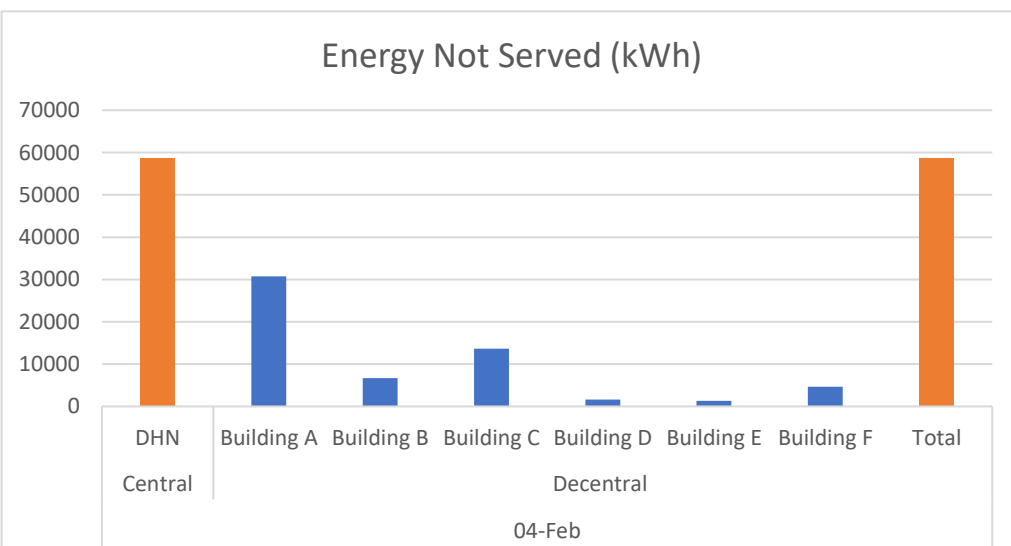

Figure 5. 13: ENS of scenarios in black sky condition on Feb.4th

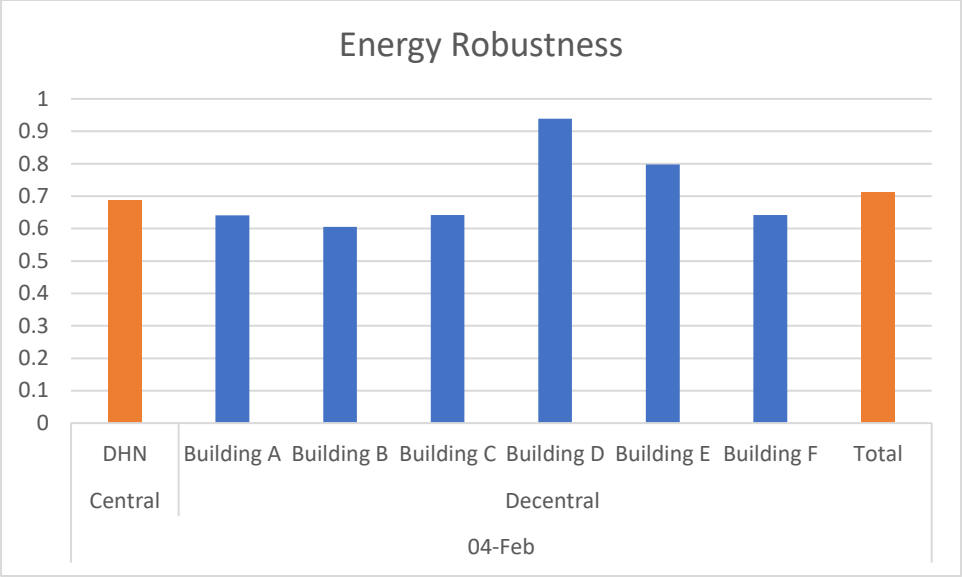

Figure 5. 14: ER of scenarios in black sky condition on Feb.4th

5.4 Resilience assessment results

The critical load was estimated for the coldest day of the year (February 4th) and two random days (April 8th and December 28th). The results indicated that both system designs covered the critical load during a 30-hour long power outage in two random days.

Regarding the February 4th, as figure 5.13 and table 5.7 demonstrate, the ENS in two scenarios is very similar. Among the individual buildings in decentral scenario, building A has the highest ENS, 30755 (kWh), this building has the greatest floor area and eight floors of its nine floors are residential. It has been assumed that between 17:00 and 07:59, 50% of the space heating demand in the residential floors needs to be provided. This assumption increases the amount of critical load in residential floors. Similar to this building A, building C has eight residential floors, and the ENS in this building is higher than other buildings, equal to 13661. Building F has eight residential floors, too. Despite two mentioned buildings (A and C), it has much less ENS (4633) because it has the lowest floor area and lower demand.

Critical demand in building B is relatively high, because healthcare facilities are located in the first floor of the building and other five floors are residential. During the night, share of critical load of residential floors are high, but during the day, because the level of criticality of the healthcare facilities are high, therefore the whole demand needs to be provided. The AENS in this building is 6 which is relatively high, on the other hand, the ER is lowest of all the buildings which reflects the need of this building to more robust backup energy resources.

Building E has the lowest number of floors (2 story), it has lowest ENS, and its ER is acceptable. Three floors of the building D are civic center, and the other three floors are educational institutes, and it means that the number of occupants in these buildings is relatively high. Level of criticality of this building's load type, considering the user type, is significant (table 5.4). Therefore, high

amount of critical load for this building, especially in a cold winter day needs to be supplied. In comparison to other buildings, ENS of this block is relatively high and could benefits from a backup emergency system.

Chapter 6: Conclusion

One of the main issues in urban energy systems is providing reliable and constant energy to the end-users. In this research, the reliability, availability, and resilience of renewable heating energy systems in urban areas are discussed. The reliability and availability assessment were done using sequential Monte Carlo (SMC) simulation which contains components' number and duration of failures, specific repair time needed for each component, random behaviour of the system, and end-user's hourly demand. The benefit of using SMC simulation over other methods is that in SMC, the real behaviour and random nature of the components and their failures are taken under consideration. In neither iteration the simulation results are identical, and the reason is random generation of components operation and repair states.

The results of the reliability simulation indicate that the centralized scenario is more reliable than the decentralized one in terms of the number of hours where energy is available to the area, and the amount of energy served to the consumers. In centralized scenario or district heating network (DHN), the Average Energy Not Served (AENS) is 7.3 kWh/customer where this number for the average of all the buildings in the second scenario is 8.6 kWh/customer.

To evaluate the resilience of heating systems, three indices including Energy Not Served (ENS), Average Energy Not Served (AENS), and Energy Robustness (ER) were proposed. The resilience of the two energy system scenarios under emergency condition in three different days of the year were investigated. The disruptive event in the black sky scenario was an off-site power outage that took thirty hours. During the black sky condition (power outage), the business-as-usual demand were replaced by the critical demand which is a percentage of the regular demand. User importance, critical ranking of the loads in the area, and time of the day are effective factors in critical load estimation.

A comparison between the resilience assessment results of the two scenarios in three different days in the year indicates that the system behaviour in both designs is mostly similar. The critical load of two randomly selected days (April 8th and December 28th), were fully covered by both heating system designs. Regarding the third day (February 4th), which has the highest demand during the year, the ENS during the thirty hours major power outage in DHN is 58667 kWh, while the cumulative ENS of all buildings in the second scenario is 58703 kWh. None of the designs were able to completely cover the critical demand. Some system improvements could be implemented to increase the energy system resilience; for example, installing PV panels on buildings rooftops to increase the share of renewables and act as backup electricity for HPs. For the building with high criticality level use type (building B that includes healthcare facilities) adding a backup generator could be a feasible solution. Another suggestion is considering a system that is able to use the waste heat of the buildings.

In conclusion, the result of the proposed reliability and availability method is in line with the literature and demonstrates that the central energy system has better performance in terms of energy availability and reliability than the decentralized energy systems. In the DHN design, the malfunctioning of each subsystem changes the delivered energy to the whole district. Since some of the buildings have higher user importance, e.g., healthcare facilities, considering a backup

system could improve the performance of the system in both normal operation and black-sky conditions.

6.1 Limitations

In the proposed framework, the random sequences of time to failure and time to repair are generated based on the underlying function of the input failure rate and repair rate data. The founded values of failure rate and repair rate of components, shown in table 5.1, follow the exponential distribution. In this distribution, the failure rate is constant, and failures happen randomly [22]. In the bathtub curve that represents three phases of a components failure, figure 6.1, only the middle section or useful life has constant failure rates, therefore, early failures or failures due to wear out have not been considered. In order to further investigate and model all three phases, other distributions rather than the exponential could be used in the proposed MCS.

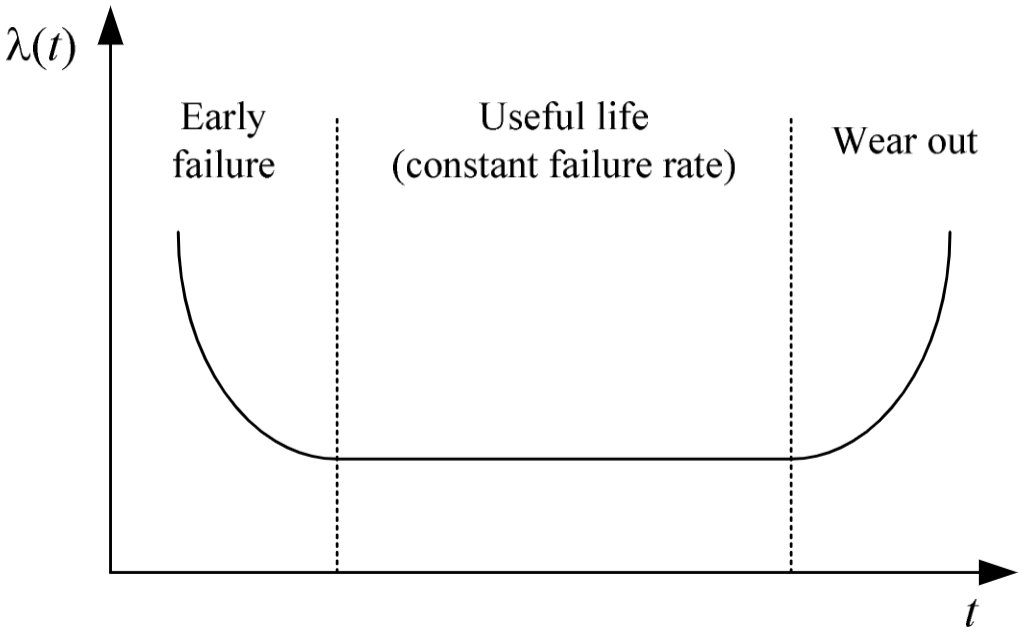

Figure 6. 1: The bathtub curve [22]

6.2 Future work

The failure and repair rate of components were gathered mostly from OREDA handbook. The available data in this reference is limited, and in future, gathering more data regarding specific modes of failures will provide a possibility to study the Failure Mode and Effect Analysis (FMEA).

It has been assumed that the fitted distribution to failure and repair rate is exponential. Therefore, only the useful life of the components is considered. Having the actual failure and maintenance data in future will provide the possibility of fitting a wide range of distributions to data and find the best fitted one using goodness of fit tests. The parameters of those distributions could be used as the inputs of the current SMC method.

A further step of the current work is predicting preventive maintenance time and finding the optimum repair time of components considering the cost. Benefits of preventive maintenance include decreasing the cost, lessening system downtime, and improving availability [59].

The resilience assessment method was limited to the ability of the system to provide the critical demand during the power outage without considering the buildings' characteristics. The critical load of a building could a function of geographical location, weather condition, dimensions of penetrations, number of rooms, use types, isolation, hour of a day, etc. The effect of each of these parameters on critical load and resilience could be further investigated.

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