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**NOVEL MODELING METHODS AND
EVALUATION FRAMEWORKS FOR ASSESSING
AND IMPROVING THE RELIABILITY OF
RENEWABLE-RICH POWER SYSTEMS**

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Thesis submitted in partial fulfillment of the requirements for the degree
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DECLARATION

I declare that this is my own work and this Thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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The above candidate has carried out research for the Doctor of Philosophy in Electrical Engineering Thesis under our supervision. We confirm that the declaration made above by the student is true and correct.

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Name of Supervisor: Dr. W. D. Prasad

Signature of the Supervisor:

Date: 07/04/2025

DEDICATION

To my wonderful teachers!

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ABSTRACT

The share of non-conventional renewable energy, such as wind and solar, is gradually increasing in many power systems. However, integrating wind and solar power on a large scale would considerably affect the reliability of power systems due to the stochastic nature of renewables. Conventional reliability evaluation methods cannot efficiently and accurately quantify power system reliability when there is a significant amount of renewable power in the system. Therefore, novel reliability evaluation techniques are required to assess the reliability of modern renewable-rich power systems. This work implements novel modeling methodologies and evaluation frameworks to quantify the reliability of renewable-rich power systems accurately. Different algorithms and techniques are developed to evaluate the reliability of generation, composite generation and transmission, and distribution subsystems because the nature of the problem and its complexity are different in each of the three subsystems. Firstly, a novel method based on Kernel Density Estimation (KDE) is proposed to model intermittency and both diurnal and seasonal variations of wind and solar power generation using historical renewable power generation data. The proposed KDE-based renewable power models are used with Non-Sequential Monte Carlo Simulation (NSMCS) to evaluate the generation system adequacy of the Institute of Electrical and Electronics Engineers (IEEE) Reliability Test System (RTS). The diurnal and seasonal variations of renewables and the correlation between the load and renewable generation are modeled in the proposed renewable power models. Secondly, the applicability of conventional MCS for composite system adequacy evaluation is investigated. It is found that a more computationally efficient reliability evaluation methodology is needed to evaluate the adequacy of composite systems. Hence, a novel population-based intelligent search method called Evolutionary Swarm Algorithm (ESA) incorporated with DC optimal power flow analysis is proposed to evaluate the adequacy of renewable-rich composite power systems. The main objective of the ESA is to find out the most probable system failure events that significantly affect the adequacy of composite systems. The identified system failure events can be directly used to estimate the system adequacy indices. The random search guiding mechanism of the ESA is based on the underlying philosophies of genetic algorithms and binary particle swarm optimization. The computational efficiency of the proposed ESA is significantly higher than that of traditional simulation methods. Thirdly, the proposed ESA is used to evaluate the reliability of solar-integrated power distribution systems. AC optimal power flow analysis is used to assess the system failure events while considering the feeder voltage levels. The annual reliability indices of renewable-rich distribution systems can be estimated using this method, which is not addressed in the prevailing literature. Apart from evaluating the power system reliability, the impact of increasing wind and solar integration on the reliability of power systems is investigated at all hierarchical levels. Further, the proposed reliability evaluation frameworks are used to identify possible methods to improve the reliability of power systems. The outcomes of this research allow precise planning and operation of modern power systems in a time-efficient manner.

Keywords: Evolutionary Swarm Algorithm, Population-based Search Methods, Power System Adequacy, Renewable Power Modelling

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LIST OF ABBREVIATIONS

Abbreviation	Description
ACO	Ant Colony Optimization
AENS	Average Energy Not Supplied
AI	Artificial Intelligence
AISs	Artificial Immune Systems
ANN	Artificial Neural Network
ARIMA	Auto-Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
BESSs	Battery Energy Storage Systems
BPSO	Binary Particle Swarm Optimization
CAIDI	Customer Average Interruption Duration Index
CAIFI	Customer Average Interruption Frequency Index
COPT	Capacity Outage Probability Table
COV	Coefficient of Variation
DGs	Distributed Generators
EDLC	Expected Duration of Load Curtailments
EENS	Expected Energy Not Supplied
EFLC	Expected Frequency of Load Curtailments
ELCC	Effective Load Carrying Capability
ESA	Evolutionary Swarm Algorithm
FLD	Fisher Linear Discriminant
FOR	Forced Outage Rate
GAs	Genetic Algorithms
GES	Grid Energy Storage
GSAE	Generation System Adequacy Evaluation
HLs	Hierarchical Levels
ICDFs	Inverse Cumulative Density Functions
IEEE	Institute of Electrical and Electronics Engineers
KDE	Kernel Density Estimation
KNN	K Nearest Neighbor
LOEE	Loss of Energy Expectation
LOLE	Loss of Load Expectation
LOLF	Loss of Load Frequency
LOLP	Loss of Load Probability

Abbreviation	Description
LPs	Load Points
MCS	Monte Carlo Simulation
ML	Machine Learning
MRTS	Modified RTS
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
NSMCS	Non-Sequential Monte Carlo Simulation
OPF	Optimal Power Flow
PDF	Probability Density Function
PHSs	Pumped Hydro Storages
PIS	Population-based Intelligent Search
PLC	Probability of Load Curtailments
PV	Photovoltaic
RBTS	Roy Billinton Test System
RTS	Reliability Test System
RWS	Roulette Wheel Selection
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SMCS	Sequential Monte Carlo Simulation
SVM	Support Vector Machine
WTGs	Wind Turbine Generators