RELIABILITY ASSESSMENT OF RESIDENTIAL DISTRIBUTION POWER SYSTEMS CONSIDERING COLD LOAD PICKUP EVENTS

BY

ABDULLAH ABDULRAHMAN ALNUJAIMI

A Thesis Presented to the
DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

ELECTRICAL ENGINEERING

APRIL 2018

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN- 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

This thesis, written by **ABDULLAH ABDULRAHMAN ALNUJAIMI** under the direction of his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN ELECTRICAL ENGINEERING.**

muhaini

Dr. Mohammad M. Al-Muhaini
(Advisor)

Dr. Mohammad A. Abido
(Member)

Dr. Muhammad Khalid
(Member)

Dr. Ali A. Al-Shaikhi

Department Chairman

Dr. Salam A. Zummo
Dean of Graduate Studies

عمادة الدراسات العليا
DEANSHIP OF GRADUATE STUDIES

7/5/18

Date

Dedicated to

My Beloved Parents,

My brother

&

My sisters

ACKNOWLEDGMENTS

بسم الله الرحمن الرحيم

In the name of Allah, the Most Gracious, the Most Merciful

I would like to acknowledge King Fahd University of Petroleum & Minerals (KFUPM) for making this accomplishment possible by accepting my part-time application and supporting the completion of the thesis through providing all possible research facilities including the online library and the software subscription plans.

I would like also to acknowledge my thesis advisor, Dr. Mohammad M. Al- Muhaini, for helping me selecting this research topic and for his guidance during the development of this work.

I would like to convey my deepest thanks and appreciations to Dr. Mohammad A. Abido, whose technical knowledge, experience and guidance helped me to through my master studies in courses work and thesis development alike.

I would also like to thank the thesis committee member Dr. Muhammad Khalid for his constructive and positive feedback.

My deepest gratitude goes to my family for their support during my master studies. Starting with my parents, “Abu Abdullah” and “Um Abdullah”, whose constant love and encouragement shaped my life and booted my progress. Without their support, I could never have made this far in my academic studies and professional career. May Allah always protect you wherever you are.

I would like also to thank my brother and my sisters for their love, care and interest in my success. My Allah protect you and in return, I will pray Allah to help you succeed in your personal and professional lives.

Last but not least, I would like to thank Mr. Salem Al-Huraish, Mr. Abdullah Al-Guraishi, Dr. Mohammed Al-Ghamdi, Mr. Hisham Al-Gurouni, Mr. Ayed Al-Anazi, Mr. Rakan Mahayni as well as all my colleagues and friends from Saudi Aramco for their continuous support to complete this research.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

ABBREVIATIONS

ACO	:	Ant Colony Optimization
ANN	:	Artificial Neural Networks
APIM	:	Adjacent Pairwise Interchange Method
ASAI	:	Average Service Availability Index
ASUI	:	Average Service Unavailability Index
BCO	:	Bee Colony Optimization
CAIDI	:	Customer Average Interruption Duration Index
CLPU	:	Cold Load Pickup
DSA	:	Differential Search Algorithm
DE	:	Differential Evaluation
DF	:	Demand Factor
DG	:	Distributed Generator
DSM	:	Demand Side Management
EC	:	Evolutionary Computation
ENS	:	Energy Not Supplied
ESS	:	Energy Storage System
EV	:	Electric Vehicles
GA	:	Genetic Algorithm
LF	:	Load Factor
LSA	:	Lightning Search Algorithm

MILP	:	Mixed-Integer Linear Programming
NEC	:	National Electric Code
NSMC	:	Non-Sequential Monte Carlo Simulation
NTCL	:	Non-Thermostatic Controlled Load
PSO	:	Particle Swarm Optimization
QLSA	:	Quantum Lightning Search Algorithm
RCGA	:	Real-Coded Genetic Algorithm
SMC	:	Sequential Monte Carlo Simulation
SAIDI	:	System Average Interruption Duration Index
SAIFI	:	System Average Interruption Frequency Index
SD	:	Standard deviation
TCL	:	Thermostatic Controlled Load
TOC	:	Time Overcurrent
TOU	:	Time-of-Use
TTR	:	Time to Repair
TTF	:	Time to Fail

SYMBOLS

α	:	Control parameters of GA non-uniform mutation
β	:	Control parameter of inertia weight in PSO algorithm
C	:	Building equivalent thermal mass
$\boldsymbol{C_i}$	:	Number of customer at load point (i) (equation 2.2)
$\boldsymbol{c_1}$	:	Parameter of particle history in PSO
$\boldsymbol{c_2}$	:	Control parameter of particle history in PSO
CR	:	Crossover probability of DE
$\mathbf{E_0}$	:	Initial energy of the scaling parameter in LSA
G	:	Building equivalent thermal conductance
F	:	DE mutation factor
$\boldsymbol{N_T}$	:	Total number of customers at each load point
$\sum \boldsymbol{N_i}$	:	Total number of interruption
$\boldsymbol{O_i}$	:	Outage duration which affected by CLPU
$\boldsymbol{P_i}$	:	Average power that would have been supplied during interruption.
Q	:	Total heat injected/drawn from building
$\mathbf{Q_C}$	:	Effective heat flowing to building
$\mathbf{Q_G}$	:	Building heat loss
$\boldsymbol{r}$	:	Repair rate of an equipment
λ	:	Failure rate of an equipment
$\mathbf{S_D}$	:	Pre-Outage diversified power demand

$\mathbf{S_U}$	:	Post Outage undiversified power demand
$\boldsymbol{\sigma}$	:	Scaling parameter of normal distribution
$\mathbf{T_b}$	:	Building temperature
$\mathbf{T_D}$	:	Lower temperature limit of thermostat
$\boldsymbol{T_i}$	:	Restoration time of load point (i) (equation 2.2)
$\mathbf{t_{ri}}$	:	Additional restoration time of load point (i)
$\mathbf{T_U}$	:	Upper temperature limit of thermostat
$\mathbf{T_{out}}$	:	Ambient temperature outside building/house
$\mathbf{TTR_i}$	:	Time to repair of load point (i) without CLPU effect
$\overline{\mathbf{TTRi}}$	:	Time to repair of load point (i) with CLPU effect
$\boldsymbol{\mu}$	:	Shaping parameter of exponential/normal distribution function
$\boldsymbol{V}$	:	Velocity of particles in PSO algorithm
$\mathbf{V_{min}}$	:	Minimum bus voltage duration restoration
$\boldsymbol{\upsilon^{max}}$	:	Maximum velocity in PSO algorithm
$\boldsymbol{\omega}$	:	Inertia weight of particles velocity PSO algorithm
$\boldsymbol{X^*}$	:	Local best of particles in PSO algorithm
$\boldsymbol{X^{**}}$	:	Global best of particles in PSO algorithm

ABSTRACT

Name	ABDULLAH ABDULRAHMAN ALNUJAIMI
Title	RELIABILITY ASSESSMENT OF RESIDENTIAL DISTRIBUTION POWER SYSTEMS CONSIDERING COLD LOAD PICKUP EVENTS
Degree	MASTER OF SCIENCE
Major Field	ELECTRICAL ENGINEERING
Date of Degree	APRIL 2018

With the introduction of smart grid, residential power networks have gained more attention than ever. Quality and continuity of the power delivered to customers become an important factor for utilities. Accurate modeling and estimation of reliability indices will lead to better investment decisions. In this thesis, a new methodology is proposed to include cold load pickup (CLPU) events in the time-based reliability indices under the assumption that utilities follow an optimal restoration plan within system and equipment constraints. Due to the randomness of the customer behaviors in the residential sectors, the proposed method deploys a stochastic load model. Moreover, a state-of-art optimization method named lightning search algorithm (LSA) is used to search the optimal restoration plan after each failure on a test system. This algorithm is compared to well-known algorithms to measure its robustness and effectiveness. In addition, the proposed method is compared to fixed-period restoration plans to show the proposed method's usefulness. The results measure CLPU effect on the reliability indices of the residential power distribution system and show a negative impact that must be considered by utilities in planning problems.

Keywords: Power System Reliability, CLPU, LSA, SAIDI, CAIDI, ENS

MASTER OF SCIENCE DEGREE

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS, DHAHRAN

APRIL 2018

ABSTRACT (ARABIC)

الاسم: **عبدالله عبدالرحمن النجيمي**

عنوان الرسالة: **حساب الاعتمادية في أنظمة التوزيع الكهربائية باعتبار حالات استعادة الحمل البارد**

الدرجة: **الماجستير في العلوم**

التخصص: **الهندسة الكهربائية**

تاريخ التخرج: **أبريل 2018**

اكتسبت أنظمة التوزيع الكهربائية اهتمامًا لم تشهده من قبل. خصوصًا مع ظهور الشبكات الذكية، أصبحت جودة واستمرارية الطاقة الموزعة إلى الأحياء السكنية مهمة. لذلك فإن التمثيل الصحيح لسلوك هذا النظام الكهربائي سيقود إلى نتائج دقيقة ومن ثم قرارات أفضل عند استثمار شركات الكهرباء في هذا النظام لتحسين الاعتمادية. هذا البحث يقدم طريقة جديدة لحساب تأثير عمليات استعادة الحمل البارد CLPU على الاعتمادية في أنظمة التوزيع السكينة تحت افتراض أن مشغل النظام سوف يتبع خطة استعادة مثالية لا تخالف شروط تشغيل النظام ولا تؤثر على القدرات الحرارية للأجهزة الكهربائية. ونظرًا لعشوائية سلوك المستخدمين في هذا النظام، فإن هذا البحث سوف يوظف تمثيلاً عشوائيًا للحمل. وسوف يوظف أيضًا طريقةً جديدةً في البحث عن الحل الأمثل. هذا الحل سوف يقارن مع الحل الناتج من النظريات التقليدية وسوف يقارن مع نتيجة الاعتمادية في حال اتبعت الشركة المشغلة للنظام توقيتًا واحدًا ثابتًا لاستعادة نقاط التوزيع المتأثرة بانقطاع الكهرباء مع حدوث حالة الـ CLPU. أظهرت النتائج تأثيرًا واضحًا لـ CLPU على نتائج الاعتمادية لنظام التوزيع الكهربائي وهو تأثير سلبي يجب على مشغلي النظام أخذه بعين الاعتبار في عمليات التخطيط المرتبطة بالنظام.

درجة الماجستير في العلوم

جامعة الملك فهد للبترول والمعادن في الظهران

أبريل 2018

CHAPTER 1

INTRODUCTION

1.1 Overview

The residential power distribution networks reliability is usually less than networks supplying industrial and commercial loads. That was due to customer requirement and load priority. However, in the past few years, residential systems and loads have gained more attentions that ever. Power delivery to these loads has become more significant than before. This has resulted from the introduction of the deregulated electricity market and smart grid applications.

In the deregulated electricity market, the reliable power supply to customers is essential. In the environment of competitive electricity markets, the reliability measures are included in the cost of operation. For lower reliability than granted, utilities will pay direct compensations for customer. This direct impact can be accompanied by indirect effects such as the effect on the company image in the media and the society. This indirect impact on the company's public perception can cause declines in number of customers [1].

Moreover, some applications of smart grids required the exploration of the power distributions systems. These applications include the demand response and smart self-healing. The load behavior is essential to implement these applications. This had led to more exploration of the power distribution network. In demand response, the system operator might gain knowledge and control of the operation of a specific load. Also, in smart self-healing applications, the implemented control system is required to be fast and precise to restore the affected load points as soon as possible. This will not be obtained unless a detailed information about the load is available [2].

These applications helped the distribution system to gain more attention in many aspects including reliability. Power distribution system reliability are measured with indices such as System Average Interruption Duration Index (SAIDI), Customer Average Interruption Duration Index (CAIDI), System Average Interruption Frequency Index (SAIFI), Average Service Availability Index (ASAI), Average Service Unavailability Index (ASUI) and Energy Not Supplied (ENS). These indices are either failure-based indices or time-based indices. These indices can be assessed using analytical techniques block diagrams or simulation techniques such as Monte Carlo methods. It considers the component failure history and maintenance time data [1].

These reliability indices can help government authorities' system operators. They can help customer to select the right system operator for their application or need. Lastly, they can guide system operators during operation and in planning of future investment in the system infrastructure. Therefore, the realistic modeling of these systems will lead to more realistic results to well serve the previous purposes. One way to ensure the realistic modeling of the system is to include non-component-based events in the system reliability model. These events include but not limited to, weather conditions, switching flexibility, customer behavior and load behavior. The first three events have been well covered in the literature and power system reliability books [1].

However, events based on load behaviors are far less present in the literature compared to the other events. Cold load pickup is one of these events that represent the load behavior under certain circumstances. Cold load pickup is the increased demand of distribution system after extended outages. This is due to loss of diversity among heating/cooling loads. A recorded Cold Load Pickup (CLPU) event data is shown in Figure 1.1 which was taken for two feeders in the USA as feeder 1202 was restored before feeder 1201 [3]. This power distribution system is not designed to handle a sudden and enduring increase in demand. Therefore, this event will cause delay in restorations since single-step restorations will not be allowed [4] [5]. This forced restoration delay events are usually not included or incorrectly included in the reliability calculations of the distribution power system. Hence, these calculations may not reflect the actual system behavior [6] [7].

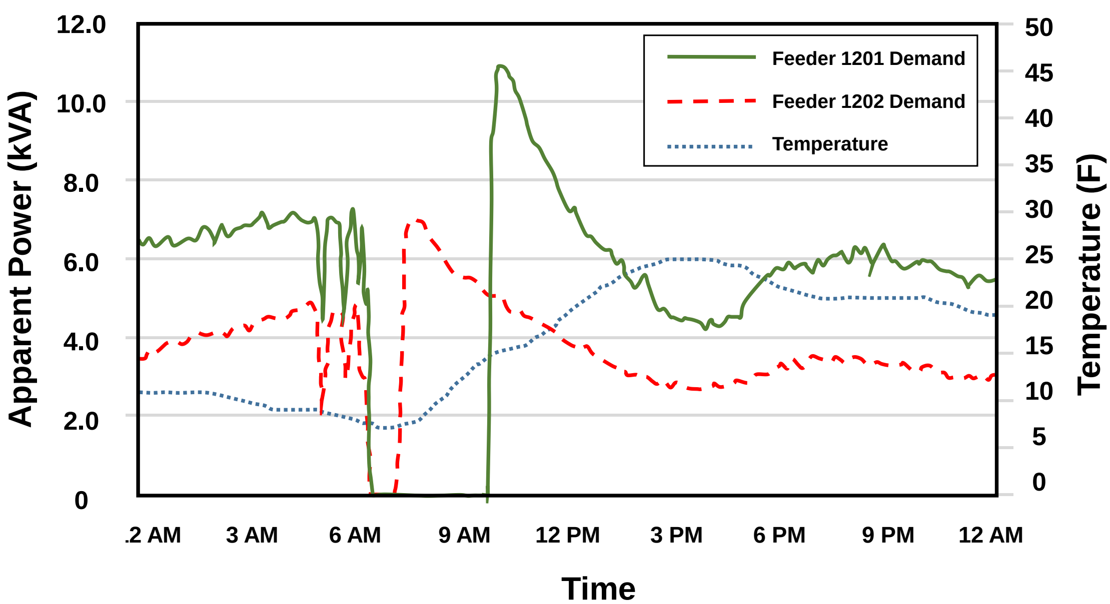

Figure 1.1: A recorded CLPU event by a power utility in January 2014 for feeders 1201 and 1202 in Seattle, USA

1.2 Motivation

Smart grid concept is introduced lately making power system industry looking more towards residential distribution system. This black box of a system is now being explored and its reliability is one of the exploration point. The residential load has its characteristics than distinguish it from commercial and industrial loads. One of these characteristics is the domination of the heating/cooling loads over other types of loads. This domination is about 70% of the total load. Therefore, these characteristics must be included in the reliability calculation along with any other study related to residential systems. The heating/cooling load, alternatively TCL, will delay restoration of power system after failures leading to more experienced outages by the customer that was not included originally on the reliability calculations. The previous effort to include CLPU events in reliability calculations, such as [6] and [7], was to calculate the number of expected additional failures due to CLPU events. In other words, CLPU events will affect SAIFI by increasing the number of failures. For example, if a customer experienced three (3) failures during the year, and one failure will cause an excessive demand that will lead to violate system constraints. This will be counted as another failure other than the original failure. Based on this method, this particular customer will be assumed to experience 4 failures during the year. This method is not accurate since this excessive demand might activate the protection system and will lead to additional unplanned delays. Moreover, this demand can damage the cable, or the transformer due to exceeding the thermal limits of the equipment. This will result in another possible outcome which will lead to further delay due to equipment maintenance or replacement. Therefore, just counting CLPU events as additional failures without incorporating their consequences is not accurate.

Another possible inclusion of CLPU events in reliability calculation is adding them to the time-based reliability indices such as SAIDI, CAIDI and ENS. This representation in CLPU will be more accurate since Utilities are aware of this issue and will delay restoration to avoid failed restoration. Based on the above, the thesis will include CLPU events in the analysis assuming that the system operator is fully aware of the impact of these events leading to more realistic approach in finding CLPU effect in system parameters.

1.3 Thesis Objective

This thesis proposes a new formulation to include CLPU events in reliability calculations of distribution power systems. The formulation contribution is to include CLPU events in time-based reliability indices including SAIDI, CAIDI and ENS hence measure CLPU effect in time. Other papers, such as [6] and [7], had the same objective but quantified CLPU impact in SAIFI calculations by finding CLPU occurrence rate.

To achieve this objective, the thesis assumes that the utility is fully aware of CLPU impact and will delay restoration at load points, as much as it is required in order not to violate system constraints. The thesis will take into account the stochastic modeling of the load which realistically mimics the real load behavior. Moreover, the thesis will utilize a newly developed optimization method, called Lightening Search Algorithm (LSA), to solve for the optimal restoration plan of the affected load points that minimizes the restoration time. The results confirm the effectiveness of the developed methodology to accurately define the distribution network reliability by considering the CLPU events.

1.4 Thesis Contribution

To achieve the objectives described in Section 1.3, the following contributions are made:

1- Develop a new methodology that integrates a Sequential Monte Carlo (SMC) simulation platform with an optimal search platform to quantify CLPU events in reliability calculations.

2- Utilize a stochastic load model for the power restoration problem to represent the residential sector load based on actual recorded data.

3- Implement a state-of-are search method to find the optimal restoration plan after extended outages.

1.5 Thesis Organization

The thesis is organized in the following order:

- Chapter 2 provides a complete literature review about all technical subjects provided in the thesis including CLPU and LSA.
- Chapter 3 discusses the modeling of each part of the selected system including load model, CLPU model, equipment details and reliability data.
- Chapter 4 discusses the problem formulation with the introduced objective function and the constraints used to direct the optimal restoration search.
- Chapter 5 discusses the methodology used to execute the problem formulation using two different platforms; SMC and LSA.

- Chapter 6 presents the results of this work for the following cases without CLPU, with CLPU considering optimal restoration, with CLPU without optimal restoration.
- Chapter 7 discusses conclusion and potential future work targeting futuristic types of distribution networks.

CHAPTER 2

LITERATURE SURVEY

This chapter will provide a comprehensive literature review of CLPU models and the responses of these models. It will provide an overview of the work that was published in the area of power system restoration and other modern power system problems considering CLPU events. The last part of this chapter will highlight the evolutionary computation techniques that will be used on this thesis with a special emphasis on LSA.

2.1 Cold Load Pickup (CLPU)

CLPU phenomenon is a relatively recent subject in power systems analysis. It was introduced in the last 40 years and its related discussions are getting deeper with the passage of time considering each time new factors and models. The first paper that discussed CLPU was published in 1979 [8]. It conducted a simple experiment on one house with a wattmeter used to measure the power demand of the thermostatic-controlled electric heater circuit. Based on the experimental results, a simple mathematical model was developed to relate the outage time and ambient temperature to the magnitude and peak of CLPU. The model is a first-degree model and it needs constants including the thermal mass and the insulation of the house under study. The system response is shown in Figure 2.1 and it shows that after an outage time of around 3 hours, CLPU demand is constant and maximum. This means that system will completely loose its diversity and all the heating system will be operated.

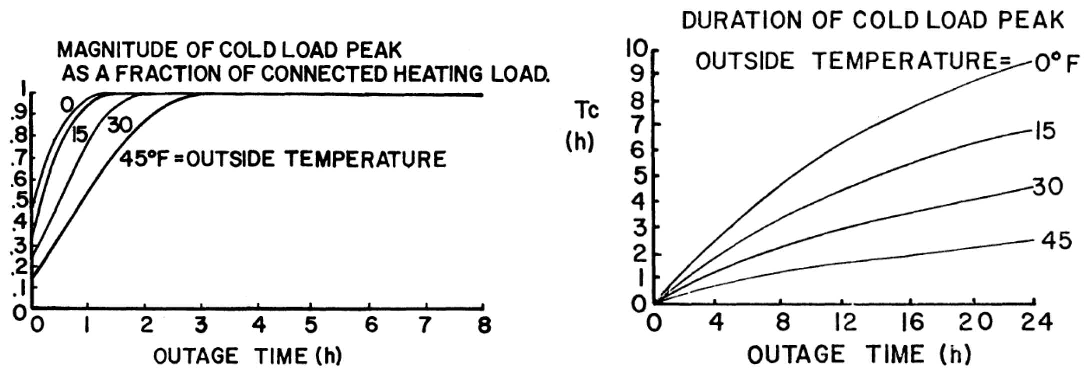

Figure 2.1: Magnitude and duration of CLPU for different ambient temperatures and outage duration based on experimental model [8].

2.1.1 CLPU Models and Effects

After recognizing the cold load pickup model, research focused on better modeling of CLPU to study its impact on the system. In 1981, a more detailed physical and probabilistic model was introduced [9]. New factors are included in this model such as: customer lifestyle and adjustable thermostat settings of heating/cooling loads. Moreover, it uses a more detailed linear model of the house thermodynamics as another improvement from [8]. It included the effect of solar intensity and wind velocity on the outside/inside ambient temperature. The physical model is then used to predict the status of each TCL after power restoration. Using utility and weather data, two examples of CLPU power demand for 10,000 houses after extended outages were produced in Figure 2.2. They show the effect of the outage duration and the diversified power demand before the outage on the CLPU characteristics.

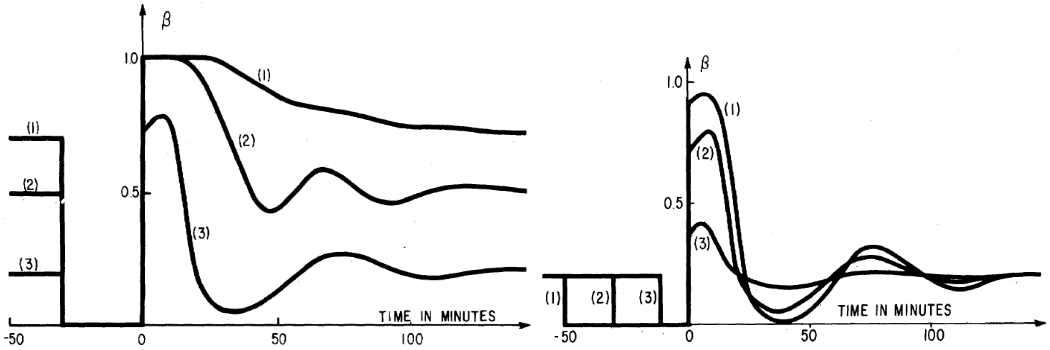

Figure 2.2: Magnitude and duration of CLPU based on physical model (β = actual MW per installed MW) with different TCL concentration and outage duration [9]

In [10], the effect of CLPU events on main transformers was studied. The effect was divided into two parts: a transient or short-term component and an enduring or long-term component. The transient component consists of the motors starting currents and the transformer's magnetizing curve. The enduring component is the demand due to underinvested load due to extended outages. The paper described the latter component as the more pronounced effect that will might lead to a more extended outage due to protective fuse failure on the transformer. It also discussed the effect on the transformer insulation lifetime due to overloading resulting from excessive demand after restoration.

Another quantification of the enduring component of CLPU was discussed on [11]. The authors insisted on the importance of quantizing CLPU magnitude and duration since it will help utilities to correctly size electrical distribution equipment and accurately predict restoration failures and hence to effectively develop restoration strategies. An analytical based probabilistic model was developed considering the thermostat setting, house thermal characteristics, ambient temperature and outage duration. As a result, the TCL demand after restoration was found for a sample of seven houses. The total demand was found be adding the Thermostatic Controlled Load (TCL) demand and NTCL (Non-Thermostatic Controlled Load) demand. The resulted demand

A new mathematical model to quantify the demand after restoration was developed [12]. It heavily depended on survey data that provided the diversity factor, use factor, demand of each type of appliances for different end-users. Based on a linear search program, the maximum possible demand after restoration is determined. This value is useful to design the distribution network based on worst-case scenario.

In a similar manner to [9], a physical based probabilistic model is re-developed with a slight modification. This model considered the aggregation behavior of TCL loads after outages rather than focusing on the post-operation of single thermostatic-controlled equipment. The resultant model is a second-order model that takes into account ambient temperature, thermostat setting and outage duration. Several relationships were obtained between these parameters. This model implied that any outage beyond 40 minutes duration when the ambient temperature is around -15C, all TCL equipment will leave their off status and will operate after power is restored [13].

The author in [14] studied CLPU effect on main distribution transformer using the physical model. The impact on the transformer was quantified in terms of loss of life percentage, insulation characteristics and hot spot temperature. The paper concluded that no protection limits are violated, however it may violate the voltage limits depending on CLPU magnitude.

An attempt to model the largest portion of residential loads which is air conditioning was presented [15]. The authors tried to find a general model that can be used to study TCL demand in any study including CLPU. In the paper, the authors build a model that considered the house thermal characteristic and TCL characteristic. The results show that the TCL loads, Air Conditioning loads specifically, have a duty factor of around 0.8 during peak hours and 0.1 during off-peak hours. It means that 0.8 of TCL population is "On" during peak hours.

In [16], again the effect of CLPU on distribution transformers was studied using a delayed exponential model which is a result from solving the second-degree equation of the physical model. The resulted model can lead to an excessive demand of around four times the normal demand. The model also assumes that the overload period and return to normal condition period are almost similar. Actual tests were carried on 16 pad-mounted and pole-mounted transformers. The hot-spot temperature, oil temperate, loss of life and wining temperature are measured and calculated during a simulated CLPU event. The authors suggested to increase distribution transformer size for loads with high TCL demand due to expected thermal stresses on these transformers during restoration.

Reference [17] went into depth in TCL modeling and simulation. It presented five (5) different models for these loads depending on the house thermal characteristic and ambient temperature. These models are physical model (deterministic differential equation), stochastic, Markov chain matrix model, hybrid partial differentia model and alternating renewal model. Simulations were conducted on these models and they showed that all of these models are almost mutually consistent. CLPU model can use any of these in order to find the magnitude and duration of the event. The authors recommended Markov chain model for CLPU application. Markov chain model requires heavy pre-work, yet it is the easiest to use. The authors also recommended that these models to be studied in conjunction with direct load control methods during extended outages in order to simulate the impact of direct load control.

Another type of excessive demand after outages is discussed on the literature under the name of cold load pickup [18]. It discussed the starting current of air conditioner motors after extended outages and its impact on the distribution system. It presents an aggregation model for air conditioners at a load point. However, the paper did not discuss the enduring part of the cold load pickup due to loss of load diversity.

Another aggregate-based load model is presented in [19]. The authors build a physical model of one type of TCL, which is the electric heater. Different post-interruption simulations were conducted to study the influence of different parameters including the house insulation level, the water heater power rating, water demand and rate of energy extraction. The model did not identify any great impact of the insulation level on the fraction of “on” electric heaters after a 50-min interruption. The number of electric heater operated after a 50-minute interruption is doubled to that number pre- interruption.

In 1994, a probabilistic model is used to model CLPU events based on the physical behavior of the thermal characteristic of the house [20]. The model would stochastically predict the time of switching on and switching off the TCL-based equipment. The probability of switching on and off will depend on the duty cycle of the equipment. The response of the model is shown in Figure 2.3. The effect of ambient temperature and outage duration on the CLPU is presented. After a certain outage duration, the enduring demand will be constant for a longer period and then it would settle gradually. However, the ambient temperature effect is not noticeable on both the magnitude and duration of CLPU event. Rather, a 15-degree Fahrenheit will have an effect of 0.1 pu of the current demand and almost no effect on the duration of the event. A similar work was done on [21] which was compared to actual utility data. The model gave a very close result in one case. In a second case, the model failed to predict the relaxation period and the utility data had a higher current demand the model response.

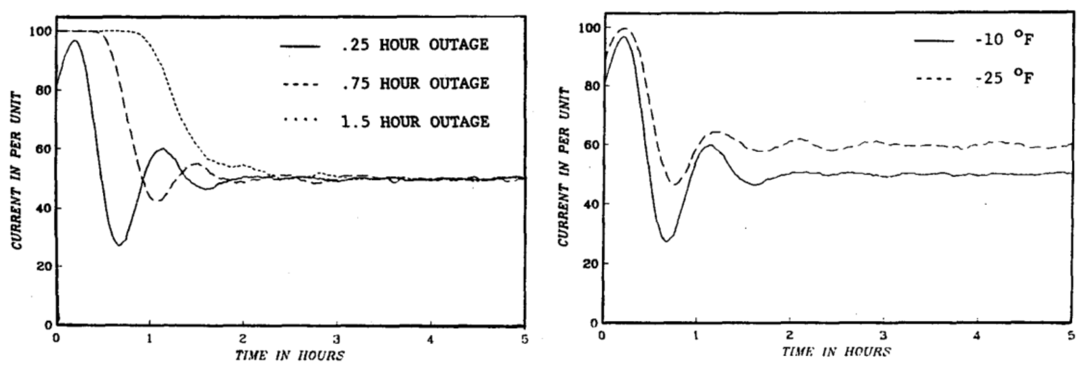

Figure 2.3: Outage duration and ambient temperature effect on CLPU probabilistic model response [20]

A similar approach was used on later work to model CLPU events [22] [23] [24]. Similar results are found and discussed as presented above.

A new CLPU model was introduced as a result of solving the first-order physical model in 1994 [4]. The model was called the delayed exponential model and it can be seen in Figure 2.4. The model represented the power demand after an extended outage where the demand increases suddenly from a diversified level before the outage $\mathbf{S_D}$ to an undiversified level after the outage $\mathbf{S_U}$. This demand will remain constant for some time and will be reduced gradually toward the diversified level. The impact on the oil-filled distribution transformer was investigated and the hottest-spot temperature, top-oil temperature and the loss of life factor were calculated using [25]. This model was the most used among the other models since then due to its simplicity and the next subsection will show example of these application.

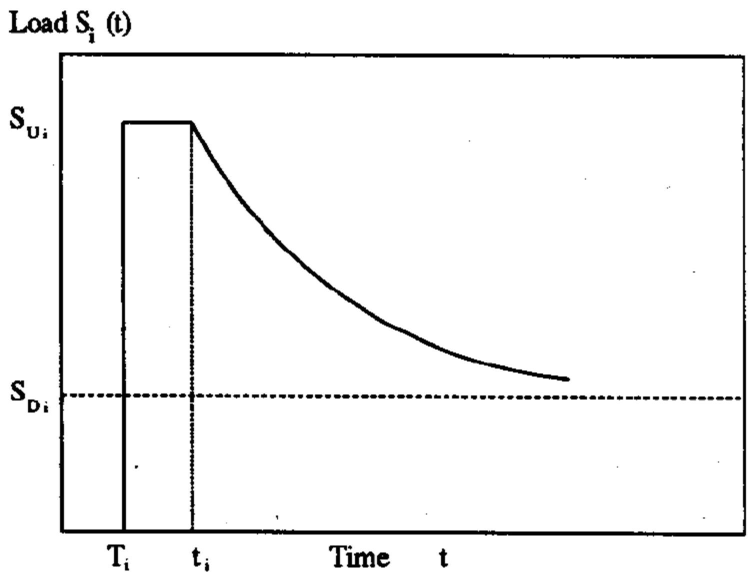

Figure 2.4: The delayed exponential model for CLPU demand [4]

This model was expressed mathematically in (2.1):

$$S(t) = S_D + (S_U - S_D)\, e^{-\alpha(t-t_i)} u(t-t_i) + S_D[1-u(t-t_i)]\, u[t-(R_i - t_i)] \quad (2.1)$$

S_D is the diversified power demand before the outage. S_U is the undiversified power demand, which is the power demand after restoration directly considering CLPU which will be affected by the operation of TCLs. The relation between S_U and S_D will be determined based on the selected model. The CLPU duration was estimated to be 30 minutes and the rate of decay α was selected to be 0.5 hr^{-1} based on recorded events and main transformer overload capability [4].

On the same year, a random variable model is developed [20]. The model deployed Non-sequential Monte Carlo Simulation (NSMC) simulation to predict the status of the appliance. The probability of the equipment being on depends on the duration of on-status and off-status in any given day. However, this probability will be altered for TCL after an extended outage. This alteration will increase the on-status probability and will depend on thermal probability of the house.

Although the results of the model are realistic, the paper did not provide enough scientific basis to the on-status alteration probability. However, it was a start for all the stochastic models related to this problem.

The water heating load in cold regions in the winter have the same impact on CLPU demand as the air conditioning in hot regions in the summer. Its impact was studied in detail in [21] with a physical model represented by an electric circuit shown in Figure 2.5.

The switch S will control the flow of the injected/drawn heat from the building based on the thermostat setting. This model shows the impact of the building characteristics on the status of the heating/cooling loads.

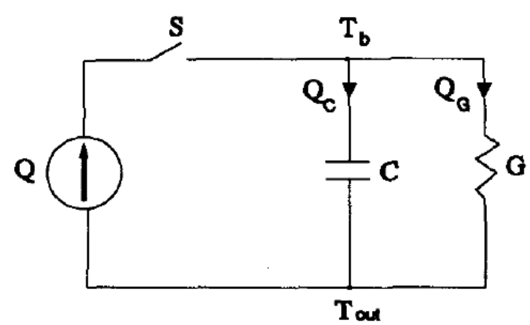

Figure 2.5: Physical model for a thermostatic-controlled load [21]

Another model is developed to predict CLPU parameters based on the harmonic model algorithm [26]. This algorithm was used to solve the differential equations for the house thermodynamics and find a steady-state response for each region on the solution. The model is applied for short outages and long outages. The CLPU period for long outages is around 20 minutes and the demand after CLPU will settle down after around 45 minutes.

In papers [27] and [28], the authors provided a method to optimize power distribution system design to accommodate CLPU events. The papers considered the outage cost, transformer operation cost and the sectionalizing switch cost. The papers used the delayed exponential model and recommended increasing the transformer size or adding more sectionalizing switches to ease restoration after CLPU events. The occurrence rate of CLPU was once every two years and CLPU duration was taken to be 30 minutes.

A similar work was presented in [29] with more constraints and more factors considered. A new cost function is introduced with all the power system component initial costs are present along with the energy loss cost and the delayed restoration cost.

In the last few years, a new stochastic model is presented depending on Ornstein-Uhlenbeck Process [30] [31]. The model showed promising results that were used to study the impact of CLPU events and ambient temperature on the main distribution transformer. The paper showed an example of a CLPU event as simulated by this stochastic model as a 4-hour outage resulted in twice power demand as the normal case with CLPU duration of around 5 hours.

Recent work on CLPU modeling includes another stochastic model of this phenomena in [3] known as multi-state model which resulted in similar behavior as actual recorded CLPU events. The introduced model resulted in a CLPU magnitude on 1.49 and a duration of 45 minutes as a result of a 3-hour outage. It was similar results to the delayed-exponential model and closely mimicked the recorded CLPU event as shown in Figure 2.6.

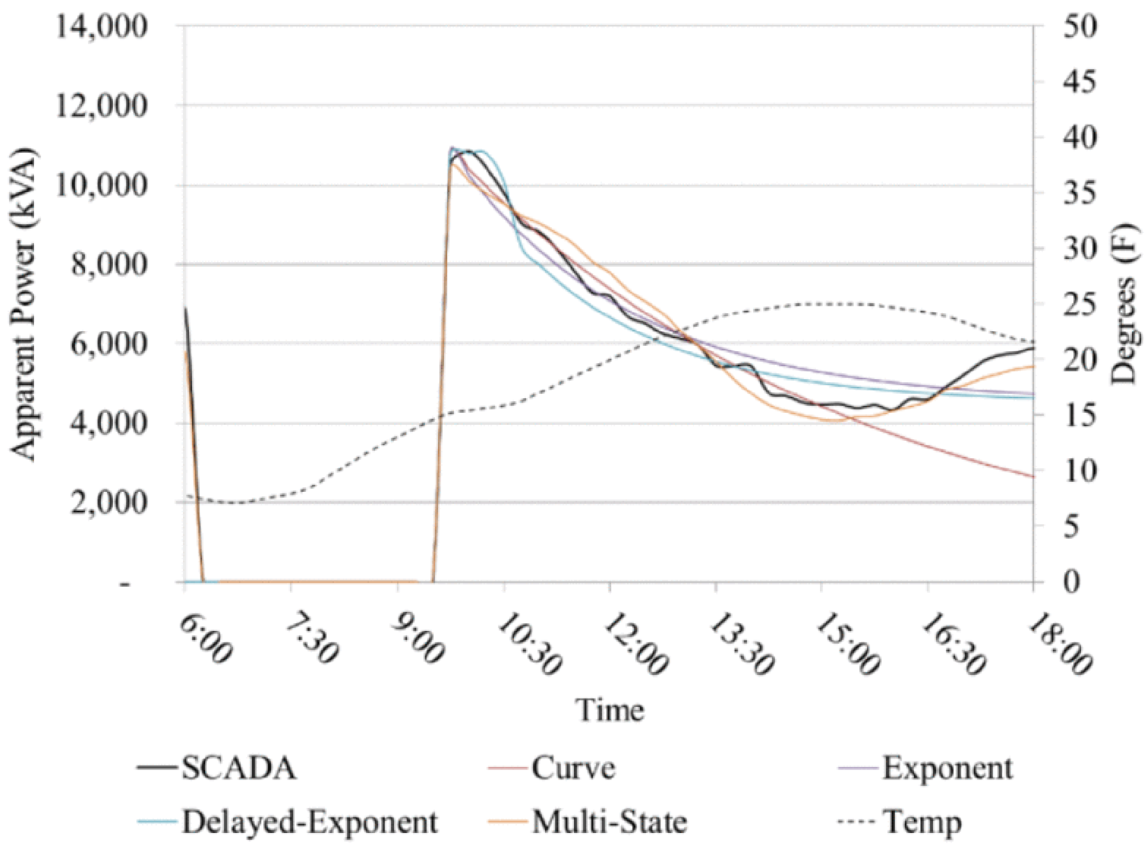

Figure 2.6: Comparison between a recorded CLPU event versus different CLPU model for a 3-hour outage [3]

Other stochastic models were explored such as fuzzy-based models in [32]. The resulted model did not show enough flexibility to be utilized in later work. All the above models in this sub-section are only an insight to explore CLPU. The problems associated with CLPU is discussed on the next sub-sections.

2.1.2 Service Restoration after CLPU

CLPU measurement and models present a clear impact on distribution equipment including transformer and cables [33]. Another impact caused by CLPU events is the activation of protection elements in the power system causing another failure [34]. This impact will have to be dealt with during restoration either by minimizing the demand current or by sectionalizing the restoration. A lot of work focused on this area using different methodologies with several optimization techniques. In [4], an optimal restoration plan was determined considering transformer overloading constraints provided in IEEE transformers loading guide [25]. The objective function was based on minimizing the time and the number of affected customers as per (2.2).

$$Minimize\left(\sum_{i=1}^{n} C_i T_i\right) \tag{2.2}$$

An optimal restoration plan was developed accordingly on a test system of ten (10) load points using a global search technique. The hot-spot and top-oil temperatures of the transformer during the restoration is shown in Figure 2.7. The exact methodology and problem formulation was followed in [35] and similar results were obtained, however using GA and in [36] using adjacent pairwise interchange method (APIM).

The same authors of the previous paper developed another restoration plan for a distribution system of ten (10) load points [5]. In this work, the same objective function and the transformer thermal capabilities constraints are used. Yet, a different CLPU characteristics at each load point is utilized. The different load points were assigned different CLPU durations, from 10 to 30 minutes, and settling times, from 100 to 160 minutes. Also, the problem was solved by APIM, which is a method used to solve sequence problems and can result in a local optimum solution.

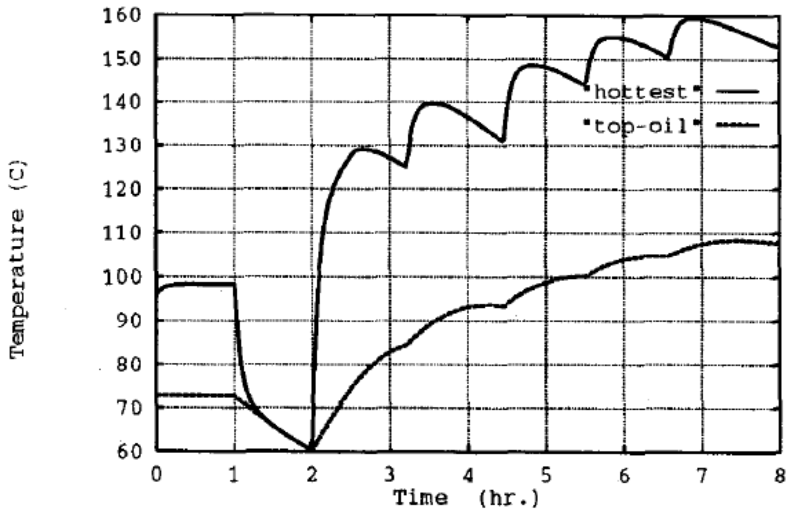

Figure 2.7: Transformer hot spot and top oil temperatures during restoration [4]

In this paper also, the authors linked the restoration plan to the reliability indices to show the importance of faster restoration. The reliability indices used to measure how fast the restoration is named CID; average customer interruption duration. This index is directly related to SAIDI and CAIDI, however it is used about one outage only unlike the latter two indices. The optimization problem was solved using GA. Several examples were simulated, and CID varied from 28.17 minutes per customer and 57.6 minutes per customer [5]. Similar analysis and results were presented in papers such as [37] [38]. Other optimization methods are used to solve the optimal restoration problem with similar objective function and constraints. The problem was solved using rule-based prediction and advanced analysis [39] and Ant Colony Optimization (ACO) method [40]. No comparison results are reported with respect to the previous methods.

An expert system was developed to determine the maximum restorable load after any failure [41]. A knowledge base must be built based on previous events and measurement. The knowledge base can contain information such as: outage duration, ambient temperature, number of affected customers and resulted voltage drop after restoration. The expert system has a human interface platform to allow system operator to use it before restoration. The expert system was applied on one feeder system with 1000 customer with equal power demand. The system outcome is the number of customer that the system operator can restore the power to. If no single-step restoration is allowed, expert system is applied again to determine when the power can be restored to the next batch of customers.

A multi-objective restoration plan is reported on [42]. The two objective functions were translated to a one objective function through weighting factors techniques. The paper provided an example of a CLPU event that has a magnitude of 2.5 of the nominal value and the complete restoration was done in 3 hours and 13 minutes.

Other constraints have been considered to guide the restoration process such as frequency constraints [43]. The sudden demand of CLPU will disturb the system frequency as shown in Figure 2.8.

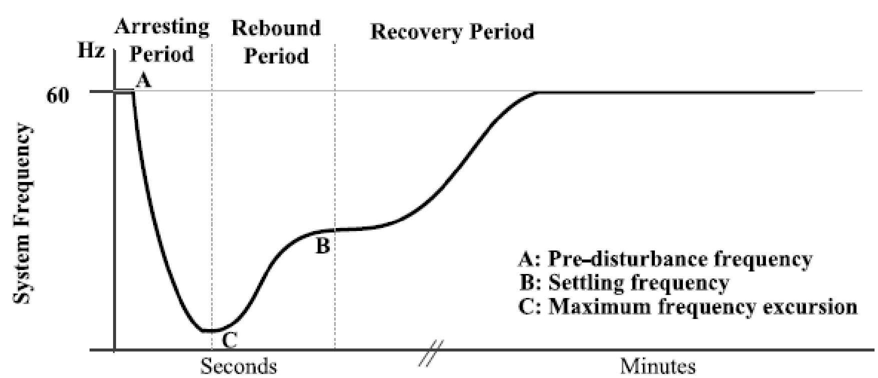

Figure 2.8: CLPU frequency response [43]

Typical synchronous machine first-order differential equations are used to represent the frequency model for distributed generators (DGs). The objective function was defined to reduce the probability that machines will neither lose synchronism nor trip during CLPU event. The results are the sequence of restoration of the affected system. It took up to 53 seconds to restore the complete system. The paper did not consider any other constraints such as the voltage limits and equipment thermal loading. Therefore, the results are in seconds and would not have much effect on reliability indices if calculated. Using the frequency response of the machines as a constraint, the authors in [44] determined the maximum restorable load after power sources restoration. The maximum restorable load without causing a CLPU event that violates frequency operation limits can reach to 20% of the total load in some cases. Lastly, other sources such as [45] [46] have studies the impact of frequency disturbances during restoration without results worth highlighting.

Other literature has focused on other practical aspects of the restoration problem [47]. The enduring power demand after CLPU event will cause protection system activation. The phase relay or overcurrent will be activated, and an adjustment must be made to avoid another outage. A CLPU delayed model is used to change the protection setting adaptively to avoid protection relays activation. The paper assumes that CLPU impact will last for 30 minutes. This problem of protection setting is also discussed in [34].

Some of the papers above have linked the restoration process to the reliability assessment of the network to show the importance of faster restoration or to introduce a cost for the outage [5] [37] [38]. However, none of these sources used the reliability indices as an objective function or a constraint. This is due to the fact that these papers have developed algorithm for single outage while reliability indices will be measured over a period of time.

The first inclusion of CLPU in reliability calculation was in [6] assuming restoration failure. A detailed experimental load model was used and found the average occurrence rate of CLPU events per year. The model found out that for 70% TCL concentration out the total load, CLPU occur with a probability reaches 90%. In other words, 9 outages out of 10 can cause CLPU events. For the best-case scenarios, under a low TCL concentration level, there is 20% chance that an outage can result in a CLPU event. Due to CLPU, the failure rate at a load point can increase from 0.47 to 0.68 per year if no restoration plan is developed. Another stochastic model [7] utilizing a Monte Carlo platform [48] is used and also found the occurrence rate of CLPU event is a distribution power network. Any restoration that caused the power demand excessing the transformer limits and the voltage buses limits is considered a CLPU. In [6] and [7], CLPU was reflected in SAIFI calculation, not in SAIDI since no restoration plan is developed.

2.1.3 CLPU in Modern Power Systems

CLPU problem appears also in modern microgrids applications including smart homes, smart self-healing and demand response. In 1994, Harmelen and others developed decentralized intelligent controllers for individual homes. The controller deployed several control methods for each type of load in the house as illustrated in Figure 2.9 [49].

Out of the four (4) network-connected controllers, an artificial neural network controller is used to alter the thermostat setting of the storage water heater. This controller is trained to response to the house temperature through electronic sensors. Subsequently, the controller can decrease the required water temperature in order to reduce the heater power demand. Such a control will reduce the power demand during cold load pickup events. The demand did not increase dramatically after restoration due to load controller operation [49].

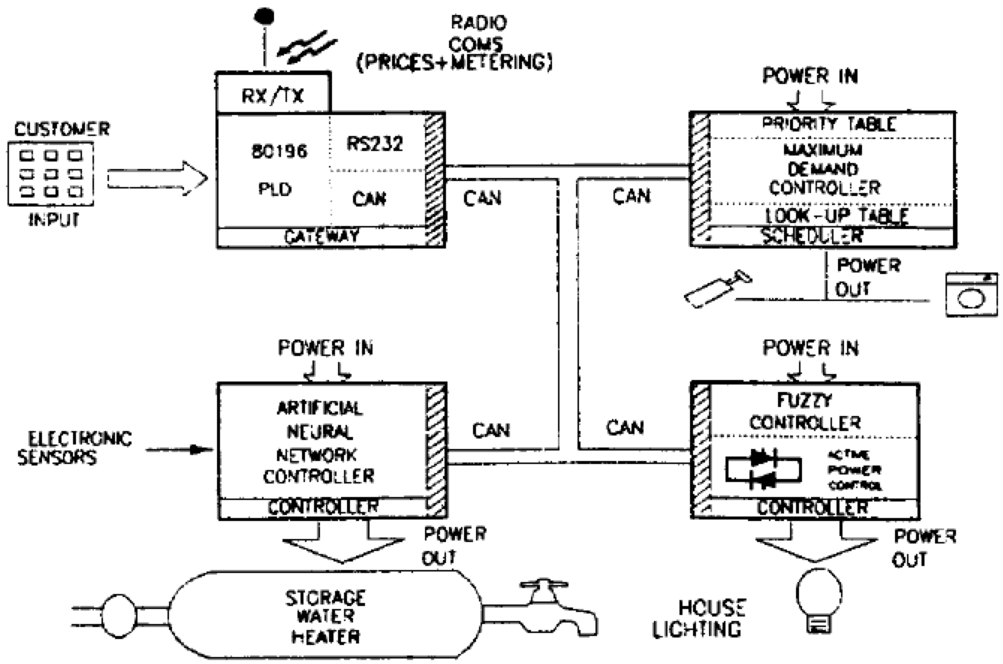

Figure 2.9: The decentralized intelligent controller [49]

CLPU problem was also linked also to demand side management (DSM) [2] [50]. As per these sources, DSM must perform well in extreme CLPU conditions as demand can reach five (5) times the original shed load for few hours. In [50], the proposed control method is centralized unlike previous work in the literature. The paper introduces the control goals and strategy to reduce the overall power demand at the main transformers. The control goals are introduced for different tariff structure, energy charge tariff and Time-of-Use (TOU) tariff. The strategy is to reduce the peak demand resulting from normal high demand during peak hours or from CLPU events by controlling the operation of the water heater. The results are promising and the peak demand after restoration was reduced to 85% of the base case and curtailed the demand to an acceptable level as shown in Figure 2.10.

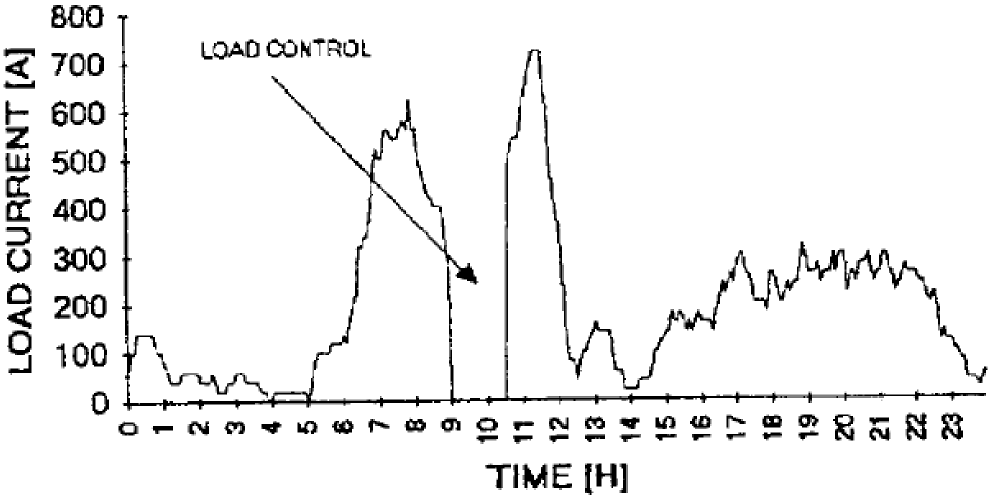

Figure 2.10: Cold load pickup event with load control [49]

Later in 2008, an innovative load control system is proposed [51]. The new load control will utilize an algorithm, after each outage, to control air conditioner operation to support faster restoration. Yet, it will work to maintain a high comfort level for customers. The system is built using a centralized DSM system.

In the same year, a patent was awarded for building a DSM system that can anticipate occurrence of a CLPU event and deactivate TCL loads remotely. The proposed system is local and can communicate with central control systems [52]. A stochastic residential load model is developed using a Markov Chain MC (MCMC) using TOU curves [53]. The paper studies the impact on the residential demand with a price-based demand response under normal and special operations including CLPU events. The automatic demand response for TCLs was modeled using optimal scheduling and thermostatic controllers. In the optimal scheduling, individual TCL is switched off/on based on the overall demand. These loads can be switched off during CLPU events. The other technique is to control the thermostatic setting of TCLs. The controller would change the upper or lower setting of the thermostatic to reduce the number of the operated devices after restoration. With automatic demand response, the maximum demand of the power network is reduced. Consequently, the impact on thermal line loading and per unit voltage at the main bus is less the base case without demand response controllers. Similar results are reported in later work showing the great impact that DSM had on reducing the effect of CLPU events [54] [55].

A novel method is introduced in [56] to restore the affected load points in future microgrids. The work assumes the existence of DGs and Energy Storage System (ESSs) at selected nodes at the grid. The objective function is to maximize the restored energy at the shortest time possible. The system voltage constraints and DGs' maximum generators are considered. The optimization problem is solved using Mixed-Integer Linear Programming (MILP).

Reference [57] provides a method of optimal size and location of DGs considering one-step restoration using genetic algorithm. The transformer loading and bus voltage limits of all load points were taken as the constraints for this problem. Optimal DG design, it terms of size and location, has led to better restoration of the distribution system as shown in Figure 2.11.

In the single-step restoration problem, DGs helped to reduce the load during the outage of the grid by supplying portion of the load. Consequently, reducing the impact of CLPU by keeping the diversity at that supplied portion. Therefore, single-step restoration is possible by designing the DG size and location for the worst-case CLPU scenario. Similar work and results are reported in [58].

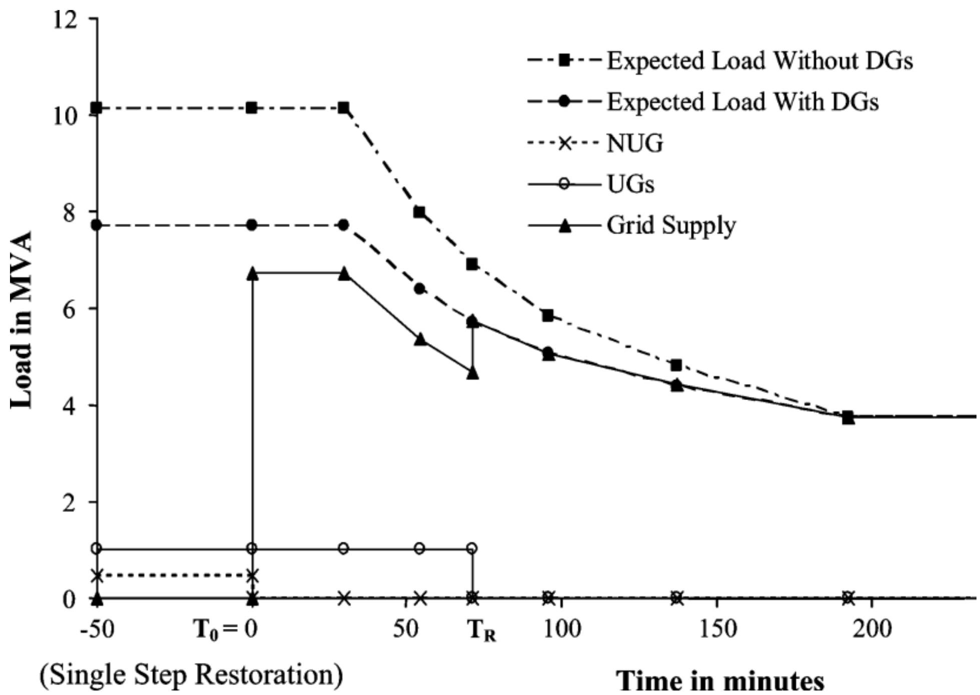

Figure 2.11: Graphical representation of the single-step restoration [57]

Finally, CLPU events was discussed under the presence of Electric Vehicle (EV) in the power network [59]. EV recharging can cause further overloading on the main distribution transformer and must be considered during planning for future power networks.

2.2 Optimization Platform

In this thesis, an optimal program is needed as this work assumes utilities' awareness about CLPU related issues. Therefore, utilities will sectionalize restoration in order to avoid violating system constraints. Utilities will apply an optimal restoration plan to restore the system as fast as possible within system limits. Different optimization methods will be used to find the restoration plan. The legacy methods will be compared with a state-of-art method for global optimization. The following sections will introduce these methods.

2.2.1 Traditional Evolutionary Computation Techniques

In this thesis, three well-known evolutionary computation (EC) methods will be used to develop the optimal restoration plans: GA, PSO and DE.

2.2.1.1 Genetic Algorithm (GA)

Since its introduction in 1975, GA has been the most popular EC technique [60]. GA algorithm mimicked some of the features of the natural evolution theory. A lot of modified versions of GA has appeared in the research. Yet, all of them depend on the same building blocks of a standard GA including tournament selection, crossover and mutation. In this thesis, a standard form of GA, called real-coded GA (RCGA), is used to solve the optimization problem. Although a lot of new EC techniques has appeared since GA introduction, GA is still one of the leading EC techniques in the literature due to its robustness and stability [60] and has been used in popular power system problems [61].

Table 2.1 shows number of GA-related publications in Google Scholar and IEEE Xplore in the past three years. The table shows high number of GA publications with respect to the fact that GA is the oldest EC technique.

Table 2.1: GA publications and citation in the past three years in IEEE and Google Scholar

	Google Scholar	IEEE Xplore
2015	108,500	3,215
2016	77,900	3,487
2017	64,500	2,961

2.2.1.2 Particle Swarm Optimization (PSO)

The second method resembles also a nature-based phenomenon and called Particle Swarm Optimization. It was the results of a cooperative work between a social scientist and an electrical engineer in 1995 [62]. In this technique, particles have two learning aspects: psychological and social. Pericles can learn from both their own experience and other particles experience. This extra information helped PSO to get better results in so many problems in different applications [63]. Such results can explain the exponential growth of PSO adaptation in research including power system problems [64] [65]. Figure 2.12 shows PSO publication and citation in the period from 1995-2006 which increases from 28 to 1230 in the span of 12 years with respect to Google Scholar measures [62]. This growth continued in the past three years and based on the search in the database of Google Scholar and IEEE Xplore, the results in Table 2.2 are obtained.

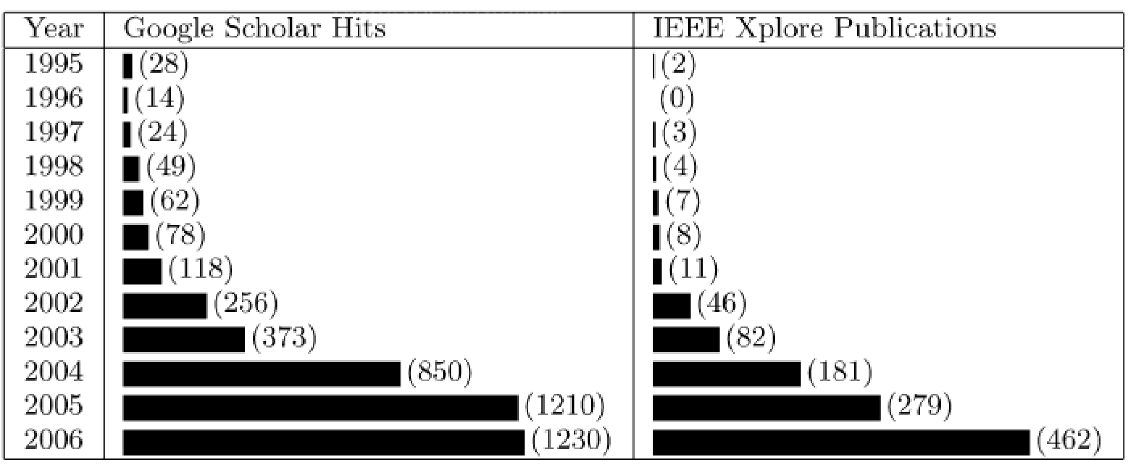

Figure 2.12: PSO publication in the period from 1995-2007 [62]

Table 2.2: PSO publications and citation in the past three years in IEEE and Google Scholar

	Google Scholar	IEEE Xplore
2015	28,500	1,750
2016	28,800	2,008
2017	17,300	1,861

Since this search is conducted early 2018, the reduction of 2017 publication might be explained by late addition of 2017 conference papers to the database.

2.2.1.3 Differential Evolution (DE)

Finally, the third method that will be utilized is Differential Evaluation (DE). DE was first introduced in 1994 by Storn [66]. It was introduced with different schemes, which are working to find the global objective functions with minimum control variables as possible.

One of these scheme is scheme #1 which is shown in Figure 2.13. Three solution vectors are selected randomly from the current population. They will be used to generate a new solution that might be closer to the objective function [67].

In the literature, DE is one of the most popular EC methods with around 125,000 publications in Google Scholar as shown in Table 2.3. Although DE is proved to be effective in all applications including power system problems [68]. However, DE has been used less in applications related to electoral and electronics since it has just above 500 publications per year.

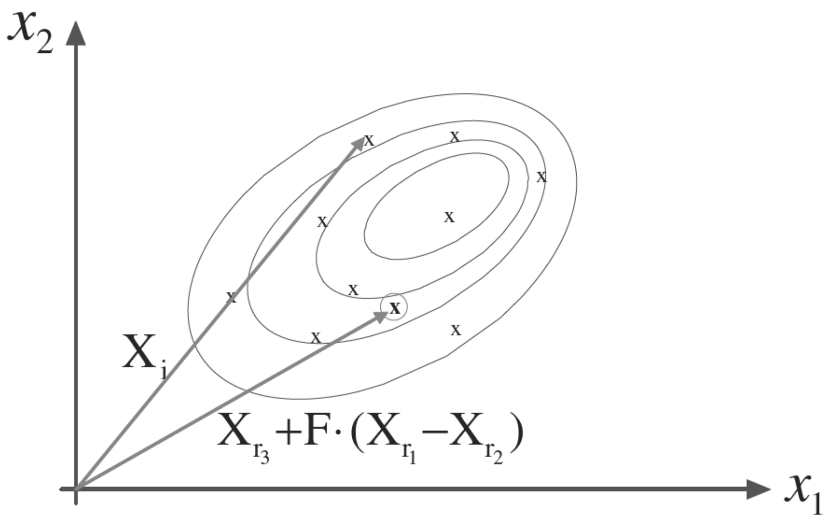

Figure 2.13: DE selection process based on scheme 1 [67]

Table 2.3: DE publications and citation in the past three years in IEEE and Google Scholar

	Google Scholar	IEEE Xplore
2015	125,000	500
2016	76,800	576
2017	36,800	523

2.2.2 Lightning Search Algorithm (LSA) Platform

In this thesis, a state-of-art optimization method is used to solve the optimization program. This optimization technique called Lightning search algorithm (LSA), which is a state-of-the-art search technique that is recently developed in 2015 [69]. LSA, like most of the search-based EC algorithms, is a nature-based technique such as GA and PSO. LSA resembles the operation of GA and PSO is several aspects. LSA has a forking possibility that can alter objective function search toward areas that were not explored before. Forking has a very low probability to happen in every iteration, around 5% to 10%, similar to the mutation operation in GA. Also, LSA updated all solutions in each iteration with respect to the global best solution in a similar fashion to PSO [69].

When LSA first developed in [69], it was tested against traditional EC techniques using 24 test functions. LSA had better performance resulting in the most optimal performance in 21 times more than any other methods. LSA showed enough robustness and stability to be considered in future optimizing problems in different applications.

LSA is utilized in [70] to find optimal PV controller parameters and the results were compared to those obtained by PSO and Differential Search Algorithm (DSA). The results revealed that LSA has a better performance in terms of convergence characteristics in comparison to the other two methods. Moreover, source [71] solve the optimization program to extract the optimal solar cell parameters in all weather conditions using LSA. LSA was again compared to PSO and Bee Colony Optimization (BCO) and showed batter results and satisfactory convergence characteristics.

LSA was also used in other power system application including optimal parameters selection for wind power model [72]. Recently, a Quantum-LSA (QLSA) was developed and used in different application including induction motor drive [73] [74] [75] [76]. LSA was further developed in [77] to a hybrid LSA-Artificial Neural Networks (ANN) design, in [78] to a multi-objective EC method and in [79] to a quantum binary lightning search algorithm leading to even better performance with various applications.

Although LSA was developed recently, yet its citation has increased dramatically over the past three years. Table 2.4 shows the citation of LSA over the period from 2015 to 2018.

Table 2.4: LSA publications in Google Scholar since 2015

	LSA in Google Scholar
2015	7
2016	16
2017	59

2.3 Conclusion

This chapter conducted a comprehensive literature review on CLPU problems. Starting with modeling and simulation problems until smart gird applications with the presence of CLPU events. A huge portion of the literature review discussed the power system restorations issues where single step restoration becomes prohibited under CLPU. This will delay restoration beyond the original expected down time which was due to the equipment failure. Some work has considered CLPU impact on the reliability indices by counting the CLPU evens as additional failures, hence impacting SAIFI. Yet, no previous work has considered measuring the impact of CLPU on the time-based reliability indices such as SAIDI, CAIDI and ENS. The impact of CLPU is correctly measured when it is reflected in the time-based reliability indices since the customer will experience a power outage that is due to the equipment down time and the restoration delay due to CLPU. Also, all the CLPU-related power restoration problems utilized exclusively a deterministic load model to model the customer behavior as shown in Subsection 2.1.2. Therefore, this work will fill this gap in the literature by reflecting CLPU in the time-based reliability indices in a realistic manner by utilizing a stochastic load model.

CHAPTER 3

SYSTEM MODELING

This chapter will discuss the modeling of the system components that will be used in this work. It will start by modeling the most important component in this problem which is the load. The load will be modeled stochasticity to reflect the random behavior of the customers. This load model will be used an input to the CLPU model in the following section. This model will be used to simulate such CLPU responses after different failures. Finally, the test system will be selected, and its component will be modeled to find the power flow study parameters and reliability study parameters.

3.1 Load Model

There are several options to model the load for any power system problem. The best option can vary depending on the problem type, the required accuracy level and the required randomness level. In this particular problem, the load points' demand during restoration is a very important detail for the system operator. Therefore, a high level of accuracy is required to estimate the demand. Moreover, in CLPU problems, there is a high correlation between the load demand and the ambient temperature and the customer behavior. In order to achieve a more realistic and accurate results, a stochastic load model is selected for this problem. The model is developed for the tested residential distribution power system using TOU curves. These TOU curves are published in several countries for research and other purposes [7] [48]. After careful search, it was found that TOU curves are not published locally. Due to the high correlation between TOU curves for TCL load and ambient temperature, international TOU curves cannot be used for CLPU problems locally. The following subsections will detail the procedure to find the stochastic load model for TCLs and NTCLs.

3.1.1 TOU Curves for Non-Thermostatic Controlled Loads (NTCLs)

For NTCLs, it will be assumed that the human behavior around the world is similar. In reference [80], National Renewable Energy Laboratory provided the energy consumption data for USA households'. Energy demand statistical reports are developed and provided for every hour in the 24-window. This information is developed using smart meters' data. Figure 3.1 shows an example for a TOU curve developed by the later reference.

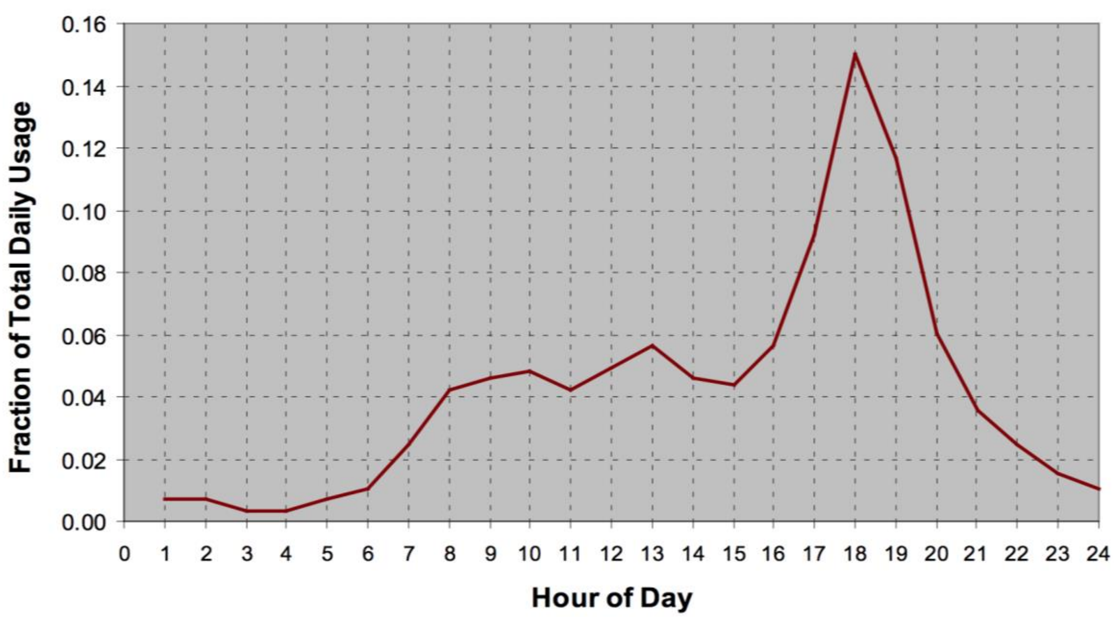

Figure 3.1: TOU curves [80]

National Renewable Energy Laboratory data will be used for this work as the TOU curves will estimate the status of the equipment for every minute in the simulation period.

3.1.2 TOU Curves for Thermostatic Controlled Loads (TCLs)

This subsection will detail the steps to develop TOU curves for TCLs. For heating/cooling loads, the local city's ambient temperature (T) will be the single factor to develop these curves. Hence, it will be the only factor to be considered to determine the probability of use AC loads. Equation (3.1) explains the relation used to generate TOU curves for TCLs. For every thermostat-controlled load, there is a dead-zone where the appliance is expected to be off. The ambient temperature during that dead-zone will be marked T_D and T_U. T_D is the lower band temperature and T_U the upper band temperature.

$$\boldsymbol{P}_{TCL} = \begin{cases} \left(\dfrac{\boldsymbol{T} - \boldsymbol{T}_U}{\boldsymbol{T}_{\max} - \boldsymbol{T}_U} \right) \boldsymbol{P}_{\max} & \forall \quad \boldsymbol{T} \geq \boldsymbol{T}_U \\ \left(\dfrac{\boldsymbol{T}_D - \boldsymbol{T}}{\boldsymbol{T}_D - \boldsymbol{T}_{\max}} \right) \boldsymbol{P}_{\max} & \forall \quad \boldsymbol{T} \leq \boldsymbol{T}_D \\ 0 & \forall \quad \boldsymbol{T}_D \leq \boldsymbol{T} \leq \boldsymbol{T}_U \end{cases} \tag{3.1}$$

As per Equation (3.1), the probability increases as the difference between the ambient temperature and the AC thermostat settings' dead-zone (between T_D and T_U) increases. The dead zone of the thermostatic control (T_D and T_U) varies based on user comfort and tariff structure in the respective country.

Figure 3.2 is developed to present the relationship between the ambient temperature and the probability of operating TCL device.

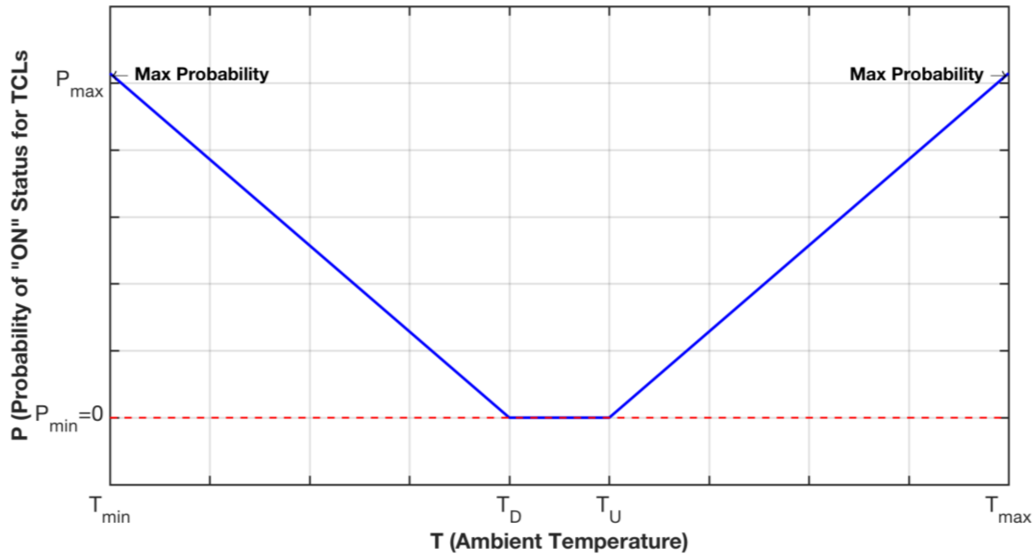

Figure 3.2: Relationship between "ON" probability and ambient temperature

3.1.3 TOU Curves Adjustment

TOU curves are produced for all appliances in TCL and NTCL categories. These curves will go through several operations to produce the excepted power demand from each appliance. TOU curves are the probability of each appliance to be turned "ON". Therefore, these curves will be adjusted to determine the probability to be "ON" at that specific hour regardless of the operation starting time. This will be achieved by multiplying the curves by two factors for each appliance. These multipliers are the load factor (LF) and the demand factor (DF) in that respective country. Multiplying the curves by LF will translate the curves to the probability of each type of appliance to be "ON" during peak demand. Multiplying the curves further by DF will translate the curves to the portability of each appliance type to be "ON" out of the installed capacity. Equations (3.2) and (3.3) defines DF and LF respectively.

$$LF = \frac{Average\ Demand}{Peak\ Demand} \tag{3.2}$$

$$DF = \frac{Peak\ Demand}{Maximum\ Possible\ Demand} \tag{3.3}$$

3.1.4 Stochastic Load Model

The methodology to produce stochastic load model is detailed in multiple steps in Figure 3.3. It starts by adjusting the curves, then determining the number of units in every load point and finally finding the status of every equipment. Subsection 3.1.4.1 to Subsection 3.1.4.4 will explain these steps in details. These steps will ensure that the given average load demand over a specific duration of time at each load point is not altered. However, the load will change stochastically to represent the stochastic customer behavior correlated with the ambient temperature.

3.1.4.1 Installed MW Capacity

The load points' information is usually provided in terms of average MVA demand over one year. In order to determine the installed capacity at each load point, the average demand shall be multiplied by the same factors used before to adjust TOU curves, which are LF and DF. Using LF will adjust the average demand to the peak demand as per (3.2). Moreover, using DF will adjust the peak demand into installed capacity as per (3.3). Finally, the MVA installed capacity is multiplied by a typical residential power factor to find the MW installed capacity at each load point.

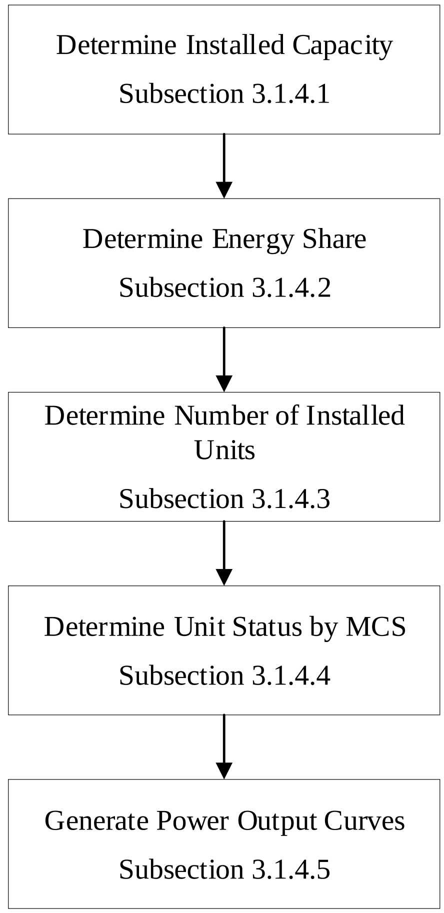

Figure 3.3: Flowchart to produce stochastic load model

3.1.4.2 Energy Share

The appliances' energy share information is published by power service regulators and providers. The energy share is how much every appliance type is consuming out of the demand. An example of the energy share information are provided in Figure 3.4 [81]. Based on the energy share data, installed capacity per appliance can be determined. If, for example, 9.5% of the energy share is water heating, then 9.5% of the installed capacity are water heaters.

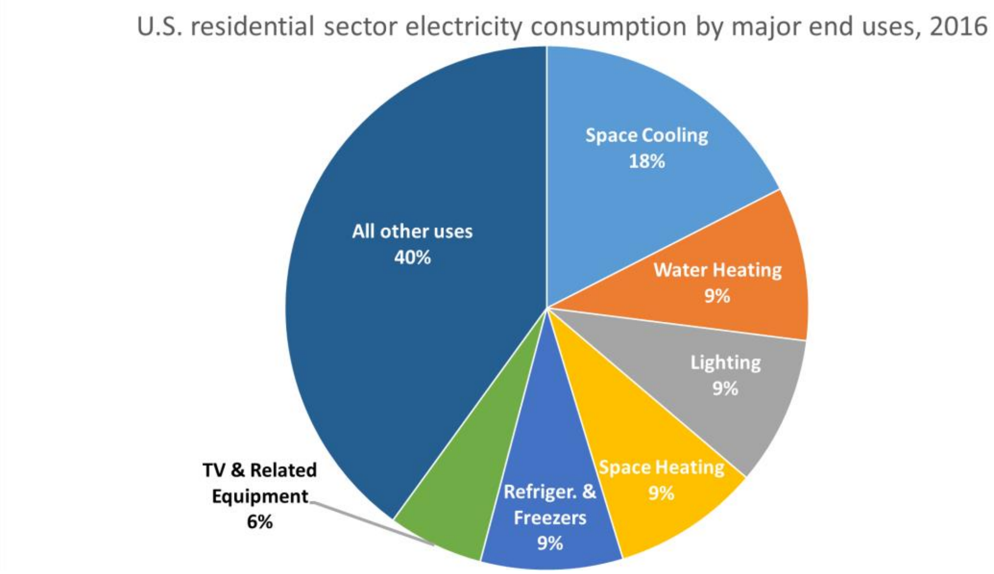

Figure 3.4: Example of energy share information in USA in 2016

3.1.4.3 Installed Appliances

The number of units at each load points will be determined by dividing the appliance installed capacity by a typical power rating of the appliance. For example, if there is 1500 kW installed capacity of air conditioners, which has a typical 1.5 kW power rating, then it can be estimated that there will be 100 air conditioners installed at the houses that belong to that load points. The same will be applied for the other types of appliances. The reactive power demand will be found based on a typical power factors for home appliances presented in [82], resistive loads such as oven have a unity power factor while AC and washing machines have a 0.8 power factors. Refrigerators and electronic appliances including TV, lighting, laptops and others will have a power factor of 0.9 [82].

3.1.4.4 Determine Individual Unit Status by NSMC

After finding the number and the type of each appliance in each load, NSMC will be used to determine the status of each appliance at any given minute of the simulation. NSMC is a sampling method used to through a random number and compare it to a certain occurring probability. In this thesis, the generated random number will be compared to the adjusted TOU curve at that specific minute and the equipment status will be found based on (3.4). NMCS will be done on a large group of equipment and will be repeated over every day for every minute. This repetition will ensure convergence toward the steady state probability and hence a smooth output is ensured. The same method was utilized in similar work in [7] [48].

$$\begin{aligned} &random\ number\ \leq TOU(minute) \rightarrow Appliance\ \ "ON" \\ &random\ number > TOU(minute) \rightarrow Appliance\ \ "OFF" \end{aligned} \tag{3.4}$$

3.1.4.5 Energy Demand Generation

After determining the status of each appliance in the load points, the power outputs of each appliance with “ON” status are added together to yield the stochastic power demand at that minute of the simulation. The same will be repeated for every minute and therefore the power demand is found for the simulation period. The resulted output is stochastic modeling the customer behavior and is correlated with the ambient temperature of TCLs.

3.2 CLPU Model

3.2.1 Selected CLPU Model

After a CLPU event, the delayed exponent model [16] will be used to simulate the sudden increase in load demand of TCLs with the other loads remain unchanged. Then, the total demand will be the adjusted TCLs demand plus the remaining unchanged non-thermostatic controlled loads (NTCLs). The exponent model is presented in Figure 3.5 [29]. It is most used CLPU model in the literature and was proven by actual recorded CLPU events in Figure 2.6. The selected delayed exponential model can be described by (3.5).

$$S(t) = S_D + (S_U - S_D)\, e^{-\alpha(t-t_i)} u(t-t_i) + S_D[1-u(t-t_i)]\, u[t-(R_i-t_i)] \quad (3.5)$$

S_D is the diversified power demand before the outage which will be found as an output of the stochastic load model. S_U is the undiversified power demand, which is the power demand after restoration directly considering CLPU which will be affected by the operation of TCLs.

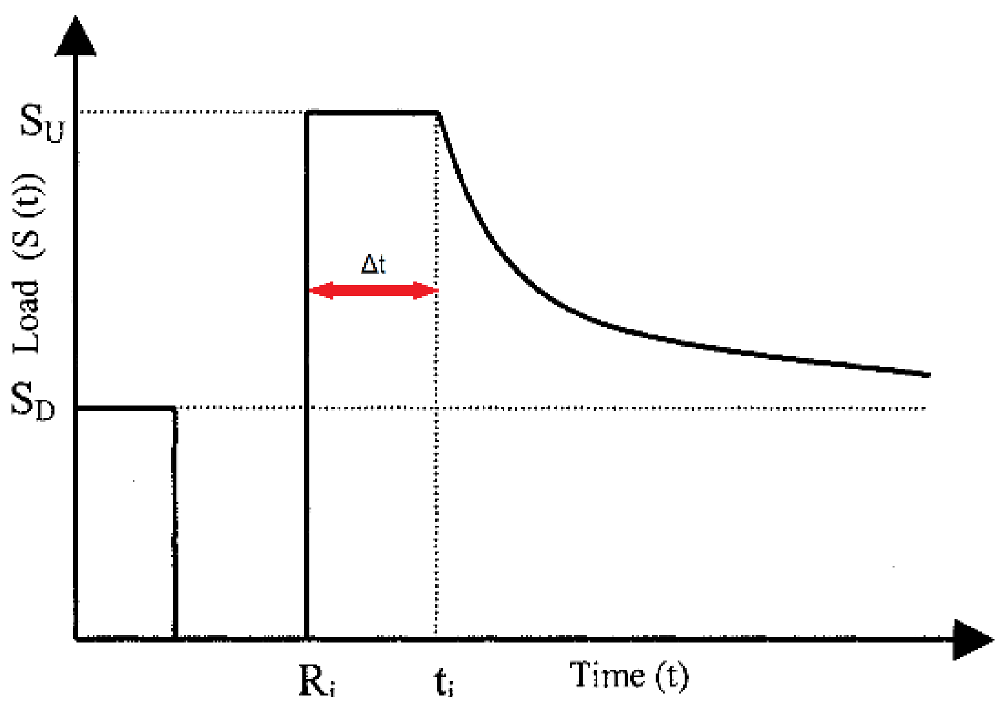

Figure 3.5: Delayed exponent model for CLPU [29]

3.2.2 CLPU Model Parameters

In the selected model, there are several parameters that must be determined after each outage. S_D will be input from the load model detailed in Section 3.1. S_U is the power demand after restoration directly. The relation between S_U and S_D is defined as CLPU magnitude as per (3.6).

$$CLPU_M = \frac{S_U}{S_D} \tag{3.6}$$

S_D as found from the load model can be broken into two terms, for TCL and NTCL loads as explained by (3.6).

$$S_D = S_{D_{TCL}} + S_{D_{NTCL}} \tag{3.7}$$

The increase in S_U value after restoration is due to loss of diversity between TCL loads. Therefore, S_U and S_D are related to each other by (3.8). In this equation, the demand of TCL loads is increased by a factor K, which will not affect other loads or NTCLs.

$$S_U = KS_{D_{TCL}} + S_{D_{NTCL}} \tag{3.8}$$

The factor K is given by (3.6) which has only one input from the analysis related to the outage duration.

$$K = \frac{\ln\left(\frac{t_{outage}}{0.107}\right)}{1.101} \tag{3.9}$$

The above relationships were based on empirical relationship between the outage duration and demand after a CLPU event as found in [6]. The input data that help to develop this empirical relationship are actual recorded CLPU events. These equations show that the longer the outage duration the more the power demand after restoration. With longer outage durations the house temperature will be more effected, and more TCLs will leave their off-status region. This increase in power demand is represented by k, which will affect only TCLs as explained. Therefore, the effect of the ambient temperature and the outage duration are included in (3.8) and (3.9). The ambient temperature impact is embedded in the values of S_D. While outage duration impact is embedded in the factor k.

The second most important parameters in CLPU model is CLPU duration. A power demand of S_U will have a duration of Δt called CLPU duration which is equal to $t_i - R_i$ as seen in Figure 3.5. Another important parameter is the rate of decay of the α of CLPU event. The variable α is the time required for the power demand to settle back to a level that would have been without an outage. The rate of the decay α and CLPU duration Δt can be found from actual recorded CLPU events. Table 3.1 summarizes the papers that found or used values of α and CLPU duration Δt.

Table 3.1: Values of CLPU duration Δt and rate of decay α

Reference	Δt	α
[3]	10 to 45 minutes	Not reported
[4]	30 minutes	0.5 hr^{-1}
[26]	20 minutes	0.75 hr^{-1}
[28]	30 minutes	Not reported
[5]	10 to 30 minutes	1.33 to 1.66 hr^{-1}
[47]	30 minutes	0.5 hr^{-1}

Based on the values reported in the literature, it was decided to use fixed values for every restoration as follows:

- Δt = 30 minutes
- $\alpha = 0.5\ hr^{-1}$

These values agree with the characteristic of air conditioners which require an average value of 30 minutes to leave or re-enter the thermostat dead zone [15].

3.3 Selected Test System

3.3.1 Circuit Configuration

The test system considered for this problem is a radial power distribution system [4] [35] shown in Figure 3.6. In this test system, it is possible to restore all loads at once, one feeder loads at once, or specific sections of different feeders with respect to embedded constraints. These embedded constraints are the inability to restore downstream feeders before upstream feeders. For example, section 2 cannot be restored before Section 1. The system is given in the literature with the average MVA demand of each load point. These values, which are reported in Table 3.2, are the undiversified power demands at each load point [4]. Other details are not given in the literature and therefore the next section will design these details.

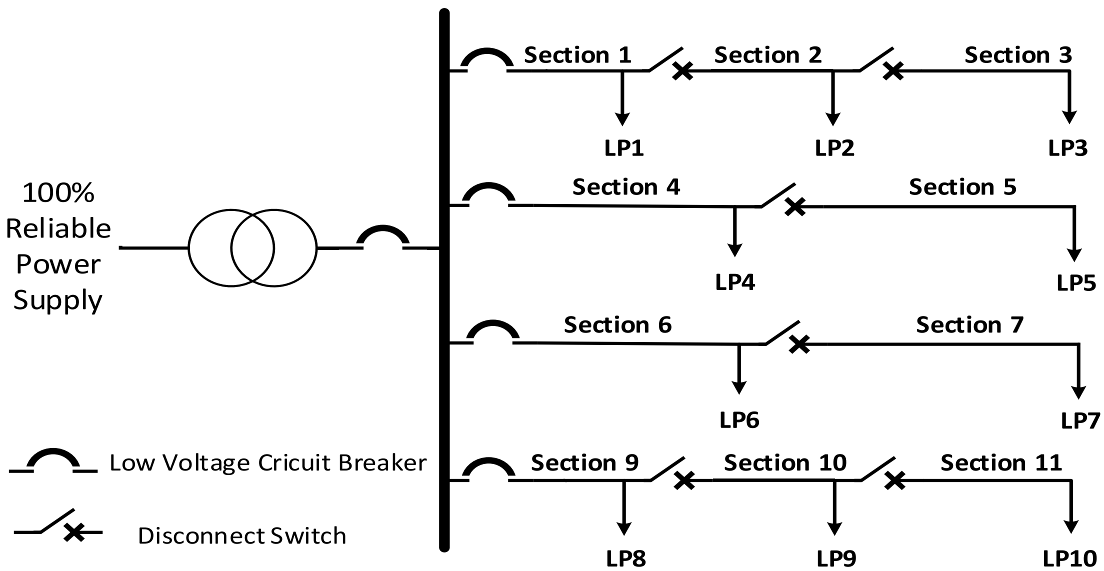

Figure 3.6: Test power distribution system

Table 3.2: Average MVA demand at selected test system

Load Point	Demand (MVA)
1	0.3000
2	0.1833
3	0.2000
4	0.1667
5	0.1667
6	0.3167
7	0.2000
8	0.2167
9	0.3667
10	0.2667

3.3.2 Transformer and Cable Sizing

Industrial best practices will be used in selecting the transformers and cable sizes. The size of the main transformer will be determined by running the load model and will be sized according to the maximum expected load in a period of 1 year. The cables will be sized to ensure a voltage level of a minimum 0.95 per unit at the end of every feeder at the worst loading scenario. Moreover, the selected sizes will be subjected to minimum loading conditions to ensure the voltage will not increase beyond 1.05 pu.

Load model results and load flow results for different loading conditions will be reported in Chapter 6. One important result of this model is the maximum demand, which was 6.47 MVA. Therefore, the transformer size will be the next standard size, 6.5 MVA. A typical voltage level of the transformer for this distribution system is 13.8/0.48 kV. The transformer type will be a pad-mounted oil-filled transformer, which is a typical type for this application.

All the cables were selected to be underground cables and designed with impedance details using National Electric Code (NEC) wiring practices to make all the buses during extreme loading conditions within ±5%. The length of the four main feeders was selected to be 600 m and divided between the sections equally. Therefore, Sections 1, 2, 3, 8, 9 and 10 are 200-meter underground cables. The remaining sections are selected to be 300-meter underground cables. The final equipment details and corresponding impedance values of the system are presented in Table 3.3.

Table 3.3: Designed impedance data of test system

Section	Length (m)	Sec. size (mm^2)	R (pu)	L (pu)
1	200	5×500	0.0026	0.0064
2	200	4×500	0.0033	0.0080
3	200	4×500	0.0033	0.0080
4	300	4×500	0.0049	0.0120
5	300	4×500	0.0049	0.0120
6	300	5×500	0.0039	0.0096
7	300	4×500	0.0049	0.0120
8	200	5×500	0.0026	0.0064
9	200	5×500	0.0026	0.0064
10	200	4×500	0.0033	0.0080

3.3.3 Reliability Data of Test System

In the previous sub-section, the details of the test system were determined. The length of the cables will determine the expected failure rate from the power system reliability data bank of IEEE Gold Book 493, Chapter 10 [83]. This standard provides average industry data for the failure rate per year and repair time in hour. This data is based on extensive survey over tens of years. These data were converted to failure rate per hour and repair rate per hour according to (3.10) and (3.11).

$$\lambda = \frac{\textit{failures per year}}{8760} \tag{3.10}$$

$$r = \frac{1}{\textit{repair time (hours)}} \tag{3.11}$$

Full details of the basis of reliability studies are presented in Table 3.4. In this table, the failure rate of the cables is different between them while the repair rate is the same. This information is given in IEEE gold book. This is due the fact that longer cables the more they are subjective to failure. However, the repair time is the same for all underground cables. This makes more scene with the availability of cable fault locator, which will locate the faulty part of the cable in the same regardless of the cable length. Moreover, the transformer has a very low failure rate with an average of 1 failure every 160 years. This means that the lifetime of the transformer can end before a failure can occur. However, the transformer has a very long repair time, around 5 days. This is due to the fact that any transformer planned/unplanned maintenance activities will likely to include oil treatment, which is a very lengthy process.

Table 3.4: Reliability data of test system

Component	**Details**	**Failure Rate (λ) /year**	**Repair Time (Hours)**	**Failure Rate (λ) /hour**	**Repair Rate (r) /hour**
Transformer	Oil-filled MV transformer between 3 and 10 MVA	0.0059	297.4	6.735E-07	0.0034
Section 1	200-meter underground LV cable with 5×500 mm^2	0.0127	15	1.450E-06	0.0667
Section 2	200-meter underground LV cable with 4×500 mm^2	0.0102	15	1.164E-06	0.0667
Section 3	200-meter underground LV cable with 4×500 mm^2	0.0102	15	1.164E-06	0.0667
Section 4	300-meter underground LV cable with 4×500 mm^2	0.0153	15	1.747E-06	0.0667
Section 5	300-meter underground LV cable with 4×500 mm^2	0.0153	15	1.747E-06	0.0667
Section 6	300-meter underground LV cable with 5×500 mm^2	0.0191	15	2.180E-06	0.0667
Section 7	300-meter underground LV cable with 4×500 mm^2	0.0153	15	1.747E-06	0.0667
Section 8	200-meter underground LV cable with 5×500 mm^2	0.0127	15	1.450E-06	0.0667
Section 9	200-meter underground LV cable with 5×500 mm^2	0.0127	15	1.450E-06	0.0667
Section 10	200-meter underground LV cable with 4×500 mm^2	0.0102	15	1.164E-06	0.0667
Circuit breakers	LV metal-clad drawout type	0.0027	147	3.082E-07	0.0068

CHAPTER 4

PROBLEM FORMULATION

This chapter will formulate the problem of including CLPU events in the reliability indices. It will start by introducing the assumptions that this formulation is based on. The following subsections will discuss the selected objective function and constraints along with the required analysis and references.

4.1 Assumptions

The main objective of thesis is to include CLPU events in the reliability assessment of distribution power systems. To formulate this objective, the following is assumed:

- Utilities are aware of CLPU and will try to sectionalize the restoration to avoid high-current demand.
- Utilities will try to minimize the sectionalizing delay as much as possible in order not to negatively affect the utilities' reliability indices.
- All load points are equally important; therefore, no ranking will be assigned to any point.
- One customer is connected at the end of each load points; therefore, the failures have the same impact along the assessment period.
- The customers will not change the equipment status during the outage neither will they change the thermostat settings during the failure.

Based on the above, an optimal restoration plan shall be developed to ensure faster restoration without violating the selected constraints.

4.2 Objective Function

An optimal restoration program is run after each failure in the assessment period. There are several options for objective functions such as minimizing a selected reliability index including ENS, SAIDI or CAIDI. A utility can decide which reliability index is more important and accordingly select the appropriate objective function. The most important index is determined by the local authorities which set a key performance index for competing utilities. In this work, a common factor between ENS, SAIDI and CAIDI will be optimized. All of these reliability indices are time-based indices. Therefore, the optimal restoration times will accordingly lead to better results in all three reliability indices.

Based on the above analysis, the objective function can be written as:

$$Minimize \quad \left(\sum_1^k \overline{TTR_i} - \sum_1^k TTR_i \right) \tag{4.1}$$

The sum of the adjusted Time to repair (TTR) is the sum of the original TTR without considering CLPU in addition to restoration times. These restoration times for the effected load points are required to avoid violating constraints. In other words, the following equation can be written:

$$\sum_1^k \overline{TTR_i} = \sum_1^k TTR_i + t_{r_1} + t_{r_2} + \ldots + t_{r_i} + \ldots + t_{r_k} \tag{4.2}$$

The variable t_{r_i} is the restoration time for load point i out of k effected load points in the subject failure. Equivalently, the objective function can be re-written as:

$$Minimize\ \left(t_{r_1} + t_{r_2} + \ldots + t_{r_i} + \ldots + t_{r_k}\right) \tag{4.3}$$

The minimization of the restoration times will automatically minimize reliability indices ENS, SAIDI and CAIDI. However, it will not affect the number of failures and hence will not affect SAIFI. This objective function will be used in the program to solve the main problem in the thesis.

With reference to the selected objective function, the optimized parameters are the additional times for CLPU load restorations, which are $[\mathrm{t}_{\mathrm{r}_1}, \ldots, \mathrm{t}_{\mathrm{r}_\mathrm{i}}, \ldots, \mathrm{t}_{\mathrm{r}_\mathrm{k}}]$. The objective function will be applied after each failure in the assessment period to find the optimal restoration times and hence the adjusted TTRs for each affected load points.

4.3 Constraints

The selected objective function will operate with respect to several embedded or non-embedded constraints. In distribution networks, some load points can be restored before others due to the nature of radial systems. Downstream sections cannot be restored before upstream sections. Therefore, an embedded mechanism in the developed program will be deployed to reject any solution that violates this embedded constraint.

Other constraints are not necessarily embedded, yet the system operator must pay attention to. The system can be restored with these constraints violated. Yet, utilities are not advised to do so since violating them might lead to bigger losses and damages for system equipment.

The first constraint is related to behavior of the protection system in the radial distribution system. The main transformer loading shall not exceed 125% of its rating. The transformer loading is limited to ensure that the protection system is not activated [84]. This limit is set by NEC in order to protect the transformer against overloading issues as explained in Table 4.1 which is taken from Table 450.3.

Table 4.1: Transformer secondary protection (percentage of transformer rated current)

Transformer Impedance	Over 1000 Volts		1000 Volts or Less
	Circuit Breaker	Fuse Rating	Circuit Breaker or Fuse Rating
Not more than 6%	300%	250%	125%
More than 6% and not more than 10%	250%	225%	125%

The second constraint is related to the voltage limits at each affected load point. Voltage magnitude shall stay between pre-determined limits at each moment of the assessment period. This is due to the fact that electrical equipment is designed to work with specific voltage. Equipment performance and health are not guaranteed outside these limits. On the other hand, equipment will perform satisfactory inside these limits. The limits are selected to be Range A of ANCI C84.1 standard as shown in Figure 4.1.

The limits of the service voltage are selected for the load points. There will be an additional voltage drop between the service point and the utilization equipment. In Range A, the limits are basically +/-5% of the nominal voltage for service voltage. Inside these limits, the equipment shall be guaranteed to work satisfactory. In range B, the service voltage shall be between +6% to -9% of the nominal voltage. However, the equipment is designed for these voltage, yet not fully guaranteed to work satisfactory all the time. Therefore, Range

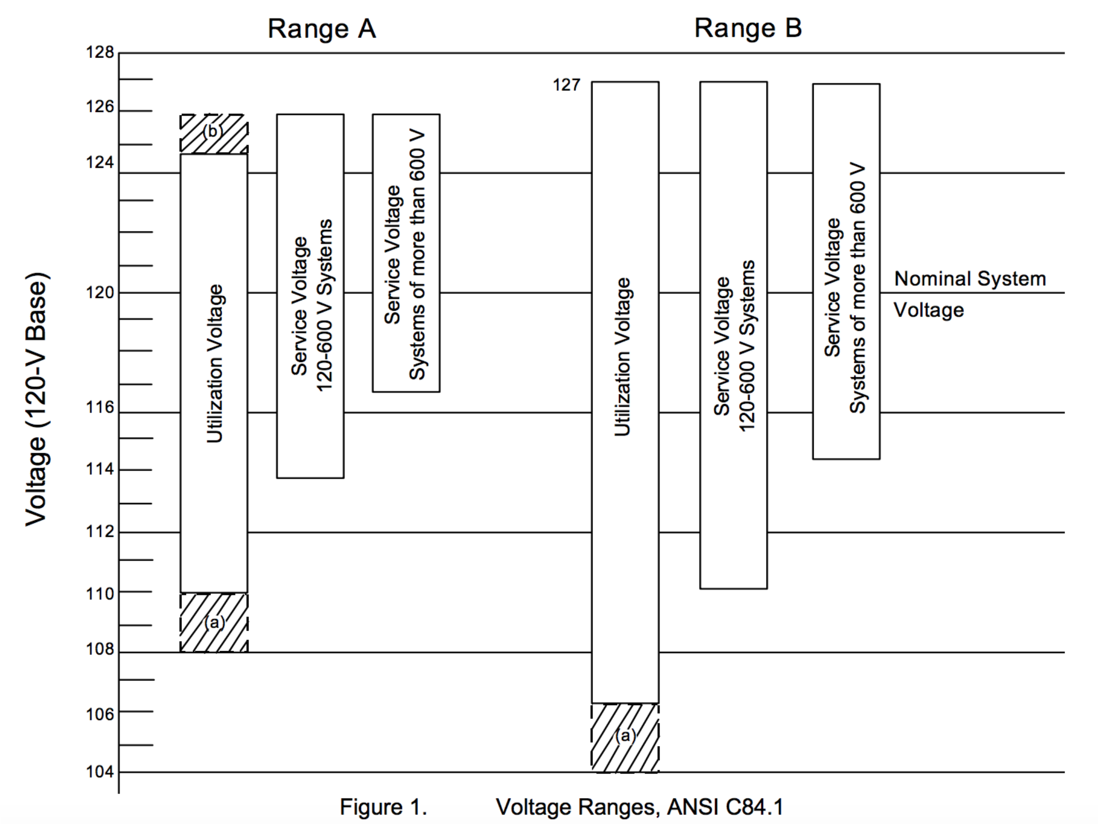

Figure 4.1: Range A and Range B of ANCI 84.1 for 120V System

A limits are selected as operational limits for this problem. Voltage shall always be within 5% of the nominal value [85].

Based on the above, the non-embedded constraints of this problem can be written mathematically as per (4.4) and (4.5).

$$S_T \le 1.25\, pu \tag{4.4}$$

$$\begin{gathered} 0.95 \le V_i \le 1.05 \quad i \in [1, N] \\ \textit{Where N is number of buses} \end{gathered} \tag{4.5}$$

Subsection 3.3.2 already determined the transformer size to be 6.5 MVA. Therefore, the total power demand at the transformer cannot exceeds 8.125 MVA at any moments, otherwise the protection system will be activated and prevent restoration.

CHAPTER 5

PROPOSED METHODOLOGY

The overall methodology will work to execute the main objective of the thesis to include CLPU in the reliability indices to measure the true performance of the power system. The system is modeled as presented in Chapter 3 and the problem is formulated as presented in Chapter 4. The following sections will explain how to use two different platforms to perform these tasks.

The first platform is a MCS platform, which is a well-known method to solve reliability problems. The second platform is for the optimization method that will adjust restoration times produced from the first platform. The optimization platforms will be based on different optimization method including GA, DE, PSO and LSA. Finally, the reliability indices are calculated after completing each presented methodology. The reliability and optimization platforms will be executed jointly to achieve the thesis results.

5.1 Sequential Monte Carlo Simulation (SMC) Platform

MCS is a very-well established method to measure the reliability indices of any system. It has the benefits of being flexible to include additional dynamics that are not easily explored by other methods such as Markov Models or block diagrams. Examples of these events include restoration using backup feeders, planned and unplanned maintenance. Other merits introduced by this method are the avoidance of detailed analytical or mathematical solutions which are required by other methods. SMC provides enough flexibility to include a dynamic event such as CLPU in the reliability analysis [1].

All presented methodology in this thesis will have a main program that is based on a SMC simulation. The purpose of this program is to find the reliability indices of the test system. The transformers, underground cables and low voltage circuit breakers are the items considered for reliability analysis in this work. These items were considered due to it relatively long TTRs. This will make them more susceptible to cause long outages. These long outages are again more susceptible to cause CLPU events.

SMC simulation will produce the equipment status during a very long period. As the simulation time increases, the accuracy of the results will be higher. These electrical components are considered in the up status at the beginning of the assessment period (T = 0). Time to fail (TTF) and Time to repair (TTR) for each component will be found based on uniformly distributed generated numbers (U) with the given failure rate (λ) and repair rate (r) of the component. TTF and TTR will are given by (5.1) and 5.2.

$$TTF = \frac{-1}{\lambda}\ln\left(U\right) \tag{5.1}$$

$$TTR = \frac{-1}{r}\ln\left(U\right) \tag{5.2}$$

Actual experiments and measurements show that the failure rate and repair rate are better modeled using uniform distribution [1]. This method is sequential, and it will continue for a selected assessment period of 200 years. After determining the status of power system components for 200 years (175200 minutes), the reliability indices are found without considering CLPU events as presented in Section 5.3. Figure 5.1 outlines the procedure in detail.

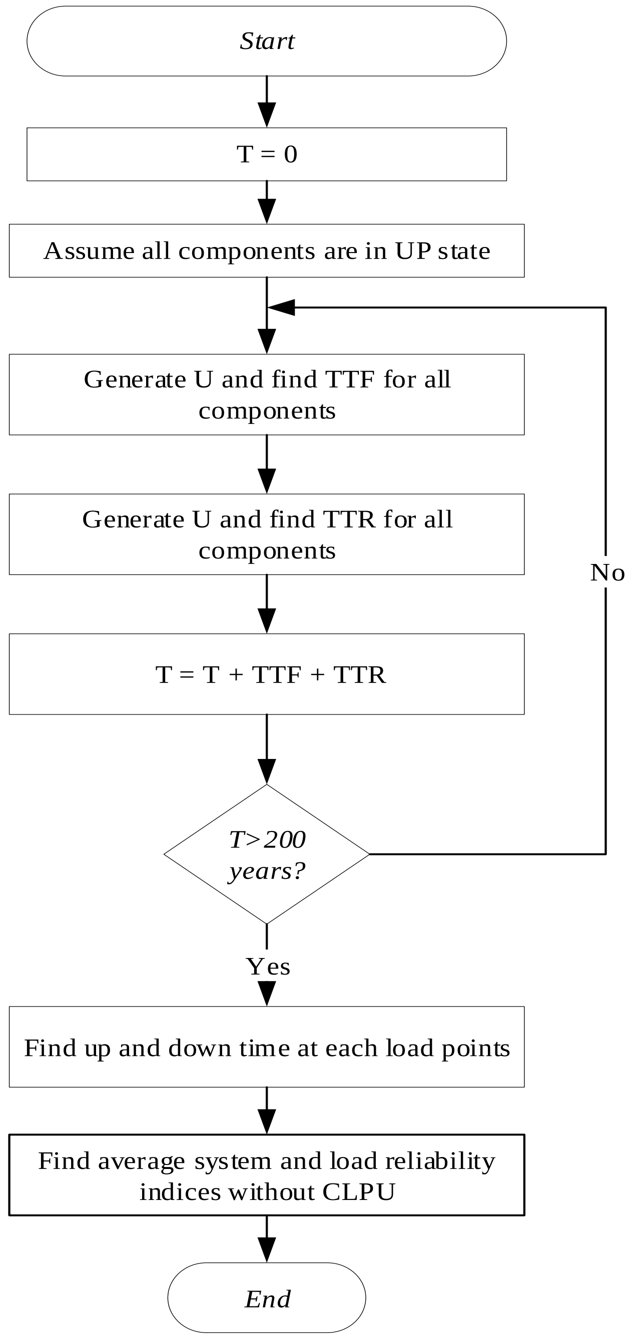

Figure 5.1: Flow chart to find system indices without CLPU

5.2 Optimization Platforms

In Section 5.1, only the system main components will affect the results of the analysis. Therefore, it will find only the reliability indices without considering CLPU events. However, in the following subsections, the program will be modified to move into a second platform which will find the adjusted TTR considering CLPU events. This will be done under the assumption that the utility will follow plans for optimal restoration that minimizes the down times of the affected load points without violating the operation constraints. Therefore, each restoration plan will go through the optimization platform of the program. The adjusted TTRs, produced by the optimization platform will be injected back to the main program. At the end of the assessment period, the reliability indices will be calculated as presented in Section 5.3 including the effect of the reliability indices. As mentioned previously, four (4) optimization platforms will be used each time and their results will be compared together. These optimization platforms have different parameters that needs tuning for each application. Different applications have different convergence and solution space characteristic. Therefore, an initial step will be introduced to each optimization platforms for manual tuning of the main parameters of the methods. Subsection from 5.2.1 to 5.2.4 will discuss these platforms.

5.2.1 GA Optimization Platform

5.2.1.1 GA Algorithm

GA platform, as the rest of the optimization platform, will be used independently to generate the optimal sequence of load points' restoration. GA platform is presented in

Figure 5.2, integrated with SMC, with every outage that triggers a CLPU event. GA program will start by generating the initial random population based on a uniform distribution. To ensure that the embedded constraints discussed in 4.3 are implemented, the generated solution, or chromosomes, will be forced so the time of restoration of the upstream load point is shorter than the downstream load point.

The next step is conducting a tournament selection between two random chromosomes in the current population. The tournament selection is repeated until a temporary population of better chromosomes is generated [60]. A representation of two chromosomes of this temporary population is shown in (5.3) and (5.4). In these equations, the chromosomes consist of restoration times of the respective failure with effected k points. The variable k can be a maximum of ten (10) restoration times if the ten (10) load points have failed [86].

$$C_1 = \left(t_{r_x}^1 , \dots , t_{r_i}^1 , \dots , t_{r_k}^1 \right) \tag{5.3}$$

$$C_2 = \left(t_{r_x}^2 , \dots , t_{r_i}^2 , \dots , t_{r_k}^2 \right) \tag{5.4}$$

Among the possible crossover operations for RCGA, a BLX-α crossover is selected. It will be performed on the temporary population to generate an offspring $H = [h_1, \dots, h_i, \dots, h_k]$. The offspring H is generated out of the two sample chromosomes C_1 and C_2. One restoration time of the generated offspring is h_i. It is generated from selecting a random number from the interval specified in (5.5). The variable α is tuned for every application and this work is no exception. This variable will determine how much different the offspring from the current population [86].

$$h_i = random\,(c_{\min} - I\cdot\alpha\,, c_{\max} + I\cdot\alpha) \tag{5.5}$$

$$\begin{aligned} Where \quad & c_{\min} = \min(t_{r_i}^1, t_{r_i}^2) \\ \& \quad & c_{\max} = \max(t_{r_i}^1, t_{r_i}^2) \\ \& \quad & I = c_{\max} - c_{\min} \end{aligned}$$

Finally, a mutation process is conducted to the new offspring generated from the crossover population. This process has a very low probability, around 5 to 10% and will alter few chromosomes per generation. It will help to discover solutions very far away from the population that might results in better objective functions. A non-uniform mutating is selected in this work, which has the form shown in (5.6) with τ selected randomly between 0 and 1. The mutation function is controlled by a function called delta Δ defined as a part of (5.6). As the generation number is increasing, the mutation will result in more focused values around the selected offspring. Another factor that effects the mutation process is the variable b, which determines the degree of dependency of the current number of iteration. This variable can also be tuned for different applications [86].

$$t_{r_i}^{'} = \begin{cases} t_{r_i} + \Delta\left(generation, t_{r_{\max}} - t_{r_i}\right) \;\; if \;\; \tau = 0 \\ t_{r_i} - \Delta\left(generation, t_{r_i} - t_{r_{\min}}\right) \;\; if \;\; \tau = 1 \end{cases}$$

$$Where \quad \Delta(t, y) = y\left(1 - r^{\left(1 - \frac{t}{number\ of\ generation}\right)b}\right) \tag{5.6}$$

The process is repeated until the final number of generation is reached. The final restoration times are added to the outage duration and fed back to the main platform.

5.2.1.2 GA Parameters Tuning

In Section 5.2.1.1, several parameters were explained to be tunable. These parameters shall be tuned for every type of application to get the best possible results and to avoid convergence to local optimum points. GA parameters that needs to be tuned: crossover probability, mutation probability, the variable α of BLX-α crossover and the variable b of the non-uniform mutation.

The tuning procedure will have the following steps:

- Step 1: Alter the crossover probability between recommended values while fixing the mutation probability, α of BLX-α crossover and b of the non-uniform mutation.
- Step 2: Alter the mutation probability between recommended values while fixing the crossover probability, α of BLX-α crossover and b of the non-uniform mutation.
- Step 3: Alter α of BLX-α crossover between recommended values as per (5.5) while fixing mutation probability, the crossover probability, and b of the non-uniform mutation.
- Step 4: Alter b of the non-uniform mutation between recommended values as per (5.6) while fixing the crossover probability, mutation probability and α of BLX-α crossover.
- Step 5: Select the best two results of all the four parameters and get the best results of all possible combinations.
- Step 6: As the method will be applied on two sample failures, the best possible combination might by different for both failures. In that case, the best combination will be applied on the other failure and the best combination will be selected for all failures.

The following values will be swept with standard increments for the following parameters [60]:

- Crossover probability: 0.6, 0.7, 0.8, 0.9 and 1.0.
- Mutation probability: 0.05, 0.10 and 0.15.
- The variable α of BLX-α crossover: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1.0.
- The variable b of the non-uniform mutation: 1, 2, 3, 4, 5 and 6.

5.2.2 PSO Optimization Platform

5.2.2.1 PSO Algorithm

PSO platform is similar in principle to the GA platform and it is shown in detail in Figure 5.3. It starts with a tuning block, optimization algorithm block and finally the results block which are fed to the main platform. The initial population is generated uniformly in the search space to form the initial particles. One sample solution is $X_n = [t_{r_1}, \dots, t_{r_i}, \dots, t_{r_k}]$ for a failure with k affected solution. Moreover, the initial velocity of the particle movement is initialized $V_n = [v_1, \dots, v_i, \dots, v_k]$ randomly based on interval between $\pm\upsilon^{max}$ which is defined in (5.7) [63].

$$\upsilon_{\max} = \frac{t_{r_{\max}} - t_{r_{\min}}}{N} \tag{5.7}$$

N is a selected number to increase the velocity range or decrease depending on the application and the size of the search space. Lastly, the weight of the previous velocities impact on the future velocity is defined as 5.8. The weight is updated through a β-factor which will reduce the weight over iterations to ensure a better local movement toward optimum values [63].

$$w(t) = \beta w(t-1) \tag{5.8}$$

Over the iteration, two best solutions are defined: the individual best and the global best. The individual best X^* is the best particle among the last produced population, which will result in the best objective function. While the global best is the best particle among all population produces so far and is donated by X^{**} [63].

After initializing the first population of particles, the weight is updated in iteration (t) using (5.8) while the velocity is updated using (5.9).

$$v(t) = w(t)v(t-1) + c_1 r_1 (X^*(t-1) - x(t-1)) + c_2 r_2 (X^{**}(t-1) - x(t-1)) \tag{5.9}$$

In (5.9), the velocity is affected by the global best, individual best and the inertia weight. The parameters r_1 and r_2 are randomly generated numbers between [0,1]. However, c_1 and c_2 are selected by the user, which is one of the tunable parameters of the problem. Using the updated velocity, the particle position can be updated in accordance with (5.10).

$$x(t) = v(t) + x(t-1) \tag{5.10}$$

Finally, the local best and the global best are updated before moving the new generation. If the final iteration is reached, the final restoration times correspond to the failure are fed back the main program to update the outage duration of the affected load points.

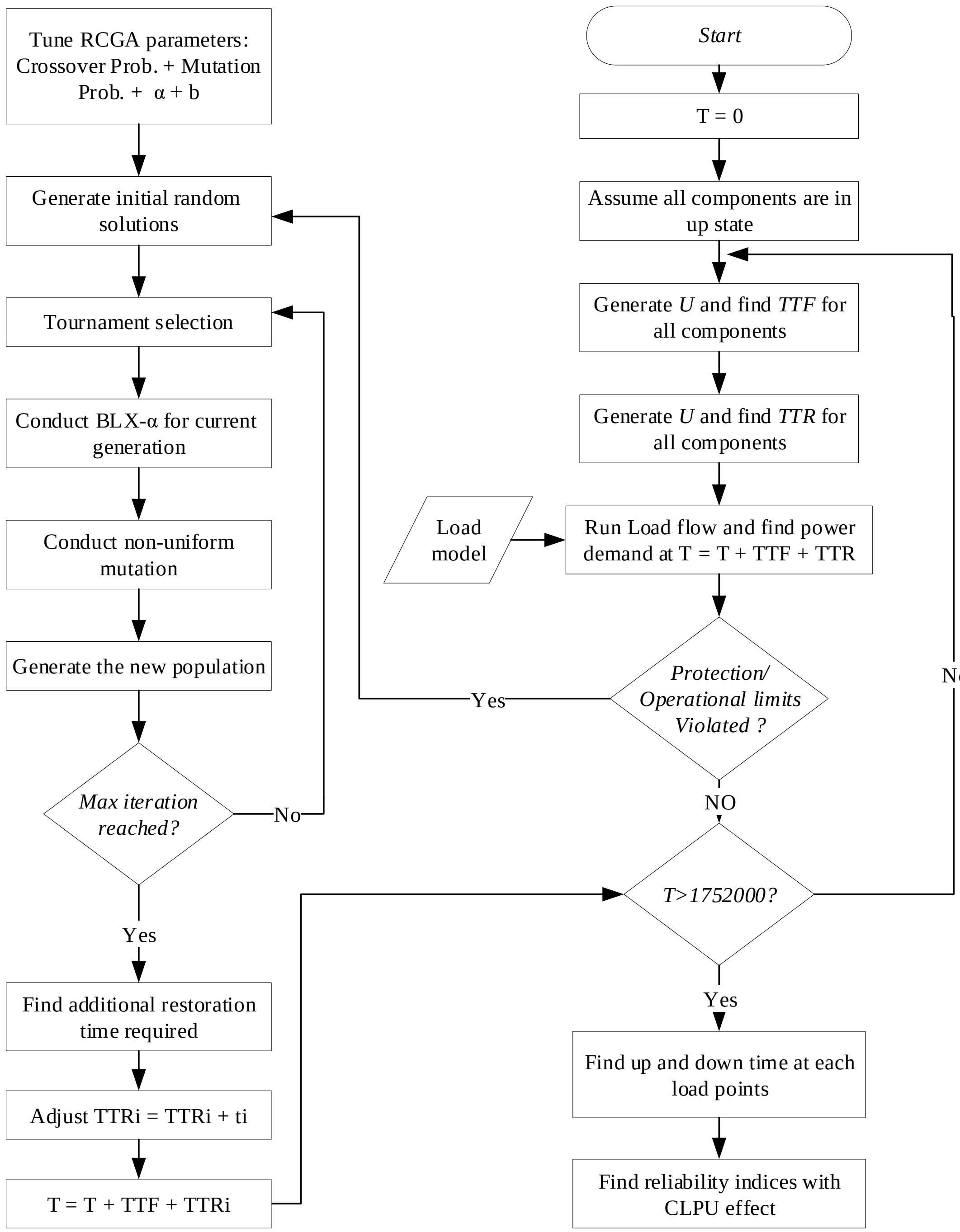

Figure 5.2: RCGA-based flowchart for find reliability indices with CLPU

5.2.2.2 PSO Parameters Tuning

In PSO algorithms, there are several parameters that are subject for tuning. These parameters will affect the convergence characteristic of the problem. The tuning of PSO will follow the same procedure planned for tuning RCGA presented in Section 5.2.1.2. One parameters will be altered while the others are fixed. Next, the value of the parameters associated with the best two results will be selected and mixed together. The best combination of the four parameters are selected. The tunable parameters of PSO includes the number of interval of velocities, which will determine how away the particle can move in every step as per (5.7). The inertia weight factor β will determine the next velocity dependence of the previous velocities as per (5.8). Finally, factors c_1 and c_2 will determine the dependence on local best and global best values as per (5.9).

Some sources in the literature were used to narrow down the acceptable range of the control parameters for different parameters [87] [88]. Therefore, the values selected for sweeping analysis are the following:

- Parameter N: 5, 10, 15 and 20.
- Inertia weight factor β: 0.80, 0.85, 0.9 and 0.95.
- Factor c_1: 0.5, 1.0, 1.5, 2.0, 2.5 and 3.0.
- Factor c_2: 0.5, 1.0, 1.5, 2.0, 2.5 and 3.0.

The best two values of each parameters from two sample failures will be combined and manual sweeping will be conducted. If the best combination is not the same for the two failures, the other combination will be tested on the other failure. The best performer is selected among all these combinations.

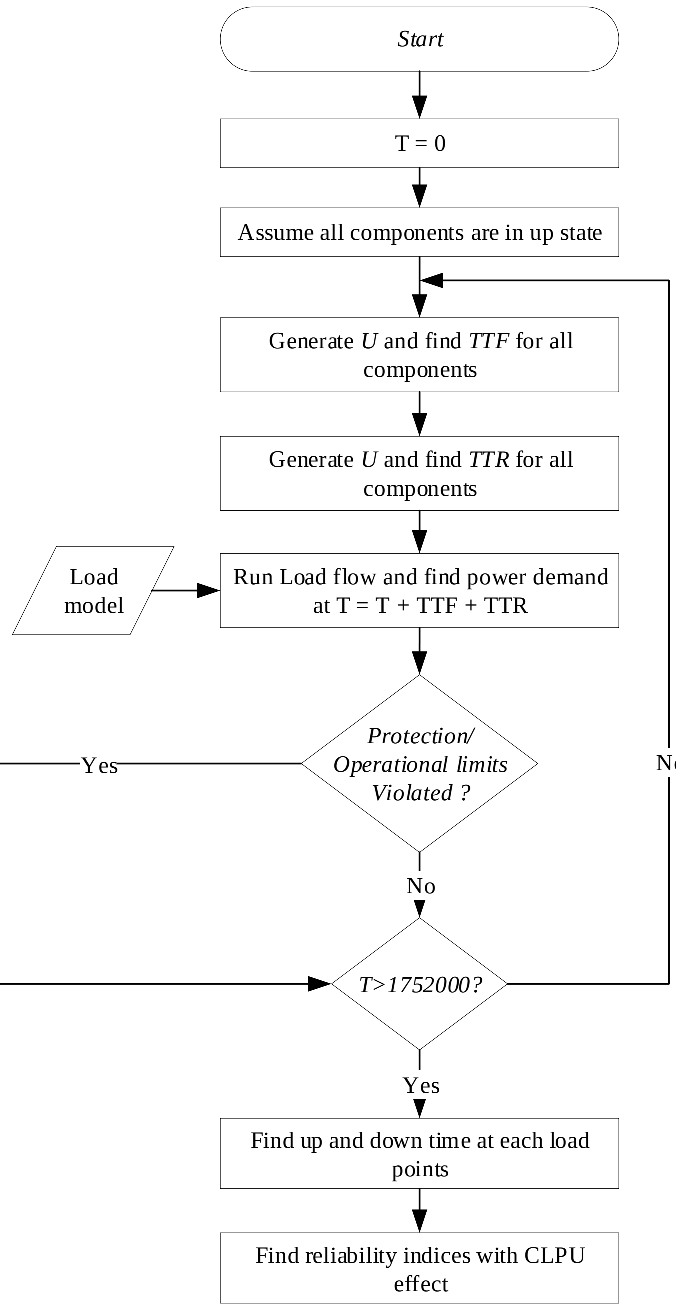

Figure 5.3: PSO-based flowchart for find reliability indices with CLPU

5.2.3 DE Optimization Platform

5.2.3.1 DE Algorithm

DE platform will start by randomly generating the initial population according to the number of effected load points. One sample solution can be donated by $X_n = [t_{r_1}, \dots, t_{r_i}, \dots, t_{r_k}]$. The initial population is manipulated first through mutation operation with four different available schemes [66]. One scheme is selected, and it is represented by (5.11).

$$V^{+} = X_1 + F\left(X_2 - X_3\right) \tag{5.11}$$

This scheme is called DE scheme no. 1 and it is used to generate a mutant vector V by selecting three (3) random solutions out of the current population. F is a mutation factor that can be selected between 0 and 1. This factor will control the algorithm by controlling the speed of convergence and controlling the covered area during searching in the solution space. Its impact can be shown in Figure 2.13 in Subsection 2.2.1.3. This factor can be tuned by the algorithm user depending on the application.

After generation a population of mutant vectors, a crossover operation is conducted. In this operation, a uniformly distributed random number is generated and compared with a previously defined crossover probability (CR). If the random number is higher than the crossover probability, the temporary vector will select the parent vector value. Otherwise the temporary vector will select the mutant vector value. Figure 5.4 explains the crossover process [66]. Finally, the generated trial vector will be compared to the current population vector and the better performer will be selected for the next population. The complete algorithm is explained in Figure 5.5 integrated into the main platform.

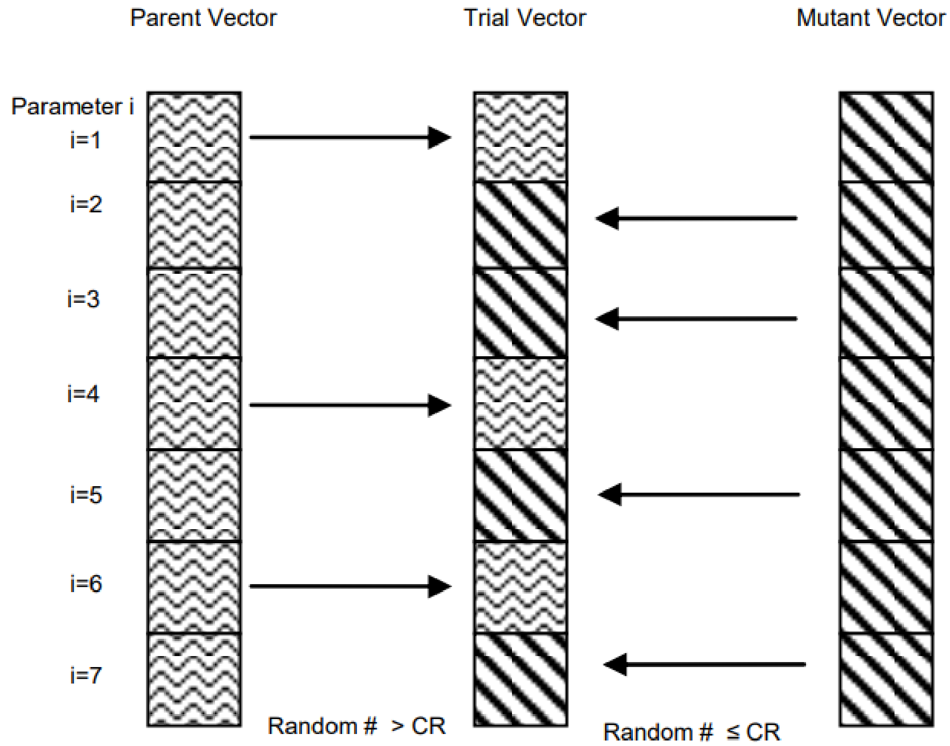

Figure 5.4: DE crossover operation [66]

5.2.3.2 DE Parameters Turning

DE case is a bit different that the previously presented algorithms: RCGA and PSO. This is due to the fact that there are few parameters to control the algorithm. Consequently, they shall be selected carefully to avoid early convergence to local optima or slow convergence which can be time consuming. As presented in the previous section, there are two (2) parameters that are tunable with respect to DE algorithm. These parameters are: crossover probability and mutation factor. These factors will determine the convergence characteristics of the algorithm. There are recommended values for DE in the literature [89] [90] and manual sweeping will be performed on these values.

- Crossover probability (CR): 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9.
- Mutation Factor (F): 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9.

Tuning will be performed around these points. The parameters that will results in the best objective function along with the better convergence characteristics, will be selected.

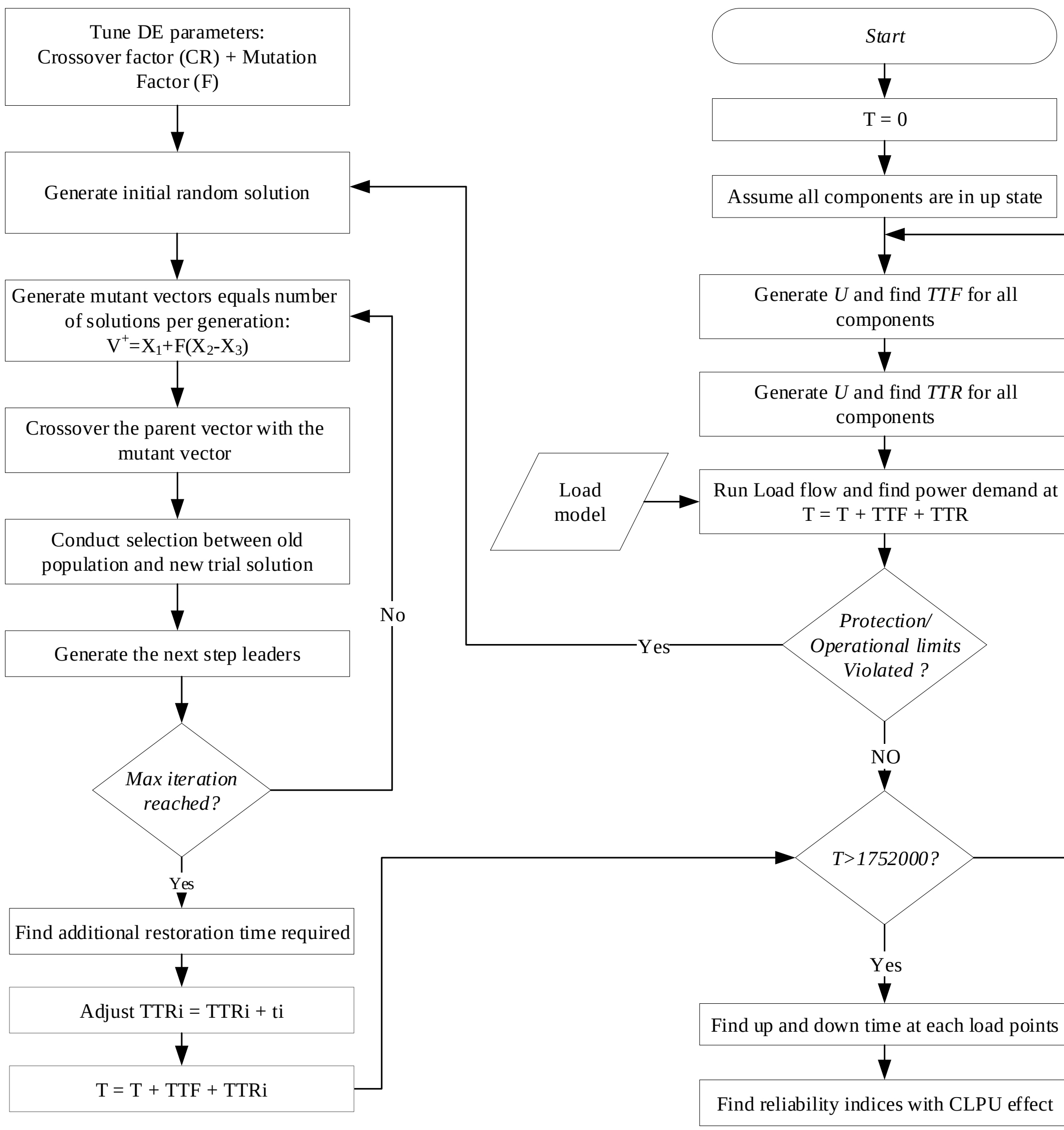

Figure 5.5: DE-based flowchart for find reliability indices with CLPU

5.2.4 LSA Optimization Platform

5.2.4.1 LSA Algorithm

As stated in 2.2.2, LSA resembles the lightning phenomena.

LSA starts by randomly generating the initial population; named transition projectiles. Each set of these transition projectiles represents a candidate solution or a step leader (SL). The nth SL is out of N step leaders is written as $SL_n = [t_{r_1}, \dots, t_{r_i}, \dots, t_{r_k}]$. These projectiles ($t_{r_1}$ to t_{r_k}) are randomly generated between the search space limits representing one outage affecting k load points (LPs). For example, for an outage at LP8, LP9 and LP10 due to Section 8 failure with maximum allowable restoration time for all load points is T_M minutes, the transition projectiles are generated in a sequence to ensure the implementation of the embedded constraints of the problem:

- t_{r_8} is generated randomly between (0, T_M).
- t_{r_9} is generated randomly between (t_{r_8}, T_M).
- $t_{r_{10}}$ is generated randomly between (t_{r_9}, T_M).

The performance of the transition projectiles forming one step leader is evaluated based on the objective function. The best step leader is the one with the lowest energy value. The best step leader is stored externally to track the objective function improvements. The space projectiles are ejected into each step leader using exponentially distributed function for the generated N SLs = [sl_1, sl_2, sl_3,…, sl_N] using (5.12).

$$t_{r_i}^{n+1} = t_{r_i}^{n} \pm exprand(\mu) \tag{5.12}$$

The parameter μ is the shaping parameter of the exponential distribution and it is dependent on the distance between this projectile and the reference projectile in the best step leader. The direction of the alteration will be determined through minor test to confirm which direction will provide a better step leader. Finally, the lead projectiles (parameters of best step leader) is altered alone with a normal distribution function using (5.13).

$$t_{r_i}^{n+1} = t_{r_i}^{n} \pm normrand(\mu, \sigma) \tag{5.13}$$

In (5.13), the normal distribution is dependent on two factors. The parameter μ is the mean of the distribution function. It is normally selected to be zero, therefore, the updated value has an equal probability to move to any direction around the best value. However, the scaling parameters of LSA is σ will determine how far away the new value of the best parameter from its current position. The scaling factor will be determined by (5.14) which is called the energy function of the normal distribution. This equation is dependent on the initial value of the energy given by E_0 and the generation number. The scaling factor will reduce at later generations in order for the best parameter to search closer to its current position.

$$\sigma = E_0\left(1 - e^{-5\left(\frac{Max\,Generation - iteration}{Max\,Generation}\right)}\right) \tag{5.14}$$

Finally, the forking process, which is a secondary operation of LSA method, is performed. Forking helps to redirect the search and promote different solutions within the search space that might not been explored before. Forking is conducted in LSA in two ways, both will cause disturbance to the subject solution vector. The first method is by initiating a counter to that at certain time will demolish the worst performing step leader and replace it with the best performing step leader. Hence, increasing the possibility of finding a better solution around the best step leader. This counter is called the channel time and it will be set initially along with the other parameters. The other realization of forking is by altering the projectile value with a very small probability using (5.15).

$$\overline{tr_i} = a + b - tr_i \tag{5.15}$$

The projectile value changes with respect to its boundary limits (a,b), which are for the first restored point at each lateral, 0 and T_M. This realization will happen only if the altered lead projectile has a higher energy or better performance than the saved non-altered projectile and could survive a probability test with 5% or even less. The forking probability can go as low as 1% or as high as 15%.

After altering the current population with the aforementioned operations, the new population of step ladders is produced. The process is continued until the maximum number of generation is reached. Figure 5.6 shows LSA functionality over 11 iterations with 5 channels. This figure explains enough about the relation between LSA and the lightning phenomena. The channels that are closest to the ground are the channels that are most likely to create lightning. All new directions produced by every iteration is tested. If better results are found, channels will change their direction. Otherwise, they will remain in the same direction [69]. In this figure (part b), forking has occurred in the third iteration along channel 5 resulting in a value that has a worse performance than the value along the channel. Hence, the temporary forked channel was not followed by the particle. In part c of the same figure, channel no. 2 was eliminated due to bad performance and the best channel was duplicated to enhance the overall quality of the solutions. LSA flowchart is shown in Figure 5.7 integrated to the main platform.

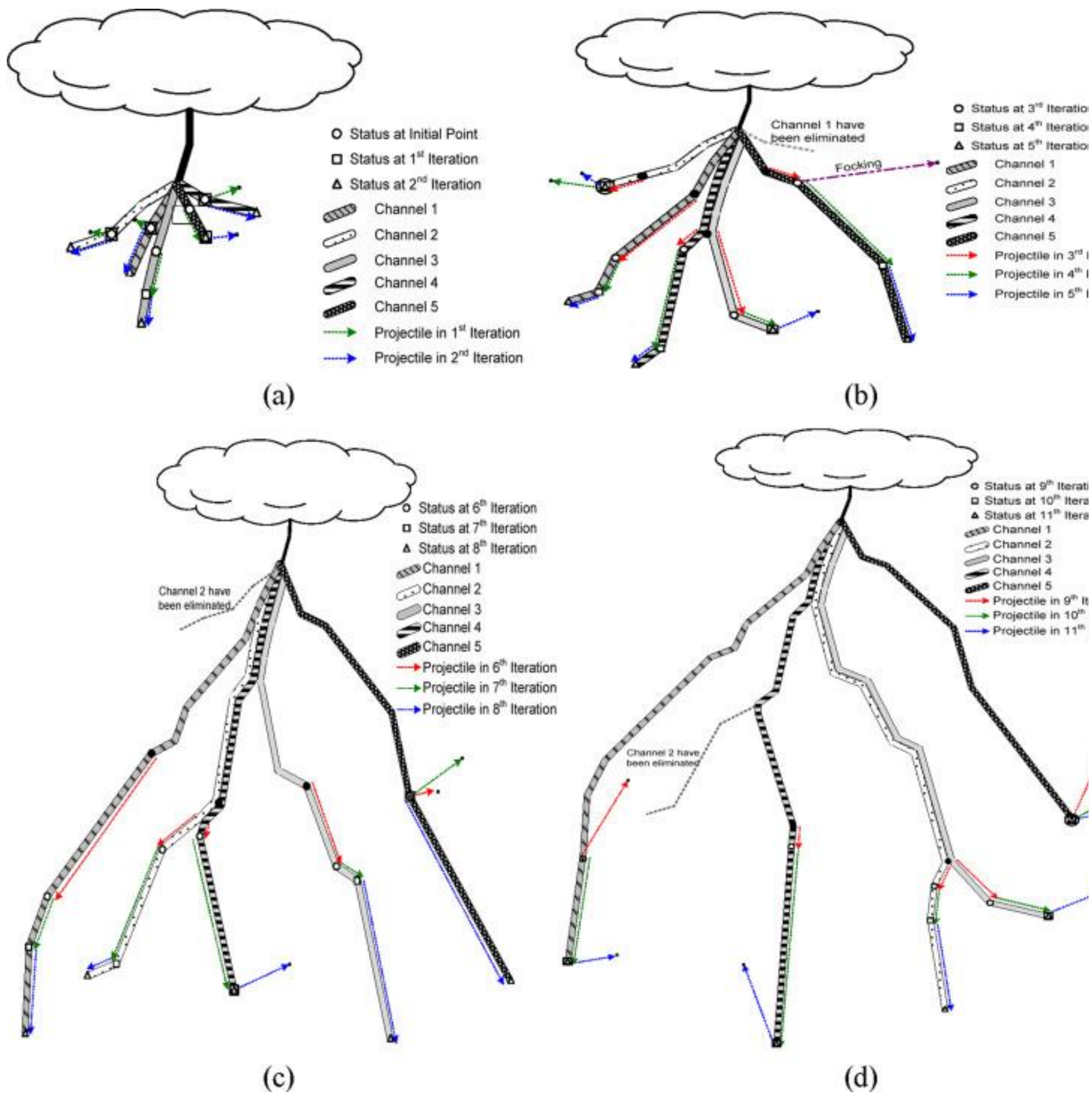

Figure 5.6: LSA functionality after (a) 2nd iteration, (b) 5th iteration, (c) 8th iteration and (d) 11th iteration [69]

5.2.4.2 LSA Parameters Turning

As per the description provided in Subsection 5.2.4.1, there are three parameters that can control LSA algorithm. These parameters control the search technique, survival of week step leaders and convergence characteristic of LSA.

These parameters are:

- The initial scaling parameters of normal distribution (E_0): 1, 2, 3, 4, 5 and 6.
- Value of the channel time: 5, 10, 15 and 20.
- Forking probability: 0.01, 0.05, 0.1 and 0.15.

The first parameter, the initial energy of scaling parameter, will affect only the best solution vectors' performances per (5.13) and (5.14). This parameter will be used to update the lead projectile. For problems with huge search space, more exploration range is required. This will be achieved by higher scaling parameters, which might lead to local optima avoidance. However, in other problems, large scaling parameters might cause slow convergence as the lead projectile might not be able to discover surrounding areas. Recommended value in literature is 2 [69] and the sweeping exercise will be done around this value, from 1 to 6.

The other two parameters of LSA tuning are concerned about the forking procedure of the algorithm. Altering these parameters will manipulate the two forms of the forking process by increasing or decreasing its occurrence frequency. Tuning will be done by first increase or decreasing the channel time. Less number of channels means forking will be performed more. For example, a channel time of 5 means that the worst performing step leader will be replaced every 5 iterations, which will lead eventually to better solution vectors. On the other hand, it might lead to convergence to local optima as all solutions concentrated around the best step leader. The other tunable forking parameter is the forking probability. As the forking probability increases, there will higher chance for discovering other solutions. However, increasing the forking procedure dramatically might cause algorithm instability for other problems.

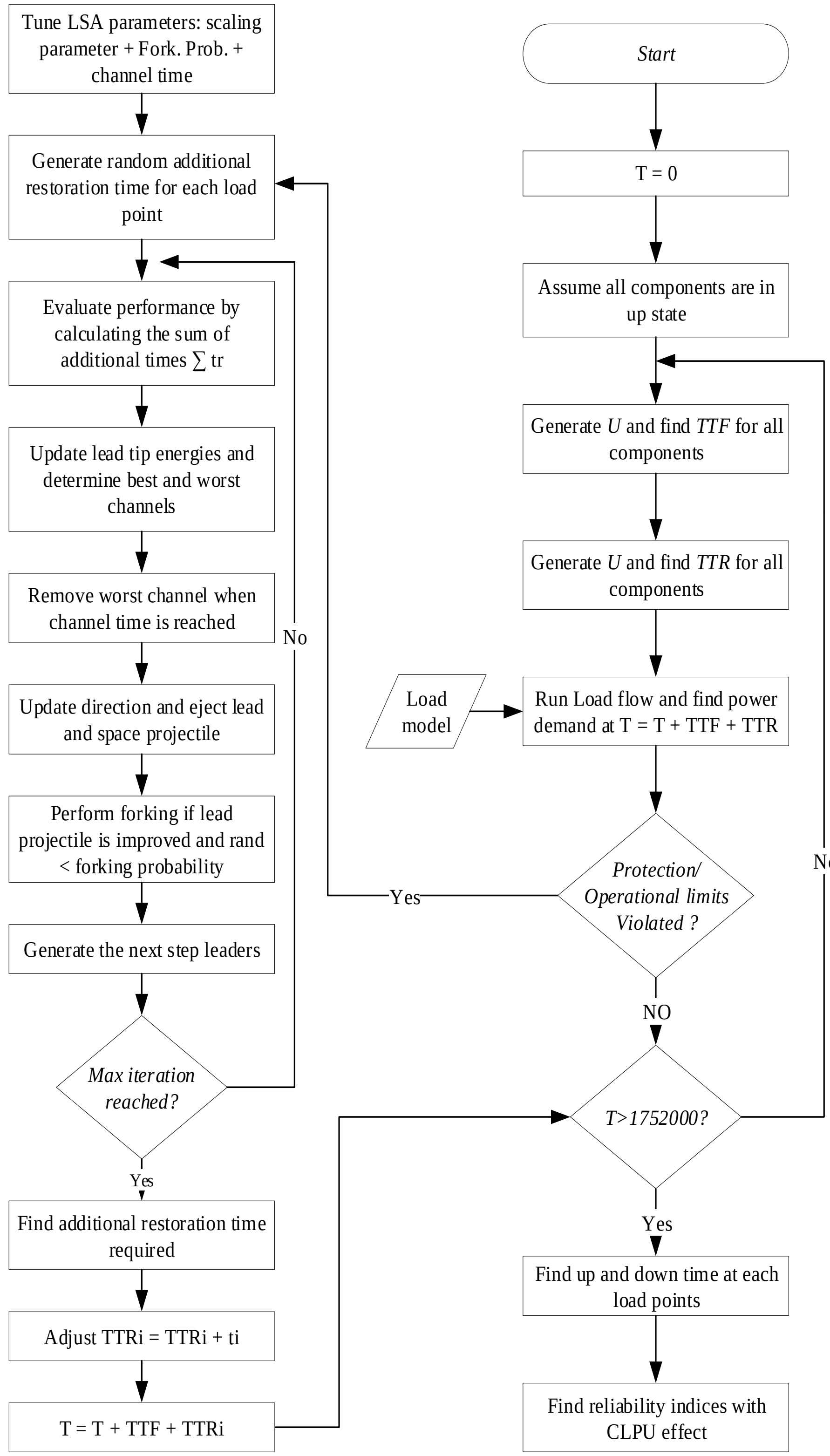

Figure 5.7: LSA-based flowchart for find reliability indices with CLPU

5.3 Reliability Indices

After running the analysis for the complete assessment period in the previous flow charts. Performance of the power system at all load points will be assessed based on its reliability indices. The reliability indices will be calculated as written from (5.16) to (5.22) [1].

$$SAIFI = \frac{Total\ number\ of\ all\ interruptions}{Total\ number\ of\ customers\ connected} = \frac{\sum N_i}{N_T}\ (Interruption/load\ \ point) \quad (5.16)$$

$$SAIDI = \frac{Total\ duration\ of\ all\ interruptions}{Total\ number\ of\ customers\ connected} = \frac{\sum O_i N_i}{N_T}\ (hours/load\ \ point) \quad (5.17)$$

$$CAIDI = \frac{Total\ duration\ of\ customer\ interruptions}{Total\ number\ of\ customers\ interrupted} = \frac{SAIDI}{SAIFI} = \frac{\sum O_i N_i}{N_T}\ (hours/load\ \ point\ interrupted) \quad (5.18)$$

$$ASAI = \frac{N_T \times Simulation\ Hours - \sum O_i N_i}{N_T \times Simulation\ Hours} \quad (5.19)$$

$$ASUI = 1 - ASAI \quad (5.20)$$

$$ENS = \sum P_i\ O_i \quad (kWh) \quad (5.21)$$

$$AENS = \frac{ENS}{Number\ of\ load\ points} \quad (kWh/load\ \ point) \quad (5.22)$$

These indices are well-known to measure distribution system performance. It can be noted that all of these indices are time-based indices except for SAIFI. Oi is the outage duration which will adjusted to include the enduring impact of CLPU events. That means as much as the outage time is reduced, these indices will be improved.

The above indices will be calculated for the original restoration times and the adjusted restoration times [1]. They will be used to compare the case with considering CLPU events and without considering them. They will also be used also to compare between different optimization methods. The best method will lead to better reliability indices by finding better sequence of restoration with the least possible restoration times.

CHAPTER 6

RESULTS AND ANALYSIS

This chapter will discuss the results of the presented problem. The first section will discuss the step-by-step results of the stochastic load model results. The following section will use the load model results to execute the power flow analysis of the system during different loading conditions to confirm that the test system is properly designed. Section 6.3 will detail the tuning analysis results of the all the optimization platforms including RCGA, PSO, DE and LSA. This section will finally present a comparison between these methods for sample failures in terms of computational time and convergence characteristics. After tuning the optimization platforms, the result of the developed flowcharted in Chapter 5 are discussed. The reliability indices without considering CLPU events are discussed in Section 6.4. The following section will discuss the optimal restoration of one failure. Finally, the reliability indices considering CLPU are discussed for both the fixed duration restoration plans and the optimal restoration plans.

6.1 Load Model Results

6.1.1 Resulted Adjusted TOU Curves

The TOU curves is produced based the load factor multiplied by the demand factor, which gives a factor of 0.285 in Saudi Arabia [91] [92]. The thermostat setting for heating/cooling loads was taken as $T_U = 22^o$ and $T_D = 20^o$. The resulted TOU curves for all appliances are shown in Figure 6.1 with an example of a winter day's and a summer day's TOU curves while remaining appliances have a fixed curve for each 24-hour segment.

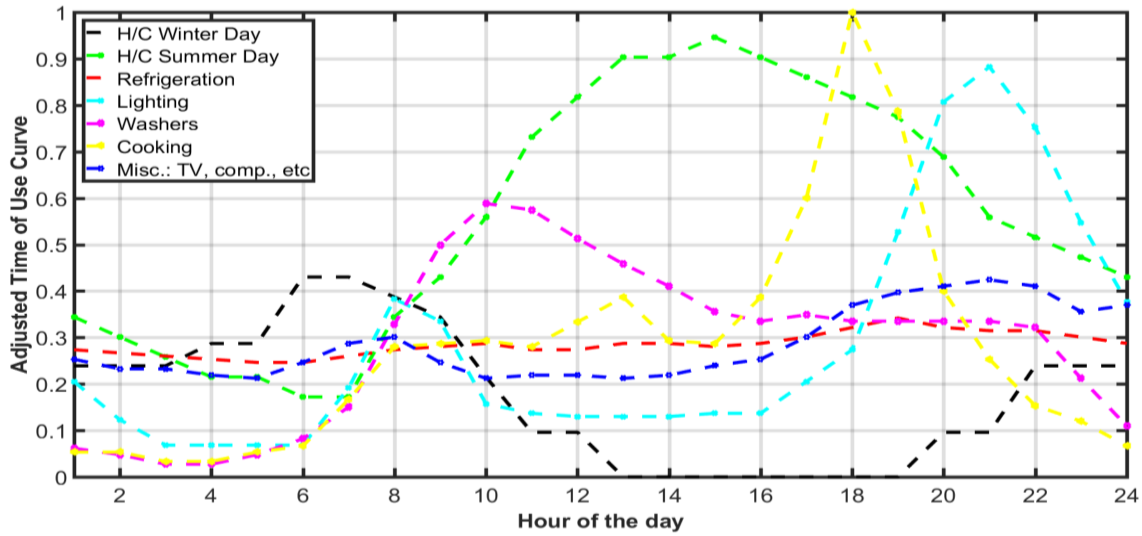

Figure 6.1: Time-of-use (TOU) curves for home appliances

6.1.2 Load Points Details

Following the procedure outlined in 3.1.4.1 to 3.1.4.3, Table 6.2 was produced accordingly. The typical values of appliances kW rating and the energy share that was used from [7] are presented in Table 6.1. Air conditioning demand are about 70% of total demand is Saudi Arabia. This agrees with the reported value by the government agency, Saudi Energy Efficiency Center (SEEC) [93]. In Table 6.2, the number of installation for each type of appliance is reported. For example, there is 510 air conditioners installed in load point 1 without necessarily knowing the number of houses or customers at that location. If the NSMC simulation that an air conditioner out of the 510 equipment is on, it will count a 1.2-kW power consumption at that load point. There will be, for example, a total of 2083 equipment at load point 1 and a total of 16534 appliances at the ten (10) load points and NSMC will simulate their status every minute of the simulation.

Table 6.1: Energy share and typical kW rating for home appliances [7]

Appliance Type	Energy Share	Typical kW rating
Air Conditioner	70.00%	1.2000
Refrigeration	4.00%	1.2000
Lighting	4.60%	0.0320
Washers	3.40%	3.4000
Cooking	3.10%	3.0000
Electronics (TV)	2.90%	0.2130
Computers	1.70%	0.2500
Miscellaneous items (remaining electronics)	10.30%	1.0000

Table 6.2: Detailed load points results

		LP 1	LP 2	LP 3	LP 4	LP 5	LP 6	LP 7	LP 8	LP 9	LP 10
Average Power Demand (pu)		0.3000	0.1833	0.2000	0.1667	0.1667	0.3167	0.2000	0.2167	0.3667	0.2667
Power factor		0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83
DF* LF		0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
Connected Load (MW)		0.87	0.53	0.58	0.49	0.49	0.92	0.58	0.63	1.07	0.78
Average Load Window (kVAR)	70.0%	611.58	373.67	407.72	339.83	339.83	645.62	407.72	441.76	747.55	543.69
	4.0%	34.95	21.35	23.30	19.42	19.42	36.89	23.30	25.24	42.72	31.07
	4.6%	40.19	24.56	26.79	22.33	22.33	42.43	26.79	29.03	49.12	35.73
	3.4%	29.71	18.15	19.80	16.51	16.51	31.36	19.80	21.46	36.31	26.41
	3.1%	27.08	16.55	18.06	15.05	15.05	28.59	18.06	19.56	33.11	24.08
	2.9%	25.34	15.48	16.89	14.08	14.08	26.75	16.89	18.30	30.97	22.52
	1.7%	14.85	9.07	9.90	8.25	8.25	15.68	9.90	10.73	18.15	13.20
	10.3%	89.99	54.98	59.99	50.00	50.00	95.00	59.99	65.00	110.00	80.00
Number of units	1.200	510	311	340	283	283	538	340	368	623	453
	1.200	29	18	19	16	16	31	19	21	36	26
	0.032	1256	767	837	698	698	1326	837	907	1535	1117
	3.400	9	5	6	5	5	9	6	6	11	8
	3.000	9	6	6	5	5	10	6	7	11	8
	0.213	119	73	79	66	66	126	79	86	145	106
	0.250	59	36	40	33	33	63	40	43	73	53
	1.000	90	55	60	50	50	95	60	65	110	80
Total no. of units		2081	1271	1387	1156	1156	2198	1387	1503	2544	1851

6.1.3 Stochastic Model Results

The results of the developed stochastic model are shown in Figure 6.2 for a winter day (January 1st) and for a summer day (August 1st). The results incorporate human behavior effect due to incorporating TOU curves and utilizing stochastic simulation method, NSMC, and ambient temperature effect in the dominating Heating/Cooling loads. Similarly, the load demand for every minute over 200 years for each load point is produced. The average load for all load points is around the original average values of the test system shown in Table 3.2.

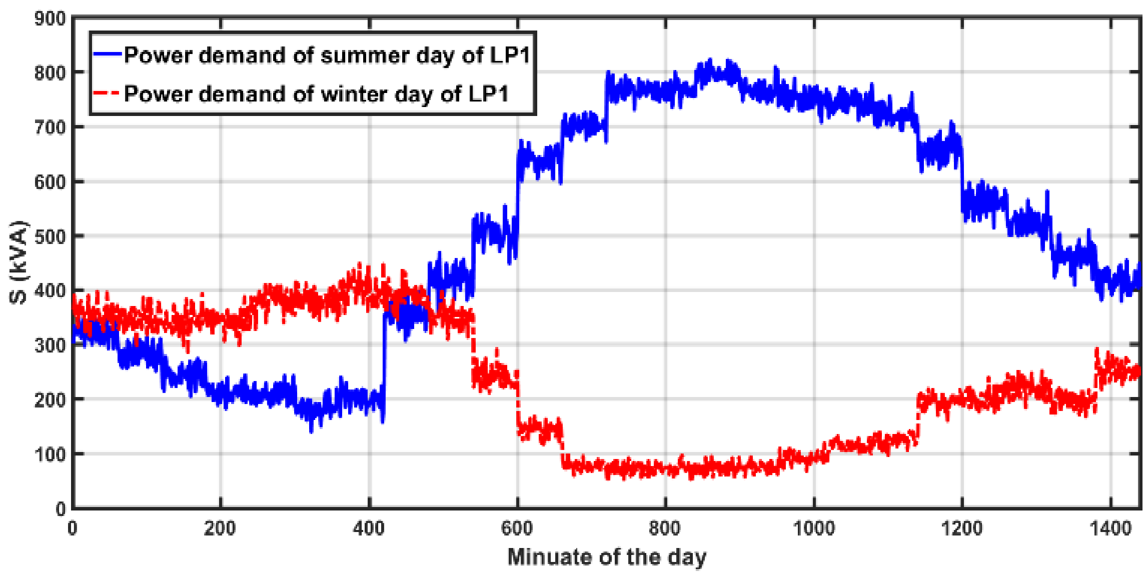

Figure 6.2: Stochastic load model for a winter day and a summer day

6.1.4 CLPU Model Results

Following the method utilized in 3.2.2, CLPU effect is produced for a simulated outage in Figure 6.3. This was based on the selected parameters in CLPU modeling, which are α = 0.5 hr-1 and $\Delta t = 30$ minutes [43]. The sample outage affected LP1, LP2 and LP3, therefore CLPU will impact only these points. Form the figure, it can be seen that the power demand of the restored points (red curve) has increased almost two times the normal power demand and therefore the overall power demand (blue curve) at the main transformer also increased suddenly.

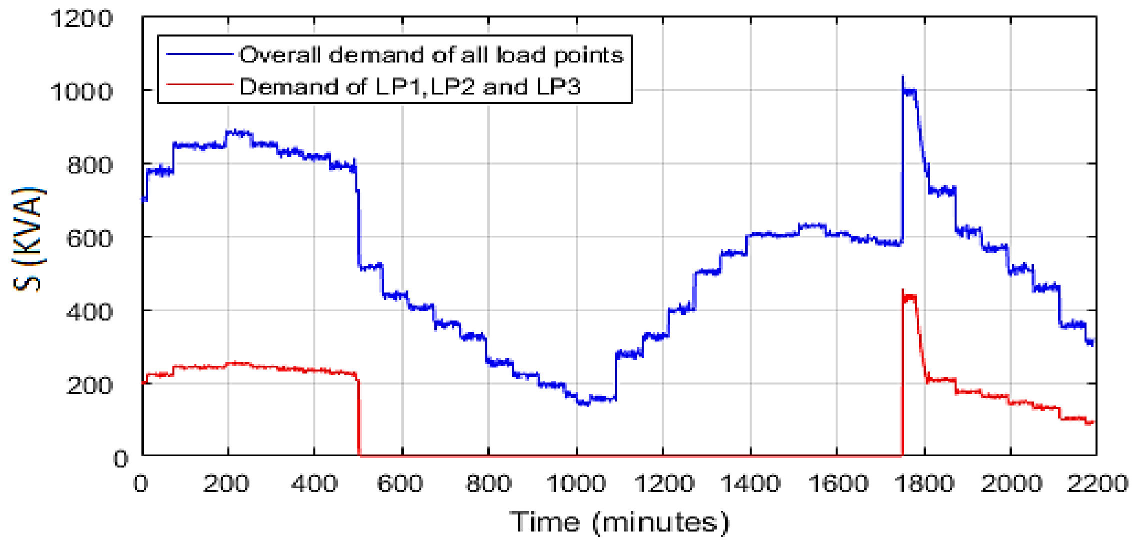

Figure 6.3: Cold load pick model results for a simulated failure

6.2 Load Flow Results

Load flow studies will be conducted to ensure that the system design presented in Chapter 3 was satisfactory. Load flow studies will be run for the system during normal operation conditions and minimum loading conditions to ensure the voltage will not exceed 1.05 pu. They will be conducted for maximum loading conditions to ensure the voltage will not drop below 0.95 pu. The admittance matrix is developed in Appendix A (Table A.1) and the following subsections will show the system's load flow results for these conditions.

6.2.1 Average Load Flow Results

During system normal operation, the system demand is around average loading condition which has the bus results in Table 6.3.

Table 6.3: The system bus results during average loading conditions

LP No.	Voltage Mag.	Angle Degree	Load MW	Load Mvar	Gen. MW	Gen. Mvar
Supply Bus	1	0	0	0	1.084345	0.713098
1	0.997895	-0.08353	0.116887	0.092296	0	0
2	0.996389	-0.15156	0.090058	0.051855	0	0
3	0.995597	-0.18772	0.101178	0.057215	0	0
4	0.998089	-0.07866	0.076414	0.048116	0	0
5	0.997134	-0.11809	0.076364	0.048112	0	0
6	0.997625	-0.09631	0.1338	0.093127	0	0
7	0.996437	-0.15045	0.101177	0.057184	0	0
8	0.997307	-0.10368	0.102144	0.064696	0	0
9	0.995301	-0.17971	0.181003	0.104553	0	0
10	0.994229	-0.21059	0.103244	0.090822	0	0
		Total	1.082269	0.707977	1.084345	0.713098

The line flow results of the system under this condition are shown in appendix A (Table A.2) with one important results to highlight. This results in the transformer MVA loading which is around 1.298 MVA during normal operation. The results are acceptable and system voltage are very close to 1 pu at all load points. The transformer loading is much less than the transformer size of 6.5 MVA.

6.2.2 Minimum Load Flow Results

In winter seasons, distribution system loading in hot regions reduces significantly. This will cause the system voltage to increase specially for very long cable causing possible issues for system insulation and during switching transients. The minimum load flow is conducted, and the results are shown in Table 6.4 and Table A.3 in Appendix A.

Table 6.4: The system bus results during minimum loading conditions

LP No.	Voltage Mag.	Angle Degree	Load MW	Load Mvar	Gen. MW	Gen. Mvar
Supply Bus	1	0	0	0	0.152756	0.07243
1	0.999771	-0.01185	0.019667	0.009525	0	0
2	0.999625	-0.01938	0.008736	0.004231	0	0
3	0.999542	-0.02369	0.011636	0.005636	0	0
4	0.999823	-0.00915	0.008437	0.004086	0	0
5	0.999737	-0.01362	0.00806	0.003904	0	0
6	0.9997	-0.01559	0.023171	0.01109	0	0
7	0.999573	-0.02219	0.011896	0.005761	0	0
8	0.99966	-0.01831	0.014242	0.005932	0	0
9	0.999395	-0.03226	0.029062	0.013572	0	0
10	0.999268	-0.03886	0.017813	0.008603	0	0
		Total	0.15272	0.072341	0.152756	0.07243

The transformer MVA loading is around 0.169 MVA under this condition. The system results are within acceptable range and there is no increase in the voltage since the cables have a very short length and the capacitance impact will not appear.

6.2.3 Maximum Load Flow Results

In the contrast of 6.2.2, the system will experience peak demands during summer seasons in hot region areas. Consequently, the voltage will decrease at all load points. In Table 6.5, the magnitude and angle of the voltages on the system buses are shown. All voltage magnitudes are within acceptable range with the minimum voltage of 0.972 pu.

Table 6.5: The system bus results during maximum loading conditions

LP No.	Voltage Mag.	Angle Degree	Load MW	Load Mvar	Gen. MW	Gen. Mvar
Supply Bus	1	0	0	0	5.035787	3.577785
1	0.989656	-0.38361	0.624417	0.434379	0	0
2	0.982344	-0.65959	0.385287	0.267901	0	0
3	0.978513	-0.80628	0.425654	0.293896	0	0
4	0.990464	-0.35739	0.354625	0.246293	0	0
5	0.985695	-0.53989	0.357473	0.244922	0	0
6	0.988384	-0.43237	0.653409	0.455651	0	0
7	0.982687	-0.64936	0.423927	0.292368	0	0
8	0.987162	-0.47231	0.453404	0.315484	0	0
9	0.977626	-0.83128	0.753234	0.525229	0	0
10	0.972559	-1.0253	0.557873	0.386998	0	0
		Total	4.989302	3.463122	5.035787	3.577785

Moreover, as seen in Appendix A (Table A.4), the transformer apparent power flow is about 6.177 MVA. This is around 95% of the transformer capacity and are still within acceptable limits. However, it is reaching the maximum acceptable loading on the transformer.

6.3 Tuning Parameters Results

6.3.1 RCGA Tuning Results

Following the steps determined in 5.2.1, the initial sweeping on each parameter is performed as per reported results in Appendix B, Table B.1 in the first sample failure and Table B.2 for the first sample failure. The best two values of each parameters are combined, and results are reported in Table 6.6 and Table 6.7 with the objective function at the generations 50, 100 and 500 and 1000 with population number of 120.

Table 6.6: RCGA tuning results for sample failure 1

P_c	P_m	α	b	f_{50}	f_{100}	f_{500}	f_{1000}
Best values mixed sweeping:							
0.7	0.05	0.3	3	1981	1524	1254	1152
0.7	0.05	0.3	5	1875	1430	1129	1078
0.7	0.05	0.6	3	1775	1775	1435	1110
0.7	0.05	0.6	5	1932	1849	1268	1063
0.7	0.1	0.3	3	2014	1825	1463	1191
0.7	0.1	0.3	5	2049	1799	1296	1176
0.7	0.1	0.6	3	2360	2046	1580	1076
0.7	0.1	0.6	5	2172	1980	1369	1057
0.9	0.05	0.3	3	1838	1489	1256	1091
0.9	0.05	0.3	5	1656	1484	1179	1129
0.9	0.05	0.6	3	1934	1741	1511	1221
0.9	0.05	0.6	5	1938	1793	1393	1181
0.9	0.1	0.3	3	2155	1917	1396	1224
0.9	0.1	0.3	5	2042	1767	1279	1174
0.9	0.1	0.6	3	1839	1758	1727	1188
0.9	0.1	0.6	5	2302	2227	1491	1215
Additional test:							
0.6	0.05	0.5	6	1628	1496	1148	1079

Table 6.7: RCGA tuning results for sample failure 2

P_c	P_m	α	b	f_{50}	f_{100}	f_{500}	f_{1000}
Best values mixed sweeping:							
0.6	0.05	0.4	4	5335	5223	5011	4917
0.6	0.05	0.4	6	5318	5161	4982	4982
0.6	0.05	0.5	4	5496	5304	5092	4957
0.6	0.05	0.5	6	5482	5324	5007	4907
0.6	0.15	0.4	4	5591	5591	5399	5116
0.6	0.15	0.4	6	5516	5454	5454	5385
0.6	0.15	0.5	4	5574	5415	5338	4974
0.6	0.15	0.5	6	5765	5665	5200	4977
0.7	0.05	0.4	4	5426	5262	5071	4979
0.7	0.05	0.4	6	5661	5277	5012	4931
0.7	0.05	0.5	4	5500	5354	5150	4954
0.7	0.05	0.5	6	5648	5360	5053	4922
0.7	0.15	0.4	4	5735	5623	5481	5164
0.7	0.15	0.4	6	5593	5541	5350	5019
0.7	0.15	0.5	4	5487	5487	5457	4982
0.7	0.15	0.5	6	5539	5539	5357	4980
Additional test:							
0.7	0.1	0.6	5	5606	5551	5198	5003

The resulted two combinations from each failure are different. Therefore, an additional test was imposed to test each sample failure's best combination on the other failure. The results show that combination (Pc = 0.6, Pm = 0.05, α = 0.5, b = 6) gives the best results for one sample failure and very satisfactory results on the other failure. Therefore, this combination of parameters will be selected for the rest of RCGA algorithms in solving all the other failures. Figures 6.4 and 6.5 shows these results along with the objective functions' trajectories along the generations.

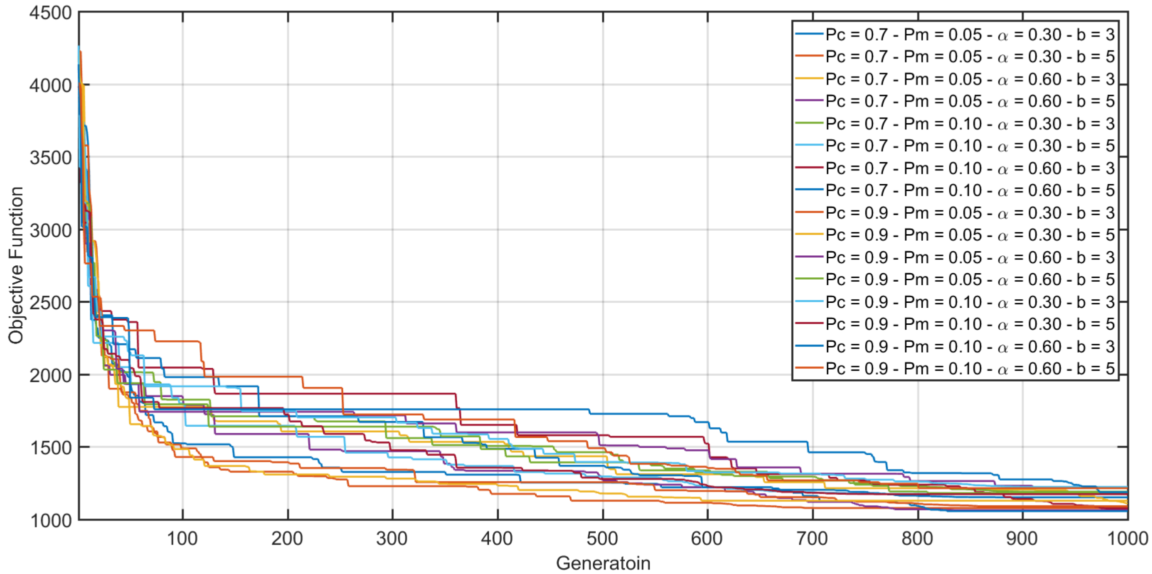

Figure 6.4: RCGA parameters tuning for sample failure 1

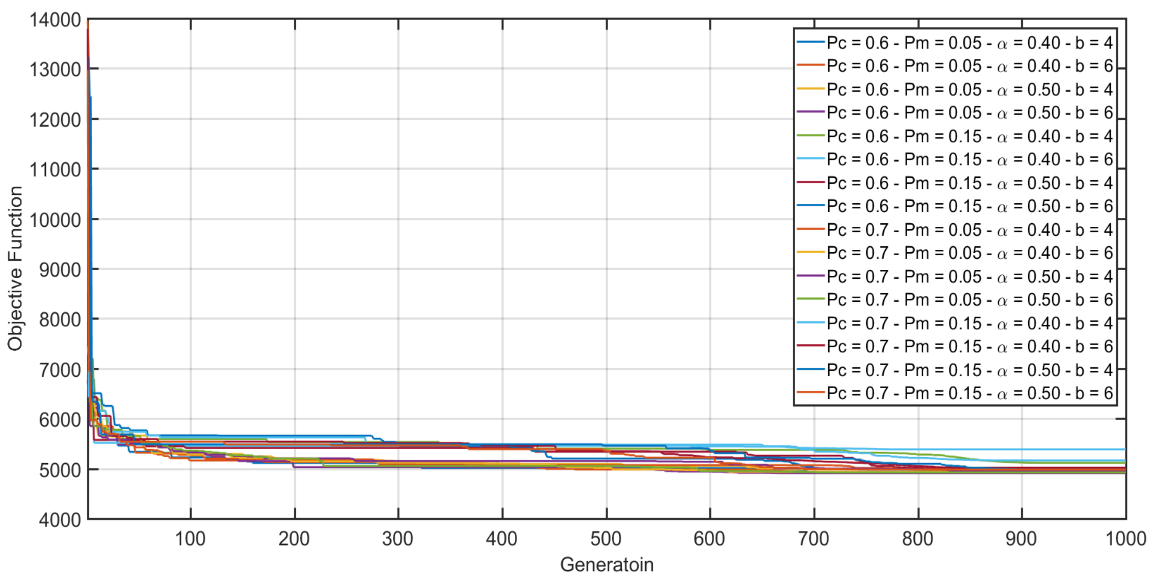

Figure 6.5: RCGA parameters tuning for sample failure 2

6.3.2 PSO Tuning Results

PSO initial sweeping results are presented in Table B.3 and Table B.4 of Appendix B. The best two values of each parameters are combined to conduct a second stage sweeping and results are presented in this section in Table 6.8 and Table 6.9 for the two sample failures. Additional tests were required since the resultant best combinations were different from each other.

Table 6.8: PSO tuning results for sample failure 1

β	**N**	**c_1**	**c_2**	**f_{50}**	**f_{100}**	**f_{500}**	**f_{1000}**
Best values mixed sweeping:							
0.9	10.0	0.5	2.0	1956.0	1620.0	1530.0	1530.0
0.9	10.0	0.5	2.5	1088.0	1044.0	1044.0	1044.0
0.9	10.0	1.0	2.0	1067.0	1030.0	1020.0	1020.0
0.9	10.0	1.0	2.5	1212.0	1110.0	1017.0	1017.0
0.9	15.0	0.5	2.0	2026.0	2026.0	2026.0	2026.0
0.9	15.0	0.5	2.5	1156.0	1125.0	1119.0	1119.0
0.9	15.0	1.0	2.0	2266.0	1510.0	1510.0	1510.0
0.9	15.0	1.0	2.5	1375.0	1295.0	1138.0	1135.0
0.95	10.0	0.5	2.0	1343.0	1338.0	1338.0	1338.0
0.95	10.0	0.5	2.5	1168.0	1132.0	1098.0	1090.0
0.95	10.0	1.0	2.0	1270.0	1204.0	1090.0	1090.0
0.95	10.0	1.0	2.5	1075.0	1010.0	994.0	967.0
0.95	15.0	0.5	2.0	1171.0	1042.0	1042.0	1042.0
0.95	15.0	0.5	2.5	1222.0	1044.0	1031.0	1031.0
0.95	15.0	1.0	2.0	1464.0	1205.0	1195.0	1195.0
0.95	15.0	1.0	2.5	1146.0	1100.0	1069.0	1069.0
Additional test:							
0.85	15	2.0	2.5	1362	1236	1086	1061

Table 6.9: PSO tuning results for sample failure 2

β	**N**	**c_1**	**c_2**	**f_{50}**	**f_{100}**	**f_{500}**	**f_{1000}**
Best values mixed sweeping:							
0.85	10	0.5	2.0	5971	5428	5428	5428
0.85	10	0.5	2.5	5114	4989	4929	4929
0.85	10	2.0	2.0	5473	5180	4789	4704
0.85	10	2.0	2.5	5687	5416	4888	4820
0.85	15	0.5	2.0	5520	5004	5004	5004
0.85	15	0.5	2.5	6165	5337	5255	5246
0.85	15	2.0	2.0	5524	5462	5233	5224
0.85	15	2.0	2.5	5841	5598	4746	4654
0.9	10	0.5	2.0	5060	4946	4922	4922
0.9	10	0.5	2.5	5379	4936	4885	4885
0.9	10	2.0	2.0	5185	4983	4841	4805
0.9	10	2.0	2.5	5670	5415	4798	4706
0.9	15	0.5	2.0	5666	5181	5096	5096
0.9	15	0.5	2.5	5390	4934	4934	4934
0.9	15	2.0	2.0	5870	5747	4897	4711
0.9	15	2.0	2.5	5983	5803	4955	4818
Additional test:							
0.95	10	1.0	2.5	5650	5487	5315	5261

Based on the two-stage sweeping of common values of PSO parameters, the following parameters are selected: initial inertia of 0.85, c_1 factor of 1.0, c_2 factor of 2.5 with 10 velocity steps. These values have given the best results of one failure and a relatively good result of a second failure. The initial sweeping results showed also that the problem is highly dependent on the global best value. The higher the c_2 factor, the better the results unlike the c_1 factor. These values will be selected for the rest of the analysis. Figures 6.6 and Figure 6.7 show these results along with the objective functions' trajectories over 1000 generations with particle number of 120. This number of solution vector is selected throughout the analysis of the tuning section.

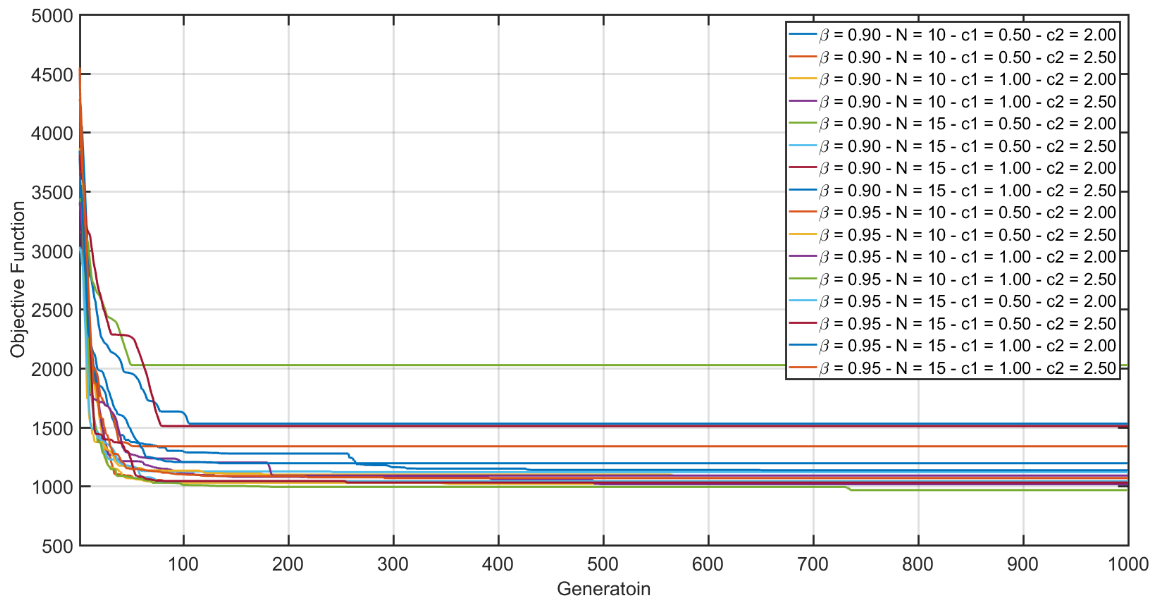

Figure 6.6: PSO parameters tuning for sample failure 1

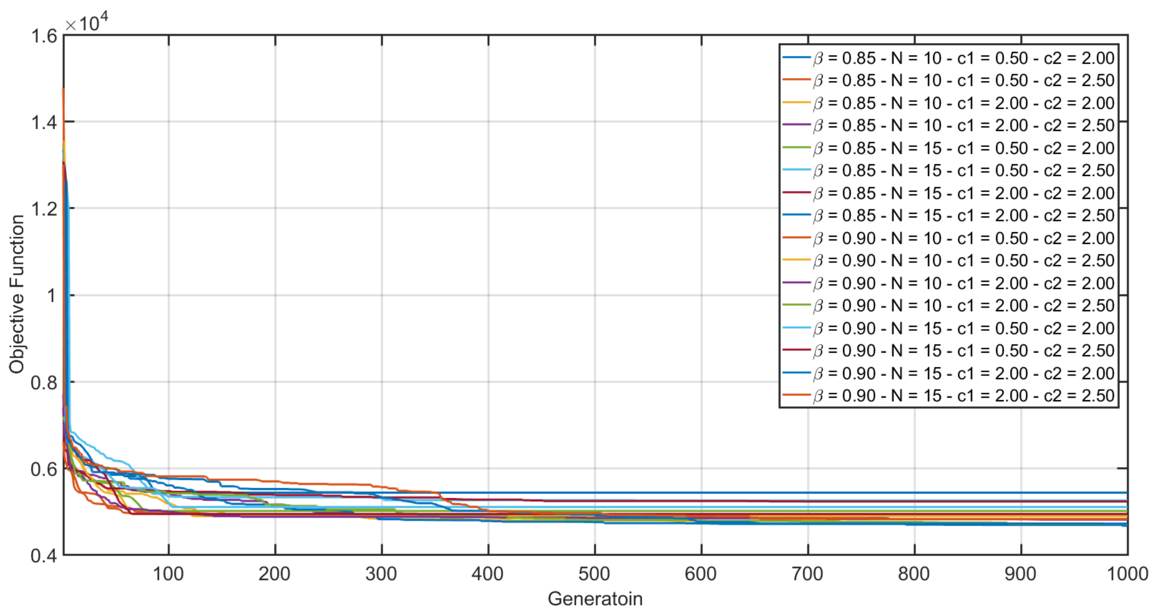

Figure 6.7: PSO parameters tuning for sample failure 2

6.3.3 DE Tuning Results

Similarly, in DE, an initial sweeping is performed in Appendix B, Table B.5 and Table B.6. The first-stage sweeping results led to selecting the best two values of CR and F. The results of the second-stage sweeping are presented in Table 6.10 and Table 6.11 along with Figure 6.8 and Figure 6.9.

Table 6.10: DE tuning results for sample failure 1

CR	**F**	**f_{50}**	**f_{100}**	**f_{500}**	**f_{1000}**
0.4	0.6	2008	2008	1412	1208
0.4	0.7	2119	1805	1389	1285
0.4	0.9	2342	2059	1549	1385
0.6	0.6	1919	1783	1358	1141
0.6	0.7	2109	1777	1347	1251
0.6	0.9	1894	1712	1353	1309
0.9	0.6	1712	1533	1217	1127
0.9	0.7	1710	1534	1277	1144
0.9	0.9	2176	1904	1348	1280

Table 6.11: DE tuning results for sample failure 2

CR	**F**	**f_{50}**	**f_{100}**	**f_{500}**	**f_{1000}**
0.4	0.4	6278	5732	5245	4990
0.4	0.6	5931	5385	5236	5147
0.4	0.8	6369	5784	5222	5089
0.7	0.4	6052	5644	5181	5019
0.7	0.6	5779	5430	5128	5077
0.7	0.8	5926	5689	5182	5098
0.9	0.4	5863	5474	5139	5021
0.9	0.6	5362	5311	5033	4984
0.9	0.8	5476	5435	5151	5104

It can be seen from the results that the best run of the optimal restoration of the two sample failures are associated with the same factors. These factors are CR of 0.9 and F 0f 0.6, which will be selected for the rest of DE analysis.

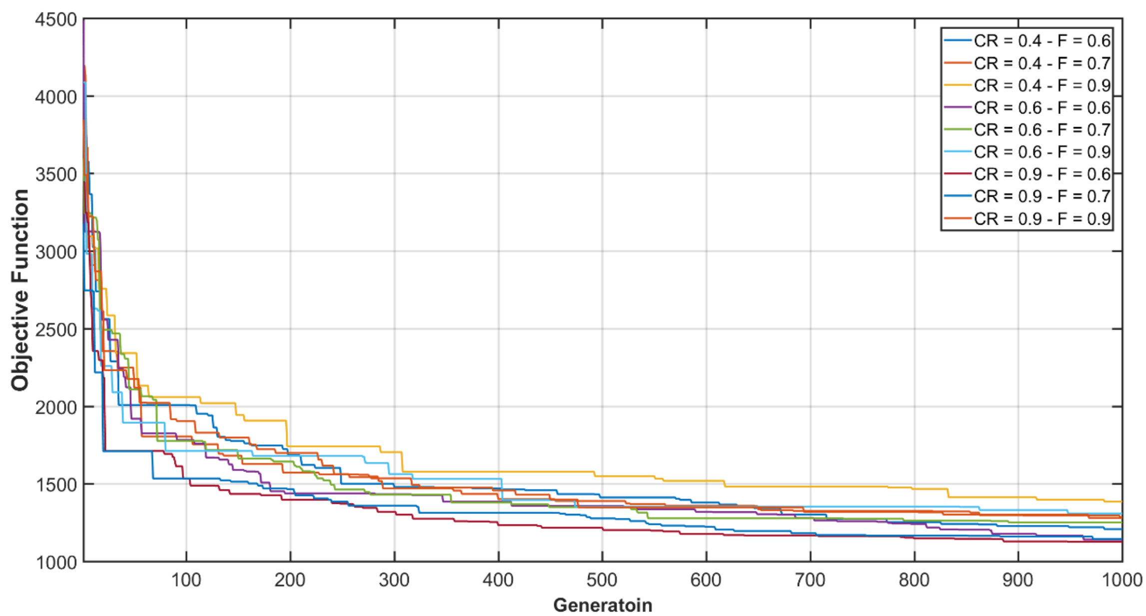

Figure 6.8: DE parameters tuning for sample failure 1

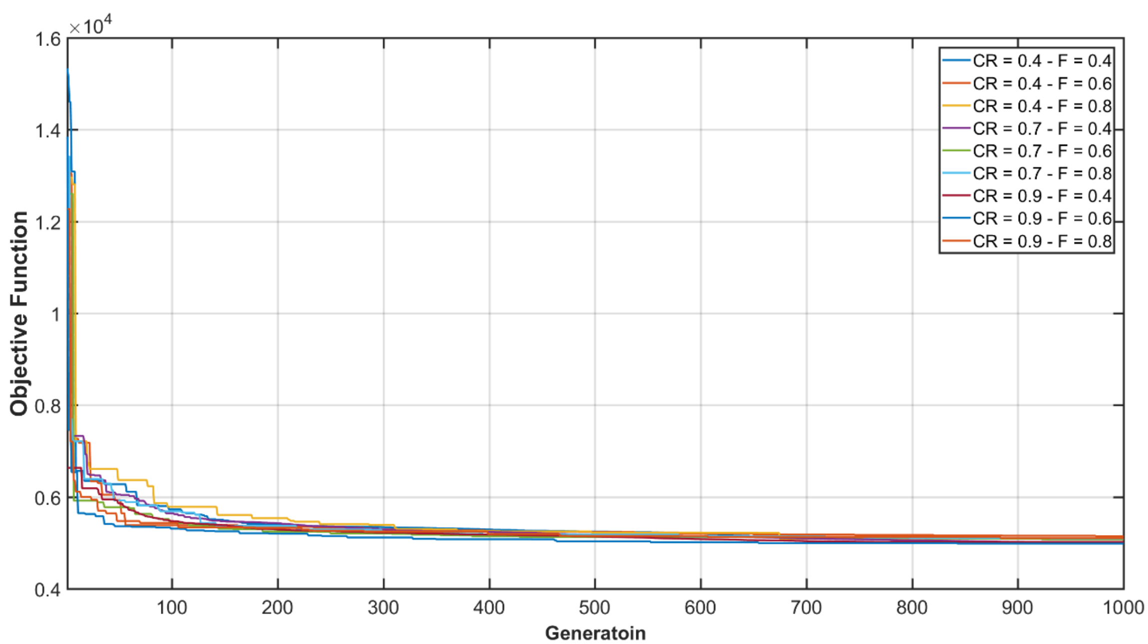

Figure 6.9: DE parameters tuning for sample failure 2

6.3.4 LSA Tuning Results

In LSA, there were three parameters to tune with respect to the application. The first-stage sweeping for two failures and results are shown in Table B.7 and Table B.8 in appendix B. The second-stage sweepings are conducted in a similar manner to GE, PSO and DE. Results are shown in Table 6.12 and Table 6.13.

These tables show that the best parameters for LSA analysis for this kind of problems are: forking probability of 10%, initial energy value of 4 with maximum channel time of 15 iterations. These values suggest that this problem is in favor of higher forking probability yet lower channel time. Also, the tuning exercise revealed that the initial energy value should be 4, since higher scaling factor would be required at early generations. Figures 6.10 and Figure 6.11 show the results of the second-stage tuning analysis.

Table 6.12: LSA tuning results for sample failure 1

Chan. Time	**FR**	**E_0**	**f_{50}**	**f_{100}**	**f_{500}**	**f_{1000}**
Best values mixed sweeping:						
5	0.01	2	1247	1112	1046	1046
5	0.01	4	1251	1137	1073	1073
5	0.10	2	1280	1075	1055	1055
5	0.10	4	1316	1126	969	967
15	0.01	2	1233	1090	1023	1005
15	0.01	4	1218	1108	1033	1024
15	0.10	2	1243	1177	1038	1038
15	0.10	4	1472	1159	1053	1048
Additional test:						
15	0.05	6	1173	1124	1068	1046

Table 6.13: LSA tuning results for sample failure 2

Chan. Time	FR	E_0	f_{50}	f_{100}	f_{500}	f_{1000}
Best values mixed sweeping:						
10	0.05	3	5112	4978	4794	4784
10	0.05	6	5031	4973	4889	4886
10	0.10	3	5193	4984	4891	4834
10	0.10	6	5182	5011	4797	4797
15	0.05	3	5127	4960	4907	4845
15	0.05	6	5100	4986	4796	4722
15	0.10	3	5122	5037	4834	4731
15	0.10	6	5072	4963	4842	4819
Additional test:						
5	0.10	4	5003	4920	4748	4746

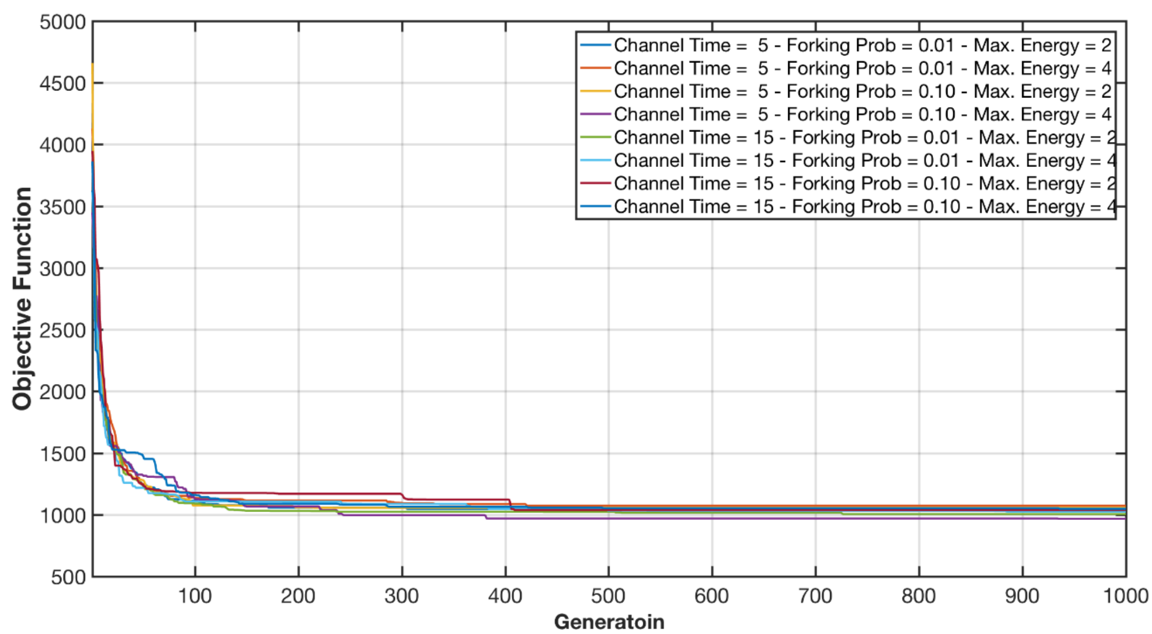

Figure 6.10: LSA parameters tuning for sample failure 1

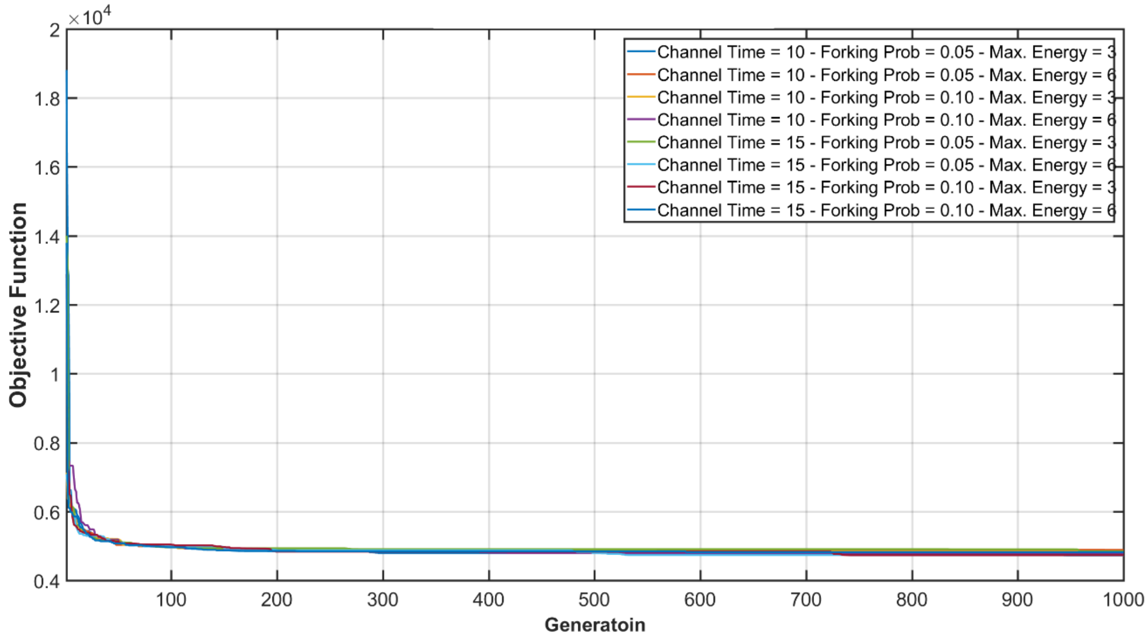

Figure 6.11: LSA parameters tuning for sample failure 2

6.3.5 Comparison Between Optimization Methods

The four algorithms were run with different initial population and parameters with 1000 iterations and population of 120 solution vectors. Based on these results, parameters are tuned accordingly. The best runs are compared together for both selected sample failures and the results are shown in Figure 6.12 and Figure 6.13 and the average computational time of all different runs in Table 6.14. Also, the best, the average and the standard deviation of the objective functions are measured at the 50th, 100th, 500th and 1000th generations in Table 6.15. These values will be used to determine the convergence characteristics and to measure the robustness of these methods. The lower these values are the better for an optimization technique since it shows ability to converge faster with different parameters.

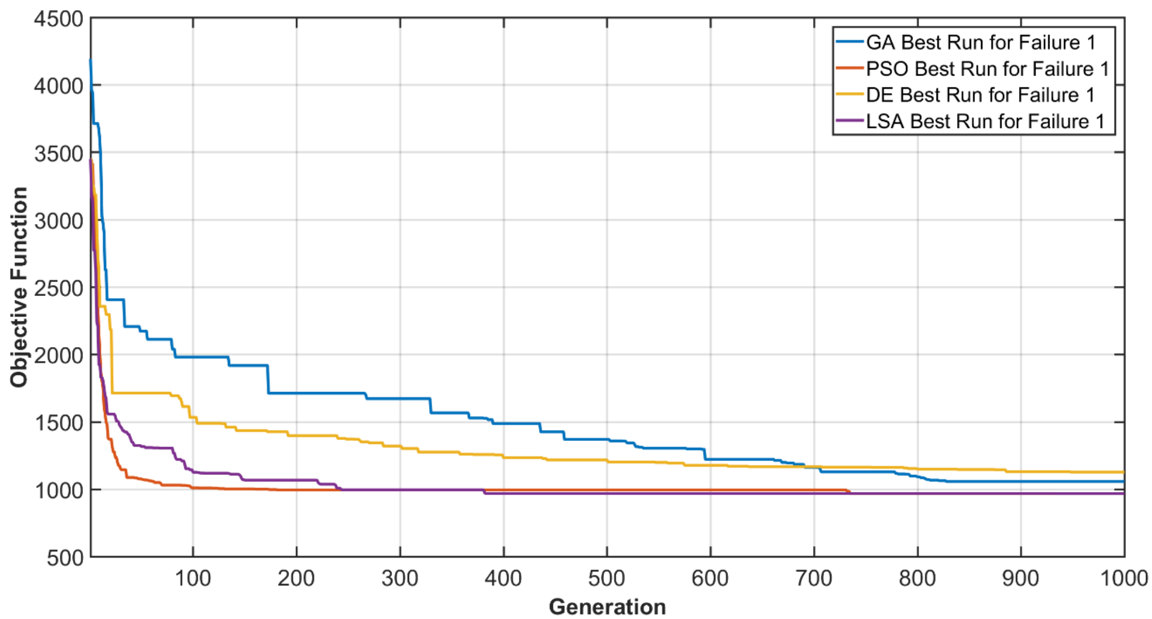

Figure 6.12: Best runs of all algorithm for failure 1

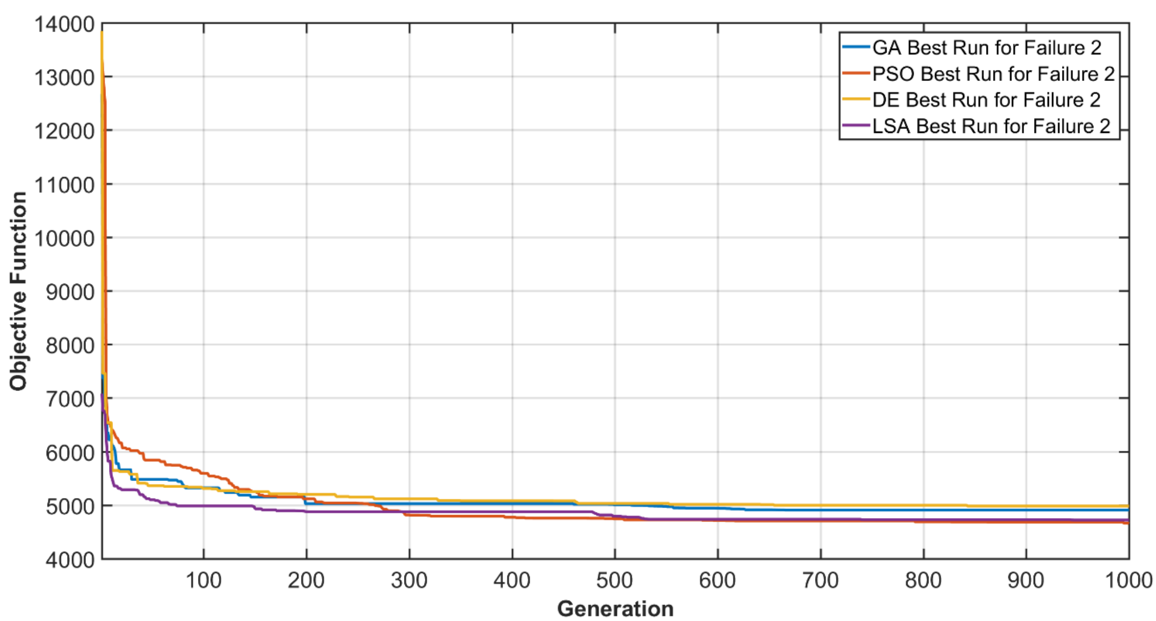

Figure 6.13: Best runs of all algorithm for failure 2

Table 6.14: Average computational time of optimization algorithm

Algorithm	Average Computational Time
GA	40 minutes
PSO	41 minutes
DE	28 minutes
LSA	29 minutes

Table 6.15: Comparison between optimization methods' robustness

		Failure 1				Failure 2			
		RCGA	PSO	DE	LSA	RCGA	PSO	DE	LSA
f_{50}	Min	1628	1067	1710	1152	5318	5060	5362	5001
	Average	1968	1372	2032	1271	5568	5687	5835	5119
	SD	186	295	219	143	118	1077	295	62
f_{100}	Min	1430	1010	1533	1063	5161	4932	5134	4816
	Average	1740	1274	1830	1121	5432	5476	5480	4959
	SD	200	247	201	34	121	1104	164	55
f_{500}	Min	1129	994	1217	969	4970	4746	5033	4710
	Average	1357	1206	1457	1038	5191	5239	5161	4821
	SD	177	254	167	35	149	1135	54	62
f_{1000}	Min	1057	967	1127	967	4907	4654	4984	4700
	Average	1189	1195	1364	1030	5026	5192	5079	4788
	SD	168	258	174	36	118	1149	46	61

From this section's results along with appendix B results, the following can be concluded:

- All four algorithms are stable and converge around each other for both failures as seen clearly in Figures 6.12 and 6.13.
- As an emerging algorithm, LSA proved its robustness by leading to the same results with different initial population and parameters. LSA has a faster convergence rate

that other methods reaching very acceptable results at the 200th generation. In Table 6.15 LSA resulted in a better convergence characteristics at different generations leading to the best results in 19 times out of 24 times in the two sample failures. LSA has the lowest standard deviations and lower average objective values at different generation showing better robustness than the other three methods with different parameters and different initial population. Moreover, LSA has an excellent componential time LSA can guide online restoration and provide solid results in around 5 minutes.

- GA has a very slow convergence rate compared to other methods, which might lead to better results at very late generations due to avoidance of local optimum points.
- LSA has a very similar behavior of PSO with very similar trajectories for both failures. This is might be due to the fact that both are moving based on a factor that is affected by the global best. However, both algorithms are subjected to local optimum convergence due to their lightning effects of reaching excellent solution at early generations. This effect might cause the problem to have less diversity among population of early generations.
- DE resulted in the worst solutions among the four methods, yet the computational time saving was huge compared to GA and PSO as per Table 6.14. LSA and DE had a similar computational time which was around 35% of the computational time of PSO and GA. In other words, the operation will have to wait for additional 10 minutes before GA and PSO provides the restoration sequence assuming the 1000 iterations case.

6.4 Reliability Assessment Without CLPU

Following the flow chart outlined in Figure 5.1, Monte Carlo Simulations (MCS) was conducted for the system over a period of 200 years. All equipment status over that period with a 1-minute accuracy were determined. The number of failures and unavailability at each load point were found accordingly.

An example of load point no. 10 status is shown between simulation time of minute 15684183 to minute 15685455 and it shows that it is being affected by status of main transformer, main circuit breaker, feeder circuit breaker, section 8, section 9, and section 10 as shown in Figure 6.14. A failure at section no. 8 caused load point no. 10 to lose power from the source. Section 8 was restored, and the power was restored accordingly to the load point.

Accordingly, MCS was conducted for 105120000 minutes (200 years) to find the average reliability indices over 1 year. Results are presented in Table 6.16. Reliability indices are found under the assumption that one customer is connected at the end of each load point. These reliability indices are resulted only due to failures of system components. Other factors affecting these reliability indices due to operation restrictions are not counted in this analysis. Hence, these values do not reflect actual reliability indices. In the next parts, one CLPU event is considered and the restoration time is optimized and then these calculations will be repeated considering the CLPU for the overall simulation period. There was a total of 37 failures over the period of 200 years. This is a very low number of the residential distribution system. This is since the test system is a small system with few components only considered for analysis.

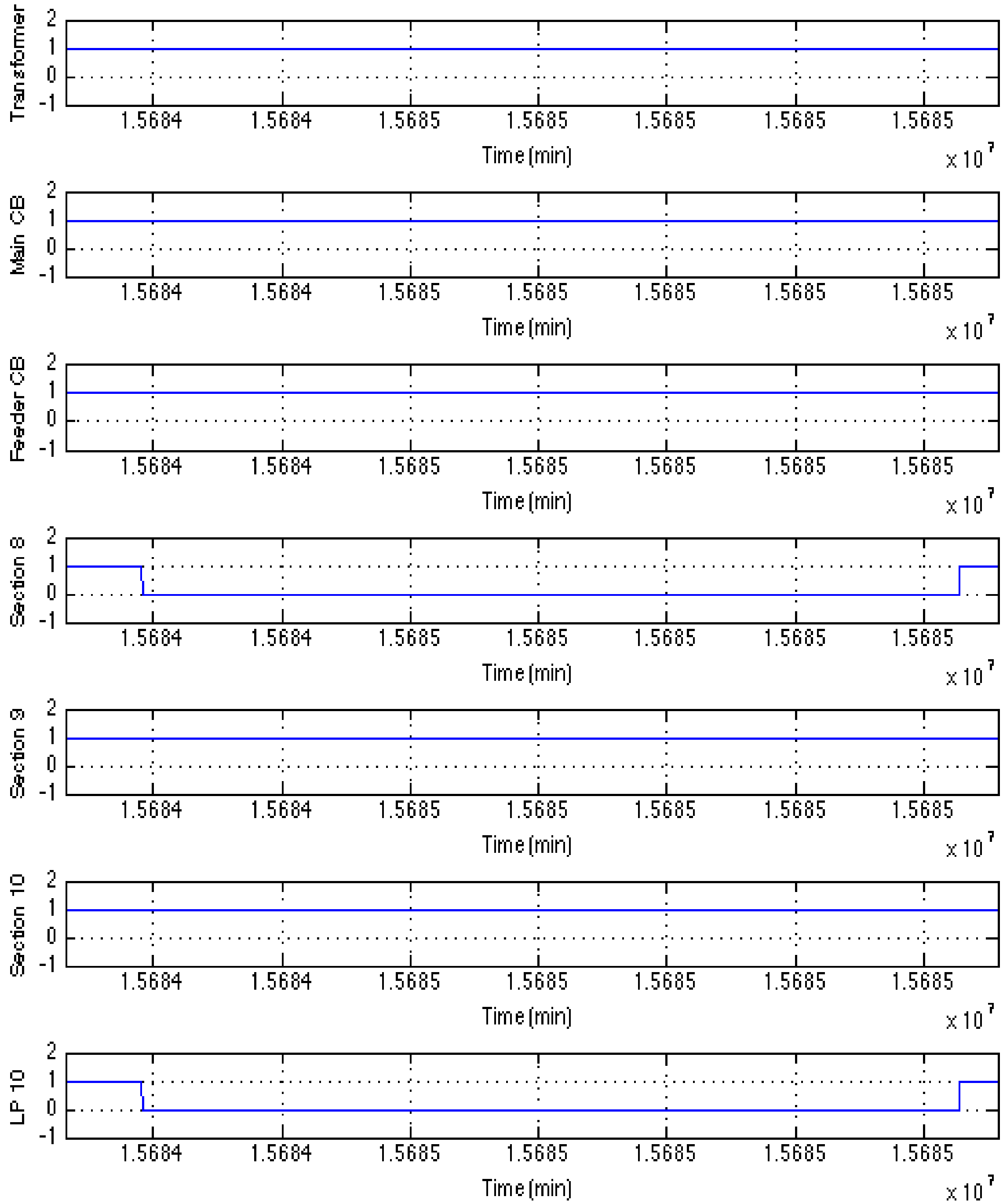

Figure 6.14: Status of section 9, section 10 and LP10 for a sample duration from the simulation time from minute 15684183 to minute 15685455

Overall, for this test system, every load point in the system would experience 487.3 minutes per year, which is around 8 hours. The failures are very rare and could happen in an average once of 18 years for every load points. The details of all failures are found in Appendix C, Table C.1.

Table 6.16: Reliability indices without CLPU

Reliability Index	Value
SAIFI (interruption/load point)	0.0535000
SAIDI (hours/load point)	8.1216667
SAIDI (minutes/load point)	487.3000000
CAIDI (hours/load point interruption)	151.8068536
CAIDI (minutes/load point interruption)	9108.4112150
ASAI	0.9990729
ASUI	0.0009271
ENS (kWh)	24083.1945836
AENS (kWh/load point)	2408.3194584

6.5 Optimal Restoration of Single Failure

Not all outages will result in a peak demand that will violate the protection settlings, or a voltage drop that will violate operational limits. However, it is expected after extended outages that there will be CLPU events, especially during summer seasons in hot regions or during peak hours of the day. All 37 failures resulted in the system have gone through a check point as illustrated in flow charts in Figures 5.2, 5.3, 5.5 and 5.7. This check point will determine if a single step restoration is possible or not. Table 6.17 lists all 37 failures and the single step restoration power demand and lowest operation voltage at any bus during restoration. For the resulted 37 outages in the simulation period, eight (8) of these failures have resulted in CLPU events as per Table 6.17. The remaining outages were either with short duration resulting in a low power demand or occurred at a time with low TCL concentrations. For example, failure no. 4 had occurred in the winter season (minute 10009869) with a very low demand. Although the outage duration was very long (more than 3 days) due to cable failure, the single step restoration was allowed with a power demand less than 1 MVA and a voltage of 1 pu as per Figure 6.15 (restoration occurred at minute 60 of the figure). Similarly, one failure that occurred in minute 34858479 and tripped LP1, LP2 and LP3 and the power was restored after 482 minutes. However, the restoration was in a low demand period with a low TCL concentration. The power demand after restoration was 6519.54 kVA and the worst voltage magnitude was 0.95 pu. Hence, no constraint is violated which means no CLPU has happened and the restoration was done in a single step without any effect at the reliability indices. The other failures violated both the power demand and the voltage limits requirements. It can be noticed from the table that the outage durations due to main transformer failure and main circuit breaker failure are very long and consequently unpractical. This is due to the fact that the repair time of these equipment is very long as per Table 3.4 in conjunction with the fact that this system is radial and there are no other alternative feeders to supply the load during the outage. In actual systems, the network has a loop-configuration to provide power supply to some or all affected load points. Therefore, the actual outage duration is less than the values presented in Table 6.17.

Table 6.17: Details of all 37 failures of the system

Seq	Hour of day	Outage Duration (min)	Season	Affected points	Single Step Restoration Demand (kVA)	Lowest Voltage (pu)	Optimal Restoration needed?
1	6:00 PM	10862	Summer	[1 2 3 4 5 6 7 8 9 10]	33353.02	0.82	Yes
2	6:00 PM	62470	Summer	[1 2 3 4 5 6 7 8 9 10]	42389.82	0.74	Yes
3	11:00 PM	678	Spring	10	5740.86	0.95	No
4	2:00 AM	4901	Winter	[6 7]	961.91	1.00	No
5	6:00 AM	1481	Fall	10	1878.21	0.99	No
6	6:00 AM	4254	Summer	5	1992.76	0.99	No
7	5:00 PM	911	Fall	5	3138.44	0.98	No
8	5:00 PM	1069	Summer	7	3142.88	0.99	No
9	5:00 AM	6081	Summer	[1 2 3 4 5 6 7 8 9 10]	9203.26	0.95	Yes
10	9:00 PM	2438	Fall	[1 2 3 4 5 6 7 8 9 10]	16604.56	0.91	Yes
11	7:00 PM	503	Fall	[9 10]	3363.27	0.97	No
12	5:00 PM	482	Spring	[1 2 3]	6519.54	0.95	No
13	10:00 PM	1160	Spring	3	1096.04	1.00	No
14	4:00 AM	311	Summer	[8 9 10]	6635.83	0.94	Yes
15	8:00 PM	7026	Summer	[4 5]	4390.83	0.96	No
16	6:00 PM	9229	Summer	[1 2 3 4 5 6 7 8 9 10]	22300.60	0.88	Yes
17	8:00 AM	910	Winter	[6 7]	2924.10	0.98	No
18	1:00 PM	118	Winter	7	1307.87	0.99	No
19	5:00 AM	73	Summer	[9 10]	4006.47	0.97	No
20	10:00 PM	424	Summer	7	5864.37	0.96	No
21	8:00 AM	3	Fall	[1 2 3]	969.68	0.99	No
22	11:00 PM	691	Winter	[4 5]	1995.28	0.99	No
23	1:00 AM	515	Spring	[6 7]	4178.74	0.97	No
24	9:00 AM	221	Fall	5	3210.37	0.99	No
25	2:00 PM	126	Spring	7	3739.44	0.98	No
26	9:00 AM	807	Spring	[4 5]	4668.22	0.97	No
27	8:00 AM	2149	Spring	[6 7]	9944.09	0.92	Yes
28	7:00 PM	459	Winter	[2 3]	2662.47	0.98	No
29	8:00 AM	970	Winter	[2 3]	1142.02	0.99	No
30	2:00 AM	3155	Spring	[4 5]	659.60	1.00	No
31	1:00 AM	256	Fall	7	1417.81	0.99	No
32	6:00 AM	580	Fall	[1 2 3]	2894.07	0.98	No
33	4:00 AM	512	Spring	[6 7]	404.62	1.00	No
34	7:00 AM	3	Spring	[1 2 3]	4087.65	0.98	No
35	4:00 AM	887	Winter	5	1701.41	0.99	No
36	12:00AM	45	Winter	5	909.66	1.00	No
37	5:00 PM	897	Summer	[8 9 10]	5457.59	0.95	Yes

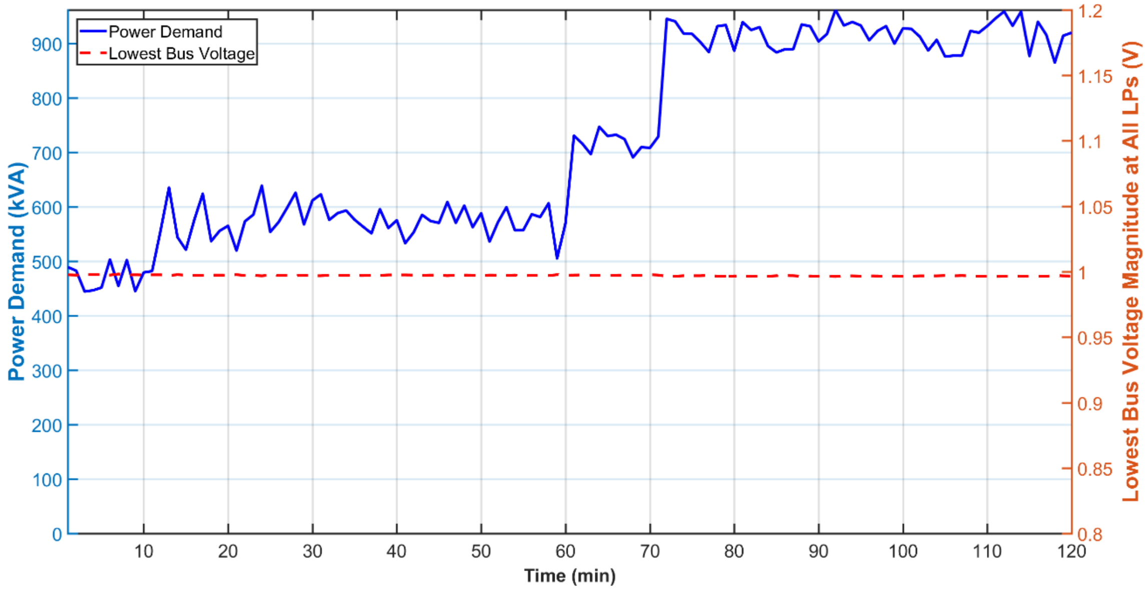

Figure 6.15: Power demand and lowest bus voltage after restoration from failure no. 4

Another failure (no. 9) has occurred at minute 27063044 in the summer season and tripped all loads points due to main transformer. The restoration was supposed to occur at 5 AM in the morning, hence much less single step restoration demand.

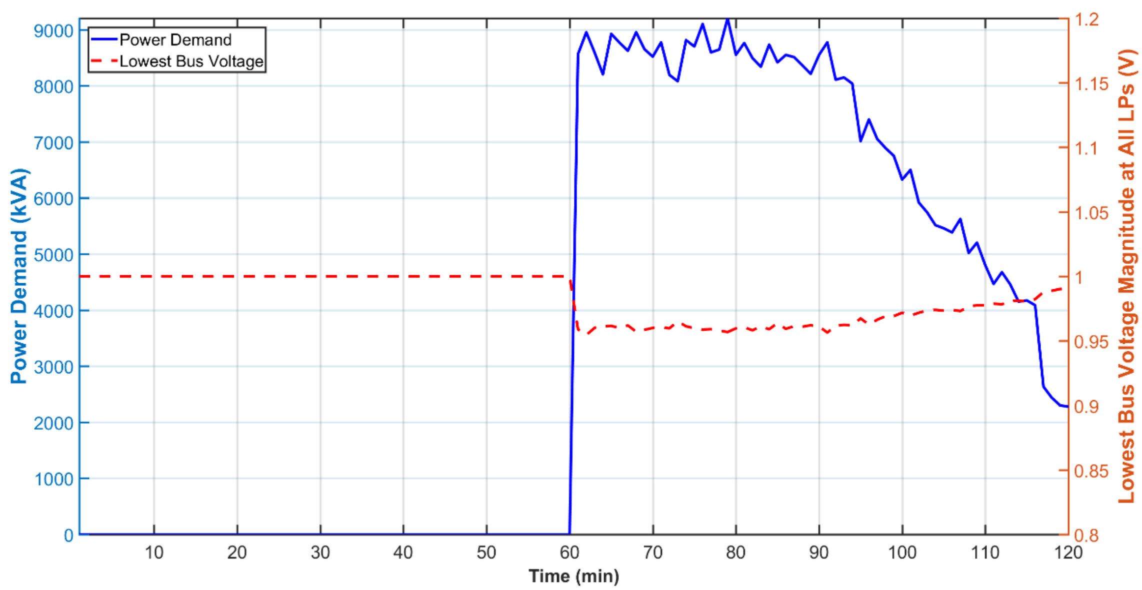

Figure 6.16: Power demand and lowest bus voltage after restoration from failure no. 9

Figure 6.16 showed the power demand and worst voltage during single step restoration if it occurred after repairing the main transformer. Although the voltage did not drop below 0.95 pu, however the power demand exceeded the 8.125 MVA limit. Hence, single step restoration will be required. The tuned algorithms were used and found that 9 load points can be restored immediately, and one load point shall be delayed 31 minutes as per tables from 31 to 34. GA found that restoration of load point no. 10 shall be delayed 31 minutes in order to restore the system safely. The original outage duration was 6081 minutes and the updated restoration times (TTRs) are found in Table 6.18.

Table 6.18: Restoration plan after failure no. 9 with restored power and k-factor

LP No.	Modified TTR	Restored kVA	K factor
LP1	6081 minutes	180.1	6.2248
LP2	6081 minutes	127.6	6.2248
LP3	6081 minutes	123.0	6.2248
LP4	6081 minutes	107.1	6.2248
LP5	6081 minutes	86.9	6.2248
LP6	6081 minutes	174.2	6.2248
LP7	6081 minutes	120.0	6.2248
LP8	6081 minutes	156.7	6.2248
LP9	6081 minutes	216.3	6.2248
LP10	6112 minutes	170.6	6.2294

The results of all algorithm are detailed in Figure 6.17 for the power demand and Figure 6.18 for the lowest voltage during restoration. All algorithms found an objective function of 31 minutes with different load points for delayed restoration.

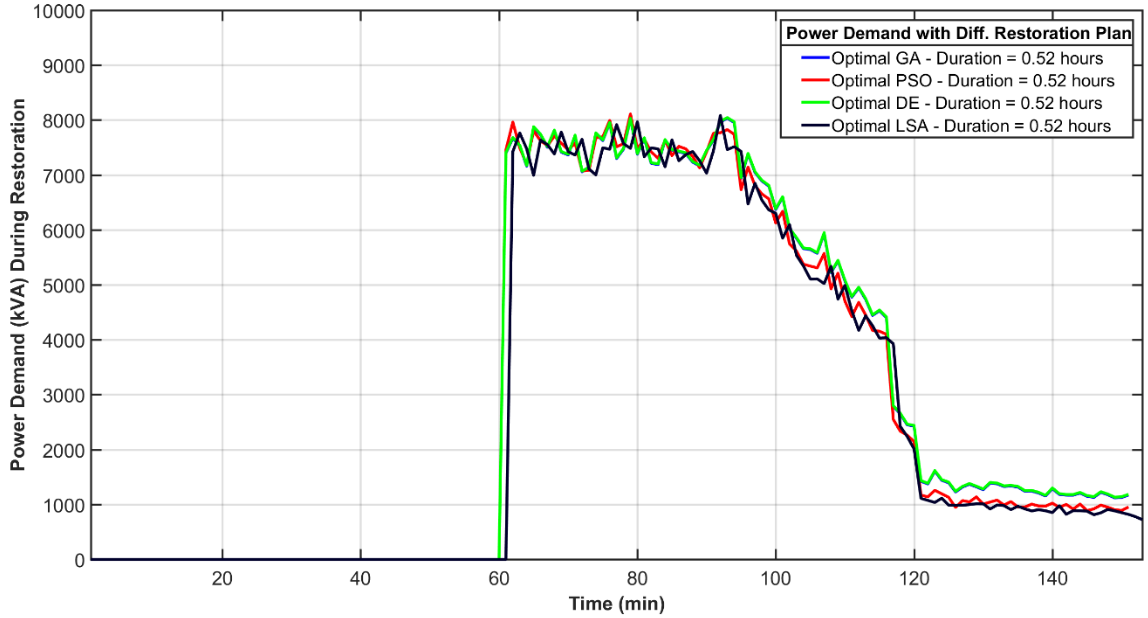

Figure 6.17: Power demand with different optimal restoration plans of failure no. 9

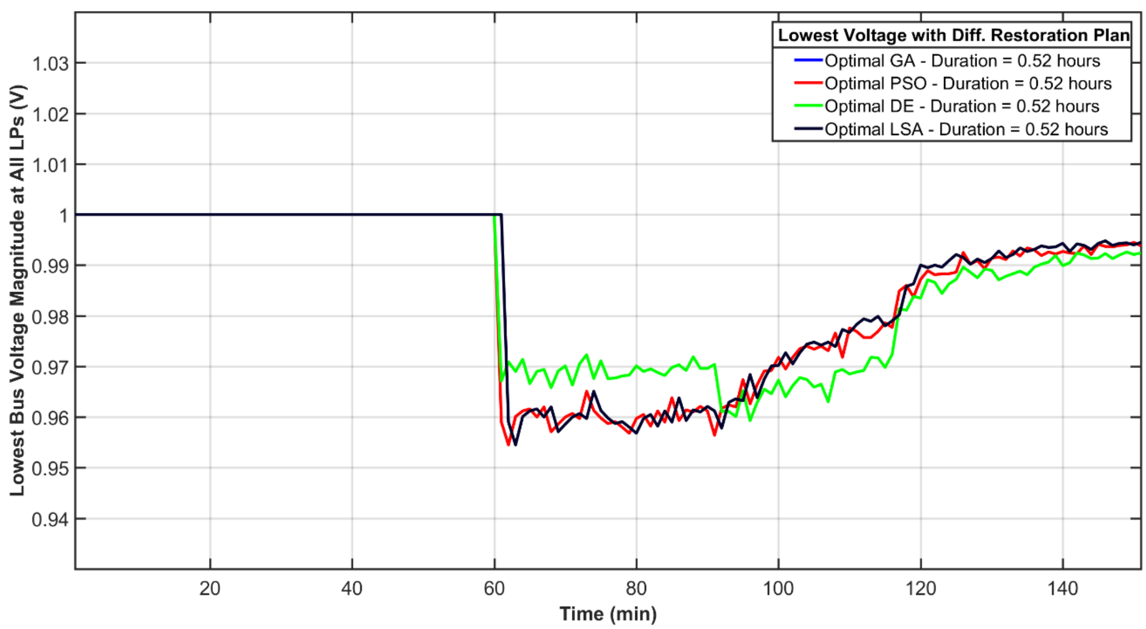

Figure 6.18: Lowest bus voltage with different optimal restoration plans of failure no. 9

The smooth restoration was at the cost of increased reliability indices such as ENS and SAIDI which will be clearer in next subsections.

6.6 Reliability Assessment Considering CLPU Events

6.6.1 Fixed Restoration Plans

To explore the importance of optimal restoration planning, an assumption is made first that the utility operator will follow a fixed procedure after extended outages to restore the systems. If the utility is aware of the possibility of having CLPU event, the operator will restore load points every 15 minutes, 30 minutes, 60 minutes or 90 minutes to avoid overloading equipment and violating protection settings. Although, the load points are restored in sequence, the system can still suffer from additional failures since additional delay might be required to avoid high sudden demand. The following subsections discussed the results and analysis of the fixed restoration plans.

6.6.1.1 Reliability Indices Results

The updated failures are found in Appendix C from Table C.2 to Table C.5 for four (4) different restoration plans. Out of these tables, the final reliability indices are found in Table 6.19.

Table 6.19: Reliability indices with CLPU assuming fixed restoration plans

Reliability Index	15-min	30-min	60-min	90-min
SAIFI (interruption/load point)	0.0535000	0.0535000	0.0535000	0.0535000
SAIDI (hours/load point)	8.1506667	8.1796667	8.2376667	8.2956667
SAIDI (minutes/load point)	489.0400000	490.7800000	494.2600000	497.7400000
CAIDI (hours/load point interr.)	152.3489097	152.8909657	153.9750779	155.0591900
CAIDI (minutes/load point interr.)	9140.9345794	9173.4579439	9238.5046729	9303.5514019
ASAI	0.9990696	0.9990662	0.9990596	0.9990530
ASUI	0.0009304	0.0009338	0.0009404	0.0009470
ENS (kWh)	25384.7138730	25564.5923005	25916.0487990	26255.3739557
AENS (kWh/load point)	2538.4713873	2556.4592300	2591.6048799	2625.5373956

It can be seen in Table 6.19 that as the duration of the fixed restoration plan increase, the reliability indices are getting even worse. For example, SAIDI increased from 487.3 minutes per load points without considering CLPU to 489.04 for the case of 15-min restoration plan. This value will increase further with increasing the duration of restoration until reaching 497.74 minutes per load point with the 90-minute fixed restoration plan. In the case of the 90-min restoration plan, on an average of 10 minutes of every failure that was not quantified in the original reliability calculations. Also, AENS has increased from 2.4 MWh per load point 2.62 MWh per load point in the 90-min restoration plan. Therefore, an additional 220 kWh per load point and 2.2 MWh for the system that was not quantified in the original reliability calculation. Needless to mention that the system still is subjected to failures since the constraints are not checked and with failures that include many load points or have a long outage duration, this becomes possible. The next subsection will explore this possibility.

6.6.1.2 Restorations' Power Demand and Voltage Drop Results

Although the new updated reliability indices are much closer to real reliability indices, yet there are some of the fixed restoration plans will cause a demand that might damage the transformer or at least activate the protection devices. It can also go below the 0.95 pu voltage limit and hence cause additional stress on electrical appliances. One example is worth mentioning is fixed restoration plans of failure no. 1 (Table 6.17). In this failure, all load points were lost due to a transformer failure. The single step restoration demand will cause a voltage drop of 0.82 with a very high demand, around five times the transformer MVA size. CLPU event will certainly occurred if the system is restored immediately.

Assuming the utility will apply a fixed restoration plan, Table 6.20 summarizes the new maximum power demand and the new worst bus voltage during restorations with four different fixed restoration plans.

Table 6.20: New maximum power demand and lowest bus voltage with fixed restorations

Fixed restoration plan	Duration (h)	Max. kVA Demand	Min. Voltage (pu)
15-min	2.25	12159	0.8784
30-min	4.50	7482	0.9075
60-min	9.00	4311.5	0.9433
90-min	13.50	5242.8	0.9456

Figures 6.19 and 6.20 show the power demand and the worst bus voltage during power restoration. Even though the restoration for all load points was delayed up to 13 hours, all of these restorations violated the system constrains. This violation is less with longer durations between every load point's restorations. It is worth mentioning that CLPU impact will end in around 60 minutes.

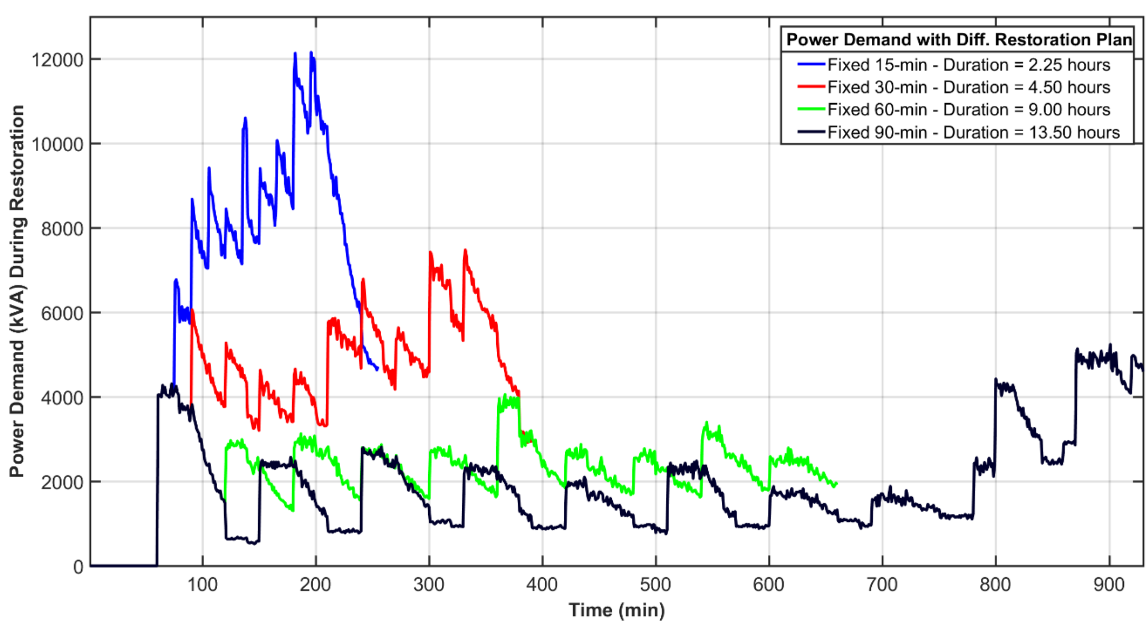

Figure 6.19: Power demand with different fixed restoration plans of failure no. 1

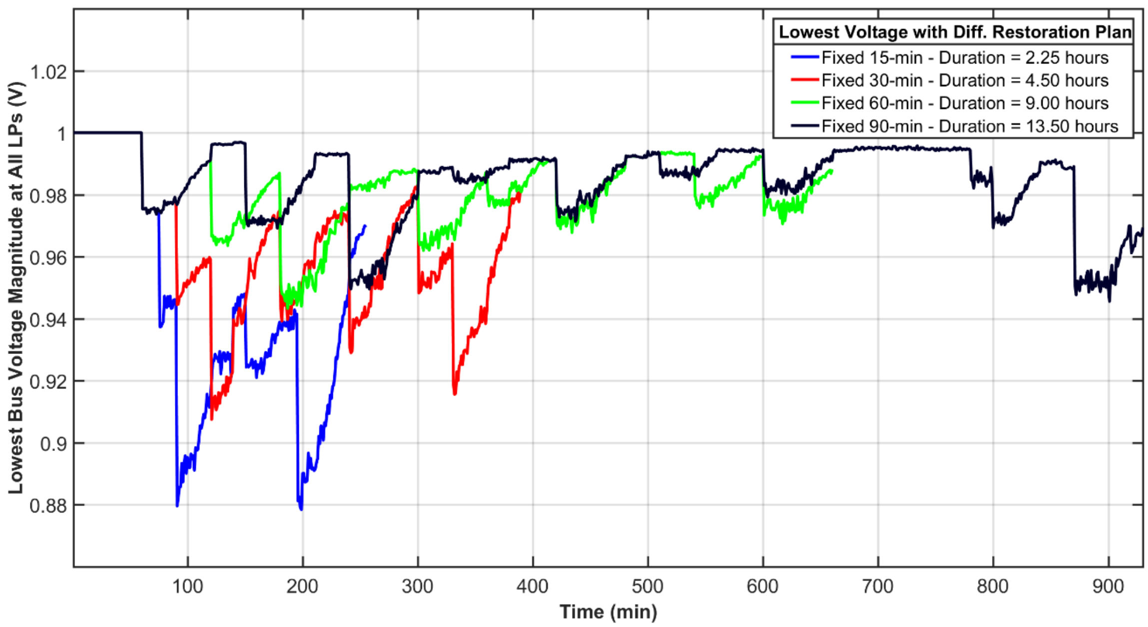

Figure 6.20: Lowest bus voltage with different fixed restoration plans of failure no. 1

Full details of the all failures along with the fixed plan restorations is shown in Table 6.21. The new maximum demand and the new worst bus voltage during restoration for the four plans. This table along with the above figure show that the 15-minute restoration plan violated all constraints during restoration. The 30-minute restorations plan violated most of the constrains, especially the voltage limits and was as low as 0.74 pu for failure no. 2, which is the most severe failure in the analysis. The 60-minute restoration plan improved the smoothness of the restorations, yet it violated some constraints and the voltage dropped to 0.9 pu during failure no. 2. The 60-min plan has improved the system results greatly due to the fact that CLPU event will settle down after approximately 60 minutes. The results were improved further with the 90-minute restorations plan leading to limited voltage limits violations.

Table 6.21: Full failure analysis using fixed restoration plans

#	Affected points	Single Step kVA	Lowest Voltage (pu)	15-min			30-min			60-min			90-min		
				Add. Time (min)	New Max. kVA	V_{min} (pu)	Add. Time (min)	New Max. kVA	V_{min} (pu)	Add. Time (min)	New Max. kVA	V_{min} (pu)	Add. Time (min)	New Max. kVA	V_{min} (pu)
1	[1 2 3 4 5 6 7 8 9 10]	33353.0	0.8200	675	12159.0	0.8784	1350	7482.2	0.9075	2700	4311.5	0.9433	4050	5242.8	0.9456
2	[1 2 3 4 5 6 7 8 9 10]	42389.8	0.7400	675	22165.7	0.7016	1350	16850.3	0.7490	2700	10502.9	0.8929	4050	8142.8	0.8892
3	10	5740.9	0.9500	NA	5740.9	0.9520	NA	5740.9	0.9520	NA	5740.9	0.9520	NA	5740.9	0.9520
4	[6 7]	961.9	1.0000	NA	961.9	1.0000	NA	961.9	1.0000	NA	961.9	1.0000	NA	961.9	1.0000
5	10	1878.2	0.9900	NA	1878.2	0.9900	NA	1878.2	0.9900	NA	1878.2	0.9900	NA	1878.2	0.9900
6	5	1992.8	0.9900	NA	1992.8	0.9900	NA	1992.8	0.9900	NA	1992.8	0.9900	NA	1992.8	0.9900
7	5	3138.4	0.9800	NA	3138.4	0.9800	NA	3138.4	0.9800	NA	3138.4	0.9800	NA	3138.4	0.9800
8	7	3142.9	0.9900	NA	3142.9	0.9900	NA	3142.9	0.9900	NA	3142.9	0.9900	NA	3142.9	0.9900
9	[1 2 3 4 5 6 7 8 9 10]	9203.3	0.9500	675	3860.9	0.9633	1350	2261.8	0.9774	2700	6626.6	0.9311	4050	8753.7	0.9072
10	[1 2 3 4 5 6 7 8 9 10]	16604.6	0.9100	675	6705.9	0.9436	1350	4045.8	0.9526	2700	2256.3	0.9703	4050	2156.6	0.9760
11	[9 10]	3363.3	0.9700	NA	3363.3	0.9700	NA	3363.3	0.9700	NA	3363.3	0.9700	NA	3363.3	0.9700
12	[1 2 3]	6519.5	0.9500	NA	6519.5	0.9506	NA	6519.5	0.9506	NA	6519.5	0.9506	NA	6519.5	0.9506
13	3	1096.0	1.0000	NA	1096.0	1.0000	NA	1096.0	1.0000	NA	1096.0	1.0000	NA	1096.0	1.0000
14	[8 9 10]	6635.8	0.9400	45	6734.8	0.9417	90	6016.3	0.9464	180	6183.9	0.9483	270	6293.2	0.9467
15	[4 5]	4390.8	0.9600	NA	4390.8	0.9600	NA	4390.8	0.9600	NA	4390.8	0.9600	NA	4390.8	0.9600
16	[1 2 3 4 5 6 7 8 9 10]	22300.6	0.8800	675	9177.8	0.9178	1350	6004.2	0.9337	2700	3637.1	0.9579	4050	5506.9	0.9424
17	[6 7]	2924.1	0.9800	NA	2924.1	0.9800	NA	2924.1	0.9800	NA	2924.1	0.9800	NA	2924.1	0.9800
18	7	1307.9	0.9900	NA	1307.9	0.9900	NA	1307.9	0.9900	NA	1307.9	0.9900	NA	1307.9	0.9900
19	[9 10]	4006.5	0.9700	NA	4006.5	0.9700	NA	4006.5	0.9700	NA	4006.5	0.9700	NA	4006.5	0.9700
20	7	5864.4	0.9600	NA	5864.4	0.9600	NA	5864.4	0.9600	NA	5864.4	0.9600	NA	5864.4	0.9600
21	[1 2 3]	969.7	0.9900	NA	969.7	0.9900	NA	969.7	0.9900	NA	969.7	0.9900	NA	969.7	0.9900
22	[4 5]	1995.3	0.9900	NA	1995.3	0.9900	NA	1995.3	0.9900	NA	1995.3	0.9900	NA	1995.3	0.9900
23	[6 7]	4178.7	0.9700	NA	4178.7	0.9700	NA	4178.7	0.9700	NA	4178.7	0.9700	NA	4178.7	0.9700
24	5	3210.4	0.9900	NA	3210.4	0.9900	NA	3210.4	0.9900	NA	3210.4	0.9900	NA	3210.4	0.9900
25	7	3739.4	0.9800	NA	3739.4	0.9800	NA	3739.4	0.9800	NA	3739.4	0.9800	NA	3739.4	0.9800
26	[4 5]	4668.2	0.9700	NA	4668.2	0.9700	NA	4668.2	0.9700	NA	4668.2	0.9700	NA	4668.2	0.9700
27	[6 7]	9944.1	0.9200	15	9946.7	0.9170	30	9795.3	0.9197	60	7730.3	0.9480	90	7730.3	0.9466
28	[2 3]	2662.5	0.9800	NA	2662.5	0.9800	NA	2662.5	0.9800	NA	2662.5	0.9800	NA	2662.5	0.9800
29	[2 3]	1142.0	0.9900	NA	1142.0	0.9900	NA	1142.0	0.9900	NA	1142.0	0.9900	NA	1142.0	0.9900
30	[4 5]	659.6	1.0000	NA	659.6	1.0000	NA	659.6	1.0000	NA	659.6	1.0000	NA	659.6	1.0000
31	7	1417.8	0.9900	NA	1417.8	0.9900	NA	1417.8	0.9900	NA	1417.8	0.9900	NA	1417.8	0.9900
32	[1 2 3]	2894.1	0.9800	NA	2894.1	0.9800	NA	2894.1	0.9800	NA	2894.1	0.9800	NA	2894.1	0.9800
33	[6 7]	404.6	1.0000	NA	404.6	1.0000	NA	404.6	1.0000	NA	404.6	1.0000	NA	404.6	1.0000
34	[1 2 3]	4087.7	0.9800	NA	4087.7	0.9800	NA	4087.7	0.9800	NA	4087.7	0.9800	NA	4087.7	0.9800
35	5	1701.4	0.9900	NA	1701.4	0.9900	NA	1701.4	0.9900	NA	1701.4	0.9900	NA	1701.4	0.9900
36	5	909.7	1.0000	NA	909.7	1.0000	NA	909.7	1.0000	NA	909.7	1.0000	NA	909.7	1.0000
37	[8 9 10]	5457.6	0.9500	45	4647.5	0.9569	90	4014.2	0.9613	180	3171.4	0.9772	270	2775.1	0.9791

Overall, CLPU can be quantified using fixed duration restorations plans in the time-based reliability indices of the power distribution system. As the fixed duration increases, the restorations are getting smother while the reliability indices are getting worse. However, restoring the system without checking the system constrains might endanger electrical equipment for stresses issues and might lead to catastrophic failures. Overall, the fixed restoration demand will make the reliability indices worse and will violate some constraints even with longer durations between load points' restorations. Therefore, a better restoration plan is needed to avoid these issues.

6.6.2 Optimal Restoration Plans

The four tuned algorithms are used now after every CLPU event during the 200-year simulation period. All the four (4) optimization methods will utilize the following parameters in search of the optimal plan:

- Generation number: 2000.
- Population number: 200.

The flowcharts in Figures 5.2, 5.3, 5.5 and 5.7 in Chapter 5 are used to execute the results of this section.

6.6.2.1 Reliability Indices Results

After conducting the optimal restoration plans after every CLPU event (Subsection 6.5), the outage durations are updated accordingly based on the selected objective function. The detailed results can be found in Appendix C from Table C.6 to Table C.9 for four (4) different optimized restoration plans. Out of these tables, the final reliability indices are found in Table 6.22.

Table 6.22: Reliability indices with CLPU with optimal restoration plans

Reliability Index	GA	PSO	DE	LSA
SAIFI (interruption/load point)	0.0535000	0.0535000	0.0535000	0.0535000
SAIDI (hours/load point)	8.1793417	8.1769917	8.1825833	8.1779875
SAIDI (minutes/load point)	490.7605000	490.6195000	490.9550000	490.6792500
CAIDI (hours/load point interr.)	152.8848910	152.8409657	152.9454829	152.8595794
CAIDI (minutes/load point interr.)	9173.0934579	9170.4579439	9176.7289720	9171.574766
ASAI	0.9990663	0.9990666	0.9990659	0.9990665
ASUI	0.0009337	0.0009334	0.0009341	0.0009335
ENS (kWh)	25627.9139387	25614.4724908	25779.3893662	25662.578429
AENS (kWh/load point)	2562.7913939	2561.4472491	2577.9389366	2566.2578429

The full restoration details are provided in Table 6.23 to Table 6.26 for the different four (4) selected optimization methods respectively.

The four different algorithms provided similar results, yet PSO results were the best among other algorithms with regard to the time-based reliability indices followed slightly by LSA in SAIDI, CAIDI, ASAI and ASUI. The difference between all algorithms was very small, within 1 minute for SAIDI, 6 minutes for CAIDI and 15 kWh for AENS. DE results were the worst between all four algorithms resulting in 490.995 minutes per load points for SAIDI. In general, the effect was about 1.7 MWh /year and average of 68 minutes per failure with the respect to the base case without considering CLPU. These values were not quantified in the base case. With comparison with the results provided with the fixed-restoration plans (Table 6.19), only the 15-min plan resulted in better indices then the optimal restoration plans. The other fixed restoration plans resulted in worse SAIDI, CAIDI, ASAI, ENS and AENS getting even worse with longer duration of fixed restorations. The optimal restoration still have another advantage related to the smoothness of the restoration which will be discussed in the next subsection.

Table 6.23: Full failure analysis with optimal RCGA restoration plan

#	Hour of day	Outage Duration (min)	Season	Affected points	Single Step Restoration Demand (kVA)	Lowest Voltage (pu)	Optimal Restoration needed?	GA Additional Time	Restoration Plan	New Maximum Restoration Demand (kVA)	New Lowest Voltage (pu)	Time
1	6:00 PM	10862	Summer	[1 2 3 4 5 6 7 8 9 10]	33353.0	0.8200	Yes	1070	[20 75 200 0 80 59 136 0 180 320]	8061.8	0.9523	2:14
2	6:00 PM	62470	Summer	[1 2 3 4 5 6 7 8 9 10]	42389.8	0.7400	Yes	4888	[0 499 799 0 679 534 735 47 740 855]	8029.3	0.9597	2:18
3	11:00 PM	678	Spring	10	5740.9	0.9520	Yes	NA	NA	5740.9	0.9520	0:19
4	2:00 AM	4901	Winter	[6 7]	961.9	1.0000	No	NA	NA	961.9	1.0000	NA
5	6:00 AM	1481	Fall	10	1878.2	0.9900	No	NA	NA	1878.2	0.9900	NA
6	6:00 AM	4254	Summer	5	1992.8	0.9900	No	NA	NA	1992.8	0.9900	NA
7	5:00 PM	911	Fall	5	3138.4	0.9800	No	NA	NA	3138.4	0.9800	NA
8	5:00 PM	1069	Summer	7	3142.9	0.9900	No	NA	NA	3142.9	0.9900	NA
9	5:00 AM	6081	Summer	[1 2 3 4 5 6 7 8 9 10]	9203.3	0.9500	Yes	31	[0 0 0 0 0 0 0 0 0 31]	8033.4	0.9593	0:43
10	9:00 PM	2438	Fall	[1 2 3 4 5 6 7 8 9 10]	16604.6	0.9100	Yes	272	[0 51 61 0 0 0 42 0 34 84]	8040.1	0.9504	1:44
11	7:00 PM	503	Fall	[9 10]	3363.3	0.9700	No	NA	NA	3363.3	0.9700	NA
12	5:00 PM	482	Spring	[1 2 3]	6519.5	0.9510	Yes	NA	NA	6519.5	0.9506	0:22
13	10:00 PM	1160	Spring	3	1096.0	1.0000	No	NA	NA	1096.0	1.0000	NA
14	4:00 AM	311	Summer	[8 9 10]	6635.8	0.9400	Yes	43	[0 0 43]	5576.0	0.9542	0:34
15	8:00 PM	7026	Summer	[4 5]	4390.8	0.9600	No	NA	NA	4390.8	0.9600	NA
16	6:00 PM	9229	Summer	[1 2 3 4 5 6 7 8 9 10]	22300.6	0.8800	Yes	449	[0 0 80 0 46 35 95 0 66 127]	8085.8	0.9515	2:01
17	8:00 AM	910	Winter	[6 7]	2924.1	0.9800	No	NA	NA	2924.1	0.9800	NA
18	1:00 PM	118	Winter	7	1307.9	0.9900	No	NA	NA	1307.9	0.9900	NA
19	5:00 AM	73	Summer	[9 10]	4006.5	0.9700	No	NA	NA	4006.5	0.9700	NA
20	10:00 AM	424	Summer	7	5864.4	0.9600	No	NA	NA	5864.4	0.9600	NA
21	8:00 AM	3	Fall	[1 2 3]	969.7	0.9900	No	NA	NA	969.7	0.9900	NA
22	11:00 PM	691	Winter	[4 5]	1995.3	0.9900	No	NA	NA	1995.3	0.9900	NA
23	1:00 AM	515	Spring	[6 7]	4178.7	0.9700	No	NA	NA	4178.7	0.9700	NA
24	9:00 AM	221	Fall	5	3210.4	0.9900	No	NA	NA	3210.4	0.9900	NA
25	2:00 PM	126	Spring	7	3739.4	0.9800	No	NA	NA	3739.4	0.9800	NA
26	9:00 AM	807	Spring	[4 5]	4668.2	0.9700	No	NA	NA	4668.2	0.9700	NA
27	8:00 AM	2149	Spring	[6 7]	9944.1	0.9200	Yes	165	[0 165]	7730.3	0.9503	0:32
28	7:00 PM	459	Winter	[2 3]	2662.5	0.9800	No	NA	NA	2662.5	0.9800	NA
29	8:00 AM	970	Winter	[2 3]	1142.0	0.9900	No	NA	NA	1142.0	0.9900	NA
30	2:00 AM	3155	Spring	[4 5]	659.6	1.0000	No	NA	NA	659.6	1.0000	NA
31	1:00 AM	256	Fall	7	1417.8	0.9900	No	NA	NA	1417.8	0.9900	NA
32	6:00 AM	580	Fall	[1 2 3]	2894.1	0.9800	No	NA	NA	2894.1	0.9800	NA
33	4:00 AM	512	Spring	[6 7]	404.6	1.0000	No	NA	NA	404.6	1.0000	NA
34	7:00 AM	3	Spring	[1 2 3]	4087.7	0.9800	No	NA	NA	4087.7	0.9800	NA
35	4:00 AM	887	Winter	5	1701.4	0.9900	No	NA	NA	1701.4	0.9900	NA
36	12:00 AM	45	Winter	5	909.7	1.0000	No	NA	NA	909.7	1.0000	NA
37	5:00 PM	897	Summer	[8 9 10]	5457.6	0.9500	Yes	3	[0 0 3]	5345.1	0.9502	0:34

Table 6.24: Full failure analysis with optimal PSO restoration plan

#	Hour of day	Outage Duration (min)	Season	Affected points	Single Step Restoration Demand (kVA)	Lowest Voltage (pu)	Optimal Restoration needed?	PSO Additional Time	Restoration Plan	New Maximum Restoration Demand (kVA)	New Lowest Voltage (pu)	Time
1	6:00 PM	10862	Summer	[1 2 3 4 5 6 7 8 9 10]	33353.0	0.8200	Yes	948	[0 62 173 19 79 53 129 0 139 294]	8034.4	0.9581	2:19
2	6:00 PM	62470	Summer	[1 2 3 4 5 6 7 8 9 10]	42389.8	0.7400	Yes	4695	[51 468 740 0 629 504 692 0 711 900]	8029.2	0.9555	2:20
3	11:00 PM	678	Spring	10	5740.9	0.9520	Yes	NA	NA	5740.9	0.9520	0:19
4	2:00 AM	4901	Winter	[6 7]	961.9	1.0000	No	NA	NA	961.9	1.0000	NA
5	6:00 AM	1481	Fall	10	1878.2	0.9900	No	NA	NA	1878.2	0.9900	NA
6	6:00 AM	4254	Summer	5	1992.8	0.9900	No	NA	NA	1992.8	0.9900	NA
7	5:00 PM	911	Fall	5	3138.4	0.9800	No	NA	NA	3138.4	0.9800	NA
8	5:00 PM	1069	Summer	7	3142.9	0.9900	No	NA	NA	3142.9	0.9900	NA
9	5:00 AM	6081	Summer	[1 2 3 4 5 6 7 8 9 10]	9203.3	0.9500	Yes	31	[0 0 31 0 0 0 0 0 0 0]	8110.8	0.9545	0:36
10	9:00 PM	2438	Fall	[1 2 3 4 5 6 7 8 9 10]	16604.6	0.9100	Yes	269	[43 50 76 0 0 0 32 0 4 64]	8029.1	0.9552	1:44
11	7:00 PM	503	Fall	[9 10]	3363.3	0.9700	No	NA	NA	3363.3	0.9700	NA
12	5:00 PM	482	Spring	[1 2 3]	6519.5	0.9510	Yes	NA	NA	6519.5	0.9506	0:19
13	10:00 PM	1160	Spring	3	1096.0	1.0000	No	NA	NA	1096.0	1.0000	NA
14	4:00 AM	311	Summer	[8 9 10]	6635.8	0.9400	Yes	442	[0 0 442]	5677.6	0.9520	0:35
15	8:00 PM	7026	Summer	[4 5]	4390.8	0.9600	No	NA	NA	4390.8	0.9600	NA
16	6:00 PM	9229	Summer	[1 2 3 4 5 6 7 8 9 10]	22300.6	0.8800	Yes	443	[0 0 60 7 46 0 95 36 69 130]	8049.2	0.9507	1:59
17	8:00 AM	910	Winter	[6 7]	2924.1	0.9800	No	NA	NA	2924.1	0.9800	NA
18	1:00 PM	118	Winter	7	1307.9	0.9900	No	NA	NA	1307.9	0.9900	NA
19	5:00 AM	73	Summer	[9 10]	4006.5	0.9700	No	NA	NA	4006.5	0.9700	NA
20	10:00 AM	424	Summer	7	5864.4	0.9600	No	NA	NA	5864.4	0.9600	NA
21	8:00 AM	3	Fall	[1 2 3]	969.7	0.9900	No	NA	NA	969.7	0.9900	NA
22	11:00 PM	691	Winter	[4 5]	1995.3	0.9900	No	NA	NA	1995.3	0.9900	NA
23	1:00 AM	515	Spring	[6 7]	4178.7	0.9700	No	NA	NA	4178.7	0.9700	NA
24	9:00 AM	221	Fall	5	3210.4	0.9900	No	NA	NA	3210.4	0.9900	NA
25	2:00 PM	126	Spring	7	3739.4	0.9800	No	NA	NA	3739.4	0.9800	NA
26	9:00 AM	807	Spring	[4 5]	4668.2	0.9700	No	NA	NA	4668.2	0.9700	NA
27	8:00 AM	2149	Spring	[6 7]	9944.1	0.9200	Yes	165	[0 165]	7730.3	0.9517	0:32
28	7:00 PM	459	Winter	[2 3]	2662.5	0.9800	No	NA	NA	2662.5	0.9800	NA
29	8:00 AM	970	Winter	[2 3]	1142.0	0.9900	No	NA	NA	1142.0	0.9900	NA
30	2:00 AM	3155	Spring	[4 5]	659.6	1.0000	No	NA	NA	659.6	1.0000	NA
31	1:00 AM	256	Fall	7	1417.8	0.9900	No	NA	NA	1417.8	0.9900	NA
32	6:00 AM	580	Fall	[1 2 3]	2894.1	0.9800	No	NA	NA	2894.1	0.9800	NA
33	4:00 AM	512	Spring	[6 7]	404.6	1.0000	No	NA	NA	404.6	1.0000	NA
34	7:00 AM	3	Spring	[1 2 3]	4087.7	0.9800	No	NA	NA	4087.7	0.9800	NA
35	4:00 AM	887	Winter	5	1701.4	0.9900	No	NA	NA	1701.4	0.9900	NA
36	12:00 AM	45	Winter	5	909.7	1.0000	No	NA	NA	909.7	1.0000	NA
37	5:00 PM	897	Summer	[8 9 10]	5457.6	0.9500	Yes	3	[0 0 3]	5345.1	0.9502	0:33

Table 6.25: Full failure analysis with optimal DE restoration plan

#	Hour of day	Outage Duration (min)	Season	Affected points	Single Step Restoration Demand (kVA)	Lowest Voltage (pu)	Optimal Restoration needed?	DE Additional Time	Restoration Plan	New Maximum Restoration Demand (kVA)	New Lowest Voltage (pu)	Time
1	6:00 PM	10862	Summer	[1 2 3 4 5 6 7 8 9 10]	33353.0	0.8200	Yes	1041	[1 56 206 19 83 66 129 0 159 322]	8097.2	0.9510	1:36
2	6:00 PM	62470	Summer	[1 2 3 4 5 6 7 8 9 10]	42389.8	0.7400	Yes	4969	[0 504 817 1 630 571 745 77 761 863]	8045.0	0.9549	1:34
3	11:00 PM	678	Spring	10	5740.9	0.9520	Yes	NA	NA	5740.9	0.9520	0:13
4	2:00 AM	4901	Winter	[6 7]	961.9	1.0000	No	NA	NA	961.9	1.0000	NA
5	6:00 AM	1481	Fall	10	1878.2	0.9900	No	NA	NA	1878.2	0.9900	NA
6	6:00 AM	4254	Summer	5	1992.8	0.9900	No	NA	NA	1992.8	0.9900	NA
7	5:00 PM	911	Fall	5	3138.4	0.9800	No	NA	NA	3138.4	0.9800	NA
8	5:00 PM	1069	Summer	7	3142.9	0.9900	No	NA	NA	3142.9	0.9900	NA
9	5:00 AM	6081	Summer	[1 2 3 4 5 6 7 8 9 10]	9203.3	0.9500	Yes	31	[0 0 0 0 0 0 0 0 0 31]	8045.8	0.9593	0:24
10	9:00 PM	2438	Fall	[1 2 3 4 5 6 7 8 9 10]	16604.6	0.9100	Yes	256	[0 0 50 0 31 40 75 0 0 60]	8031.6	0.9552	1:04
11	7:00 PM	503	Fall	[9 10]	3363.3	0.9700	No	NA	NA	3363.3	0.9700	NA
12	5:00 PM	482	Spring	[1 2 3]	6519.5	0.9510	Yes	NA	NA	6519.5	0.9506	0:13
13	10:00 PM	1160	Spring	3	1096.0	1.0000	No	NA	NA	1096.0	1.0000	NA
14	4:00 AM	311	Summer	[8 9 10]	6635.8	0.9400	Yes	393	[0 0 393]	5879.5	0.9568	0:22
15	8:00 PM	7026	Summer	[4 5]	4390.8	0.9600	No	NA	NA	4390.8	0.9600	NA
16	6:00 PM	9229	Summer	[1 2 3 4 5 6 7 8 9 10]	22300.6	0.8800	Yes	452	[0 0 80 0 46 35 95 0 66 130]	8059.5	0.9507	1:15
17	8:00 AM	910	Winter	[6 7]	2924.1	0.9800	No	NA	NA	2924.1	0.9800	NA
18	1:00 PM	118	Winter	7	1307.9	0.9900	No	NA	NA	1307.9	0.9900	NA
19	5:00 AM	73	Summer	[9 10]	4006.5	0.9700	No	NA	NA	4006.5	0.9700	NA
20	10:00 AM	424	Summer	7	5864.4	0.9600	No	NA	NA	5864.4	0.9600	NA
21	8:00 AM	3	Fall	[1 2 3]	969.7	0.9900	No	NA	NA	969.7	0.9900	NA
22	11:00 PM	691	Winter	[4 5]	1995.3	0.9900	No	NA	NA	1995.3	0.9900	NA
23	1:00 AM	515	Spring	[6 7]	4178.7	0.9700	No	NA	NA	4178.7	0.9700	NA
24	9:00 AM	221	Fall	5	3210.4	0.9900	No	NA	NA	3210.4	0.9900	NA
25	2:00 PM	126	Spring	7	3739.4	0.9800	No	NA	NA	3739.4	0.9800	NA
26	9:00 AM	807	Spring	[4 5]	4668.2	0.9700	No	NA	NA	4668.2	0.9700	NA
27	8:00 AM	2149	Spring	[6 7]	9944.1	0.9200	Yes	165	[0 165]	7730.3	0.9528	0:21
28	7:00 PM	459	Winter	[2 3]	2662.5	0.9800	No	NA	NA	2662.5	0.9800	NA
29	8:00 AM	970	Winter	[2 3]	1142.0	0.9900	No	NA	NA	1142.0	0.9900	NA
30	2:00 AM	3155	Spring	[4 5]	659.6	1.0000	No	NA	NA	659.6	1.0000	NA
31	1:00 AM	256	Fall	7	1417.8	0.9900	No	NA	NA	1417.8	0.9900	NA
32	6:00 AM	580	Fall	[1 2 3]	2894.1	0.9800	No	NA	NA	2894.1	0.9800	NA
33	4:00 AM	512	Spring	[6 7]	404.6	1.0000	No	NA	NA	404.6	1.0000	NA
34	7:00 AM	3	Spring	[1 2 3]	4087.7	0.9800	No	NA	NA	4087.7	0.9800	NA
35	4:00 AM	887	Winter	5	1701.4	0.9900	No	NA	NA	1701.4	0.9900	NA
36	12:00 AM	45	Winter	5	909.7	1.0000	No	NA	NA	909.7	1.0000	NA
37	5:00 PM	897	Summer	[8 9 10]	5457.6	0.9500	Yes	3	[0 0 3]	5345.1	0.9502	0:22

Table 6.26: Full failure analysis with optimal LSA restoration plan

#	Hour of day	Outage Duration (min)	Season	Affected points	Single Step Restoration Demand (kVA)	Lowest Voltage (pu)	Optimal Restoration needed?	LSA Additional Time	Restoration Plan	New Maximum Restoration Demand (kVA)	New Lowest Voltage (pu)	Time
1	6:00 PM	10862	Summer	[1 2 3 4 5 6 7 8 9 10]	33353.0	0.8200	Yes	1055	[37 79 158 0 81 0 129 60 192 319]	8033.7	0.9513	1:37
2	6:00 PM	62470	Summer	[1 2 3 4 5 6 7 8 9 10]	42389.8	0.7400	Yes	4632	[0 468 753 0 631 504 686 47 740 803]	8109.2	0.9596	1:40
3	11:00 PM	678	Spring	10	5740.9	0.9520	Yes	NA	NA	5740.9	0.9520	0:16
4	2:00 AM	4901	Winter	[6 7]	961.9	1.0000	No	NA	NA	961.9	1.0000	NA
5	6:00 AM	1481	Fall	10	1878.2	0.9900	No	NA	NA	1878.2	0.9900	NA
6	6:00 AM	4254	Summer	5	1992.8	0.9900	No	NA	NA	1992.8	0.9900	NA
7	5:00 PM	911	Fall	5	3138.4	0.9800	No	NA	NA	3138.4	0.9800	NA
8	5:00 PM	1069	Summer	7	3142.9	0.9900	No	NA	NA	3142.9	0.9900	NA
9	5:00 AM	6081	Summer	[1 2 3 4 5 6 7 8 9 10]	9203.3	0.9500	Yes	31	[0 0 0 0 0 0 31 0 0 0]	8082.8	0.9545	1:01
10	9:00 PM	2438	Fall	[1 2 3 4 5 6 7 8 9 10]	16604.6	0.9100	Yes	261	[0 0 50 0 40 36 75 0 0 60]	8059.4	0.9552	1:24
11	7:00 PM	503	Fall	[9 10]	3363.3	0.9700	No	NA	NA	3363.3	0.9700	NA
12	5:00 PM	482	Spring	[1 2 3]	6519.5	0.9510	Yes	NA	NA	6519.5	0.9506	0:30
13	10:00 PM	1160	Spring	3	1096.0	1.0000	No	NA	NA	1096.0	1.0000	NA
14	4:00 AM	311	Summer	[8 9 10]	6635.8	0.9400	Yes	43	[0 0 43]	5576.0	0.9542	0:31
15	8:00 PM	7026	Summer	[4 5]	4390.8	0.9600	No	NA	NA	4390.8	0.9600	NA
16	6:00 PM	9229	Summer	[1 2 3 4 5 6 7 8 9 10]	22300.6	0.8800	Yes	449	[0 0 80 0 46 35 95 0 66 127]	8050.7	0.9515	1:35
17	8:00 AM	910	Winter	[6 7]	2924.1	0.9800	No	NA	NA	2924.1	0.9800	NA
18	1:00 PM	118	Winter	7	1307.9	0.9900	No	NA	NA	1307.9	0.9900	NA
19	5:00 AM	73	Summer	[9 10]	4006.5	0.9700	No	NA	NA	4006.5	0.9700	NA
20	10:00 AM	424	Summer	7	5864.4	0.9600	No	NA	NA	5864.4	0.9600	NA
21	8:00 AM	3	Fall	[1 2 3]	969.7	0.9900	No	NA	NA	969.7	0.9900	NA
22	11:00 PM	691	Winter	[4 5]	1995.3	0.9900	No	NA	NA	1995.3	0.9900	NA
23	1:00 AM	515	Spring	[6 7]	4178.7	0.9700	No	NA	NA	4178.7	0.9700	NA
24	9:00 AM	221	Fall	5	3210.4	0.9900	No	NA	NA	3210.4	0.9900	NA
25	2:00 PM	126	Spring	7	3739.4	0.9800	No	NA	NA	3739.4	0.9800	NA
26	9:00 AM	807	Spring	[4 5]	4668.2	0.9700	No	NA	NA	4668.2	0.9700	NA
27	8:00 AM	2149	Spring	[6 7]	9944.1	0.9200	Yes	165	[0 165]	7730.3	0.9571	0:26
28	7:00 PM	459	Winter	[2 3]	2662.5	0.9800	No	NA	NA	2662.5	0.9800	NA
29	8:00 AM	970	Winter	[2 3]	1142.0	0.9900	No	NA	NA	1142.0	0.9900	NA
30	2:00 AM	3155	Spring	[4 5]	659.6	1.0000	No	NA	NA	659.6	1.0000	NA
31	1:00 AM	256	Fall	7	1417.8	0.9900	No	NA	NA	1417.8	0.9900	NA
32	6:00 AM	580	Fall	[1 2 3]	2894.1	0.9800	No	NA	NA	2894.1	0.9800	NA
33	4:00 AM	512	Spring	[6 7]	404.6	1.0000	No	NA	NA	404.6	1.0000	NA
34	7:00 AM	3	Spring	[1 2 3]	4087.7	0.9800	No	NA	NA	4087.7	0.9800	NA
35	4:00 AM	887	Winter	5	1701.4	0.9900	No	NA	NA	1701.4	0.9900	NA
36	12:00 AM	45	Winter	5	909.7	1.0000	No	NA	NA	909.7	1.0000	NA
37	5:00 PM	897	Summer	[8 9 10]	5457.6	0.9500	Yes	3	[0 0 3]	5345.1	0.9502	0:31

6.6.2.2 Restorations' Power Demand and Voltage Drop Results

The developed flowcharts were able to execute the program and found the optimal restoration sequence without violating the system constraints as per Table 6.22 to Table 6.25. The final results of optimal restoration of failure no. 1 and failure no. 2 are provided in Figures from 6.21 to 6.24. Figure 6.21 shows the power demand and Figure 6.22 worst bus voltage magnitude during restoration for failure no. 1. Figures 6.23 and 6.24 are dedicated to failure no. 2.

All methods provided similar results in terms of the objective function and time until restoration is completed. However, in contrast to the tuning results in Section 6.3, PSO has provided better resulted for failure no. 1 with an objective function of 948 minutes. The restoration will be completed after 4.9 hours. The other methods provided similar results with GA being the worst with an objective function of 1071 minutes.

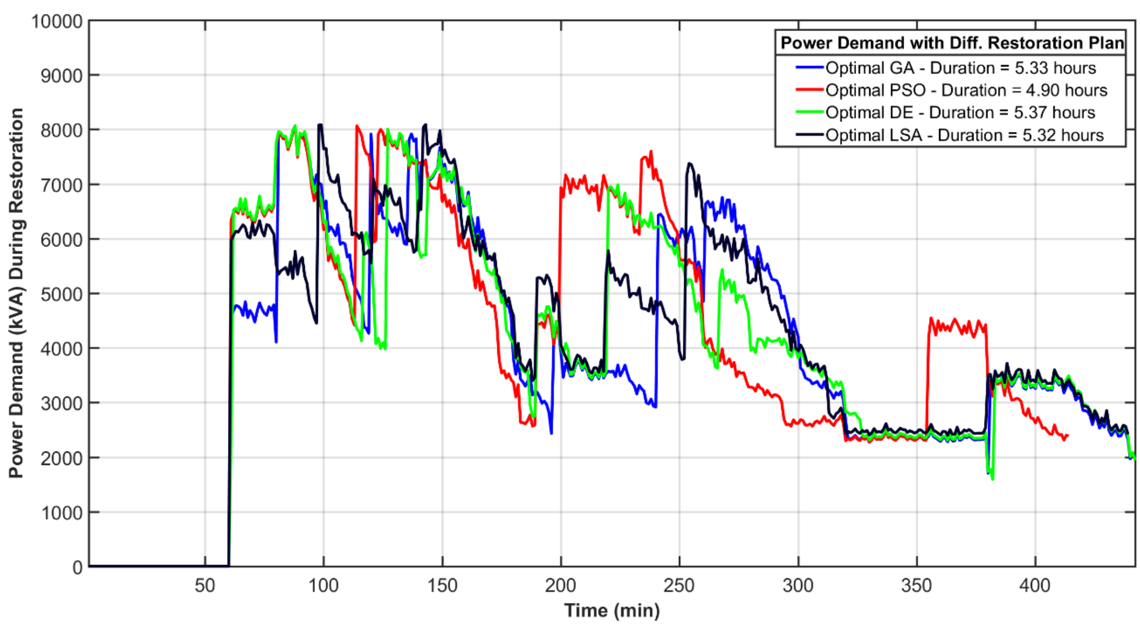

Figure 6.21: Power demand with different optimal restoration plans of failure no. 1

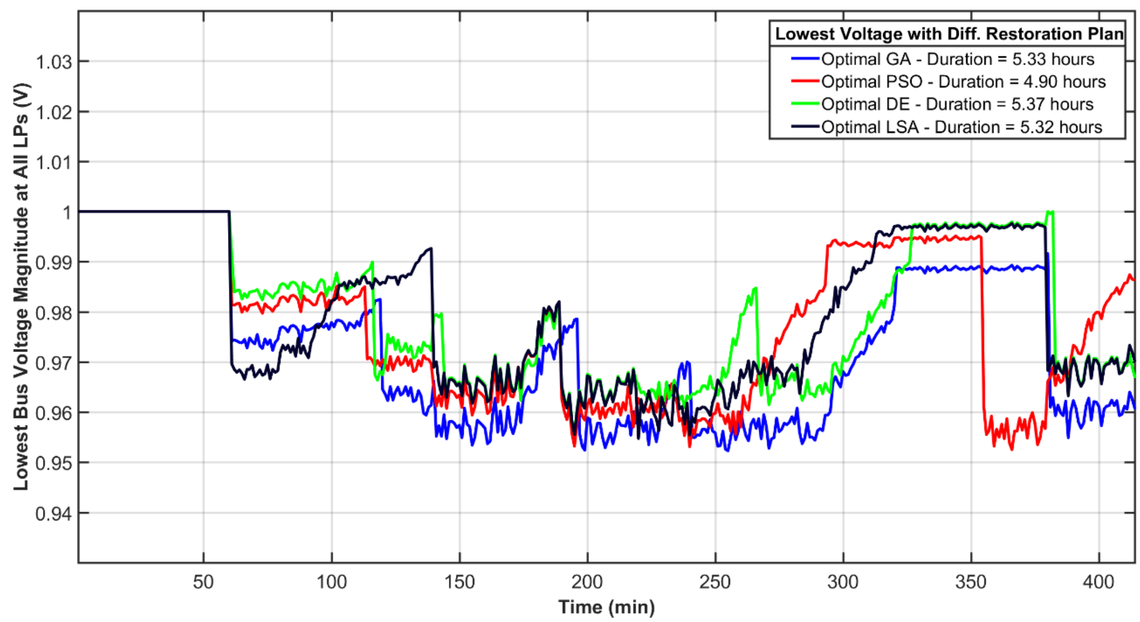

Figure 6.22: Lowest bus voltage with different optimal restoration plans of failure no. 1

The system constraints were not violated unlike the fixed restoration plan, and the duration of the restoration plan was kept minimal and comparable to the 30-min restoration plan.

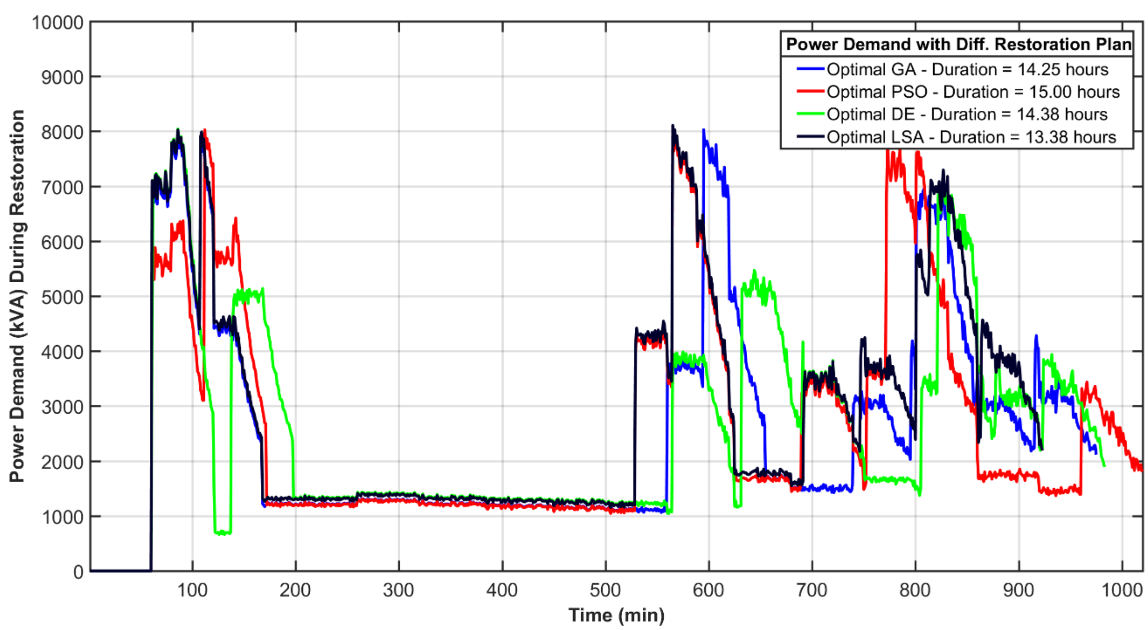

Figure 6.23: Power demand with different optimal restoration plans of failure no. 2

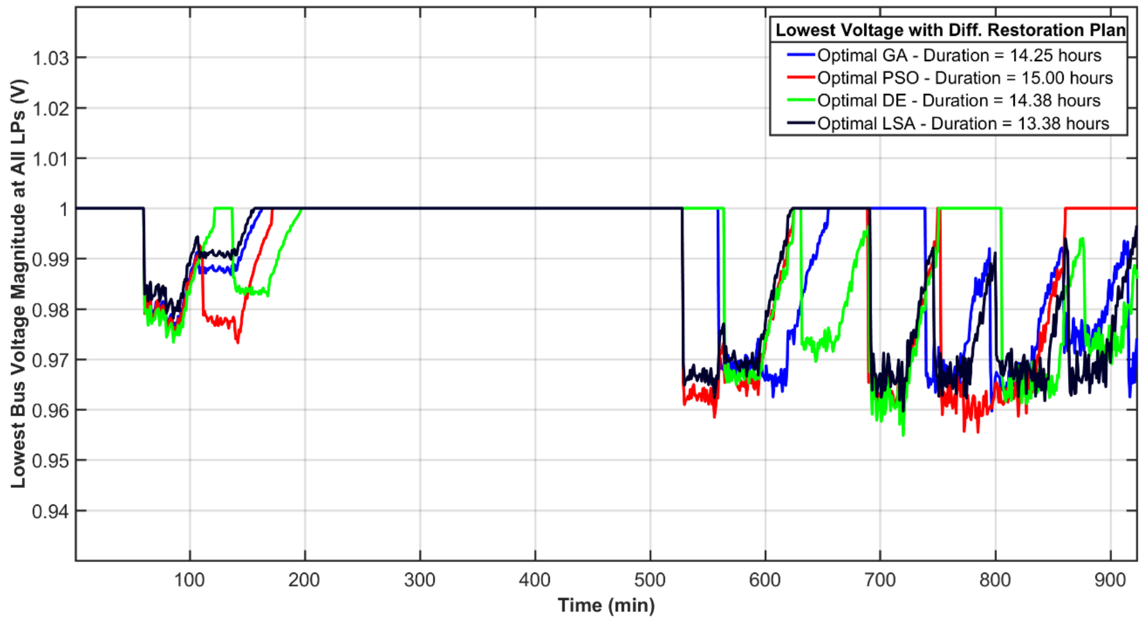

Figure 6.24: Lowest bus voltage with different optimal restoration plans of failure no. 2

In Figures 6.23 and 6.24, the restoration of the power system after failure no. 2 was lengthy. Since the failure was in summer and the outage duration was the highest during the 200-year analysis period. The restoration was restricted during a period of around 6 hours (200th minute to 500th minute in the figure). This period has a high peak demand and restoration was resumed after midnight.

In terms of duration of the restoration, LSA found the optimal results since all restoration activity can be completed within 13.3 hours. Also, LSA provided the best results in terms of the minimum additional time for restoring the affected load points. The other methods also have also provided similar results with PSO being the worst. PSO generated a restoration sequence that will last for around 15 hours with an additional time of around 4969 minutes that will directly impact the time-based reliability indices. In general, the correct assessment of CLPU events will lead to a delayed restoration yet a smooth operation. This delayed restoration was even better than the 30-minute, 60-minute and 90-minute restoration plans without violating any system constraints. However, the 15-minute fixed restoration plans was better in terms of reliability indices but will violate every protection and operation constraints.

CHAPTER 7

CONCLUSION & FUTURE WORK

7.1 Conclusion

In conclusion, the problem of CLPU events was discussed in detail. The thesis aimed to realistically reflect the impact of CLPU on the reliability indices on residential power distribution system. A problem was formulated to optimally restore the system after each outage considering the operational and the protection systems constraints. The problem was applied on a test system with a stochastic load model that was developed to simulate accurate power demand while CLPU model used a proven delayed exponential model. The model considered factors such as ambient temperature, stochastic customer behavior and outage duration. The optimal restoration program deployed four different EC algorithms including GA, PSO, DE and, the new algorithm LSA. These algorithms were tuned this application to ensure optimal and reliable results.

The reliability indices with the optimal restoration plans were compared to the base case. The effect was about 1.7 MWh /year in AENS and average of 68 minutes per failure in CAIDI with the respect to the base case without considering CLPU. This impact is around 1% of the reliability indices for this simple system. This percentage can increase further with larger systems with more components to consider in the reliability assessment and consequently more chances for CLPU events.

In comparison with the fixed restoration plans, the resulted showed that the system performance might improve for short intervals such as 15-minutes interval. However, the failures might happen, and the system equipment might be subjected to stresses due to blind restoration. Moreover, for longer fixed intervals, the reliability indices were worse than the case with optimal restoration plans. Also, the possibility of violating the system constrains still exists and might lead to power system component failures.

It is worth noting that the results presented a more realistic representation of CLPU effect in reliability calculations of power systems. Previous work had included CLPU failures in SAIFI calculations assuming that every CLPU failure is another failure and it will impact the total number of failures that an end-user will experience and consequently will impact SAIFI only. However, this work added CLPU events impact on the time-based reliability indices including SAIDI, CAIDI and ENS.

LSA was compared extensively with the other traditional optimization algorithms. LSA led to overall all better results in terms of robustness and convergence characteristics in conjunction of an excellent computational time making it more applicable for online applications. However, in terms of reliability indices, the four methods led to similar results with PSO being the best among the four methods. LSA had better results than DE and GA in SAIDI, CAIDI, ASAI and ASUI while GA had better results than DE and LSA in ENS and AENS. Overall, LSA showed enough robustness to be used in future optimization problems.

7.2 Future Work

This work can be enhanced in the future in many aspects. The following topics are recommended for further investigation:

1. CLPU event can be modeled stochastically also to include other stochastic factors such as customer behavior, effect of demand response, house thermal insulation, and effect of vacations and so on. Such models might lead to better estimation of CLPU magnitude and duration. Two-state load model [3] and Markov chain approach [94] are examples of such approaches. Such models can vary the period of the constant CLPU demand and the settling down time of the model based on the ambient temperature and outage duration.
2. Appliance modeling can be further enhanced by taken into consideration the load demand under varying voltage conditions and ambient temperature dynamics.
3. The problem can be re-formulated to minimize the reliability cost to show the economic importance of CLPU inclusion in the reliability calculations. Inclusion of any non-component-based interruptions for more accurate reliability measurements can be also investigated. For even more accurate results, the same methodology can be applied on larger and actual power distribution networks with loop design to avoid very long outages since alternative feeders will be available to feed partial or all the affected load points. Overall, any inclusion of real-case scenarios in the analysis will lead to accurate results and better estimation of CLPU impact.

4. Such work can be used as a starting point to include smart gird applications with common distribution system problems. Applications such as demand response smart self-healing are mainly concerned with the load conditions in order to apply them. Specifically, demand response can be modeled along with this work to reduce CLPU effect after restoration by controlling the thermostat setting or direct control of TCL load breakers.

Finally, extra attention can be given to conduct a more detailed reliability analysis by including more equipment such as sectionalizes and buses. However, their effect on CLPU events is minor since their restoration times are very short.

APPENDICES

Appendix A: Load Flow Analysis

Table A.1: Y-bus of the test system

Bus	0	1	2	3	4	5	6	7	8	9	10
0	173.4505-427.8443i	-54.20331+133.7013i	0	0	-28.9084+71.3074i	0	-36.1355+89.1343i	0	-54.20331+133.7013i	0	0
1	-54.20331+133.7013i	97.56594-+240.6624i	-43.36262+106.9611i	0	0	0	0	0	0	0	0
2	0	-43.36262+106.9611i	86.72525-+213.9222i	-43.36262+106.9611i	0	0	0	0	0	0	0
3	0	0	-43.36262+106.9611i	43.36262-+106.9611i	0	0	0	0	0	0	0
4	-28.9084+71.3074i	0	0	0	57.81679-+142.6148i	-28.9084+71.3074i	0	0	0	0	0
5	0	0	0	0	-28.9084+71.3074i	28.9084-+71.3074i	0	0	0	0	0
6	-36.1355+89.1343i	0	0	0	0	0	65.0439-+160.4417i	-28.9084+71.3074i	0	0	0
7	0	0	0	0	0	0	-28.9084+71.3074i	28.9084-+71.3074i	0	0	0
8	-54.20331+133.7013i	0	0	0	0	0	0	0	108.4066-+267.4027i	-54.20331+133.7013i	0
9	0	0	0	0	0	0	0	0	-54.20331+133.7013i	97.56594-+240.6624i	-43.36262+106.9611i
10	0	0	0	0	0	0	0	0	0	-43.36262+106.9611i	43.36262-+106.9611i

Table A.2: Line flow during average loading conditions

line		Power at bus & line flow			Line loss	
From	To	Mw	Mvar	MVA	Mw	Mvar
1		1.084	0.713	1.298		
	2	0.309	0.203	0.369	0	0.001
	5	0.153	0.097	0.181	0	0
	7	0.235	0.151	0.28	0	0.001
	9	0.387	0.262	0.468	0.001	0.001
2		-0.117	-0.092	0.149		
	1	-0.308	-0.202	0.369	0	0.001
	3	0.191	0.11	0.221	0	0
3		-0.09	-0.052	0.104		
	2	-0.191	-0.109	0.22	0	0
	4	0.101	0.057	0.116	0	0
4		-0.101	-0.057	0.116		
	3	-0.101	-0.057	0.116	0	0
5		-0.076	-0.048	0.09		
	1	-0.153	-0.096	0.181	0	0
	6	0.076	0.048	0.09	0	0
6		-0.076	-0.048	0.09		
	5	-0.076	-0.048	0.09	0	0
7		-0.134	-0.093	0.163		
	1	-0.235	-0.15	0.279	0	0.001
	8	0.101	0.057	0.116	0	0
8		-0.101	-0.057	0.116		
	7	-0.101	-0.057	0.116	0	0
9		-0.102	-0.065	0.121		
	1	-0.387	-0.261	0.467	0.001	0.001
	10	0.285	0.196	0.346	0	0.001
10		-0.181	-0.105	0.209		
	9	-0.284	-0.196	0.345	0	0.001
	11	0.103	0.091	0.138	0	0
11		-0.103	-0.091	0.138		
	10	-0.103	-0.091	0.138	0	0
			Total loss		0.002	0.005

Table A.3: Line flow during minimum loading conditions

line		Power at bus & line flow			Line loss	
From	To	Mw	Mvar	MVA	Mw	Mvar
1		0.153	0.072	0.169		
	2	0.040	0.019	0.045	0.000	0.000
	5	0.016	0.008	0.018	0.000	0.000
	7	0.035	0.017	0.039	0.000	0.000
	9	0.061	0.028	0.067	0.000	0.000
2		-0.020	-0.010	0.022		
	1	-0.040	-0.019	0.044	0.000	0.000
	3	0.020	0.010	0.023	0.000	0.000
3		-0.009	-0.004	0.010		
	2	-0.020	-0.010	0.023	0.000	0.000
	4	0.012	0.006	0.013	0.000	0.000
4		-0.012	-0.006	0.013		
	3	-0.012	-0.006	0.013	0.000	0.000
5		-0.008	-0.004	0.009		
	1	-0.016	-0.008	0.018	0.000	0.000
	6	0.008	0.004	0.009	0.000	0.000
6		-0.008	-0.004	0.009		
	5	-0.008	-0.004	0.009	0.000	0.000
7		-0.023	-0.011	0.026		
	1	-0.035	-0.017	0.039	0.000	0.000
	8	0.012	0.006	0.013	0.000	0.000
8		-0.012	-0.006	0.013		
	7	-0.012	-0.006	0.013	0.000	0.000
9		-0.014	-0.006	0.015		
	1	-0.061	-0.028	0.067	0.000	0.000
	10	0.047	0.022	0.052	0.000	0.000
10		-0.029	-0.014	0.032		
	9	-0.047	-0.022	0.052	0.000	0.000
	11	0.018	0.009	0.020	0.000	0.000
11		-0.018	-0.009	0.020		
	10	-0.018	-0.009	0.020	0.000	0.000
			Total loss		0.000	0.000

Table A.4: Line flow during maximum loading conditions

line		Power at bus & line flow			Line loss	
From	To	Mw	Mvar	MVA	Mw	Mvar
1		5.036	3.578	6.177		
	2	1.448	1.027	1.775	0.008	0.02
	5	0.717	0.503	0.876	0.004	0.009
	7	1.086	0.768	1.33	0.007	0.017
	9	1.786	1.28	2.197	0.013	0.031
2		-0.624	-0.434	0.761		
	1	-1.44	-1.007	1.757	0.008	0.02
	3	0.815	0.572	0.996	0.003	0.008
3		-0.385	-0.268	0.469		
	2	-0.812	-0.564	0.989	0.003	0.008
	4	0.427	0.296	0.519	0.001	0.002
4		-0.426	-0.294	0.517		
	3	-0.426	-0.294	0.517	0.001	0.002
5		-0.355	-0.246	0.432		
	1	-0.713	-0.494	0.867	0.004	0.009
	6	0.358	0.247	0.435	0.001	0.002
6		-0.357	-0.245	0.433		
	5	-0.357	-0.245	0.433	0.001	0.002
7		-0.653	-0.456	0.797		
	1	-1.079	-0.751	1.315	0.007	0.017
	8	0.425	0.296	0.518	0.001	0.003
8		-0.424	-0.292	0.515		
	7	-0.424	-0.292	0.515	0.001	0.003
9		-0.453	-0.315	0.552		
	1	-1.773	-1.249	2.169	0.013	0.031
	10	1.32	0.933	1.616	0.007	0.017
10		-0.753	-0.525	0.918		
	9	-1.313	-0.916	1.601	0.007	0.017
	11	0.559	0.391	0.683	0.002	0.004
11		-0.558	-0.387	0.679		
	10	-0.558	-0.387	0.679	0.002	0.004
			Total loss		0.046	0.115

Appendix B: Tuning Results

Table B.1: RCGA tuning results for sample failure 1

P_c	P_m	α	b	f_{50}	f_{100}	f_{500}	f_{1000}
Crossover probability variance							
0.6	0.05	0.5	5	1783	1523	1210	1101
0.8	0.05	0.5	5	1962	1620	1264	1116
0.9	0.05	0.5	5	1855	1713	1299	1100
1	0.05	0.5	5	2060	1792	1274	1170
Mutation probability variance							
0.8	0.05	0.5	5	1931	1721	1243	1102
0.8	0.15	0.5	5	2181	2048	1382	1114
α-factor variance							
0.8	0.05	0.1	5	1841	1677	1236	1210
0.8	0.05	0.2	5	1893	1507	1171	1121
0.8	0.05	0.3	5	1739	1445	1138	1085
0.8	0.05	0.4	5	1837	1507	1249	1141
0.8	0.05	0.5	5	1926	1640	1230	1089
0.8	0.05	0.7	5	2073	1870	1435	1284
0.8	0.05	0.8	5	2118	1677	1677	1649
0.8	0.05	0.9	5	2285	1894	1711	1711
0.8	0.05	1	5	2462	2262	1889	1807
b-factor variance							
0.8	0.05	0.5	1	1885	1680	1480	1235
0.8	0.05	0.5	2	1808	1718	1378	1160
0.8	0.05	0.5	4	1896	1702	1297	1120
0.8	0.05	0.5	5	1937	1775	1260	1104
0.8	0.05	0.5	6	1851	1699	1228	1155

Table B.2: RCGA tuning results for sample failure 2

P_c	P_m	α	b	f_{50}	f_{100}	f_{500}	f_{1000}
Crossover probability variance							
0.7	0.05	0.5	5	5551	5351	5094	4926
0.8	0.05	0.5	5	5645	5396	5060	4969
0.9	0.05	0.5	5	5491	5426	5150	4983
1	0.05	0.5	5	5699	5535	5150	4992
Mutation probability variance							
0.8	0.05	0.5	5	5520	5424	5102	4972
0.8	0.1	0.5	5	5400	5400	5331	5008
α-factor variance							
0.8	0.05	0.1	5	5891	5673	5125	5105
0.8	0.05	0.2	5	5622	5410	4970	4970
0.8	0.05	0.3	5	5594	5580	5003	4965
0.8	0.05	0.4	5	5465	5345	5072	4962
0.8	0.05	0.6	5	5633	5433	5147	5000
0.8	0.05	0.7	5	5669	5547	5271	5042
0.8	0.05	0.8	5	5433	5433	5382	5209
0.8	0.05	0.9	5	5712	5503	5371	5305
0.8	0.05	1	5	5461	5461	5379	5379
b-factor variance							
0.8	0.05	0.5	1	5576	5429	5241	5088
0.8	0.05	0.5	2	5537	5296	5204	5011
0.8	0.05	0.5	3	5715	5282	5187	4977
0.8	0.05	0.5	4	5542	5484	5145	4968
0.8	0.05	0.5	5	5589	5443	5077	4969

Table B.3: PSO tuning results for sample failure 1

β	**N**	**c_1**	**c_2**	**f_{50}**	**f_{100}**	**f_{500}**	**f_{1000}**
Inertia weight factor (β) variance							
0.8	5	1.5	3	1337	1297	1160	1138
0.85	5	1.5	3	1327	1262	1135	1128
0.95	5	1.5	3	1182	1181	1127	1081
Velocity steps (N) variance							
0.9	5	1.5	3	1350	1237	1122	1122
0.9	10	1.5	3	1141	1103	1038	1011
0.9	20	1.5	3	1307	1174	1079	1055
c_1 variance							
0.9	5	1	3	1152	1107	1027	1014
0.9	5	1.5	3	1333	1277	1159	1042
0.9	5	2	3	1424	1373	1205	1205
0.9	5	2.5	3	1525	1501	1259	1259
c_2 variance							
0.9	5	1.5	0.5	2056	2053	2048	2045
0.9	5	1.5	1	1459	1459	1459	1459
0.9	5	1.5	1.5	1468	1248	1235	1235
0.9	5	1.5	2	1180	1126	1059	1055
0.9	5	1.5	3	1310	1296	1140	1117

Table B.4: PSO tuning results for sample failure 2

β	**N**	**c_1**	**c_2**	**f_{50}**	**f_{100}**	**f_{500}**	**f_{1000}**
Inertia weight factor (β) variance							
0.8	5	1.5	3	5234	5135	4987	4939
0.9	5	1.5	3	5194	5135	4979	4888
0.95	5	1.5	3	5224	5019	4965	4889
Velocity steps (N) variance							
0.9	5	1.5	3	5256	5206	5091	5088
0.9	10	1.5	3	5456	5177	4897	4748
0.9	20	1.5	3	5904	5831	4838	4753
c_1 variance							
0.9	5	1	3	11430	11430	11430	11430
0.9	5	1.5	3	5344	5273	5094	5060
0.9	5	2	3	5357	5253	5058	4975
0.9	5	2.5	3	5257	5257	5073	5066
c_2 variance							
0.9	5	1.5	0.5	6050	5914	5802	5797
0.9	5	1.5	1	5725	5572	5560	5537
0.9	5	1.5	1.5	5162	5162	5162	5162
0.9	5	1.5	2	5065	4932	4788	4776
0.9	5	1.5	3	5183	5100	4999	4898

Table B.5: DE tuning results for sample failure 1

CR	F	f_{50}	f_{100}	f_{500}	f_{1000}
Crossover (CR) variance					
0.3	0.5	2474	2241	1614	1584
0.5	0.5	2123	1871	1541	1541
0.6	0.5	1943	1813	1540	1540
0.7	0.5	2053	1719	1602	1602
0.8	0.5	2127	1763	1679	1679
Mutation variance					
0.8	0.4	2372	2248	1920	1581
0.8	0.5	1791	1572	1387	1386
0.8	0.8	1721	1721	1331	1255
0.8	0.9	1989	1877	1353	1254

Table B.6: DE tuning results for sample failure 2

CR	F	f_{50}	f_{100}	f_{500}	f_{1000}
Crossover (CR) variance					
0.3	0.5	5701	5612	5238	5112
0.4	0.5	5774	5437	5156	5065
0.5	0.5	6307	5566	5198	5122
0.6	0.5	5512	5302	5126	5073
0.8	0.5	5483	5331	5115	5112
Mutation variance					
0.8	0.5	5695	5369	5098	5094
0.8	0.7	5904	5506	5158	5123
0.8	0.8	5517	5134	5116	5077
0.8	0.9	6094	5497	5180	5120

Table B.7: LSA tuning results for sample failure 1

Chan. Time	**FR**	**E_0**	**f_{50}**	**f_{100}**	**f_{500}**	**f_{1000}**
Channel time variance						
10	0.01	2	1251	1116	1025	1019
15	0.01	2	1169	1076	1003	979
20	0.01	2	1177	1063	1009	1007
Forking probability variance						
10	0.05	2	1152	1100	1034	1023
10	0.10	2	1217	1169	990	989
10	0.15	2	1246	1155	1124	1124
Initial energy variance						
10	0.01	1	1264	1106	1065	1065
10	0.01	3	1243	1145	1066	1061
10	0.01	4	1187	1073	987	986
10	0.01	5	1260	1127	1055	1019
10	0.01	6	1826	1174	1035	1020

Table B.8: LSA tuning results for sample failure 2

Chan. Time	**FR**	**E_0**	**f_{50}**	**f_{100}**	**f_{500}**	**f_{1000}**
Channel time variance						
5	0.01	2	5122	4946	4793	4792
15	0.01	2	5001	4955	4781	4781
20	0.01	2	5132	5014	4942	4942
Forking probability variance						
10	0.01	2	5205	4964	4879	4762
10	0.05	2	5063	4816	4733	4733
10	0.15	2	5173	4999	4858	4858
Initial energy variance						
10	0.01	1	5207	4988	4728	4728
10	0.01	2	5160	5024	4802	4777
10	0.01	4	5119	4896	4837	4809
10	0.01	5	5072	4913	4864	4711
10	0.01	6	5179	4852	4710	4700

Appendix C: Failures Details

Table C.1: Interruption effects without CLPU events in a given 200 calendar years

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption. d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
1	1	1	409.392	181.033	181.033	74113.615
1	2	1	249.628	181.033	181.033	45190.979
1	3	1	272.644	181.033	181.033	49357.726
1	4	1	226.965	181.033	181.033	41088.150
1	5	1	227.101	181.033	181.033	41112.884
1	6	1	432.026	181.033	181.033	78211.068
1	7	1	272.845	181.033	181.033	49394.123
1	8	1	295.163	181.033	181.033	53434.269
1	9	1	500.331	181.033	181.033	90576.510
1	10	1	363.742	181.033	181.033	65849.428
2	1	1	389.750	1041.167	1041.167	405794.708
2	2	1	237.819	1041.167	1041.167	247608.739
2	3	1	259.681	1041.167	1041.167	270371.264
2	4	1	216.204	1041.167	1041.167	225104.758
2	5	1	216.291	1041.167	1041.167	225194.567
2	6	1	411.269	1041.167	1041.167	428199.237
2	7	1	259.747	1041.167	1041.167	270440.118
2	8	1	281.171	1041.167	1041.167	292745.354
2	9	1	476.506	1041.167	1041.167	496121.922
2	10	1	346.289	1041.167	1041.167	360544.121
3	10	1	135.542	11.300	11.300	1531.626
4	6	1	238.472	81.683	81.683	19479.150
4	7	1	145.489	81.683	81.683	11884.043
5	10	1	152.203	24.683	24.683	3756.883
6	5	1	418.486	70.900	70.900	29670.648
7	5	1	287.963	15.183	15.183	4372.243
8	7	1	415.928	17.817	17.817	7410.459
9	1	1	369.488	101.350	101.350	37447.563
9	2	1	225.473	101.350	101.350	22851.725
9	3	1	246.149	101.350	101.350	24947.158
9	4	1	204.882	101.350	101.350	20764.833
9	5	1	162.529	101.350	101.350	16472.307
9	6	1	202.891	101.350	101.350	20562.954
9	7	1	128.003	101.350	101.350	12973.092
9	8	1	266.321	101.350	101.350	26991.653
9	9	1	451.631	101.350	101.350	45772.840
9	10	1	13.496	101.350	101.350	1367.782
10	1	1	222.388	40.633	40.633	9036.356
10	2	1	136.077	40.633	40.633	5529.249
10	3	1	148.514	40.633	40.633	6034.617
10	4	1	123.629	40.633	40.633	5023.458
10	5	1	59.653	40.633	40.633	2423.899
10	6	1	972.030	40.633	40.633	39496.800
10	7	1	121.770	40.633	40.633	4947.935
10	8	1	160.849	40.633	40.633	6535.826
10	9	1	271.726	40.633	40.633	11041.120
10	10	1	82.158	40.633	40.633	3338.335
11	9	1	331.130	8.383	8.383	2775.973
11	10	1	2725.852	8.383	8.383	22851.724
12	1	1	260.016	8.033	8.033	2088.796
12	2	1	159.083	8.033	8.033	1277.966

Table C.1 (Continued)

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption. d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
12	3	1	173.533	8.033	8.033	1394.048
13	3	1	80.625	19.333	19.333	1558.754
14	8	1	242.079	5.183	5.183	1254.775
14	9	1	326.127	5.183	5.183	1690.423
14	10	1	4812.957	5.183	5.183	24947.158
15	4	1	419.596	117.100	117.100	49134.650
15	5	1	195.147	117.100	117.100	22851.725
16	1	1	357.861	153.817	153.817	55045.023
16	2	1	218.304	153.817	153.817	33578.777
16	3	1	6.797	153.817	153.817	1045.564
16	4	1	198.650	153.817	153.817	30555.687
16	5	1	32.575	153.817	153.817	5010.507
16	6	1	377.965	153.817	153.817	58137.241
16	7	1	39.211	153.817	153.817	6031.231
16	8	1	258.212	153.817	153.817	39717.348
16	9	1	9.974	153.817	153.817	1534.198
16	10	1	52.364	153.817	153.817	8054.446
17	6	1	149.082	15.167	15.167	2261.072
17	7	1	2213.985	15.167	15.167	33578.778
18	7	1	214.791	1.967	1.967	422.423
19	9	1	373.657	1.217	1.217	454.616
19	10	1	634.129	1.217	1.217	771.523
20	7	1	357.275	7.067	7.067	2524.745
21	1	1	107.604	0.050	0.050	5.380
21	2	1	63.043	0.050	0.050	3.152
21	3	1	733749.438	0.050	0.050	36687.472
22	4	1	126.303	11.517	11.517	1454.592
22	5	1	2604.163	11.517	11.517	29991.278
23	6	1	343.296	8.583	8.583	2946.627
23	7	1	159.291	8.583	8.583	1367.245
24	5	1	357.123	3.683	3.683	1315.404
25	7	1	349.715	2.100	2.100	734.401
26	4	1	495.348	13.450	13.450	6662.431
26	5	1	2496.563	13.450	13.450	33578.775
27	6	1	370.633	35.817	35.817	13274.842
27	7	1	7.291	35.817	35.817	261.133
28	2	1	297.233	7.650	7.650	2273.836
28	3	1	0.412	7.650	7.650	3.152
29	2	1	133.745	16.167	16.167	2162.211
29	3	1	86.285	16.167	16.167	1394.949
30	4	1	83.788	52.583	52.583	4405.858
30	5	1	16.822	52.583	52.583	884.569
31	7	1	119.523	4.267	4.267	509.966
32	1	1	123.668	9.667	9.667	1195.453
32	2	1	144.305	9.667	9.667	1394.949
32	3	1	0.400	9.667	9.667	3.864
33	6	1	140.664	8.533	8.533	1200.333
33	7	1	179.961	8.533	8.533	1535.666
34	1	1	418.314	0.050	0.050	20.916
34	2	1	26553.705	0.050	0.050	1327.685
34	3	1	30457.344	0.050	0.050	1522.867
35	5	1	172.076	14.783	14.783	2543.857
36	5	1	68.197	0.750	0.750	51.148
37	8	1	523.130	14.950	14.950	7820.787
37	9	1	2246.072	14.950	14.950	33578.777
37	10	1	124.286	14.950	14.950	1858.072

Table C.2: Interruption effects with CLPU events using fixed 15-min restoration

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
1	1	1	409.392	181.033	181.033	74113.615
1	2	1	250.126	181.283	181.283	45343.640
1	3	1	273.687	181.533	181.533	49683.316
1	4	1	228.247	181.783	181.783	41491.510
1	5	1	228.801	182.033	182.033	41649.444
1	6	1	436.050	182.283	182.283	79484.629
1	7	1	275.806	182.533	182.533	50343.855
1	8	1	298.855	182.783	182.783	54625.782
1	9	1	507.361	183.033	183.033	92863.957
1	10	1	369.414	183.283	183.283	67707.407
2	1	1	389.750	1041.167	1041.167	405794.708
2	2	1	237.895	1041.417	1041.417	247747.775
2	3	1	259.852	1041.667	1041.667	270679.506
2	4	1	216.422	1041.917	1041.917	225493.940
2	5	1	216.585	1042.167	1042.167	225717.770
2	6	1	411.969	1042.417	1042.417	429443.091
2	7	1	260.288	1042.667	1042.667	271393.743
2	8	1	281.863	1042.917	1042.917	293959.755
2	9	1	477.859	1043.167	1043.167	498486.971
2	10	1	347.406	1043.417	1043.417	362488.930
3	10	1	271.084	11.300	11.300	3063.252
4	6	1	476.943	81.683	81.683	38958.301
4	7	1	290.978	81.683	81.683	23768.085
5	10	1	304.406	24.683	24.683	7513.767
6	5	1	836.972	70.900	70.900	59341.296
7	5	1	575.927	15.183	15.183	8744.485
8	7	1	831.857	17.817	17.817	14820.919
9	1	1	369.488	101.350	101.350	37447.563
9	2	1	225.754	101.600	101.600	22936.636
9	3	1	246.753	101.850	101.850	25131.783
9	4	1	205.638	102.100	102.100	20995.668
9	5	1	163.428	102.350	102.350	16726.847
9	6	1	204.303	102.600	102.600	20961.503
9	7	1	129.148	102.850	102.850	13282.885
9	8	1	268.294	103.100	103.100	27661.144
9	9	1	455.351	103.350	103.350	47060.546
9	10	1	22.251	103.600	103.600	2305.156
10	1	1	222.388	40.633	40.633	9036.356
10	2	1	137.516	40.883	40.883	5622.102
10	3	1	151.565	41.133	41.133	6234.371
10	4	1	127.474	41.383	41.383	5275.288
10	5	1	63.097	41.633	41.633	2626.930
10	6	1	977.591	41.883	41.883	40944.749
10	7	1	127.548	42.133	42.133	5374.011
10	8	1	172.098	42.383	42.383	7294.107
10	9	1	293.193	42.633	42.633	12499.789
10	10	1	86.234	42.883	42.883	3697.997
11	9	1	662.260	8.383	8.383	5551.946
11	10	1	2725.852	8.383	8.383	22851.724
12	1	1	260.016	8.033	8.033	2088.796
12	2	1	166.194	8.283	8.283	1376.638
12	3	1	189.077	8.533	8.533	1613.453
13	3	1	161.250	19.333	19.333	3117.508
14	8	1	484.158	5.183	5.183	2509.550
14	9	1	658.964	5.433	5.433	3580.370
14	10	1	4824.773	5.683	5.683	27420.793

Table C.2 (Continued)

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
15	4	1	839.191	117.100	117.100	98269.299
15	5	1	195.147	117.100	117.100	22851.725
16	1	1	357.861	153.817	153.817	55045.023
16	2	1	218.719	154.067	154.067	33697.297
16	3	1	7.055	154.317	154.317	1088.756
16	4	1	199.763	154.567	154.567	30876.661
16	5	1	33.914	154.817	154.817	5250.445
16	6	1	381.472	155.067	155.067	59153.523
16	7	1	41.589	155.317	155.317	6459.491
16	8	1	261.460	155.567	155.567	40674.412
16	9	1	16.286	155.817	155.817	2537.633
16	10	1	56.923	156.067	156.067	8883.853
17	6	1	298.163	15.167	15.167	4522.145
17	7	1	2213.985	15.167	15.167	33578.778
18	7	1	429.582	1.967	1.967	844.845
19	9	1	747.314	1.217	1.217	909.232
19	10	1	1268.257	1.217	1.217	1543.046
20	7	1	714.551	7.067	7.067	5049.490
21	1	1	107.604	0.050	0.050	5.380
21	2	1	63.043	0.050	0.050	3.152
21	3	1	733749.438	0.050	0.050	36687.472
22	4	1	252.606	11.517	11.517	2909.184
22	5	1	5208.326	11.517	11.517	59982.556
23	6	1	686.593	8.583	8.583	5893.254
23	7	1	318.581	8.583	8.583	2734.491
24	5	1	714.247	3.683	3.683	2630.809
25	7	1	699.429	2.100	2.100	1468.801
26	4	1	990.696	13.450	13.450	13324.862
26	5	1	2496.563	13.450	13.450	33578.775
27	6	1	741.266	35.817	35.817	26549.683
27	7	1	15.101	36.067	36.067	544.635
28	2	1	594.467	7.650	7.650	4547.671
28	3	1	0.412	7.650	7.650	3.152
29	2	1	267.490	16.167	16.167	4324.422
29	3	1	86.285	16.167	16.167	1394.949
30	4	1	167.576	52.583	52.583	8811.717
30	5	1	33.644	52.583	52.583	1769.138
31	7	1	239.046	4.267	4.267	1019.932
32	1	1	123.668	9.667	9.667	1195.453
32	2	1	144.305	9.667	9.667	1394.949
32	3	1	0.400	9.667	9.667	3.864
33	6	1	281.328	8.533	8.533	2400.667
33	7	1	359.922	8.533	8.533	3071.333
34	1	1	418.314	0.050	0.050	20.916
34	2	1	26553.705	0.050	0.050	1327.685
34	3	1	30457.344	0.050	0.050	1522.867
35	5	1	344.152	14.783	14.783	5087.714
36	5	1	136.395	0.750	0.750	102.296
37	8	1	1046.259	14.950	14.950	15641.574
37	9	1	2250.342	15.200	15.200	34205.203
37	10	1	253.526	15.450	15.450	3916.981

Table C.3: Interruption effects with CLPU events using fixed 30-min restoration

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
1	1	1	409.392	181.033	181.033	74113.615
1	2	1	250.596	181.533	181.533	45491.540
1	3	1	274.673	182.033	182.033	49999.593
1	4	1	229.439	182.533	182.533	41880.231
1	5	1	230.291	183.033	183.033	42150.924
1	6	1	439.393	183.533	183.533	80643.280
1	7	1	278.257	184.033	184.033	51208.477
1	8	1	301.870	184.533	184.533	55705.048
1	9	1	512.973	185.033	185.033	94917.108
1	10	1	373.816	185.533	185.533	69355.410
2	1	1	389.750	1041.167	1041.167	405794.708
2	2	1	237.975	1041.667	1041.667	247890.377
2	3	1	260.034	1042.167	1042.167	270998.477
2	4	1	216.656	1042.667	1042.667	225899.805
2	5	1	216.907	1043.167	1043.167	226270.516
2	6	1	412.750	1043.667	1043.667	430773.576
2	7	1	260.882	1044.167	1044.167	272404.244
2	8	1	282.616	1044.667	1044.667	295239.639
2	9	1	479.332	1045.167	1045.167	500982.053
2	10	1	348.616	1045.667	1045.667	364535.809
3	10	1	271.084	11.300	11.300	3063.252
4	6	1	476.943	81.683	81.683	38958.301
4	7	1	290.978	81.683	81.683	23768.085
5	10	1	304.406	24.683	24.683	7513.767
6	5	1	836.972	70.900	70.900	59341.296
7	5	1	575.927	15.183	15.183	8744.485
8	7	1	831.857	17.817	17.817	14820.919
9	1	1	369.488	101.350	101.350	37447.563
9	2	1	226.033	101.850	101.850	23021.430
9	3	1	247.338	102.350	102.350	25315.044
9	4	1	206.209	102.850	102.850	21208.583
9	5	1	164.810	103.350	103.350	17033.154
9	6	1	206.723	103.850	103.850	21468.167
9	7	1	131.074	104.350	104.350	13677.525
9	8	1	270.015	104.850	104.850	28311.071
9	9	1	458.568	105.350	105.350	48310.119
9	10	1	31.745	105.850	105.850	3360.209
10	1	1	222.388	40.633	40.633	9036.356
10	2	1	138.902	41.133	41.133	5713.503
10	3	1	154.600	41.633	41.633	6436.517
10	4	1	131.180	42.133	42.133	5527.065
10	5	1	67.262	42.633	42.633	2867.621
10	6	1	982.004	43.133	43.133	42357.123
10	7	1	135.972	43.633	43.633	5932.920
10	8	1	181.119	44.133	44.133	7993.392
10	9	1	310.248	44.633	44.633	13847.419
10	10	1	91.051	45.133	45.133	4109.455
11	9	1	662.260	8.383	8.383	5551.946
11	10	1	2725.852	8.383	8.383	22851.724
12	1	1	260.016	8.033	8.033	2088.796
12	2	1	172.998	8.533	8.533	1476.253
12	3	1	203.887	9.033	9.033	1841.778
13	3	1	161.250	19.333	19.333	3117.508
14	8	1	484.158	5.183	5.183	2509.550
14	9	1	665.747	5.683	5.683	3783.660
14	10	1	4836.213	6.183	6.183	29903.919
15	4	1	839.191	117.100	117.100	98269.299

Table C.3 (Continued)

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
15	5	1	195.147	117.100	117.100	22851.725
16	1	1	357.861	153.817	153.817	55045.023
16	2	1	219.121	154.317	154.317	33813.971
16	3	1	7.295	154.817	154.817	1129.399
16	4	1	200.821	155.317	155.317	31190.829
16	5	1	35.131	155.817	155.817	5473.938
16	6	1	384.546	156.317	156.317	60110.923
16	7	1	43.561	156.817	156.817	6831.135
16	8	1	264.188	157.317	157.317	41561.154
16	9	1	23.892	157.817	157.817	3770.536
16	10	1	60.477	158.317	158.317	9574.552
17	6	1	298.163	15.167	15.167	4522.145
17	7	1	2213.985	15.167	15.167	33578.778
18	7	1	429.582	1.967	1.967	844.845
19	9	1	747.314	1.217	1.217	909.232
19	10	1	1268.257	1.217	1.217	1543.046
20	7	1	714.551	7.067	7.067	5049.490
21	1	1	107.604	0.050	0.050	5.380
21	2	1	63.043	0.050	0.050	3.152
21	3	1	733749.438	0.050	0.050	36687.472
22	4	1	252.606	11.517	11.517	2909.184
22	5	1	5208.326	11.517	11.517	59982.556
23	6	1	686.593	8.583	8.583	5893.254
23	7	1	318.581	8.583	8.583	2734.491
24	5	1	714.247	3.683	3.683	2630.809
25	7	1	699.429	2.100	2.100	1468.801
26	4	1	990.696	13.450	13.450	13324.862
26	5	1	2496.563	13.450	13.450	33578.775
27	6	1	741.266	35.817	35.817	26549.683
27	7	1	15.621	36.317	36.317	567.318
28	2	1	594.467	7.650	7.650	4547.671
28	3	1	0.412	7.650	7.650	3.152
29	2	1	267.490	16.167	16.167	4324.422
29	3	1	86.285	16.167	16.167	1394.949
30	4	1	167.576	52.583	52.583	8811.717
30	5	1	33.644	52.583	52.583	1769.138
31	7	1	239.046	4.267	4.267	1019.932
32	1	1	123.668	9.667	9.667	1195.453
32	2	1	144.305	9.667	9.667	1394.949
32	3	1	0.400	9.667	9.667	3.864
33	6	1	281.328	8.533	8.533	2400.667
33	7	1	359.922	8.533	8.533	3071.333
34	1	1	418.314	0.050	0.050	20.916
34	2	1	26553.705	0.050	0.050	1327.685
34	3	1	30457.344	0.050	0.050	1522.867
35	5	1	344.152	14.783	14.783	5087.714
36	5	1	136.395	0.750	0.750	102.296
37	8	1	1046.259	14.950	14.950	15641.574
37	9	1	2254.476	15.450	15.450	34831.648
37	10	1	258.487	15.950	15.950	4122.865

Table C.4: Interruption effects with CLPU events using fixed 60-min restoration

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
1	1	1	409.392	181.033	181.033	74113.615
1	2	1	251.510	182.033	182.033	45783.144
1	3	1	276.459	183.033	183.033	50601.260
1	4	1	231.488	184.033	184.033	42601.518
1	5	1	232.820	185.033	185.033	43079.476
1	6	1	444.991	186.033	186.033	82783.102
1	7	1	282.065	187.033	187.033	52755.495
1	8	1	306.181	188.033	188.033	57572.142
1	9	1	520.343	189.033	189.033	98362.117
1	10	1	379.191	190.033	190.033	72058.978
2	1	1	389.750	1041.167	1041.167	405794.708
2	2	1	238.141	1042.167	1042.167	248182.905
2	3	1	260.421	1043.167	1043.167	271662.146
2	4	1	217.151	1044.167	1044.167	226741.932
2	5	1	217.576	1045.167	1045.167	227402.884
2	6	1	414.345	1046.167	1046.167	433474.056
2	7	1	262.081	1047.167	1047.167	274442.992
2	8	1	284.127	1048.167	1048.167	297811.986
2	9	1	482.204	1049.167	1049.167	505912.886
2	10	1	350.907	1050.167	1050.167	368510.944
3	10	1	271.084	11.300	11.300	3063.252
4	6	1	476.943	81.683	81.683	38958.301
4	7	1	290.978	81.683	81.683	23768.085
5	10	1	304.406	24.683	24.683	7513.767
6	5	1	836.972	70.900	70.900	59341.296
7	5	1	575.927	15.183	15.183	8744.485
8	7	1	831.857	17.817	17.817	14820.919
9	1	1	369.488	101.350	101.350	37447.563
9	2	1	226.578	102.350	102.350	23190.245
9	3	1	248.167	103.350	103.350	25648.054
9	4	1	207.384	104.350	104.350	21640.541
9	5	1	168.766	105.350	105.350	17779.484
9	6	1	212.967	106.350	106.350	22649.084
9	7	1	135.890	107.350	107.350	14587.823
9	8	1	273.684	108.350	108.350	29653.647
9	9	1	467.355	109.350	109.350	51105.290
9	10	1	49.309	110.350	110.350	5441.213
10	1	1	222.388	40.633	40.633	9036.356
10	2	1	141.692	41.633	41.633	5899.112
10	3	1	160.109	42.633	42.633	6825.972
10	4	1	137.377	43.633	43.633	5994.206
10	5	1	77.725	44.633	44.633	3469.131
10	6	1	990.148	45.633	45.633	45183.743
10	7	1	161.444	46.633	46.633	7528.693
10	8	1	195.343	47.633	47.633	9304.823
10	9	1	335.236	48.633	48.633	16303.636
10	10	1	103.515	49.633	49.633	5137.814
11	9	1	662.260	8.383	8.383	5551.946
11	10	1	2725.852	8.383	8.383	22851.724
12	1	1	260.016	8.033	8.033	2088.796
12	2	1	186.737	9.033	9.033	1686.854
12	3	1	233.101	10.033	10.033	2338.779
13	3	1	161.250	19.333	19.333	3117.508
14	8	1	484.158	5.183	5.183	2509.550
14	9	1	678.961	6.183	6.183	4198.242
14	10	1	4852.422	7.183	7.183	34856.564

Table C.4 (Continued)

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Interruption Case
15	4	1	839.191	117.100	117.100	98269.299
15	5	1	195.147	117.100	117.100	22851.725
16	1	1	357.861	153.817	153.817	55045.023
16	2	1	219.928	154.817	154.817	34048.554
16	3	1	7.733	155.817	155.817	1204.887
16	4	1	202.657	156.817	156.817	31780.036
16	5	1	37.158	157.817	157.817	5864.201
16	6	1	389.671	158.817	158.817	61886.287
16	7	1	46.828	159.817	159.817	7483.964
16	8	1	268.353	160.817	160.817	43155.630
16	9	1	39.297	161.817	161.817	6358.963
16	10	1	65.481	162.817	162.817	10661.442
17	6	1	298.163	15.167	15.167	4522.145
17	7	1	2213.985	15.167	15.167	33578.778
18	7	1	429.582	1.967	1.967	844.845
19	9	1	747.314	1.217	1.217	909.232
19	10	1	1268.257	1.217	1.217	1543.046
20	7	1	714.551	7.067	7.067	5049.490
21	1	1	107.604	0.050	0.050	5.380
21	2	1	63.043	0.050	0.050	3.152
21	3	1	733749.438	0.050	0.050	36687.472
22	4	1	252.606	11.517	11.517	2909.184
22	5	1	5208.326	11.517	11.517	59982.556
23	6	1	686.593	8.583	8.583	5893.254
23	7	1	318.581	8.583	8.583	2734.491
24	5	1	714.247	3.683	3.683	2630.809
25	7	1	699.429	2.100	2.100	1468.801
26	4	1	990.696	13.450	13.450	13324.862
26	5	1	2496.563	13.450	13.450	33578.775
27	6	1	741.266	35.817	35.817	26549.683
27	7	1	16.294	36.817	36.817	599.873
28	2	1	594.467	7.650	7.650	4547.671
28	3	1	0.412	7.650	7.650	3.152
29	2	1	267.490	16.167	16.167	4324.422
29	3	1	86.285	16.167	16.167	1394.949
30	4	1	167.576	52.583	52.583	8811.717
30	5	1	33.644	52.583	52.583	1769.138
31	7	1	239.046	4.267	4.267	1019.932
32	1	1	123.668	9.667	9.667	1195.453
32	2	1	144.305	9.667	9.667	1394.949
32	3	1	0.400	9.667	9.667	3.864
33	6	1	281.328	8.533	8.533	2400.667
33	7	1	359.922	8.533	8.533	3071.333
34	1	1	418.314	0.050	0.050	20.916
34	2	1	26553.705	0.050	0.050	1327.685
34	3	1	30457.344	0.050	0.050	1522.867
35	5	1	344.152	14.783	14.783	5087.714
36	5	1	136.395	0.750	0.750	102.296
37	8	1	1046.259	14.950	14.950	15641.574
37	9	1	2262.784	15.950	15.950	36091.408
37	10	1	266.728	16.950	16.950	4521.045

Table C.5: Interruption effects with CLPU events using fixed 90-min restoration

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
1	1	1	409.392	181.033	181.033	74113.615
1	2	1	252.360	182.533	182.533	46064.062
1	3	1	278.079	184.033	184.033	51175.729
1	4	1	233.250	185.533	185.533	43275.738
1	5	1	234.776	187.033	187.033	43910.910
1	6	1	448.727	188.533	188.533	84599.989
1	7	1	284.394	190.033	190.033	54044.389
1	8	1	308.772	191.533	191.533	59140.049
1	9	1	524.924	193.033	193.033	101327.796
1	10	1	383.607	194.533	194.533	74624.353
2	1	1	389.750	1041.167	1041.167	405794.708
2	2	1	238.314	1042.667	1042.667	248481.630
2	3	1	260.814	1044.167	1044.167	272333.663
2	4	1	217.659	1045.667	1045.667	227599.172
2	5	1	218.240	1047.167	1047.167	228533.659
2	6	1	415.888	1048.667	1048.667	436128.395
2	7	1	263.211	1050.167	1050.167	276415.032
2	8	1	285.417	1051.667	1051.667	300164.050
2	9	1	484.398	1053.167	1053.167	510151.516
2	10	1	352.463	1054.667	1054.667	371730.540
3	10	1	271.084	11.300	11.300	3063.252
4	6	1	476.943	81.683	81.683	38958.301
4	7	1	290.978	81.683	81.683	23768.085
5	10	1	304.406	24.683	24.683	7513.767
6	5	1	836.972	70.900	70.900	59341.296
7	5	1	575.927	15.183	15.183	8744.485
8	7	1	831.857	17.817	17.817	14820.919
9	1	1	369.488	101.350	101.350	37447.563
9	2	1	226.946	102.850	102.850	23341.366
9	3	1	249.136	104.350	104.350	25997.313
9	4	1	208.384	105.850	105.850	22057.473
9	5	1	174.427	107.350	107.350	18724.696
9	6	1	219.571	108.850	108.850	23900.300
9	7	1	141.824	110.350	110.350	15650.313
9	8	1	283.259	111.850	111.850	31682.533
9	9	1	489.946	113.350	113.350	55535.384
9	10	1	57.933	114.850	114.850	6653.552
10	1	1	222.388	40.633	40.633	9036.356
10	2	1	144.334	42.133	42.133	6081.253
10	3	1	164.866	43.633	43.633	7193.650
10	4	1	142.962	45.133	45.133	6452.349
10	5	1	90.180	46.633	46.633	4205.376
10	6	1	1002.160	48.133	48.133	48237.288
10	7	1	192.206	49.633	49.633	9539.844
10	8	1	204.268	51.133	51.133	10444.924
10	9	1	349.212	52.633	52.633	18380.177
10	10	1	114.677	54.133	54.133	6207.844
11	9	1	662.260	8.383	8.383	5551.946
11	10	1	2725.852	8.383	8.383	22851.724
12	1	1	260.016	8.033	8.033	2088.796
12	2	1	200.339	9.533	9.533	1909.894
12	3	1	261.672	11.033	11.033	2887.117
13	3	1	161.250	19.333	19.333	3117.508
14	8	1	484.158	5.183	5.183	2509.550
14	9	1	690.273	6.683	6.683	4613.322
14	10	1	4871.364	8.183	8.183	39863.998

Table C.5 (Continued)

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
15	4	1	839.191	117.100	117.100	98269.299
15	5	1	195.147	117.100	117.100	22851.725
16	1	1	357.861	153.817	153.817	55045.023
16	2	1	220.685	155.317	155.317	34276.004
16	3	1	8.101	156.817	156.817	1270.423
16	4	1	204.301	158.317	158.317	32344.185
16	5	1	38.898	159.817	159.817	6216.479
16	6	1	393.576	161.317	161.317	63490.436
16	7	1	49.042	162.817	162.817	7984.911
16	8	1	271.648	164.317	164.317	44636.235
16	9	1	52.572	165.817	165.817	8717.260
16	10	1	67.916	167.317	167.317	11363.442
17	6	1	298.163	15.167	15.167	4522.145
17	7	1	2213.985	15.167	15.167	33578.778
18	7	1	429.582	1.967	1.967	844.845
19	9	1	747.314	1.217	1.217	909.232
19	10	1	1268.257	1.217	1.217	1543.046
20	7	1	714.551	7.067	7.067	5049.490
21	1	1	107.604	0.050	0.050	5.380
21	2	1	63.043	0.050	0.050	3.152
21	3	1	733749.438	0.050	0.050	36687.472
22	4	1	252.606	11.517	11.517	2909.184
22	5	1	5208.326	11.517	11.517	59982.556
23	6	1	686.593	8.583	8.583	5893.254
23	7	1	318.581	8.583	8.583	2734.491
24	5	1	714.247	3.683	3.683	2630.809
25	7	1	699.429	2.100	2.100	1468.801
26	4	1	990.696	13.450	13.450	13324.862
26	5	1	2496.563	13.450	13.450	33578.775
27	6	1	741.266	35.817	35.817	26549.683
27	7	1	16.876	37.317	37.317	629.746
28	2	1	594.467	7.650	7.650	4547.671
28	3	1	0.412	7.650	7.650	3.152
29	2	1	267.490	16.167	16.167	4324.422
29	3	1	86.285	16.167	16.167	1394.949
30	4	1	167.576	52.583	52.583	8811.717
30	5	1	33.644	52.583	52.583	1769.138
31	7	1	239.046	4.267	4.267	1019.932
32	1	1	123.668	9.667	9.667	1195.453
32	2	1	144.305	9.667	9.667	1394.949
32	3	1	0.400	9.667	9.667	3.864
33	6	1	281.328	8.533	8.533	2400.667
33	7	1	359.922	8.533	8.533	3071.333
34	1	1	418.314	0.050	0.050	20.916
34	2	1	26553.705	0.050	0.050	1327.685
34	3	1	30457.344	0.050	0.050	1522.867
35	5	1	344.152	14.783	14.783	5087.714
36	5	1	136.395	0.750	0.750	102.296
37	8	1	1046.259	14.950	14.950	15641.574
37	9	1	2270.567	16.450	16.450	37350.825
37	10	1	273.818	17.950	17.950	4915.030

Table C.6: Interruption effects with CLPU events using RCGA

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
1	1	1	410.472	181.367	181.367	74445.875
1	2	1	251.958	182.283	182.283	45927.707
1	3	1	278.596	184.367	184.367	51363.851
1	4	1	226.965	181.033	181.033	41088.150
1	5	1	229.342	182.367	182.367	41824.305
1	6	1	435.201	182.017	182.017	79213.900
1	7	1	277.116	183.300	183.300	50795.424
1	8	1	295.163	181.033	181.033	53434.269
1	9	1	510.320	184.033	184.033	93915.909
1	10	1	375.209	186.367	186.367	69926.368
2	1	1	389.750	1041.167	1041.167	405794.708
2	2	1	240.774	1049.483	1049.483	252688.558
2	3	1	264.275	1054.483	1054.483	278673.898
2	4	1	216.204	1041.167	1041.167	225104.758
2	5	1	219.742	1052.483	1052.483	231274.380
2	6	1	416.694	1050.067	1050.067	437556.640
2	7	1	264.113	1053.417	1053.417	278221.268
2	8	1	281.467	1041.950	1041.950	293274.711
2	9	1	484.544	1053.500	1053.500	510467.625
2	10	1	352.631	1055.417	1055.417	372173.130
3	10	1	271.084	11.300	11.300	3063.252
4	6	1	476.943	81.683	81.683	38958.301
4	7	1	290.978	81.683	81.683	23768.085
5	10	1	304.406	24.683	24.683	7513.767
6	5	1	836.972	70.900	70.900	59341.296
7	5	1	575.927	15.183	15.183	8744.485
8	7	1	831.857	17.817	17.817	14820.919
9	1	1	369.488	101.350	101.350	37447.563
9	2	1	225.473	101.350	101.350	22851.725
9	3	1	246.149	101.350	101.350	24947.158
9	4	1	204.882	101.350	101.350	20764.833
9	5	1	162.529	101.350	101.350	16472.307
9	6	1	202.891	101.350	101.350	20562.954
9	7	1	128.003	101.350	101.350	12973.092
9	8	1	266.321	101.350	101.350	26991.653
9	9	1	451.631	101.350	101.350	45772.840
9	10	1	15.390	101.867	101.867	1567.726
10	1	1	222.388	40.633	40.633	9036.356
10	2	1	140.853	41.483	41.483	5843.047
10	3	1	154.705	41.650	41.650	6443.476
10	4	1	123.629	40.633	40.633	5023.458
10	5	1	59.653	40.633	40.633	2423.899
10	6	1	972.030	40.633	40.633	39496.800
10	7	1	123.700	41.333	41.333	5112.937
10	8	1	160.849	40.633	40.633	6535.826
10	9	1	278.083	41.200	41.200	11457.031
10	10	1	85.034	42.033	42.033	3574.274
11	9	1	662.260	8.383	8.383	5551.946
11	10	1	2725.852	8.383	8.383	22851.724
12	1	1	260.016	8.033	8.033	2088.796
12	2	1	159.083	8.033	8.033	1277.966
12	3	1	173.533	8.033	8.033	1394.048
13	3	1	161.250	19.333	19.333	3117.508
14	8	1	484.158	5.183	5.183	2509.550
14	9	1	652.253	5.183	5.183	3380.846
14	10	1	4829.877	5.900	5.900	28496.277
15	4	1	839.191	117.100	117.100	98269.299

Table C.6 (Continued)

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
15	5	1	195.147	117.100	117.100	22851.725
16	1	1	357.861	153.817	153.817	55045.023
16	2	1	218.304	153.817	153.817	33578.777
16	3	1	7.449	155.150	155.150	1155.748
16	4	1	198.650	153.817	153.817	30555.687
16	5	1	33.603	154.583	154.583	5194.480
16	6	1	379.632	154.400	154.400	58615.193
16	7	1	41.714	155.400	155.400	6482.320
16	8	1	258.212	153.817	153.817	39717.348
16	9	1	13.261	154.917	154.917	2054.301
16	10	1	56.681	155.933	155.933	8838.520
17	6	1	298.163	15.167	15.167	4522.145
17	7	1	2213.985	15.167	15.167	33578.778
18	7	1	429.582	1.967	1.967	844.845
19	9	1	747.314	1.217	1.217	909.232
19	10	1	1268.257	1.217	1.217	1543.046
20	7	1	714.551	7.067	7.067	5049.490
21	1	1	107.604	0.050	0.050	5.380
21	2	1	63.043	0.050	0.050	3.152
21	3	1	733749.438	0.050	0.050	36687.472
22	4	1	252.606	11.517	11.517	2909.184
22	5	1	5208.326	11.517	11.517	59982.556
23	6	1	686.593	8.583	8.583	5893.254
23	7	1	318.581	8.583	8.583	2734.491
24	5	1	714.247	3.683	3.683	2630.809
25	7	1	699.429	2.100	2.100	1468.801
26	4	1	990.696	13.450	13.450	13324.862
26	5	1	2496.563	13.450	13.450	33578.775
27	6	1	741.266	35.817	35.817	26549.683
27	7	1	18.391	38.567	38.567	709.290
28	2	1	594.467	7.650	7.650	4547.671
28	3	1	0.412	7.650	7.650	3.152
29	2	1	267.490	16.167	16.167	4324.422
29	3	1	86.285	16.167	16.167	1394.949
30	4	1	167.576	52.583	52.583	8811.717
30	5	1	33.644	52.583	52.583	1769.138
31	7	1	239.046	4.267	4.267	1019.932
32	1	1	123.668	9.667	9.667	1195.453
32	2	1	144.305	9.667	9.667	1394.949
32	3	1	0.400	9.667	9.667	3.864
33	6	1	281.328	8.533	8.533	2400.667
33	7	1	359.922	8.533	8.533	3071.333
34	1	1	418.314	0.050	0.050	20.916
34	2	1	26553.705	0.050	0.050	1327.685
34	3	1	30457.344	0.050	0.050	1522.867
35	5	1	344.152	14.783	14.783	5087.714
36	5	1	136.395	0.750	0.750	102.296
37	8	1	1046.259	14.950	14.950	15641.574
37	9	1	2246.072	14.950	14.950	33578.777
37	10	1	249.126	15.000	15.000	3736.889

Table C.7: Interruption effects with CLPU events using PSO

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
1	1	1	411.324	181.650	181.650	74716.983
1	2	1	252.075	182.350	182.350	45965.887
1	3	1	277.504	183.667	183.667	50968.290
1	4	1	226.965	181.033	181.033	41088.150
1	5	1	229.366	182.383	182.383	41832.613
1	6	1	432.026	181.033	181.033	78211.068
1	7	1	276.920	183.183	183.183	50727.042
1	8	1	297.380	182.033	182.033	54133.085
1	9	1	510.891	184.233	184.233	94123.150
1	10	1	375.186	186.350	186.350	69915.918
2	1	1	389.750	1041.167	1041.167	405794.708
2	2	1	240.596	1048.967	1048.967	252376.665
2	3	1	264.108	1053.717	1053.717	278295.486
2	4	1	216.204	1041.167	1041.167	225104.758
2	5	1	219.560	1051.683	1051.683	230907.141
2	6	1	416.422	1049.567	1049.567	437062.423
2	7	1	263.918	1052.600	1052.600	277799.797
2	8	1	281.467	1041.950	1041.950	293274.711
2	9	1	484.544	1053.500	1053.500	510467.625
2	10	1	352.435	1054.550	1054.550	371660.681
3	10	1	271.084	11.300	11.300	3063.252
4	6	1	476.943	81.683	81.683	38958.301
4	7	1	290.978	81.683	81.683	23768.085
5	10	1	304.406	24.683	24.683	7513.767
6	5	1	836.972	70.900	70.900	59341.296
7	5	1	575.927	15.183	15.183	8744.485
8	7	1	831.857	17.817	17.817	14820.919
9	1	1	369.488	101.350	101.350	37447.563
9	2	1	225.473	101.350	101.350	22851.725
9	3	1	246.149	101.350	101.350	24947.158
9	4	1	204.882	101.350	101.350	20764.833
9	5	1	162.529	101.350	101.350	16472.307
9	6	1	202.891	101.350	101.350	20562.954
9	7	1	128.324	101.867	101.867	13071.974
9	8	1	266.321	101.350	101.350	26991.653
9	9	1	451.631	101.350	101.350	45772.840
9	10	1	13.496	101.350	101.350	1367.782
10	1	1	222.388	40.633	40.633	9036.356
10	2	1	136.077	40.633	40.633	5529.249
10	3	1	153.589	41.467	41.467	6368.838
10	4	1	123.629	40.633	40.633	5023.458
10	5	1	61.881	41.300	41.300	2555.692
10	6	1	974.965	41.233	41.233	40201.043
10	7	1	126.323	41.883	41.883	5290.810
10	8	1	160.849	40.633	40.633	6535.826
10	9	1	271.726	40.633	40.633	11041.120
10	10	1	84.469	41.633	41.633	3516.738
11	9	1	662.260	8.383	8.383	5551.946
11	10	1	2725.852	8.383	8.383	22851.724
12	1	1	260.016	8.033	8.033	2088.796
12	2	1	159.083	8.033	8.033	1277.966
12	3	1	182.486	8.317	8.317	1517.673
13	3	1	161.250	19.333	19.333	3117.508
14	8	1	484.158	5.183	5.183	2509.550
14	9	1	652.253	5.183	5.183	3380.846
14	10	1	4829.877	5.900	5.900	28496.277
15	4	1	839.191	117.100	117.100	98269.299

Table C.7 (Continued)

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
15	5	1	195.147	117.100	117.100	22851.725
16	1	1	357.861	153.817	153.817	55045.023
16	2	1	218.304	153.817	153.817	33578.777
16	3	1	7.295	154.817	154.817	1129.399
16	4	1	198.884	153.967	153.967	30621.434
16	5	1	33.603	154.583	154.583	5194.480
16	6	1	377.965	153.817	153.817	58137.241
16	7	1	40.960	154.900	154.900	6344.631
16	8	1	259.364	154.417	154.417	40050.056
16	9	1	14.836	155.400	155.400	2305.501
16	10	1	57.465	156.400	156.400	8987.561
17	6	1	298.163	15.167	15.167	4522.145
17	7	1	2213.985	15.167	15.167	33578.778
18	7	1	429.582	1.967	1.967	844.845
19	9	1	747.314	1.217	1.217	909.232
19	10	1	1268.257	1.217	1.217	1543.046
20	7	1	714.551	7.067	7.067	5049.490
21	1	1	107.604	0.050	0.050	5.380
21	2	1	63.043	0.050	0.050	3.152
21	3	1	733749.438	0.050	0.050	36687.472
22	4	1	252.606	11.517	11.517	2909.184
22	5	1	5208.326	11.517	11.517	59982.556
23	6	1	686.593	8.583	8.583	5893.254
23	7	1	318.581	8.583	8.583	2734.491
24	5	1	714.247	3.683	3.683	2630.809
25	7	1	699.429	2.100	2.100	1468.801
26	4	1	990.696	13.450	13.450	13324.862
26	5	1	2496.563	13.450	13.450	33578.775
27	6	1	741.266	35.817	35.817	26549.683
27	7	1	18.391	38.567	38.567	709.290
28	2	1	594.467	7.650	7.650	4547.671
28	3	1	0.412	7.650	7.650	3.152
29	2	1	267.490	16.167	16.167	4324.422
29	3	1	86.285	16.167	16.167	1394.949
30	4	1	167.576	52.583	52.583	8811.717
30	5	1	33.644	52.583	52.583	1769.138
31	7	1	239.046	4.267	4.267	1019.932
32	1	1	123.668	9.667	9.667	1195.453
32	2	1	144.305	9.667	9.667	1394.949
32	3	1	0.400	9.667	9.667	3.864
33	6	1	281.328	8.533	8.533	2400.667
33	7	1	359.922	8.533	8.533	3071.333
34	1	1	418.314	0.050	0.050	20.916
34	2	1	26553.705	0.050	0.050	1327.685
34	3	1	30457.344	0.050	0.050	1522.867
35	5	1	344.152	14.783	14.783	5087.714
36	5	1	136.395	0.750	0.750	102.296
37	8	1	1046.259	14.950	14.950	15641.574
37	9	1	2246.072	14.950	14.950	33578.777
37	10	1	249.126	15.000	15.000	3736.889

Table C.8: Interruption effects with CLPU events using DE

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
1	1	1	409.447	181.050	181.050	74130.322
1	2	1	251.389	181.967	181.967	45744.331
1	3	1	278.734	184.467	184.467	51417.179
1	4	1	227.534	181.350	181.350	41263.227
1	5	1	229.414	182.417	182.417	41848.887
1	6	1	435.572	182.133	182.133	79332.201
1	7	1	276.920	183.183	183.183	50727.042
1	8	1	295.163	181.033	181.033	53434.269
1	9	1	509.311	183.683	183.683	93551.915
1	10	1	375.251	186.400	186.400	69946.731
2	1	1	389.750	1041.167	1041.167	405794.708
2	2	1	240.801	1049.567	1049.567	252736.778
2	3	1	264.326	1054.783	1054.783	278806.680
2	4	1	216.209	1041.183	1041.183	225113.318
2	5	1	219.556	1051.667	1051.667	230899.855
2	6	1	417.015	1050.683	1050.683	438151.046
2	7	1	264.151	1053.583	1053.583	278305.189
2	8	1	281.664	1042.450	1042.450	293620.829
2	9	1	484.684	1053.850	1053.850	510783.741
2	10	1	352.659	1055.550	1055.550	372249.429
3	10	1	570.960	18.567	18.567	10600.818
4	6	1	476.943	81.683	81.683	38958.301
4	7	1	290.978	81.683	81.683	23768.085
5	10	1	304.406	24.683	24.683	7513.767
6	5	1	836.972	70.900	70.900	59341.296
7	5	1	575.927	15.183	15.183	8744.485
8	7	1	831.857	17.817	17.817	14820.919
9	1	1	369.488	101.350	101.350	37447.563
9	2	1	225.473	101.350	101.350	22851.725
9	3	1	246.149	101.350	101.350	24947.158
9	4	1	204.882	101.350	101.350	20764.833
9	5	1	162.529	101.350	101.350	16472.307
9	6	1	202.891	101.350	101.350	20562.954
9	7	1	128.003	101.350	101.350	12973.092
9	8	1	266.321	101.350	101.350	26991.653
9	9	1	451.631	101.350	101.350	45772.840
9	10	1	15.390	101.867	101.867	1567.726
10	1	1	222.388	40.633	40.633	9036.356
10	2	1	136.077	40.633	40.633	5529.249
10	3	1	153.589	41.467	41.467	6368.838
10	4	1	123.629	40.633	40.633	5023.458
10	5	1	61.324	41.150	41.150	2523.476
10	6	1	975.285	41.300	41.300	40279.254
10	7	1	126.323	41.883	41.883	5290.810
10	8	1	160.849	40.633	40.633	6535.826
10	9	1	271.726	40.633	40.633	11041.120
10	10	1	84.469	41.633	41.633	3516.738
11	9	1	662.260	8.383	8.383	5551.946
11	10	1	2725.852	8.383	8.383	22851.724
12	1	1	260.016	8.033	8.033	2088.796
12	2	1	159.083	8.033	8.033	1277.966
12	3	1	173.533	8.033	8.033	1394.048
13	3	1	161.250	19.333	19.333	3117.508
14	8	1	484.158	5.183	5.183	2509.550
14	9	1	652.253	5.183	5.183	3380.846
14	10	1	4933.293	11.733	11.733	57883.977

Table C.8 (Continued)

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
15	4	1	839.191	117.100	117.100	98269.299
15	5	1	195.147	117.100	117.100	22851.725
16	1	1	357.861	153.817	153.817	55045.023
16	2	1	218.304	153.817	153.817	33578.777
16	3	1	7.449	155.150	155.150	1155.748
16	4	1	198.650	153.817	153.817	30555.687
16	5	1	33.603	154.583	154.583	5194.480
16	6	1	379.632	154.400	154.400	58615.193
16	7	1	41.714	155.400	155.400	6482.320
16	8	1	258.212	153.817	153.817	39717.348
16	9	1	13.261	154.917	154.917	2054.301
16	10	1	56.773	155.983	155.983	8855.643
17	6	1	298.163	15.167	15.167	4522.145
17	7	1	2213.985	15.167	15.167	33578.778
18	7	1	429.582	1.967	1.967	844.845
19	9	1	747.314	1.217	1.217	909.232
19	10	1	1268.257	1.217	1.217	1543.046
20	7	1	714.551	7.067	7.067	5049.490
21	1	1	107.604	0.050	0.050	5.380
21	2	1	63.043	0.050	0.050	3.152
21	3	1	733749.438	0.050	0.050	36687.472
22	4	1	252.606	11.517	11.517	2909.184
22	5	1	5208.326	11.517	11.517	59982.556
23	6	1	686.593	8.583	8.583	5893.254
23	7	1	318.581	8.583	8.583	2734.491
24	5	1	714.247	3.683	3.683	2630.809
25	7	1	699.429	2.100	2.100	1468.801
26	4	1	990.696	13.450	13.450	13324.862
26	5	1	2496.563	13.450	13.450	33578.775
27	6	1	741.266	35.817	35.817	26549.683
27	7	1	18.391	38.567	38.567	709.290
28	2	1	594.467	7.650	7.650	4547.671
28	3	1	0.412	7.650	7.650	3.152
29	2	1	267.490	16.167	16.167	4324.422
29	3	1	86.285	16.167	16.167	1394.949
30	4	1	167.576	52.583	52.583	8811.717
30	5	1	33.644	52.583	52.583	1769.138
31	7	1	239.046	4.267	4.267	1019.932
32	1	1	123.668	9.667	9.667	1195.453
32	2	1	144.305	9.667	9.667	1394.949
32	3	1	0.400	9.667	9.667	3.864
33	6	1	281.328	8.533	8.533	2400.667
33	7	1	359.922	8.533	8.533	3071.333
34	1	1	418.314	0.050	0.050	20.916
34	2	1	26553.705	0.050	0.050	1327.685
34	3	1	30457.344	0.050	0.050	1522.867
35	5	1	344.152	14.783	14.783	5087.714
36	5	1	136.395	0.750	0.750	102.296
37	8	1	1046.259	14.950	14.950	15641.574
37	9	1	2246.072	14.950	14.950	33578.777
37	10	1	249.126	15.000	15.000	3736.889

Table C.9: Interruption effects with CLPU events using LSA

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
1	1	1	411.324	181.650	181.650	74716.983
1	2	1	252.075	182.350	182.350	45965.887
1	3	1	277.504	183.667	183.667	50968.290
1	4	1	226.965	181.033	181.033	41088.150
1	5	1	229.366	182.383	182.383	41832.613
1	6	1	432.026	181.033	181.033	78211.068
1	7	1	276.920	183.183	183.183	50727.042
1	8	1	297.380	182.033	182.033	54133.085
1	9	1	510.891	184.233	184.233	94123.150
1	10	1	375.186	186.350	186.350	69915.918
2	1	1	389.750	1041.167	1041.167	405794.708
2	2	1	240.596	1048.967	1048.967	252376.665
2	3	1	264.108	1053.717	1053.717	278295.486
2	4	1	216.204	1041.167	1041.167	225104.758
2	5	1	219.560	1051.683	1051.683	230907.141
2	6	1	416.422	1049.567	1049.567	437062.423
2	7	1	263.918	1052.600	1052.600	277799.797
2	8	1	281.467	1041.950	1041.950	293274.711
2	9	1	484.544	1053.500	1053.500	510467.625
2	10	1	352.435	1054.550	1054.550	371660.681
3	10	1	271.084	11.300	11.300	3063.252
4	6	1	476.943	81.683	81.683	38958.301
4	7	1	290.978	81.683	81.683	23768.085
5	10	1	304.406	24.683	24.683	7513.767
6	5	1	836.972	70.900	70.900	59341.296
7	5	1	575.927	15.183	15.183	8744.485
8	7	1	831.857	17.817	17.817	14820.919
9	1	1	369.488	101.350	101.350	37447.563
9	2	1	225.473	101.350	101.350	22851.725
9	3	1	246.149	101.350	101.350	24947.158
9	4	1	204.882	101.350	101.350	20764.833
9	5	1	162.529	101.350	101.350	16472.307
9	6	1	202.891	101.350	101.350	20562.954
9	7	1	128.324	101.867	101.867	13071.974
9	8	1	266.321	101.350	101.350	26991.653
9	9	1	451.631	101.350	101.350	45772.840
9	10	1	13.496	101.350	101.350	1367.782
10	1	1	222.388	40.633	40.633	9036.356
10	2	1	136.077	40.633	40.633	5529.249
10	3	1	153.589	41.467	41.467	6368.838
10	4	1	123.629	40.633	40.633	5023.458
10	5	1	61.881	41.300	41.300	2555.692
10	6	1	974.965	41.233	41.233	40201.043
10	7	1	126.323	41.883	41.883	5290.810
10	8	1	160.849	40.633	40.633	6535.826
10	9	1	271.726	40.633	40.633	11041.120
10	10	1	84.469	41.633	41.633	3516.738
11	9	1	662.260	8.383	8.383	5551.946
11	10	1	2725.852	8.383	8.383	22851.724
12	1	1	260.016	8.033	8.033	2088.796
12	2	1	159.083	8.033	8.033	1277.966
12	3	1	182.486	8.317	8.317	1517.673
13	3	1	161.250	19.333	19.333	3117.508
14	8	1	484.158	5.183	5.183	2509.550
14	9	1	652.253	5.183	5.183	3380.846
14	10	1	4829.877	5.900	5.900	28496.277

Table C.9 (Continued)

Interruption Case	Load Point Affected	Number of Customers Disconnected (NC)	Load Curtailed Lc (kW)	Duration of Interruption d (hours)	Customer Hours Curtailed NC_d	Energy Not Supplied LC_d (kWh)
15	4	1	839.191	117.100	117.100	98269.299
15	5	1	195.147	117.100	117.100	22851.725
16	1	1	357.861	153.817	153.817	55045.023
16	2	1	218.304	153.817	153.817	33578.777
16	3	1	7.295	154.817	154.817	1129.399
16	4	1	198.884	153.967	153.967	30621.434
16	5	1	33.603	154.583	154.583	5194.480
16	6	1	377.965	153.817	153.817	58137.241
16	7	1	40.960	154.900	154.900	6344.631
16	8	1	259.364	154.417	154.417	40050.056
16	9	1	14.836	155.400	155.400	2305.501
16	10	1	57.465	156.400	156.400	8987.561
17	6	1	298.163	15.167	15.167	4522.145
17	7	1	2213.985	15.167	15.167	33578.778
18	7	1	429.582	1.967	1.967	844.845
19	9	1	747.314	1.217	1.217	909.232
19	10	1	1268.257	1.217	1.217	1543.046
20	7	1	714.551	7.067	7.067	5049.490
21	1	1	107.604	0.050	0.050	5.380
21	2	1	63.043	0.050	0.050	3.152
21	3	1	733749.438	0.050	0.050	36687.472
22	4	1	252.606	11.517	11.517	2909.184
22	5	1	5208.326	11.517	11.517	59982.556
23	6	1	686.593	8.583	8.583	5893.254
23	7	1	318.581	8.583	8.583	2734.491
24	5	1	714.247	3.683	3.683	2630.809
25	7	1	699.429	2.100	2.100	1468.801
26	4	1	990.696	13.450	13.450	13324.862
26	5	1	2496.563	13.450	13.450	33578.775
27	6	1	741.266	35.817	35.817	26549.683
27	7	1	18.391	38.567	38.567	709.290
28	2	1	594.467	7.650	7.650	4547.671
28	3	1	0.412	7.650	7.650	3.152
29	2	1	267.490	16.167	16.167	4324.422
29	3	1	86.285	16.167	16.167	1394.949
30	4	1	167.576	52.583	52.583	8811.717
30	5	1	33.644	52.583	52.583	1769.138
31	7	1	239.046	4.267	4.267	1019.932
32	1	1	123.668	9.667	9.667	1195.453
32	2	1	144.305	9.667	9.667	1394.949
32	3	1	0.400	9.667	9.667	3.864
33	6	1	281.328	8.533	8.533	2400.667
33	7	1	359.922	8.533	8.533	3071.333
34	1	1	418.314	0.050	0.050	20.916
34	2	1	26553.705	0.050	0.050	1327.685
34	3	1	30457.344	0.050	0.050	1522.867
35	5	1	344.152	14.783	14.783	5087.714
36	5	1	136.395	0.750	0.750	102.296
37	8	1	1046.259	14.950	14.950	15641.574
37	9	1	2246.072	14.950	14.950	33578.777
37	10	1	249.126	15.000	15.000	3736.889

REFERENCES

[1] R. Billinton and R. N. Allan, Reliability Evaluation of Power Systems, Springer, 1996.

[2] J. Medina, N. Muller and I. Roytelman, "Demand Response and Distribution Grid Operations: Opportunities and Challenges," *IEEE Transactions on Smart Grid,* vol. 1, no. 2, pp. 193 - 198, 2010.

[3] K. P. Schneider, E. Sortomme, S. S. Venkata, M. T. Miller and L. Ponder, "Evaluating the Magnitude and Duration of Cold Load Pick-up on Residential Distribution Feeders Using Multi-State Load Models," *IEEE Transactions on Power Systems,* vol. 31, no. 5, pp. 3765-3774, 2016.

[4] C. UGak and A. Pahwa, "An Analytical Approach for Step-By-Step Restoration of Distribution Systems Following Extended Outages," *IEEE Transactions on Power Delivery,* vol. 9, no. 3, pp. 1717-1723, 1994.

[5] C. UGak and A. Pahwa, "Optimal step-by-step restoration of distribution systems during excessive loads due to cold load pickup," *Electric Power Systems Research,* vol. 32, no. 2, pp. 121-128, 1995.

[6] M. Gilvanejad, H. A. Abyaneh and K. Mazlumi, "Estimation of Cold-Load Pickup Occurrence Rate in Distribution Systems," *IEEE Transactions on Power Delivery,* vol. 28, no. 2, pp. 1138 - 1147, 2013.

[7] A. Alnujaimi and M. Almuhaini, "Inclusion of Cold Load Pickup Events in Reliability Calculation for Residential Power Distribution Systems," in *The 9th IEEE-GCC conference*, Bahrain, 2017.

[8] J. E. McDonald and A. M. Bruning, "Cold Load Pickup," *IEEE Transactions on Power Apparatus and Systems,* no. 4, pp. 1384-1386, 1979.

[9] S. Ihara and F. C. Schweppe, "Physically Based Modeling of Cold Load Pickup," *IEEE Transactions on Power Apparatus and Systems,* no. 9, pp. 4142-4150, 1981.

[10] R. L. Wilde, "The Effects of Cold Load Pickup on Distribution Transformers," *IEEE Transactions on Power Apparatus and Systems,* vol. 100, no. 5, pp. 2433 - 2437, 1981.

[11] W. W. Lang, M. D. Anderson and D. R. Fannin, "An Analytical Method for Quantifying the Electrical Space Heating Component of a Cold Load Pick Up," *IEEE Transactions on Power Apparatus and Systems*, vol. 101, no. 4, pp. 924 - 932, 1982.

[12] M. H. Yolcu, Z. Zabar, L. Birenbaum and S. A. Granek, "Adaptation of the Simplex Algorithm to Modeling of Cold Load Pickup of a Large Secondary Network Distribution System," *IEEE Transactions on Power Apparatus and Systems* , vol. 102, no. 7, 1983.

[13] C.-y. Chong and R. P. Malhami, "Statistical Synthesis of Physically Based Load Models with Applications to Cold Load Pickup," *IEEE Transactions on Power Apparatus and Systems*, no. 7, pp. 1621-1628, 1984.

[14] R. L. Wilde, "Effects of Cold Load Pickup at The Distribution Substation Transformer," *IEEE Transactions on Power Apparatus and Systems*, no. 3, pp. 704-710, 1985.

[15] A. Pahwa and C. W. Brice, "Modeling and System Identification of Residential Air Conditioning Load," *IEEE Transactions on Power Apparatus and Systems*, vol. 104, no. 6, pp. 1418 - 1425, 1985.

[16] J. Aubin, R. Bergeron and R. Morin, "Distribution Transformer Overloading Capability Under Cold-Load Pickup Conditions," *IEEE Transactions on Power Delivery*, vol. 5, no. 4, pp. 1883-1891, 1990.

[17] R. E. Mortensen and K. P. Haggerty, "Dynamics of heating and cooling loads: models, simulation, and actual utility data," *IEEE Transactions on Power Systems*, vol. 5, no. 1, pp. 243 - 249 , 1990.

[18] N. D. Hatziargyriou and P. M. Papadopoulos, "Cold load pickup studies in extended distribution networks," in *Electrotechnical Conference*, LJubljana, Slovenia, 1991.

[19] J. C. Laurent and R. P. Malhame, "A physically-based computer model of aggregate electric water heating loads," *IEEE Transactions on Power Systems*, vol. 9, no. 3, pp. 1209-1217, 1994.

[20] D. Athow and J. Law, "Development and applications of a random variable model for cold load pickup," *IEEE Transactions on Power Delivery*, vol. 9, no. 3, pp. 1647-1653, 1994.

[21] M. H. Nehrir, P. S. Dolan, V. Gerez and W. J. Jameson, "Development and validation of a physically-based computer model for predicting winter electric heating loads," *IEEE Transactions on Power Systems*, vol. 10, no. 1, pp. 266-272, 1995.

[22] E. Bompard, E. Carpaneto, G. Chicco and R. Napoli, "Contribution of loads with thermostatic control to the long-term dynamics," in *International Conference on Electric Power Engineering*, Hungary, 1999.

[23] T. Babnik, S. Gasperic, A. F. Gubina and F. Gubina, "Influence of load behavior on service restoration," in *International Conference on Electric Power Engineering*, Hungary, 1999.

[24] E. Agneholm and J. Daalder, "Cold load pick-up of residential load," *IEE Proceedings - Generation, Transmission and Distribution*, vol. 147, no. 1, pp. 44-50, 2000.

[25] *IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators, IEEE C57.91*, 2011.

[26] J. Law, D. Minford, L. Elliott and M. Storms, "Measured and predicted cold load pick up and feeder parameter determination using the harmonic model algorithm," *IEEE Transactions on Power Systems* , vol. 10, no. 4, pp. 1756 - 1764, 1995.

[27] J. J. Wakileh and A. Pahwa, "Distribution system design optimization for cold load pickup," *IEEE Transactions on Power Systems,* vol. 11, no. 4, pp. 1879 - 1884, 1996.

[28] J. J. Wakileh and A. Pahwa, "Optimization of distribution system design to accommodate cold load pickup," *IEEE Transactions on Power Delivery,* vol. 12, no. 1, pp. 339 - 345, 1997.

[29] V. Gupta and A. Pahwa, "A Voltage Drop-Based Approach to Include Cold Load Pickup in Design of Distribution Systems," *IEEE Transactions on Power Systems,* vol. 19, no. 2, pp. 957-963, 2004.

[30] F. Edström, J. H. P. Rosenlind and L. Söder, "Modeling Impact of Cold Load Pickup on Transformer Aging Using Ornstein-Uhlenbeck Process," *IEEE Transactions on Power Delivery,* vol. 27, no. 2, pp. 590-595, 2012.

[31] F. Edström, J. Rosenlind, K. Alvehag, P. Hilber and L. Söder, "Influence of Ambient Temperature on Transformer Overloading During Cold Load Pickup," *IEEE Transactions on Power Delivery*, vol. 28, no. 1, pp. 153-161, 2013.

[32] A. A. Mota, L. T. Mota and A. Morelato, "Load behaviour prediction under blackout conditions using a fuzzy expert system," *IET Generation, Transmission & Distribution*, vol. 1, no. 3, pp. 379-387, 2007.

[33] R. Singh and A. Singh, "Causes of failure of distribution transformers in India," in *International Conference on Environment and Electrical Engineering* , Prague, 2010.

[34] B. Vandiver, "Why testing digital relays are becoming so difficult! Part 3 advanced feeder protection," in *Annual Conference for Protective Relay Engineers (CPRE)*, TX, 2016.

[35] S. Chavali, A. Pahwa and S. Das, "A genetic algorithm approach for optimal distribution feeder restoration during cold load pickup," in *IEEE Congress on Evolutionary Computation*, Honolulu, 2002.

[36] R. Pérez-Guerrero, G. T. Heydt, N. J. Jack, B. K. Keel and A. R. Castelhano, "Optimal Restoration of Distribution Systems Using Dynamic Programming," *IEEE Transactions on Power Delivery*, vol. 23, no. 3, pp. 1589-1596, 2008.

[37] A. Pahwa, "Role of distribution automation in restoration of distribution systems after emergencies," in *Power Engineering Society Summer Meeting*, Canada, 2001.

[38] S. Chavali and A. D. S. Pahwa, "A Genetic Algorithm Approach for Optimal Distribution Feeder Restoration During Cold Load Pickup," in *Congress on Evolutionary Computation* , Honolulu, 2002.

[39] T. D. Nielsen, "Improving outage restoration efforts using rule-based prediction and advanced analysis," in *Power Engineering Society Winter Meeting*, New York, 2002.

[40] I. Mohanty, J. Kalita, S. Das, A. Pahwa and E. Buehler, "Ant algorithms for the optimal restoration of distribution feeders during cold load pickup," in *IEEE Swarm Intelligence Symposium*, Indianapolis, 2003.

[41] V. Singh and N. Rao, "An expert system for cold load pickup," in *Canadian Conference on Electrical and Computer Engineering*, Halifax, 1994.

[42] V. Kumar, R. k. Gupta and H. O. Gupta, "Stepwise Restoration of Power Distribution Network under Cold Load Pickup," in *International Conference on Power Electronics, Drives and Energy Systems*, New Delhi, 2006.

[43] D. R. Medina, E. Rappold, O. Sanchez, X. Luo, S. R. Rodriguez, D. Wu and J. N. Jiang, "Fast Assessment of Frequency Response of Cold Load Pickup in Power System Restoration," *IEEE Transactions on Power Systems*, vol. 31, no. 4, p. 3249, 2016.

[44] H. Qu and Y. Liu, "General model for determining maximum restorable load," in *IEEE Power and Energy Society General Meeting*, 2012.

[45] A. Rautiainen, S. Repo and P. Jarventausta, "Using frequency dependent electric space heating loads to manage frequency disturbances in power systems," in *IEEE Bucharest PowerTech*, Bucharest, 2009.

[46] C. Perfumo, J. Braslavsky, J. K. Ward and E. Kofman, "An analytical characterisation of cold-load pickup oscillations in thermostatically controlled loads," in *3rd Australian Control Conference (AUCC)*, Fremantle, 2013.

[47] O. H. Mirza, "Usage of CLPU curve to deal with the cold load pickup problem," *IEEE Transactions on Power Delivery* , vol. 12, no. 2, pp. 660 - 667, 1997.

[48] R. Torquato, Q. Shi, W. Xu and W. Freitas, " A Monte Carlo Simulation Platform for Studying Low Voltage Residential Networks," *IEEE Transactions on Smart Grid* , vol. 5, no. 6, pp. 2766 - 2776, 2014.

[49] G. L. Harmelen, I. E. Lane and G. P. Hancke, "System impact of decentralised AI controllers operating on domestic devices in the intelligent home," in *Advanced Instrumentation and Measurement Technology Conference*, Japan, 1994.

[50] K. V. Tonder and I. E. Lane, "A load model to support demand management decisions on domestic storage water heater control strategy," *IEEE Transactions on Power Systems,* vol. 11, no. 4, pp. 1844 - 1849, 1996 .

[51] B. Ramanathan and V. Vittal, "A Framework for Evaluation of Advanced Direct Load Control With Minimum Disruption," *IEEE Transactions on Power Systems,* vol. 23, no. 4, pp. 1681 - 1688, 2008.

[52] D. P. Flohr, "Methods, Circuits, And Computer Program Products for Disabling of Electrical Appliances During Cold Load Pickup". United States of America Patent 0319091, 24 December 2009.

[53] K. McKenna and A. Keane, "Residential Load Modeling of Price-Based Demand Response for Network Impact Studies," *IEEE Transactions on Smart Grid*, vol. 7, no. 5, pp. 2285 - 2294, 2015.

[54] N. Saker, M. Petit and J. L. Coullon, "Demand side management of electrical water heaters and evaluation of the Cold Load Pick-Up characteristics (CLPU)," in *IEEE Trondheim PowerTech*, Norway, 2011.

[55] H. Johal, K. Anaparthi and J. Black, "Demand response as a strategy to support grid operation in different time scales," in *IEEE Energy Conversion Congress and Exposition*, Raleigh, 2012.

[56] B. Chen, C. Chen, J. Wang and K. L. Butler-Purry, "Multi-Time Step Service Restoration for Advanced Distribution Systems and Microgrids," *IEEE Transactions on Smart Grid*, vol. PP, no. 99, pp. 1-1, 2017.

[57] V. Kumar, R. H. Kumar, I. Gupta and H. O. Gupta, "DG Integrated Approach for Service Restoration under Cold Load Pickup," *IEEE Transactions on Power Delivery*, vol. 25, no. 1, pp. 398-406, 2010.

[58] A. M. El-Zonkoly, "Distributed generation approach for single step system restoration during cold load pickup," in *IEEE PES Transmission and Distribution Conference and Exposition* , Orlando , 2012.

[59] C. Desbiens, "Electric Vehicle Model for Estimating," in *IEEE PES Innovative Smart Grid Technologies (ISGT)* , Washington, 2012.

[60] S. N. Sivanandam and S. N. Deepa, Introduction to Genetic Algorithms, springer, 2008.

[61] Y. L. Abdel-Magid and M. A. Abido, "Optimal multiobjective design of robust power system stabilizers using genetic algorithms," *IEEE Transactions on Power Systems*, vol. 18, no. 3, pp. 1125 - 1132 , 2003.

[62] R. Poli, J. Kennedy and T. Blackwell, "Particle swarm optimization," *Swarm Intelligence*, vol. 1, no. 1, p. 33–57 , 2007.

[63] J. Kennedy, "The particle swarm: social adaptation of knowledge," in *IEEE International Conference on Evolutionary Computation*, Indianapolis, 1997.

[64] M. A. Abido, "Optimal Design of Power–System Stabilizers Using Particle Swarm Optimization," *IEEE Transactions on Energy Conversion*, vol. 17, no. 3, pp. 406-413, 2002.

[65] M. A. Hassan and M. A. Abido, "Optimal Design of Microgrids in Autonomous and Grid-Connected Modes Using Particle Swarm Optimization," *IEEE Transactions on Power Electronics* , vol. 26, no. 3, pp. 755-769, 2011.

[66] R. Storn, "On the usage of differential evolution for function optimization," in *Biennial Conference of the North American Fuzzy Information Processing Society*, Berkeley, 1996.

[67] G. C. Onwubolu and B. V. Babu, New Optimization Techniques in Engineering, Berlin: Springer, 2003.

[68] A. A. Abou El Ela, M. A. Abido and S. R. Spea, "Optimal power flow using differential evolution algorithm," *Electric Power Systems Research*, vol. 80, no. 7, pp. 878-885, 2010.

[69] H. Shareef, A. A. Ibrahim and A. H. Mutlag, "Lightning search algorithm," *Applied Soft Computing*, no. 36, pp. 315-333, 2015.

[70] H. Shareef, A. H. Mutlag and A. Mohamed, "A novel approach for fuzzy logic PV inverter controller optimization using lightning search algorithm," *Neurocomputing,* no. 168, pp. 435-453, 2015.

[71] R. Sirjani and H. Shareef, "Parameter Extraction of Solar Cell Models Using the Lightning Search Algorithm in Different Weather Conditions," *Solar Energy Engineering*, vol. 138, pp. 1-11, 2016.

[72] R. Sirjani and E. C. Okonkwo, "A new wind power model using the lightning search algorithm," in *HONET-ICT*, Nicosia, 2016.

[73] J. A. Ali, M. A. Hannan and A. Mohamed, "A Novel Quantum-Behaved Lightning Search Algorithm Approach to Improve the Fuzzy Logic Speed Controller for an Induction Motor Drive," *Energies*, no. 8, p. 13112–13136, 2015.

[74] J. Abd Ali, M. A. Hannan and M. Azah, "Optimized speed controller for induction motor drive using quantum lightning search algorithm," in *IEEE International Conference on Power and Energy (PECon)*, Melaka, 2016.

[75] M. A. Hannan, J. Abd Ali, U. A. Amirulddin, M. N. Uddin and N. M. Tan, "Quantum-behaved lightning search algorithm to improve indirect field-oriented fuzzy-PI control for IM drive," in *IEEE Industry Applications Society Annual Meeting*, Cincinnati, 2017.

[76] M. A. Hannan, J. Abd Ali, A. Hussain, F. H. Hasim, U. A. Amirulddin, M. N. Uddin and F. Blaabjerg, "A Quantum Lightning Search Algorithm-Based Fuzzy Speed Controller for Induction Motor Drive," *IEEE Access* , vol. 6, pp. 1214 - 1223, 2018.

[77] M. S. Ahmed, A. Mohamed, R. Z. Homod and H. Shareef, "Hybrid LSA-ANN Based Home Energy Management Scheduling Controller for Residential Demand Response Strategy," *Energies,* no. 9, p. 716, 2016.

[78] Y. Thangara and R. Kuppan, "Multi-objective simultaneous placement of DG and DSTATCOM using novel lightning search algorithm," *Journal of Applied Research and Technology,* vol. 15, no. 5, pp. 477-491, 2017.

[79] A. Aljanad, A. Mohamed, H. Shareef and T. Khatib, "A novel method for optimal placement of vehicle-to-grid charging stations in distribution power system using a quantum binary lightning search algorithm," *Sustainable Cities and Society,* vol. 38, pp. 174-183, 2018.

[80] R. Hendron and C. Engebrecht, "Building America Research Benchmark Definition," National Renewable Energy Laboratory, 2009.

[81] "Electricity consumption in the United States was about 3.85 trillion kilowatthours (kWh) in 2016," The U.S. Energy Information Administration (EIA), 2017. [Online]. Available: https://www.eia.gov/energyexplained/index.cfm?page=electricity_use. [Accessed 21 February 2018].

[82] I. Richardsona, M. Thomsona, D. Infieldb and C. Cliffordc, "Domestic electricity use: A high-resolution energy demand model," *Energy and Buildings*, vol. 42, no. 10, p. 1878–1887, 2010.

[83] "IEEE 493 Recommended Practice for the Design of Reliable Industrial and Commercial Power Systems," IEEE, 2007.

[84] "National Electric Code (NEC)," in *Article 450.3*, 2015.

[85] American National Standard for Electric Power Systems and Equipment—Voltage Ratings (60 Hz), NEMA, 2016.

[86] F. Herrera, M. Lozano and J. L. Verdegay, "Tackling real-coded genetic algorithms: Operators and tools for behavioural analysis," *Artificial intelligence review* , vol. 12, no. 4, pp. 265-319, 1996.

[87] C. Ströÿner, "Particle Swarm Optimization & Parameter Selection," Die Technische Universität München (TUM), München , 2014.

[88] J. Robinson and Y. Rahmat-Samii, "Particle swarm optimization in electromagnetics," *IEEE Transactions on Antennas and Propagation* , vol. 52, no. 2, pp. 397 - 407, 2004.

[89] S. Das and P. N. Suganthan, "Differential Evolution: A Survey of the State-of-the-Art," *IEEE Transactions on Evolutionary Computation* , vol. 15, no. 1, pp. 4 - 31 , 2011.

[90] R. A. Sarker, S. M. Elsayed and T. Ray, "Differential Evolution With Dynamic Parameters Selection for Optimization Problems," *IEEE Transactions on Evolutionary Computation,* vol. 18, no. 5, pp. 689 - 707, 2014.

[91] "Distribution Planning Standard," Saudi Electric Compnay (SEC), 2004.

[92] A. Jeffreys, "The Report: Saudi Arabia.," Oxford Business Group, 2010.

[93] "Saudi Energy Efficiency Center (SEEC)," 2016. [Online]. Available: www.seec.gov.sa/en/buildings-en. [Accessed 26 Febraury 2018].

[94] J. Widen, A. Nilsson and E. Wackelgard, "A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand," *Energy and Buildings* , vol. 41, pp. 1001-1012, 2009.

[95] A. Augugliaro, L. Dusonchet and E. R. Sanseverino, "Multiobjective service restoration in distribution networks using an evolutionary approach and fuzzy sets," *International Journal of Electrical Power & Energy Systems,* vol. 22, no. 2, p. 103–110, 2000.

[96] L. L. Grigsby, "Distribution System Modeling and Analysis," in *Electric Power Generation, Transmission, and Distribution*, CRC Press, 2007, p. 512.

LIST OF PUBLICATIONS

As a result of this work, two (2) papers has been published and they are as follows:

Conference Publication:

A. Alnujaimi and M. Almuhaini, "Inclusion of Cold Load Pickup Events in Reliability Calculation for Residential Power Distribution Systems," in *The 9th IEEE-GCC conference,* Bahrain, 2017.

Journal Publication:

A. Alnujaimi, M. A. Abido and M. Almuhaini, “Distribution Power System Reliability Assessment Considering Cold Load Pickup Events," in *The IEEE Transactions on Power Systems*, Volume: PP, Issue: 99, 2018.

VITAE

- Abdullah Abdulrahman Alnujaimi
- Born in Rijal Almaa near Abha, Asir Region on December 25, 1990.
- Obtained a Bachelor of Science (B.S.) degree in Electrical Engineering from King Fahd University of Petroleum & Minerals (KFUM), Dhahran, Saudi Arabia in May 2013.
- Joined Saudi Aramco, Consulting Services Department (CSD) in June 2013 as a Power System Analysis and Design Engineer.
- Had a two-year assignment with Saudi Aramco, Ras Tanura Refinery (RTR) from February 2014 to February 2016 as a technical support engineer.
- Joined KFUPM back in 2015 as a part-time Master Degree student.
- Contact details:

  - Mobile Phone Number: +966 557280859
  - Present Email: abdullah.alnujaimi@aramco.com
  - Permanent Email: abd_n90@live.com
  - Address: 7912-1, Al-Khobar 34445-2161, Saudi Arabia.
