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METHODOLOGY TO ECONOMICALLY DISPATCH HYBRID ISOLATED OFFSHORE POWER SYSTEMS

São Paulo
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Resumo

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A incorporação de Energias Renováveis (ER) no sistema de energia convencional de uma plataforma de Petróleo e Gás (P&G) pode resultar em uma redução significativa nos custos operacionais e nas emissões. No entanto, a penetração de energias renováveis no sistema de energia convencional pode causar sérias instabilidades devido à natureza intermitente, especialmente nos sistemas de energia híbridos autônomos. Portanto, a flexibilidade do sistema de energia convencional deve ser avaliada previamente, para acomodar e compensar a penetração variável da energia renovável. Nesta tese, um método inovador é introduzido para realizar o despacho econômico das unidades geradoras do sistema de energia híbrido autônomo, garantindo a segurança do sistema de energia. Este método considera: **(a)** a curva de eficiência das Turbinas a Gás (TGs) para simular cenários do mundo real de forma robusta, **(b)** as restrições de ROCOF (Taxa de Variação de Frequência) e reserva girante para melhorar a segurança do sistema, restringindo a variação de frequência durante eventos de contingência, e **(c)** a análise de flexibilidade do sistema de energia convencional autônomo de uma plataforma de P&G para avaliar a capacidade do sistema de energia em acomodar a demanda e as variações de ER. Para o problema de Despacho Econômico (DE), a fim de minimizar o custo operacional global (incluindo combustível, custo de inicialização, desligamento e manutenção) do sistema de energia, o LGridPy adota a técnica de Programação Não Linear com Variáveis Inteiras Mistas e resolve o sistema com a ajuda do *solver* MindtPy, utilizando o resolvedor Gurobi para o Problema Linear de Variáveis Inteiras Mistas (PLVIM) e o resolvedor IPOPT para o Problema Não Linear (PNL). O novo método considera vários Indicadores-Chave de Desempenho (ICDs) e indicadores de flexibilidade para o modelo do sistema de energia, a fim de avaliar a resposta do sistema em diferentes condições e estudos de caso.

Palavras-chave: Sistema de Energia de Petróleo e Gás; Análise de Flexibilidade, Ferramenta LGridPy, Otimização; Despacho Econômico.

Abstract

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. 145 p. Ph.D. Thesis – Polytechnic School, University of São Paulo, 2023.

The incorporation of Renewable Energy (RE) into the conventional standalone power system of an Oil and Gas (OG) platform can result in a significant reduction in operational cost and emissions. Whereas, the penetration of renewables into the conventional power system can cause serious instabilities due to the intermittent nature, especially in the standalone hybrid power systems. Therefore, the flexibility of the conventional power system should be assessed before, to accommodate and compensate for the variable renewable power penetration. In this thesis, a novel method is introduced to economically dispatch the generating units of the Standalone Hybrid Power System (SHPS), while ensuring the power system security. This method considers **(a).** the efficiency curve of Gas Turbine (GT) to simulate the robust real world scenario, **(b).** the Rate of Change of Frequency (ROCOF) and Spinning Reserves (SR) constraints to enhance the system security by restricting the frequency deviation during the contingency events, and **(c).** the flexibility analysis of the conventional standalone power system of an OG platform to access the ability of the power system to accommodate the demand and RE variations. A novel method has been developed and implemented in a Python-based tool, LGridPy. This method adopts the Mixed-Integer Nonlinear Programming (MINLP) technique to minimize the overall operational cost (including fuel, startup, shut-down, and maintenance cost) of the power system for the Economic Dispatch (ED) problem. It uses the MindtPy solver, which leverages the Gurobi solver for the MINLP and the IPOPT solver for the NLP. The new method considers various Key Performance Indicators (KPIs) and flexibility indicators for the power system model, to access the response of the system under different conditions and case studies.

Keywords: Oil and Gas Power System; Flexibility Analysis, LGridPy Tool, Optimization; Economic Dispatch.

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List of Acronyms

AUFLS Automatic Under Frequency Load Shedding

ACO Ant Colony Optimization

ANN Artificial Neural Network

CO_2 Carbon Dioxide

CHP Combined Heat and Power

CAES Compressed Air Energy Storage

Conv Conventional

DG Diesel Generator

DERs Distributed Energy Resources

DGen Distributed Generation

DR Demand Response

ED Economic Dispatch

ESS Energy Storage System

ECP Extended Cutting Plane

FPSO Floating Production Storage and Offloading

GT Gas Turbine

GA Genetic Algorithms

IP Integer Programming

IEA International Energy Agency

IRENA International Renewable Energy Agency

KPIs Key Performance Indicators

LP Linear Programming

LGrid Advanced Electrical Networks Laboratory

MILP Mixed-Integer Linear Programming

MINLP Mixed-Integer Nonlinear Programming

MIP Mixed-Integer Programming

MHOM Meta-Heuristic Optimization Methods

NLP Nonlinear Problem

NO_2 Nitrogen Dioxide

OPF Optimal Power Flow

OCGT Open Cycle Gas Turbine

OG Oil and Gas

OA Outer Approximation

PyPSA Python for Power System Analysis

PSO Particle Swarm Optimization

PV PhotoVoltaic

RE Renewable Energy

RERs Renewable Energy Resources

ROCOF Rate of Change of Frequency

RSR Required Spinning Reserve

RORs Required Operating Reserves

SHPS Standalone Hybrid Power System

SR Spinning Reserves

SOA State-of-the-Art

SA Simulated Annealing

ST Energy Storage System

TLP Tension-Leg Platform

UC Unit Commitment

WT Wind Turbine

VER Variable Energy Resources

List of Symbols

$\boldsymbol{p}$	Active power injections
$\boldsymbol{v}$	Voltage magnitudes
$\boldsymbol{x}$	Vector of continuous variables
$\boldsymbol{y}$	Vector of integer variables
η_c	Efficiency for charging
η_d	Efficiency for discharging
η_{sl}	Efficiency for self losses
$\mathbb{Z}^n$	Set of integer-valued vectors of length n
$\mathbf{A}$	Matrix of constraint coefficients
$\mathbf{b}$	Vector of constraint right-hand sides
$\mathbf{c}$	Vector of objective function coefficients
$\mathbf{x}$	Vector of decision variables
Ω	Feasible region of the decision variables
θ_i	Phase angle at bus i
θ_j	Phase angle at bus j
A	Constraint matrix
a	Quadratic parameter of the efficiency curve fitting
b	Linear parameter of the efficiency curve fitting; Right-hand side vector

c	Cost vector
$C(\boldsymbol{x})$	Total cost of the system
$C_i(\boldsymbol{x})$	Cost associated with the ith non-renewable resource
$c_{s,t}$	Charge power of storage s at snapshot t
$d_{s,t}$	Discharge power of storage s at snapshot t
$E_i(\boldsymbol{x})$	Emissions associated with the ith generator or pollutant
$ef(p)$	Efficiency at dispatch p (per unit)
$f(\boldsymbol{x}, \boldsymbol{y})$	Objective function to be minimized
$f(x)$	Nonlinear objective function
$FuelCost_{g,t}$	Fuel cost of generator g at snapshot t
$FuelPrice$	Price of the fuel
$g_i(\boldsymbol{x}, \boldsymbol{y})$	Inequality constraints
$g_i(x)$	Nonlinear inequality constraints
G_{ij}	Conductance of the transmission lines
$h_j(\boldsymbol{x}, \boldsymbol{y})$	Equality constraints
IP	Integer Programming
LP	Linear Programming
$MC_{g,t}$	Maintenance cost of generator g at snapshot t
mdt_g	Minimum downtime of generator g
mut_g	Minimum uptime of generator g
P_i	Active power injection at bus i
P_{fuel}	Power consumed by the generator (fuel power)
$P_{g,t}$	Dispatch of generator g at snapshot t
$P_{max,i}$	Maximum active power limit at bus i
$P_{max}g$	Maximum power dispatch of generator g
$P_{min,i}$	Minimum active power limit at bus i

$P_{min}g$	Minimum power dispatch of generator g
P_{nom}	Nominal power
$P_{nom}s$	Nominal power of storage s
Q_i	Reactive power injection at bus i
$R(\boldsymbol{x})$	Revenue obtained from power generation and distribution
$R_i(\boldsymbol{x})$	Output from the ith renewable energy source
r_{ij}	Resistance of the transmission lines
$ROCOF$	Rate of change of frequency
RSR	Required spinning reserve
rud_g	Ramp-down limit for generator g
rul_g	Ramp-up limit for generator g
$SDC_{g,t}$	Shut-down cost of generator g at snapshot t
$soc_{s,-1}$	Initial state of charge for a storage unit
$soc_{s,final}$	Final state of charge for a storage unit
$soc_{s,T}$	State of charge of storage s at the last snapshot
$socs,t$	State of charge of storage s at snapshot t
SR_t	Spinning reserve at snapshot t
$SUC_{g,t}$	Start-up cost of generator g at snapshot t
u	Gas generator status
$U_{ij}(r_{ij}, p_i, v_i)$	Outage costs or reliability cost function
$uc_{s,t}$	Storage s charge status at snapshot t
$ud_{s,t}$	Storage s discharge status at snapshot t
ug,t	Generator g status at snapshot t
V_i	Voltage magnitude at bus i
V_j	Voltage magnitude at bus j
$v_{g,t}$	Availability of gas generator g at snapshot t

$V_{max,i}$	Maximum voltage limit at bus i
$V_{min,i}$	Minimum voltage limit at bus i
$V_{ref,i}$	Reference voltage at bus i
x_{ij}	Reactance of the transmission lines

Contents

CHAPTER 1

Introduction

1.1 Background

Climate change has nowadays raised greater concern and on a global scale calls for actions [1]. Renewables are expected to take the central role in energy transition and additionally, help revive economy in a post-pandemic context [2]. In comparison to 1990 statistics for Brazil, the energy production has hiked up to 198.82%, the electricity final consumption has grown to around 150.68%, resulting an increase in the total greenhouse gas emissions (caused by the fuel combustion) of 122.45% [3]. The Figure 1 and 2 depicts the Brazil's electricity generation by each resources and greenhouse gas emissions from energy generating resources from 1990-2020, respectively. Therefore, International Energy Agency (IEA) set a target for renewables to account for 67% in total energy supply and 88% in electricity supply by 2050 in their Net Zero Emission scenario [3], while International Renewable Energy Agency (IRENA) further lift the goal up to 74% and 90% respectively in their 1.5 ºC pathway [4], which are largely made up by solar and wind power.

The need for sustainability at a global level encourages the implementation of greener solutions, especially in the most polluting industrial sectors, such as Oil and Gas (OG) production systems [5], which significantly contribute to Carbon Dioxide (CO_2) and Nitrogen Dioxide (NO_2) emissions in its extraction installations. The OG industry plays an important role in providing the world with affordable and reliable energy to meet expanding demand. Whereas, the industry is also under pressure to reduce extraction costs and emissions [6] [7], especially in maritime regions. Maximizing oil recovery from new and existing fields is therefore of paramount importance. In this case, water injection is used, which is often applied as a highly effective and low cost means of improving oil recovery in reservoirs [8].

However, conventional methods involve high energy consumption, significant emissions and costly infrastructure, especially in systems installed in deep waters, with the difficulty of deploying new Diesel Generators (DGs) or Gas Turbines (GTs) to supply power to growing loads to be feeded from the exploration platform, due to structural and space restrictions [9]. In

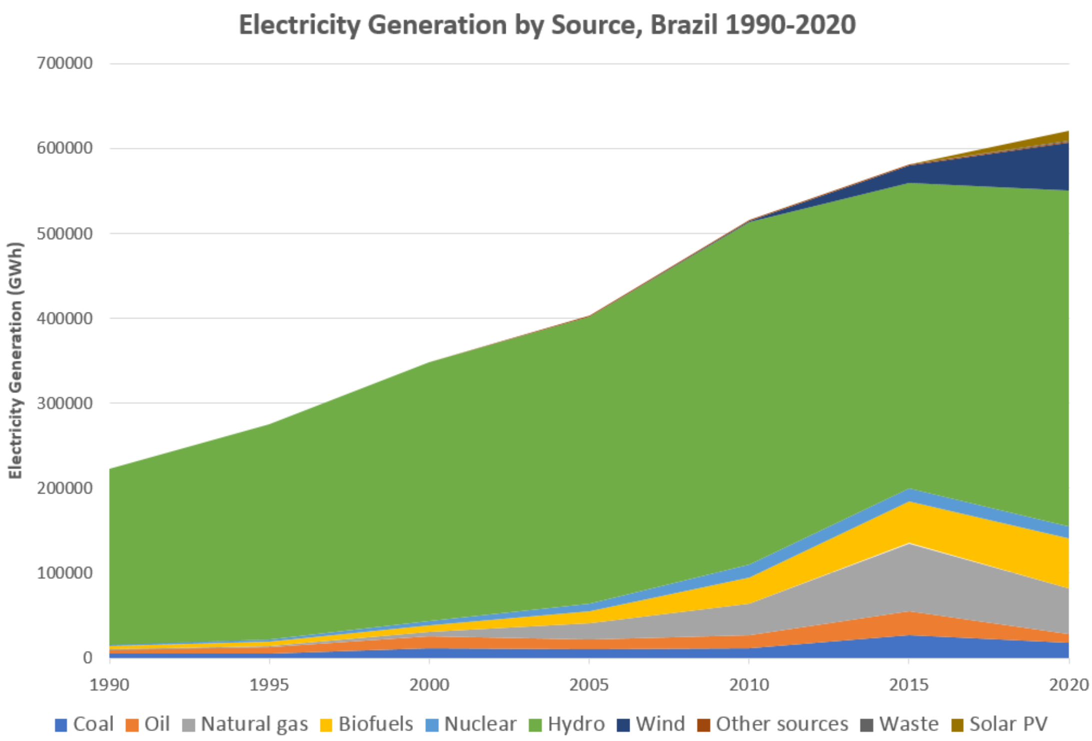

Figure 1 – Electricity Generation by Source, Brazil 1990-2020 [3]

this context, the use of floating wind turbines appears as an adequate solution for feeding not only water injection systems in oil wells located in deep waters, but also in other subsea systems or vessels [8] [9].

Wind Turbine (WT) technology has matured over the years and has become competitive with other conventional sources [10]. Recent studies show the great potential of Brazil for the development of projects at sea. The results of studies carried out for 100m of tower height indicate a technical potential of 1,064.2 GW, with the potential considering environmental and social issues, more restricted, reaching 330.5 GW [11]. With the reduction of sites available on land with high potential for wind generation, due to environmental restrictions on the use of the best locations (case of Germany), the installation of wind power generation at sea has gained increasing attention. The UK alone reached just over 8 GW at the end of 2018, followed by Germany (with just over 6 GW) and China (close to 4 GW) [12]. The vast majority of turbines installed so far are restricted to operation in shallow water depths, up to 60 m, however explorations in deeper waters with the use of floating platforms is the new technological trend [13].

Isolated power generation systems (off-grid or stand-alone systems) are grid forming entities since they are not connected to the power grid [14]. Therefore, the storage capacity and system control are very critical in these systems due to no grid support and the energy delivered by the WT varies with wind speed [9]. The intermittency of wind sources significantly affects the quality of the power supplied to the load, although power electronics can contribute to reduce

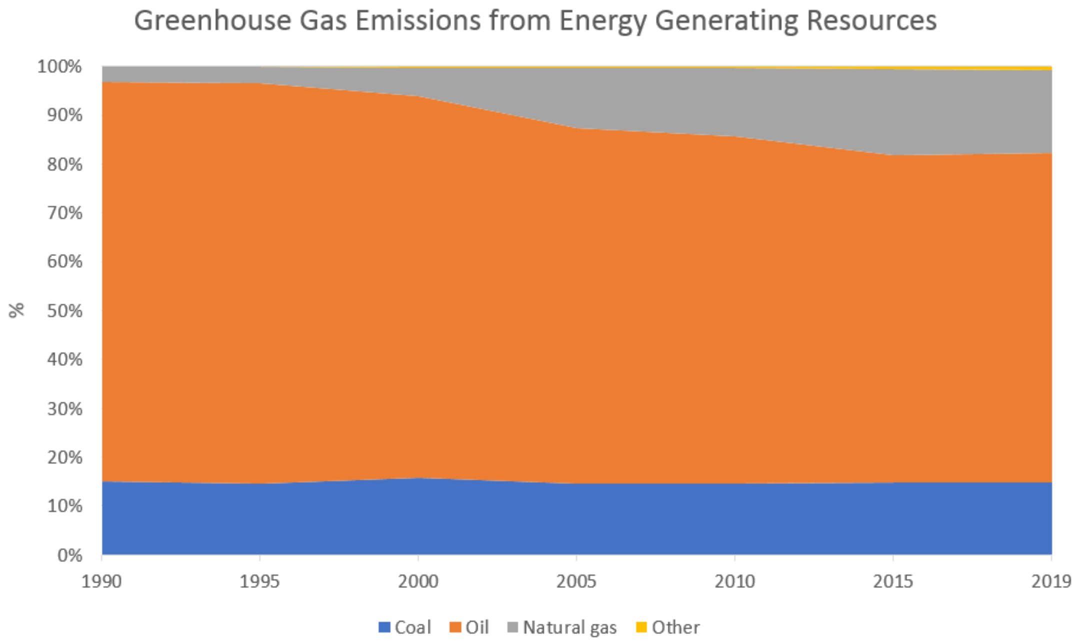

Figure 2 – Greenhouse Gas Emissions from Energy Generating Resources. [3]

the problem. These conditions present challenges for the control of the system, which must continually maintain stability of the voltage and frequency [15].

The current power system is undergoing through significant changes due to the availability of the low-cost Variable Energy Resources (VER), due to the implementation of Distributed Energy Resources (DERs), the progress in the digitisation, and the increasing possibilities for electrification. To speedup the power system transition, different assets can be utilized to provide the flexibility [16]. According to [17], the conventional power system can play a vital role in the flexibility of the power system as it can absorb and accommodate the variation in the load and the variable power produced by the VERs. The transformation of the conventional power plants to flexible power plant can revitalise the modern power system to accommodate the higher shares of VERs for green energy, absorb the instabilities and variations in the power system. The power plant flexibility can be achieved with different approaches like turning the power plant minimum output power to lower level without triggering the shutdown, starting and stopping the power plants more quickly, changing the output of the plant rapidly to meeting the variation [16].

Flexibility is defined as the capability of the power system to incorporate the higher share of power from the variable energy resources while ensuring the system's reliability and system operation at a low cost at any time series [18] [19]. From the generation perspective, flexibility can be defined as the ability of the power plant to adjust the generation upon the deviation in the intentional or unintentional demand variation, within the constrained area of operation [20][21]. Whereas, the power system flexibility is categorized into long-term and short-term planning but there is not a single definition that can define flexibility. Different researchers and organizations have come up with different definitions and perspectives of analyzing the flexibility of the power system. Traditionally, the flexibility is analyzed from the generation side (supply side) of the power system to balance any deviation at the demand/user side but the flexibility can also be analyzed in different sectors of the power system. The flexibility options can be categorized into 5 key areas of the overall power system, i.e. **a.** System (power markets and operational structure of the power system), **b.** Supply (generation side flexibility), **c.** Demand (user side flexibility), **d.** Network (transmission side flexibility), and **e.** Energy Storage [22].

To enhance the energy transition in power generation side, we must heighten system flexibility via demand response, high-ramping gas turbines, battery storage, and a robust dispatch strategy. An emphasis on dispatchable energy sources, interruptible loads, and other controllable mechanisms is pivotal to ensure system robustness while integrating increased renewable resources [16][17].

1.2 Motivation

The integration of renewable energy resources into the power system has introduced new complexities and uncertainties, making system operation less reliable [23]. To address these challenges, there is a critical need for a new method to economically dispatch standalone power systems while considering the efficiency curve of GTs along with robust constraints. This method will be implemented as a new python-based tool, providing researchers and system manufacturers with a comprehensive modeling platform to better understand system responses.

Several power system modeling tools are available in the market, each with its own capabilities and focus. Tools such as PowerWorld, DIgSILENT PowerFactory, NEPLAN, PSAT, PYPOWER, MATPOWER, MOST, oemof, PowerGAMA, PRIMES, PLEXOS, urbs PSS/E, HOMER Pro/Grid, among others, offer platforms to model electrical power systems and analyze system behavior under various conditions, including time series, electrical demand, weather conditions, and power source attributes. However, many of these tools lack the ability to analyze power system flexibility [16, 24], consideration of efficiency curves, and the incorporation of robust constraints such as Rate of Change of Frequency (ROCOF) limits for generators. It is due to the non-convex nature of the efficiency curves, used in optimization problems. While PyPSA [25] provides valuable insights into power system flexibility at the generation side [21] but it falls short by assuming a constant efficiency value for generators instead of utilizing an efficiency curve. The inclusion of an efficiency curve is essential for accurately assessing generator performance and flexibility under different conditions, particularly for hybrid standalone power systems.

1.3 Objectives

The main objective is to formulate a method to economically dispatch the standalone hybrid power system, considering the efficiency curve of the generating units, along with the consideration of the maximum allowed ROCOF constraint during the contingency periods (N-1 scenarios) and also perform the flexibility analysis for the retrofitted gas turbines. This novel method will be implemented within a Python-based environment, known as LGridPy tool, developed by the Advanced Electrical Networks Laboratory (LGrid) of the University of Sao Paulo, to bridge the gap between the power system analysis tools. LGridPy will be able to model the economic dispatch of standalone system power system and perform a flexibility analysis. Unlike conventional tools, which considers the constant efficiency value for the generators model like PyPSA. Whereas, the LGridPy optimizes the power system by including the efficiency curve for generators, which is crucial for the economical dispatch and flexibility calculations for the smaller standalone hybrid power system. LGridPy also models for WT and consider constraints such as wind turbine power curve, electromechanical efficiency conversion, wind speed time series, wind power penetration and also the Energy Storage System (ESS) along with its relative constraints. Whereas, the addition of the maximum allowed ROCOF constraint in the LGridPy model shows the novelty of the newly developed tool in comparison with the other available software/tools. In addition, LGridPy is a free, transparent, and user-extendable software thus the source code is available for revisions and improvements for all users and the motivation of the tool is the PyPSA software [26, 25].

1.4 Main Contribution

This thesis contributes to the literature by presenting a novel strategy to economically dispatching standalone hybrid power systems, implemented in python-based LGridPy tool. Implementing gas turbine efficiency curves and robust constraints like ROCOF limit are key additions, offering a more realistic and secure system operation. A flexibility analysis of conventional and state-of-the-art OCGTs were also performed, emphasizing the significance of balance and proportionate dispatch. The tool was verified against proven PyPSA software, authenticating its accuracy and reliability.

1.5 Scope of the Thesis

The globe is moving fast in the direction of energy transition, shifting its dependency from fossil fuel to the more environmental friendly and sustainable energy resources [27]. For this reason, researchers are the key to analyse this rapid change and develop novel tools and methods to compete with the ever-changing society. Therefore, a method is required for the power system analysis, especially for the hybrid standalone power system, to optimize the system based on the least cost, with the consideration of more realistic and robust constraints. The novel method will primarily focus on the planning side of the hybrid standalone power system and will perform the flexibility analysis to help the future energy transition goals and to achieving the 100% renewable penetration in the future. The Figure 3 illustrates the main components, operations, and analysis of the novel method. It should be noted that this method exclusively addresses the unit commitment and the economic dispatch problem (rather than the optimal dispatch problem) within the context of the Oil and Gas (OG) platform.

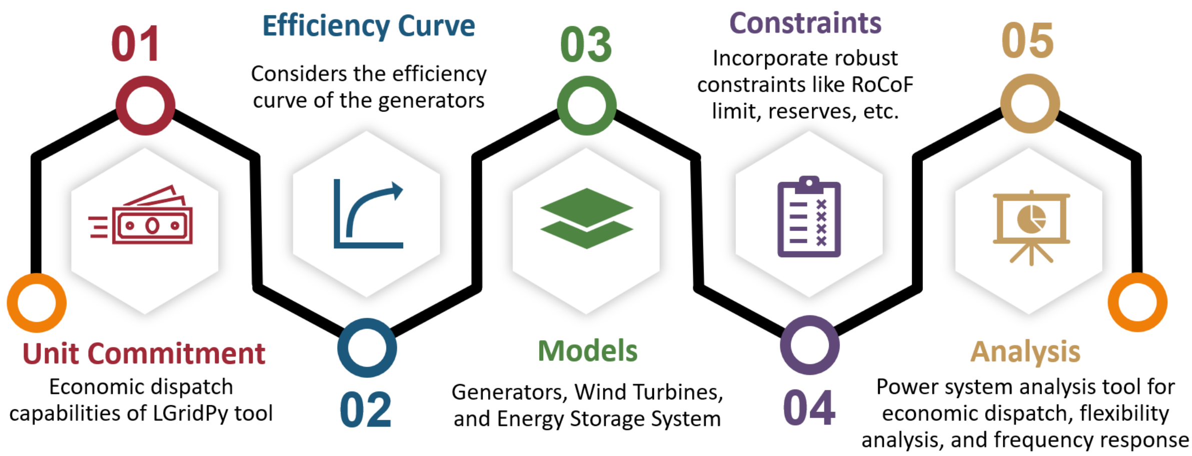

Figure 3 – The main components, operations, and analysis of the novel method.

1.6 Organization of the thesis

This thesis consists of 6 Chapters as follows; - In the Chapter 1, an overview of the thesis is presented. - In chapter 2, the in depth review of the literature is presented. – In chapter 3, the novel methodology is discussed along with the results. - In the chapter 4, the tradeoff between the economic operation and the security of the standalone power system is discussed.- In the chapter 5, the flexibility analysis is performed on the standalone power system of OG platform. - In the last chapter 6, the thesis is concluded along with the future prospects.

CHAPTER 2

Literature Review

2.1 Introduction

The rising demand for electricity, combined with the growing requirement for sustainable and reliable power systems, has driven research and development in the subject of power system optimization [28, 29]. With the help of optimization techniques, this field of study aims to raise the efficiency of electrical power networks in terms of generation, transmission, distribution, and consumption [30]. Finding a balance among technical, financial viability, and environmental sustainability is the ultimate objective. Therefore, in the context of the global energy environment, power system optimization has emerged as a crucial subject of research. [31].

The purpose of the literature review is to provide an in-depth assessment of the most recent approaches and methods in power system optimization. It begins by outlining the benefits and drawbacks of conventional optimization techniques such as Linear Programming (LP), Nonlinear Problem (NLP), Integer Programming (IP), Mixed-Integer Programming (MIP), and MINLP [31, 32]. The review then looks into Meta-Heuristic Optimization Methods (MHOM), looking at their applicability to power system optimization issues. These include Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Simulated Annealing (SA), and Artificial Neural Network (ANN) [31, 32, 33].

The review then looks at the trade-offs and difficulties in balancing these goals in actual power system optimization problems and emphasis then moves to the incorporation of renewable energy sources and ESSs in OG platform standalone power systems. This section looks at the challenges and opportunities of combining wind power and ESSs into OG platform power systems, which are typically powered by conventional energy sources.

Finally, a detailed evaluation of the integration of wind and storage systems in OG platform standalone power systems concludes the literature assessment. This section examines the features of various energy storage and wind power generation systems, followed by an examination of optimization models and case examples.

In this thesis, we investigate the optimisation of standalone power systems, specifically hybrid power systems that integrate renewable and non-renewable energy sources. To improve the operational performance and economic efficiency of these power systems, we use traditional optimisation techniques such as Unit Commitment (UC) and Economic Dispatch (ED). We further utilized the Mixed Integer Nonlinear Programming (MINLP) strategy to address challenging, multidimensional optimisation challenges in power systems. This thesis is not meant to cover all elements of power system optimisation, but rather to concentrate on the application of these strategies to standalone hybrid power systems.

2.2 Power System Optimization Techniques

The field of power system optimization is extensive and diversified, comprising a wide range of techniques and procedures that address various problem formulations and limitations [30]. Traditional optimization methods and meta-heuristic optimization algorithms are two broad groups into which these methods can be classified. Each group has its own distinct traits, advantages, and disadvantages, making it appropriate for various power system optimization issues [31, 32]. The goal of this part is to give a thorough overview of the most popular strategies in both categories, underlining their benefits, drawbacks, and applicability for various power system optimization problems. Table 1 shows the comparison between the traditional and meta-heuristic optimization methods.

Power system optimization has long relied on conventional optimization techniques including LP, NLP, IP, and MIP. They are well-suited to problems with well-defined restrictions, objectives, and solution spaces because to their well-established theoretical foundations and mathematical rigor. These methods are particularly effective in solving problems with continuous or discrete variables, linear or nonlinear relationships, and convex or non-convex solution spaces. However, complex, high-dimensional issues with non-differentiability or discontinuity may be a challenge for them. [31]

In contrast, meta-heuristic optimization methods like GA, PSO, ACO, SA, and ANN provide a more adaptable and comprehensive method for power system optimization. These algorithms are particularly good at addressing non-linear, non-convex, and non-differentiable problems that may be difficult for conventional optimization methods since they are inspired by natural processes and search for optimal solutions using heuristics. They have emerged greatly in popularity in recent years as a result of their capacity to efficiently address challenging, high-dimensional optimization issues. However, they frequently need careful parameter improvement and can experience problems with convergence or become stuck in local optima. [33, 34]

Table 1 – Comparison of Traditional Optimization Methods and Meta-heuristic Optimization Algorithms [30, 31, 32, 33]

Method	Traditional Optimization Methods	Meta-heuristic Optimization Algorithms
Subcategories	Linear Programming (LP) Nonlinear Problem (NLP) Integer Programming (IP) Mixed-Integer Programming (MIP) Mixed-Integer Non lin. Prog. (MINLP)	Genetic Algorithms (GA) Particle Swarm Optimization (PSO) Ant Colony Optimization (ACO) Simulated Annealing (SA) Artificial Neural Network (ANN)
Problem Types	Well-defined constraints, objectives, and solution spaces; continuous or discrete variables; linear or nonlinear relationships	Complex, non-convex, high-dimensional optimization problems; non-linear, non-convex, non-differentiable problems
Advantages	Mathematical rigor, well-established theoretical foundations, systematic and robust approach	Flexible, versatile, inspired by natural processes, relatively low computational effort
Limitations	May struggle with complex, high-dimensional, non-differentiable or discontinuous problems	Requires careful parameter tuning, may be susceptible to convergence issues or getting trapped in local optima
Applications	Economic dispatch, unit commitment, optimal power flow, transmission expansion planning	Load forecasting, network reconfiguration, renewable energy integration, demand-side management

2.2.1 Traditional Optimization Methods

Traditional optimization methods have been widely used in power system optimization because of their rigorous mathematical framework and well-established theoretical foundations. These methods offer a systematic and robust approach to problem-solving with well-defined restrictions, objectives, and solution spaces. LP, NLP, IP, and MIP are the four primary subcategories of classical optimization techniques. Each of these approaches has been developed to deal with particular categories of optimization issues that can be represented by continuous or discrete variables and linear or nonlinear connections.

2.2.1.1 Linear Programming

Linear Programming (LP) is a popular optimization technique for finding the best solution to a linear objective function subject to linear equality and inequality constraints [35]. LP is frequently utilized in power system optimization challenges such as economic dispatch and unit commitment [30].

The general form of a linear programming problem is:

Table 2 – Characteristics of Power System Optimization Techniques. [30, 31, 32, 33, 34, 35, 36]

Technique	**Characteristics**
Linear Programming (LP)	- Handles linear objective functions and constraints - Solves efficiently with Simplex method or Interior-Point method
Nonlinear Problem (NLP)	- Handles nonlinear objective functions and constraints - Requires iterative solution methods, such as gradient-based or trust-region
Integer Programming (IP)	- Handles discrete decision variables - Solves with branch and bound, branch and cut, or dynamic programming
Mixed-Integer Programming (MIP)	- Handles both continuous and discrete decision variables - Solves with extensions of IP methods
Mixed-Integer Nonlinear Prog. (MINLP)	- Handles nonlinear objective functions, constraints, and discrete decision variables - Requires hybrid solution methods, combining NLP and MIP techniques
Genetic Algorithms (GA)	- Population-based, stochastic search - Mimics natural evolution: selection, crossover, and mutation - Works well with complex, non-linear, non-convex problems
Particle Swarm Optimization (PSO)	- Population-based, stochastic search - Inspired by the social behavior of birds and fish - Searches for optimal solution using velocity and position updates
Ant Colony Optimization (ACO)	- Population-based, stochastic search - Inspired by the foraging behavior of ants - Uses pheromone trails to guide search for optimal solutions
Simulated Annealing (SA)	- Single-solution, stochastic search - Inspired by the annealing process in metallurgy - Uses random search with decreasing temperature parameter to escape local optima
Artificial Neural Network (ANN)	- Data-driven, machine learning approach - Inspired by the structure and function of biological neural networks - Requires training data and a suitable loss function

$$\text{Minimize } c^T x \tag{1}$$

$$\text{subject to } Ax \leq b \tag{2}$$

$$x \geq 0, \tag{3}$$

where c is the cost vector, x is the decision variable vector, A is the constraint matrix, and b is the right-hand side vector. The objective is to minimize the cost function $c^T x$ subject to the linear constraints $Ax \leq b$ and $x \geq 0$.

LP problems can be addressed using a variety of algorithms, including the simplex approach, the interior-point method, and the primal-dual method. The most used algorithm for resolving LP problems is the simplex method. It begins with a feasible initial solution and incrementally improves the answer until the best one is found [30].

There are numerous uses for LP in power systems. For instance, LP can be utilized to reduce a power system's operational costs while meeting transmission and demand requirements. The economic dispatch problem, which requires figuring out the best power output of each generator to meet demand while lowering costs, can likewise be solved using LP [31].

2.2.1.2 Nonlinear Programming

Nonlinear Problem (NLP) is the optimization of a nonlinear objective function and/or nonlinear constraints. This kind of optimization can be applied to power systems to solve issues with optimal power flow, unit commitment, and economic dispatch. [30]

The general form of a nonlinear optimization problem can be written as:

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & f(x) \\ \text{subject to} \quad & g_i(x) \leq 0, \quad i = 1, \ldots, m \\ & h_j(x) = 0, \quad j = 1, \ldots, p \end{aligned} \tag{4}$$

where $f(x)$ is the nonlinear objective function, $g_i(x)$ and $h_j(x)$ are the nonlinear inequality and equality constraints, respectively, and x is the vector of decision variables.

NLP problems, unlike LP, lack a closed-form solution and so require the application of numerical optimization methods. One typical strategy is to employ gradient-based approaches, which use the gradient of the objective function and/or restrictions to iteratively search for the optimal solution [37]. The Newton-Raphson method, quasi-Newton methods, and conjugate gradient methods are a few examples of gradient-based techniques [31].

Another alternative is to employ derivative-free approaches, which do not rely on gradient information. The Nelder-Mead approach and the pattern search method are two derivative-free methods [38].

2.2.1.3 Integer Programming

Integer Programming (IP) is an optimization branch that deals with optimizing a linear function subject to linear equality and inequality constraints, with the additional restriction that some or all of the decision variables be integers. [39]

Mathematically, IP can be represented as:

$$\max_{\mathbf{x}} \ \mathbf{c}^T\mathbf{x} \quad \text{s.t.} \quad \mathbf{A}\mathbf{x} \leq \mathbf{b}, \ \mathbf{x} \in \mathbb{Z}^n \tag{5}$$

where $\mathbf{x}$ is the vector of decision variables, $\mathbf{c}$ is the vector of objective function coefficients, $\mathbf{A}$ is the matrix of constraint coefficients, $\mathbf{b}$ is the vector of constraint right-hand sides, and $\mathbb{Z}^n$ is the set of integer-valued vectors of length n.

In power systems, IP has a wide range of applications, including unit commitment, optimal power flow, and transmission expansion planning. Since it is not possible to partially switch on a unit, the decision variables used in unit commitment, for instance, represent the on/off status of the generating units and must be integers [31].

2.2.1.4 Mixed-Integer Programming

Mixed-Integer Programming (MIP) is a mathematical optimization technique used to handle problems where some of the decision variables must be integer values while others can be continuous. In power system research, this kind of optimization problem frequently arises when discrete decisions, like the number of power plants to build or the choice of transmission lines, are represented by integer variables. [31, 32]

MIP can be formulated as follows:

$$\min_{\boldsymbol{x},\boldsymbol{y}} \quad f(\boldsymbol{x},\boldsymbol{y}) \tag{6}$$

$$\text{s.t.} \quad \boldsymbol{x} \in \mathbb{R}^n, \boldsymbol{y} \in \mathbb{Z}^m \tag{7}$$

$$g_i(\boldsymbol{x},\boldsymbol{y}) \leq 0, \quad i = 1, 2, \ldots, p \tag{8}$$

$$h_j(\boldsymbol{x},\boldsymbol{y}) = 0, \quad j = 1, 2, \ldots, q \tag{9}$$

where $\boldsymbol{x}$ is a vector of n continuous variables, $\boldsymbol{y}$ is a vector of m integer variables, $f(\boldsymbol{x},\boldsymbol{y})$ is the objective function to be minimized, $g_i(\boldsymbol{x},\boldsymbol{y})$ are inequality constraints, and $h_j(\boldsymbol{x},\boldsymbol{y})$ are equality constraints.

2.2.1.5 Mixed-Integer Nonlinear Programming

Mixed-Integer Nonlinear Programming (MINLP) is a form of an optimization problem that combines both continuous and discrete choice variables, as well as nonlinear objective functions and constraints [36]. It is computationally difficult to solve this problem because of the objective function's and constraints' nonlinearities and nonconvexities, especially when the number of integer variables is high. [40, 41]

The general form of MINLP is given by:

$$\begin{aligned}
&\min_{\boldsymbol{x}\,\boldsymbol{y}} f(\boldsymbol{x}, \boldsymbol{y}) \\
&s.t. \quad g_i(\boldsymbol{x}, \boldsymbol{y}) \leq 0, \quad i = 1, ..., m \\
&\quad h_j(\boldsymbol{x}, \boldsymbol{y}) = 0, \quad j = 1, ..., p \\
&\quad \boldsymbol{x} \in \mathbb{R}^n, \quad \boldsymbol{y} \in \mathbb{Z}^q, \quad \boldsymbol{y} \in 0, 1^q
\end{aligned} \tag{10}$$

where $\boldsymbol{x}$ represents the continuous decision variables, $\boldsymbol{y}$ represents the integer decision variables, $f(\boldsymbol{x}, \boldsymbol{y})$ is the objective function, $g_i(\boldsymbol{x}, \boldsymbol{y})$ are the inequality constraints, $h_j(\boldsymbol{x}, \boldsymbol{y})$ are the equality constraints, and $\boldsymbol{x} \in \mathbb{R}^n, \boldsymbol{y} \in \mathbb{Z}^q, \boldsymbol{y} \in 0, 1^q$ denote the feasible regions of the decision variables.

The Table 2 summarizes all the different optimization techniques based on their characteristics. These techniques range from LP to more complex methods like GA. For this thesis, we will focus on the utilization of MINLP, due to its capability to handle nonlinear objective functions, constraints, and discrete decision variables.

Table 3 – Comparison of Power System Optimization Techniques

Optimization Technique	**Advantages**	**Disadvantages**	**Typical Applications**	**Scalability**
Linear Programming (LP) [30, 31, 35]	Simple to implement Efficient algorithms Convex solution space Global optimum guaranteed	Limited to linear relationships	Economic dispatch Unit commitment Optimal power flow	Good for small to medium-scale problems
Nonlinear Problem (NLP) [30, 31, 35, 37]	Can handle nonlinear relationships Flexible	Sensitive to initial conditions May converge to local optima	Reactive power optimization	Good for small to medium-scale problems

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Table 3 – continued from previous page

Optimization Technique	Advantages	Disadvantages	Typical Applications	Scalability
Integer Programming (IP) [30, 31, 39]	Can handle discrete variables	Computationally intensive	Transmission expansion planning Generation expansion planning Capacitor placement	Limited for large-scale problems
Mixed-Integer Programming (MIP) [30, 31]	Can handle both continuous and discrete variables	Computationally intensive	Unit commitment Distribution network reconfiguration	Limited for large-scale problems
Mixed-Integer Nonlinear Programming (MINLP) [36, 40, 41]	Can handle nonlinear relationships Handles both continuous and discrete variables	Computationally intensive May converge to local optima	Optimal power flow with discrete controls Transmission and generation expansion planning	Limited for large-scale problems
Genetic Algorithms (GA) [30, 31, 32, 33, 34, 42]	Global search capability Handles complex problems	Slow convergence Requires parameter tuning	Optimal power flow Reactive power optimization	Good for large-scale problems
Particle Swarm Optimization (PSO) [31, 32, 33, 34, 43, 44, 45, 46]	Easy to implement Fast convergence	May converge to local optima Requires parameter tuning	Optimal power flow Reactive power optimization	Good for large-scale problems

Continued on next page

Table 3 – continued from previous page

Optimization Technique	Advantages	Disadvantages	Typical Applications	Scalability
Ant Colony Optimization (ACO) [47, 48, 49, 50, 51, 52]	Global search capability Handles discrete problems	Computationally intensive Requires parameter tuning	Transmission expansion planning Distribution network reconfiguration	Good for large-scale problems
Simulated Annealing (SA) [53, 54, 55, 56, 57, 54]	Global search capability Handles complex problems	Slow convergence Requires parameter tuning	Optimal power flow Reactive power optimization	Good for large-scale problems
Artificial Neural Network (ANN) [30, 58, 59]	Can handle nonlinear relationships Fast computation after training	Requires large training data Black-box approach	Load forecasting	Good for large-scale problems

2.2.2 Meta-Heuristic Optimization Algorithms

Power systems are complicated and dynamic, making it difficult to identify optimal solutions to numerous challenges. By looking for the best answers in a large search space, meta-heuristic optimization algorithms offer a practical method for resolving these issues. Meta-heuristic algorithms are heuristic-based and inspired by natural processes like evolution, swarm behavior, and biological systems, in contrast to conventional optimization techniques that are based on mathematical models. In power system research, nonlinear, non-convex, and multi-objective problems can be effectively handled by these methods [30, 34].

In power system research, meta-heuristic optimization methods are frequently employed to address a range of issues, including optimal power flow, unit commitment, and economic dispatch. For example, GA, PSO, ACO, SA, and ANN are some of the well-liked meta-heuristic methods employed in power system research [33]. We will go into more depth about each of these algorithms and their uses in power system research in the sections that follow.

2.2.2.1 Genetic Algorithms

Genetic Algorithms (GA) are a form of meta-heuristic optimization algorithm that is influenced by the natural process of evolution. GAs are very useful for tackling optimization problems with an extensive number of potential variables and non-convex objective functions, which makes them ideal for power system optimization [33]. due to their capacity to effectively manage nonlinearity and nonconvexity, GA have been applied to a wide range of optimization issues in power systems. GA have been used to optimize numerous problems in power systems, including power flow, unit commitment, economic dispatch, and optimal sizing and positioning of renewable energy sources [32, 33, 34, 42].

GA have been utilized in power flow optimization to decrease total system losses or voltage variations while meeting system restrictions. GA were utilized to identify the optimal on/off schedules of power generators while keeping operational restrictions and fuel costs in mind. GA have been employed in an economic dispatch to find the optimal power output of each generator, subject to load demand and generator limits, in order to reduce total fuel cost [30, 31, 42].

Furthermore, GA have been used to optimize the sizing and location of renewable energy sources such as WTs and solar PVs to maximize power output while minimizing installation and operational costs. This involves establishing the appropriate capacity, location, and configuration of renewable energy sources while taking available resources, environmental circumstances, and grid integration challenges into consideration [33].

2.2.2.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique based on bird flocking or fish schooling [43]. The process starts by populating the search environment with particles with random placements and velocities. Each particle changes its velocity and position based on its own best solution (personal best) and the best solution of all particles in the population (global best). The program then iteratively alters the particle locations and velocities in search of the most optimal solution [34, 43].

PSO has been used in power systems to solve a variety of optimization problems such as economic dispatch [44], unit commitment [45], and optimal power flow [60]. PSO can deal with nonlinear and non-convex objective functions and constraints, as well as seek huge solution spaces efficiently. As an instance, in the economic dispatch problem, PSO can optimize multiple units' power generation while meeting demand and operational restrictions such as ramp rate limits and unit commitment status [44].

One of PSO's benefits is its simplicity and ease of deployment. However, the technique is susceptible to premature convergence, which occurs when the particles arrive at suboptimal solutions too rapidly. To address this issue, numerous modifications and versions of PSO, such as hybrid PSO with other meta-heuristic algorithms, dynamic PSO with adaptive parameters, and multi-objective PSO, have been proposed [33].

2.2.2.3 Ant Colony Optimization

Ant Colony Optimization (ACO) is a meta-heuristic optimization algorithm developed using real-world ant behavior. Pheromones are used by ants to communicate and to locate the quickest path between their nest and food source[47]. ACO simulates this behavior by constructing a swarm of artificial ants that move through the solution space, depositing pheromones along the way. The number of pheromones deposited is proportional to the solution's quality [47, 48].

ACO has been used in power systems to solve a range of problems such as optimal power flow, economic dispatch, and unit commitment [49]. ACO, for example, has been used to find the best set points for controllable devices in the power system such as generators, transformers, and shunt capacitors in the optimal power flow problem [50]. ACO has also been utilized for economic dispatch, which entails scheduling generators so that the cost of providing power is minimized while meeting demand [49].

ACO's capacity to handle discrete decision variables is one of the benefits it offers, making it suitable for situations involving integer or binary variables. ACO can also avoid local optima by searching the solution space more completely than conventional optimization techniques [48].

Regardless of its benefits, ACO has numerous limitations, including sensitivity to settings and difficulties fine-tuning these parameters. Many research efforts, however, have been performed to address these limitations and improve ACO performance [51, 52].

2.2.2.4 Simulated Annealing

Simulated Annealing (SA) is another powerful optimization tool that is seeing widespread adoption in power system applications. The SA stochastic search method was driven by the metallurgical annealing procedure. The algorithm begins with a beginning solution and then explores the solution space iteratively by modifying the solution that already exists and adopting new solutions based on a probability function. The likelihood of accepting a new solution is determined by the difference in objective function values between the present and new solutions, as well as a temperature parameter that determines the search intensity. As the temperature declines, the algorithm becomes more discriminating and only accepts solutions that decrease the objective function [33, 34].

SA has extensive and amazing real-world applications in power systems [34, 53]. It has shown to be a game changer in solving issues such as optimal power flow, unit commitment, and economic dispatch. For example, SA has demonstrated its value in resolving economic dispatch challenges in a power system that uses renewable energy sources. In this scenario, it's all about achieving the optimal balance between decreasing overall generation costs and meeting demand and renewable energy limits . In an additional scenario, SA proved essential in resolving the optimal power flow problem in a distribution network with distributed generating. The goal here is twofold: decrease active power loss while adhering to voltage and capacity limits [57, 54].

However, the SA algorithm also has some limitations as the temperature parameter, which is critical to the method's success, must be carefully adjusted. This parameter must be carefully maintained throughout time in order to establish a healthy balance between the investigation of new ideas and the utilization of the existing solution space. This is where annealing schedules can provide an organized approach, leading the appropriate temperature parameter modifications [55, 56].

2.2.2.5 Artificial Neural Networks

Artificial Neural Network (ANN) are a form of machine learning approach that replicate the structure and function of biological neural networks. ANNs are made up of linked layers of artificial neurons which analyze information via a sequence of weighted connections and activation functions [61]. These networks may learn to recognize patterns and relationships in data and can be utilized in a wide range of power system applications, including load forecasting, problem diagnostics, and optimal power flow [58].

ANNs have been employed in power systems for load forecasting, which is a vital responsibility for power system operators to assure the system's reliability. ANNs can be trained on past load data to identify patterns and correlations, and then utilized to estimate anticipated demand. ANNs have also been utilized for fault diagnostics, which means finding and diagnosing issues in the power system. ANNs can be trained on sensor and other data to understand the patterns associated with various sorts of defects, and then used to detect abnormalities in real time [33, 58].

Another application of ANNs in power systems is optimal power flow (OPF) , which includes determining the optimum configuration of control variables such as generator outputs and transformer taps for lowering system operating costs while meeting limitations. ANNs can be used to represent the link between the control variables and the objective function and constraints, and then utilized to solve the Optimal Power Flow (OPF) issue using optimization techniques [32, 33, 59].

In this research work, we used the traditional optimization technique, especially the MINLP approach as discussed in section 2.2.1.5. MINLP is an advanced optimization approach that can handle nonlinear objective functions, constraints, and discrete decision variables. We can efficiently solve the complicated and multidimensional optimization difficulties in power systems by using MINLP. This method combines the advantages of nonlinear and integer programming, allowing us to optimize power system operations while taking into account discrete decisions and nonlinear relations. Using MINLP, we want to produce efficient and economical solutions that improve the performance and sustainability of power systems.

2.3 Optimization Objectives in Power Systems

Optimization plays an essential role in accomplishing the goals of a power system. The primary goal of power system optimization is to figure out the optimal operating conditions that satisfy various restrictions and objectives [32]. Optimization objectives in power systems can be broken down into three categories: economic, technical, and environmental.

Economic goals seek to maximize revenue from the sale of energy or minimize the cost of generating, distributing, and transmitting electric power. Technical goals aim to enhance power system performance through reducing power losses, optimizing voltage profiles, improving reliability, load balancing, and increasing stability [62, 63]. Environmental goals aim to mitigate the environmental effect of power systems through decreasing emissions, incorporating renewable energy, and preserving resources [64].

Different optimization techniques, including as LP, NLP, MIP, and meta-heuristic optimization algorithms, are employed to fulfill these goals, as explained in the section 2.2. Each of these strategies has advantages and disadvantages, and the optimal technique relies on the individual situation being treated.

2.3.1 Economic Objectives

Economic objectives in power system optimization incorporate minimizing costs [62] or increasing income while maintaining system dependability and satisfying demand. In general, economic objectives can be divided into three categories: cost minimization, revenue maximization, and market efficiency.

2.3.1.1 Cost Minimization

The ultimate objective of cost reduction is to lower the operational expenses of power systems [62, 65]. The objective function is expressed as follows:

$$\min_{\boldsymbol{x}} \quad C(\boldsymbol{x}) \quad s.t. \quad f(\boldsymbol{x}) \leq 0 \qquad \boldsymbol{x} \in \Omega \tag{11}$$

where $\boldsymbol{x}$ represents the decision variables such as power generation, transmission, and distribution, $C(\boldsymbol{x})$ is the total cost of the system, $f(\boldsymbol{x})$ represents the constraints, and Ω denotes the feasible region of the decision variables.

2.3.1.2 Revenue Maximization

The revenue maximization objective seeks to increase the revenue of power system operators [63]. The objective function is expressed as follows:

$$\max_{\boldsymbol{x}} \quad R(\boldsymbol{x}) \quad s.t. \quad f(\boldsymbol{x}) \leq 0 \qquad \boldsymbol{x} \in \Omega \tag{12}$$

where $R(\boldsymbol{x})$ is the revenue obtained from power generation and distribution, and other decision variables, $f(\boldsymbol{x})$ represents the constraints, and Ω denotes the feasible region of the decision variables.

2.3.1.3 Market Efficiency

The market efficiency objective attempts to optimize resource allocation and guarantee that the power market operates effectively [66]. The objective function is expressed as follows:

$$\min_{\boldsymbol{x}} \quad LMP(\boldsymbol{x}) \quad s.t. \quad f(\boldsymbol{x}) \leq 0 \qquad \boldsymbol{x} \in \Omega \tag{13}$$

where $LMP(\boldsymbol{x})$ is the locational marginal price, which is the market clearing price of electricity at each node in the power system, $f(\boldsymbol{x})$ stands for the constraints, and Ω denotes the feasible region of the decision variables.

Economic objectives are crucial for the functioning of power systems and have a substantial impact on energy costs and the power industry's sustainability. The optimization strategies employed to attain these goals have the potential to increase the power system's efficiency, reliability, and environmental sustainability [65, 64, 66].

In my research, we used cost minimization of power system by optimizing the overall operational cost. We intend to achieve cost-effective system operation by decreasing operational costs through efficient power generating decision-making. This goal helps to improve the efficiency, reliability, and long-term viability of power systems.

2.3.2 Technical Objectives

Technical objectives in power systems are optimization goals that strive to improve the system's overall technical performance. Minimizing power losses, optimizing voltage profiles, increasing system reliability, balancing loads, and improving system stability are among the goals.

2.3.2.1 Power Loss Minimization

Power loss reduction is an essential technological goal in power systems because it can result in substantial savings in expenses and a reduction in energy consumption [67]. The objective function for minimizing power loss can be written as.

$$\begin{aligned} &\min_{\boldsymbol{p}} \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N}} r_{ij} p_i p_j \\ &s.t. \quad V_i - V_j + r_{ij} p_i - x_{ij} q_i \geq 0, \quad \forall (i,j) \in \mathcal{E} \\ &\quad P_{min,i} \leq p_i \leq P_{max,i}, \quad \forall i \in \mathcal{N} \end{aligned} \tag{14}$$

where $\boldsymbol{p}$ represents the active power injections, r_{ij} and x_{ij} represent the resistance and reactance of the transmission lines, V_i and V_j represent the voltage magnitudes at buses i and

Table 4 – Technical Objectives Optimization of the Power System

Objective	Description	Key Component	Mathematical Representation
Power Loss Minimization	Minimize the sum of power losses in the system.	Active power injections, reactance, resistance, power limits, voltage magnitude.	$\min_{\boldsymbol{p}} \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}} r_{ij} p_i p_j$
Voltage Profile Improvement	Minimize the deviation of voltage magnitudes from reference values.	Active and reactive power injections, conductance, phase angles, voltage limits.	$\min_{\boldsymbol{v}} \sum_{i\in\mathcal{N}} (V_i - V_{ref,i})^2$
Reliability Enhancement	Improve the availability and quality of power supply to consumers.	Component reliability, system topology, redundancy, protection schemes.	(Various methods depending on specific reliability measures)
Load Balancing	Distribute power consumption across the network in a balanced manner to avoid overloading of components.	Power consumption at nodes, total number of nodes.	$\min \left\| \frac{\sum_{i=1}^{n} P_i}{n} - P_i \right\|$
Stability Improvement	Enhance the power system's ability to maintain its operating state in the presence of disturbances.	Controller parameters, damping controllers, system topology.	(Eigenvalues of the system's Jacobian matrix)

j, and $P_{min,i}$ and $P_{max,i}$ represent the minimum and maximum active power limits at bus i, respectively.

2.3.2.2 Voltage Profile Improvement

In order to maintain the reliability and stability of the system, voltage profile optimization is another crucial technical goal in power systems [68]. The objective function for voltage profile improvement can be formulated as:

$$
\begin{aligned}
&\min_{\boldsymbol{v}} \sum_{i \in \mathcal{N}} (V_i - V_{ref,i})^2 \\
&s.t. \quad P_i - V_i \sum_{j \in \mathcal{N}} G_{ij} \cos(\theta_i - \theta_j) - Q_i \sum_{j \in \mathcal{N}} G_{ij} \sin(\theta_i - \theta_j) = 0, \quad \forall i \in \mathcal{N} \\
&\quad V_{min,i} \leq V_i \leq V_{max,i}, \quad \forall i \in \mathcal{N}
\end{aligned}
\tag{15}
$$

where $\boldsymbol{v}$ represents the voltage magnitudes, $V_{ref,i}$ represents the reference voltage at bus i, P_i and Q_i represent the active and reactive power injections at bus i, respectively, G_{ij} represents the conductance of the transmission lines, and θ_i and θ_j represent the phase angles at buses i and j, respectively. $V_{min,i}$ and $V_{max,i}$ represent the minimum and maximum voltage limits at bus i, respectively.

2.3.2.3 Reliability Enhancement

Enhancing reliability is a major technological priority in power systems because it is able to enhance the availability and quality of power supply to users [69, 70]. The objective function for increasing reliability can be represented as:

$$
\begin{aligned}
&\min_{\boldsymbol{p},\boldsymbol{v},\boldsymbol{r}} \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N}} U_{ij}(r_{ij}, p_i, v_i) \\
&s.t. \quad P_i - V_i \sum_{j \in \mathcal{N}} G_{ij} \cos(\theta_i - \theta_j) - Q_i \sum_{j \in \mathcal{N}} G_{ij} \sin(\theta_i - \theta_j) = 0, \quad \forall i \in \mathcal{N} \\
&\quad V_i - V_j + r_{ij} p_i - x_{ij} q_i \geq 0, \quad \forall (i,j) \in \mathcal{E} \\
&\quad P_{min,i} \leq p_i \leq P_{max,i}, \quad \forall i \in \mathcal{N} \\
&\quad V_{min,i} \leq V_i \leq V_{max,i}, \quad \forall i \in \mathcal{N}
\end{aligned}
\tag{16}
$$

where $U_{ij}(r_{ij}, p_i, v_i)$ represents the outage costs or reliability cost function, which quantifies the cost associated with power outages at bus i, considering the resistance r_{ij}, active power p_i, and voltage magnitude v_i. This cost function can be defined in various ways depending on the specific details of the system, including the value of the lost load, the probability of outages, the duration of outages, and the capacity of the backup supply.

2.3.2.4 Load Balancing

Load balancing tries to distribute electrical energy across the network in a balanced way to prevent the overloading of particular components. It involves reducing the difference between the maximum and least load of all network nodes [71]. It can be expressed mathematically as follows:

$$
\min \left| \frac{\sum_{i=1}^{n} P_i}{n} - P_i \right| \tag{17}
$$

where n is the total number of nodes in the network, P_i is the power consumption at node i.

2.3.2.5 Stability Improvement

The ability of the power system to sustain its normal state in the presence of disturbances is referred to as stability. Stability improvement includes improving the power system's capacity to remain stable under different conditions [72]. Stability can be expressed mathematically by the eigenvalues of the system's Jacobian matrix. Stability can be improved using a variety of approaches, including optimizing controller parameters, adding damping controllers, and modifying the power system topology [73].

In this research work, stability enhancement was not specifically addressed as a technical objective. However, we evaluated the stability element by including the ROCOF limit constraint and the minimum required spinning reserve constraint into our optimization approach. These limitations indirectly contribute to increased system stability by ensuring that the power system runs within safe and stable limits. By applying the ROCOF limit constraint, we regulate the rate of frequency change, limiting large deviations that might lead to instability. Furthermore, the minimum Required Spinning Reserve (RSR) limitation guarantees that a enough reserve capacity is available to promptly respond to changes and retain system stability. By including these constraints into our optimization model, we may indirectly address power system stability enhancement.

2.3.3 Environmental Objectives

Environmental considerations have recently become an essential part of power system planning and operation. Optimization approaches can be used to achieve a variety of environmental goals, including lowering emissions, encouraging the use of renewable energy, and preserving resources [74, 75, 76].

2.3.3.1 Emission Reduction

Emission reduction is an important environmental concern for power systems. Emissions can be reduced by improving the operation of power generation and transmission networks [74]. The objective function can be implemented to reduce emissions from power generation while considering fuel type and emission requirements [76, 77, 78]. Specific pollutants, such as carbon dioxide, sulfur dioxide, and nitrogen oxides, may be subject to emission limits.

The objective function for emission reduction can be represented as follows:

$$\min_{\boldsymbol{x}} \sum_{i=1}^{n} E_i(\boldsymbol{x}) \tag{18}$$

where $\boldsymbol{x}$ represents the decision variables, $E_i(\boldsymbol{x})$ is the emissions associated with the ith generator or pollutant, and n is the total number of generators or pollutants.

2.3.3.2 Renewable Energy Integration

Solar, wind, and hydroelectric power are growing more pivotal in power systems due to their environmental benefits. Optimization techniques can be used to promote the integration of renewable energy sources into the power system [78]. The objective function can be implemented to optimize the utilization of renewable power sources while guaranteeing the power system's reliability and effectiveness. The constraints can be limitations on the capacity of renewable energy sources and the volatility of their output [77, 79].

The objective function for renewable energy incorporation can be written as follows:

$$\max_{\boldsymbol{x}} \sum_{i=1}^{n} R_i(\boldsymbol{x}) \tag{19}$$

where $\boldsymbol{x}$ represents the decision variables, $R_i(\boldsymbol{x})$ is the output from the ith renewable energy source, and n is the total number of renewable energy sources.

2.3.3.3 Resource Conservation

Another important environmental objective for power systems is resource conservation [80]. Optimization techniques have the potential to be used to decrease the consumption of nonrenewable resources like coal and oil. The objective function can be designed to minimize the use of nonrenewable resources while ensuring the power system's performance and reliability [81]. In this case, the constraints tend to involve the accessibility of nonrenewable resources as well as the capacity of the power system.

The objective function for resource conservation can be represented as follows:

$$\min_{\boldsymbol{x}} \sum_{i=1}^{n} C_i(\boldsymbol{x}) \tag{20}$$

where $\boldsymbol{x}$ represents the decision variables, $C_i(\boldsymbol{x})$ is the cost associated with the ith non-renewable resource, and n is the total number of non-renewable resources.

In this research, we did not directly highlight emission reduction as an environmental goal but our focus was on decreasing the total operational costs, mostly coming through reduced consumption of fuel, indirectly helps to emission reduction. By improving system operation for economic efficiency, we support environmentally friendly methods for power systems. The above described Technical Objectives of power system optimization are summed up in Table 4 below.

2.3.4 Unit Commitment, Economic Dispatch, and Optimal Power Flow: Applications of Traditional Optimization Methods

This section explores the practical uses of traditional optimization techniques in power system optimization, based on the earlier study of such techniques in section 2.2.1. We will primarily focus on three fundamental techniques: (1). Unit Commitment (UC), (2). Economic Dispatch (ED), and (3). Optimal Power Flow (OPF), which are all widely used in power systems [30, 31]. These techniques all use traditional optimization techniques to improve the performance of power systems, despite their objectives and decision variables and the Table 5 provides a overall summary of the key differences between these methods.

Table 5 – Main Differences between Power System Optimization Techniques

	Unit Commitment [30, 31, 32, 45, 57]	**Economic Dispatch** [30, 31, 32, 44, 49, 57]	**Optimal Power Flow** [30, 31, 32, 50, 54, 59, 60]
Main Objective	Determines the on/off status of generators over a certain period considering startup/shutdown costs to meet the predicted demand reliably.	Allocates load to online generators in the most cost-effective manner, considering the generator's cost function.	Determines the optimal settings of power system controls to minimize costs, losses, or improve voltage profiles while respecting the system's physical and operational constraints.
Decision Variables	Binary variables indicating the on/off status of each generator.	Continuous variables representing the power output of each generator.	Both continuous (generator output, voltage levels) and discrete variables (transformer tap settings, shunt devices).
Main Constraint	Total generation must meet demand plus reserve, taking into account the generator's min/max capacity, ramp rates, and minimum updown time.	Output of each generator must be within its min/max limits, and total generation must meet the demand.	Must satisfy power balance equation, generator and voltage limits, transmission line flow constraints, and other operational constraints.
Time Frame	Typically solved on a daily basis with an hourly or half-hourly time step.	Short term, typically carried out every 5-15 minutes.	Real-time to short term, can be run as often as every few seconds to several minutes.
Optimization Technique	MIP due to binary decision variables.	NLP due to the non-linear cost function of generators.	NLP and MIP due to the non-linear nature of power flow equations and possible discrete control variables.

2.3.4.1 Unit Commitment

UC is a crucial optimization process in power systems. It decides the on/off status of the generating units to meet the predicted demand over a specified period while satisfying various technical and operational constraints. The UC problem aims to minimize the total cost of operation, which includes startup costs, shutdown costs, and production costs of the generating units [30, 31, 32].

The UC plays a significant role in achieving the economic objectives of the power system. By determining the optimal operation schedule of the generating units, it helps in minimizing the overall operational cost and maximizing the revenue. It also contributes to achieving technical objectives by ensuring a reliable power supply and maintaining system stability. Moreover, it supports environmental objectives by considering the emission constraints during the scheduling process [45, 57, 82].

2.3.4.2 Economic Dispatch

ED is another essential optimization technique in power systems. It determines the optimal distribution of load demand among the committed generating units such that the total fuel cost is minimized while satisfying the power balance constraint and the generator operating limits [30, 31, 32].

The ED directly supports the economic objectives by efficiently distributing the load among the generators to minimize the fuel cost [49]. It also indirectly contributes to the technical and environmental objectives. By efficiently utilizing the available resources, it helps in reducing power losses and enhancing system reliability. Moreover, by considering the emission characteristics of the generators, it can contribute to reducing the total emissions [31, 44, 57].

2.3.4.3 Optimal Power Flow

Optimal Power Flow (OPF) is a fundamental optimization problem in power systems. It seeks to optimize a certain objective function such as the cost of generation or the power loss while satisfying various equality and inequality constraints including power balance equations, voltage limits, and generator capacity limits [30, 31, 32].

The OPF plays a key role in accomplishing the optimization objectives in power systems. It helps in achieving the economic objectives by minimizing the generation cost or maximizing the system efficiency [60]. It supports the technical objectives by optimizing the power flow in the network to reduce power losses, maintain voltage profiles, and enhance system stability. It also contributes to the environmental objectives by incorporating renewable energy sources into the dispatch process and considering emission constraints [50, 54, 59]. Whereas, the differences between all 3 techniques are tabulated in Table 5.

In this research study, the use of traditional optimization methods, particularly UC and ED, in power system optimization is covered. While ED optimally distributes the load demand across committed generators in order to minimize fuel costs, UC focuses on defining the best on/off state of generating units to dependably satisfy demand. This research tries to improve power systems' operational performance and economic efficiency by integrating UC and ED.

2.4 Power System Types

In this section, we discuss various power system types, with a focus on grid-connected and standalone systems. Power system types play a crucial role in the design, planning, and operation of electrical networks. The choice of power system type influences the optimization objectives, techniques, and challenges associated with the network. We begin by providing an overview of grid-connected power systems and discussing centralized and distributed generation. We then explore standalone power systems, including microgrids, nanogrids, and hybrid power systems. Lastly, we compare grid-connected and standalone systems and discuss the factors influencing the choice of a power system type. This overview aims to provide a comprehensive understanding of different power system types and their unique characteristics, setting the stage for a more in-depth discussion of standalone systems and their optimization challenges.

2.4.1 Grid-Connected Power Systems

Grid-connected systems are interconnected and synchronized power networks that allow electricity to be distributed between numerous generation sources and loads. These systems often include both centralized and distributed generating, both of which are critical to satisfying energy demands and preserving network stability [83]. Grid-connected power systems have various benefits, including higher reliability, economies of scale, and operational flexibility. They may, however, bring additional problems in grid management, transmission losses, and the risk of cascading failures [84].

Grid-connected systems benefit from the inertial advantages offered by the rotational mass of synchronous generators in terms of power system stability. This intrinsic inertia contributes to the system's frequency and voltage stability amid disruptions such as rapid changes in load or generation. In addition, grid-connected systems enable the effective mixing of spinning reserves, which improves their ability to respond to potential risks and maintain stability [85].

However, when renewable energy sources such as solar and wind become more widely integrated, the inertia of grid-connected systems may be compromised, because these energy sources frequently use power electronic converters that do not contribute to system inertia [86]. This tendency needs new tactics to assure the stability of grid-connected power systems, such as enhanced control approaches, energy storage technologies, and the use of synthetic inertia.[87]

The two primary components of grid-connected power systems are discussed in the following sections: centralized generation and distributed generation. We will look at their functions in the network, both their advantages and disadvantages, and how they affect power system optimization and stability.

2.4.1.1 Centralized Generation

Large-scale power generation facilities that produce electricity in bulk are referred to as centralized generation, which is an important aspect of grid-connected power systems. These facilities, which can be found in areas far from load centers and include coal, natural gas, nuclear, and hydroelectric power plants, require the deployment of substantial transmission and distribution networks. [88]

Characteristics of Centralized Generation

Centralized generation facilities typically have the following features [89, 90, 91]:

- ❏ Large-Scale Generation Capacity: Centralized power plants are capable of producing enormous amounts of electricity, frequently in the hundreds of megawatts to gigawatts range.
- ❏ Long Construction Time: Due to its size and complexity, the building of centralized generation facilities might take several years.
- ❏ High Capital Costs: The initial expenditure required for the construction of centralized power plants is significant, owing mostly to the costs of land acquisition, construction, and equipment.
- ❏ Remote Locations: Centralized power plants are frequently located far from load centers in order to reduce land costs and accommodate the necessary infrastructure.

Advantages of Centralized Generation

Centralized generation offers several benefits to grid-connected power systems [91], such as:

- ❏ Economies of Scale: Large-scale power plants are able to produce electricity at reduced costs per unit because of their size and efficiency.
- ❏ Reliability: A constant and dependable supply of electricity is provided by centralized generation facilities, particularly those that use conventional energy sources, which helps to increase the overall reliability of the power system.
- ❏ Expertise and Specialization: Centralized power plants are frequently monitored by specialized teams to ensure optimal operation and maintenance.
- ❏ Inertia Contribution: Large synchronous generators used in centralized power plants greatly contribute to system inertia, enhancing frequency and voltage stability.

Disadvantages of Centralized Generation

Despite its advantages, centralized generation also has several drawbacks [90, 92]

- ❏ Transmission and Distribution losses: The Long transmission lines are necessary due to the centralized generation facilities' remote location, which increases energy losses and raises transmission costs.

- ❏ Environmental Impacts: Large-scale operations can have a substantial negative impact on the environment, adding to waste production, air and water pollution, and changes in land usage.

- ❏ Vulnerability to Disruption: The system may be more susceptible to unforeseen outages or natural disasters due to its reliance on a small number of large-scale power facilities.

- ❏ Slow Adaptation to New Technologies: Centralized power facilities need significant capital expenditures and take a long time to build, which can delay the adoption of cutting-edge technologies.

Impact on Power System Optimization and Stability

Power system optimization and stability depend significantly on centralized generation. When it comes to managing and optimizing power flow, voltage management, and system reliability, it is simpler to manage because of its large-scale nature and predictable output [91]. Also, centralized generation facilitates the significant inertia that contributes to the grid's flexibility during outages [93]. It may be necessary to reassess the role of centralized generation in optimization and stability as power systems develop toward the integration of increasingly dispersed generation and renewable energy sources. In order to handle both centralized and distributed generation sources, new optimization approaches and stability strategies must be developed due to the rising penetration of renewable energy sources, which are frequently variable and decentralized [91].

2.4.1.2 Distributed Generation

The term Distributed Generation (DGen) refers to the process of producing energy from locally situated, small-scale, decentralized power sources. These sources include both non-renewable energy sources like fuel cells and natural gas-fired microturbines as well as renewable energy sources like solar PhotoVoltaic (PV) systems, WTs, and biomass [89].

Characteristics of Distributed Generation

Distributed generation systems exhibit the following features [91, 94]:

- ❏ Small-Scale Generation Capacity: The typical capacity of DGen systems ranges from a few kilowatts to many megawatts.
- ❏ Proximity to Load Centers: DGen sources are usually situated adjacent to or inside end-user's buildings, minimizing transmission and distribution losses.
- ❏ Modular and Scalable: DGen systems can be scaled up or down by adding or removing individual units, enabling flexible capacity expansion.
- ❏ Diverse Energy Sources: In order to increase the power system's reliability and sustainability, distributed generation can make use of a wide range of renewable and non-renewable energy sources.

Advantages of Distributed Generation

Distributed generation offers several benefits to grid-connected power systems [88]:

- ❏ Reduced Transmission and Distribution Losses: DGen systems can reduce losses associated with long transmission and distribution lines by generating power closer to the point of consumption.
- ❏ Improved Reliability and Resilience: The decentralized traits of DGen sources can improve the power system's ability to withstand challenges and recover from power shortages.
- ❏ Environmental Benefits: Many DGen technologies, notably renewable energy sources, have a smaller environmental impact than large-scale, centralized generation facilities.
- ❏ Flexibility and Adaptability: The power system's flexibility is increased by the rapid deployment and simple adaptation of DGen systems to shifting load patterns and energy demands.

Disadvantages of Distributed Generation

Despite its benefits, distributed generation also presents several challenges [95, 96]:

- ❏ Intermittency and Variability: Some renewable DGen sources, such as solar PV and WTs, have intermittent or variable output, which can complicate grid management and stability.
- ❏ Higher Unit Costs: DGen systems may have higher per-unit costs than a centralized generation because of their smaller size, especially when initial investment, operation, and maintenance costs are taken into account.
- ❏ Integration and Coordination: It can be challenging to integrate numerous different and scattered DGen sources into the grid, demanding sophisticated management and coordination systems.

Table 6 – Comparison of Centralized and Distributed Generation.

Characteristics	**Centralized Generation [88, 89, 90, 91, 92]**	**Distributed Generation [88, 91, 92, 93, 94, 96]**
Generation capacity	Large-scale	Small-scale
Construction time	Long	Quick
Capital costs	High	Higher per-unit costs
Location	Remote	Proximity to load centers
Economies of scale	Yes	No
Reliability	Yes	Improved resilience
Expertise and specialization	Yes	Flexibility and adaptability
Inertia contribution	Yes	Reduced system inertia
Vulnerability to disruption	Yes	Intermittency and variability
Adaptation to new technologies	Slow	Environmental benefits

- ❏ Reduced System Inertia: Many DGen sources, particularly those that use power electronic converters, don't add to system inertia, which may have an impact on frequency and voltage stability.

Impact on Power System Optimization and Stability

The incorporation of distributed generation into grid-connected power systems has major consequences for optimization and stability [97]. Because DGen sources are diverse, decentralized, and frequently intermittent, new optimization techniques and control strategies are necessary to ensure efficient and dependable grid operation. To overcome the variability of renewable DGen sources, these might incorporate demand-side management, energy storage integration, and advanced forecasting approaches[95, 97].

Furthermore, the lower inertia involvement of numerous DGen sources can have an impact on grid stability during disruptions [96, 98]. Grid operators and researchers are looking into several ways to solve this problem.

The comparison between centralized and distributed generation, considering various characteristics, is presented in Table 6.

2.4.2 Standalone Power Systems

Standalone power systems, commonly referred to as off-grid power systems, are intended to run independently from the main grid, usually in distant or rural locations. Microgrids, nanogrids, and hybrid power systems are examples of these systems and the comparison is provided in the Table 7. The standalone power system can utilize a mix of renewable and non-renewable energy sources [99].

Table 7 – Comparison of Microgrids, Nanogrids, and Hybrid Power Systems

System Type	Advantages	Challenges	Inertia	Control Strategies
Microgrids	Energy security, cost savings, renewable energy sources [100, 101]	Small size, variable output, frequency stability [102]	Low [103]	Advanced [104]
Nanogrids	Energy security, cost savings, renewable energy sources [102, 105]	Small size, variable output, frequency stability [102]	Absent [106]	Advanced [107]
Hybrid Power Systems	Reliable and sustainable power supply, take advantage of benefits of both grid-connected and standalone systems [108, 109, 110, 111, 112]	Integration of different components and energy sources, higher capital costs [113, 114]	Present in grid-connected component, absent in standalone component [115]	Advanced [114]

2.4.2.1 Microgrids

Microgrids are small-scale standalone power systems that can operate independently or in parallel with the main grid. They typically serve a single community, building, or campus and can employ a variety of generation sources, including renewable energy technologies such as solar PVs, WTs, and biomass, as well as non-renewable sources such as DGs [116]. The characteristics, advantages, and disadvantages of microgrids, as well as their impact on power system optimization and stability are discussed as follow.

Characteristics of Microgrids

Microgrid systems exhibit the following features [100, 116, 117]:

- Integration of DERs: Microgrids use a variety of small-scale DERs, including Renewable Energy Resources (RERs) (solar PVs, WTs), Energy Storage System (ESS) (batteries, flywheels), and traditional generation units (DGs, GTs).
- Autonomous Operation: Microgrids have the ability to function autonomously, independently managing their operations based on the availability and demands of their energy resources. This includes the operation of various types of DERs, balancing power generation from renewable (RERs) and traditional sources (DGs, GTs), and implementing necessary power adjustments to maintain system stability and efficiency.

- ❏ Advanced Control and Communication Systems: Advanced control, monitoring, and communication systems are used by microgrids to guarantee efficient and dependable operation, maximize the usage of DERs, and enable Demand Response (DR), load management, and energy trading.

- ❏ Enhanced Reliability and Resilience: Microgrids promote reliability and robustness by enabling self-healing, instantaneous responses to small disturbances, and minimizing the impact of large-scale grid breakdowns on connected loads.

Advantages of Microgrids

Microgrid systems offer numerous benefits, including [100, 101]:

- ❏ Increased Energy Efficiency: Microgrids can improve energy efficiency by optimizing the usage of local DERs, lowering transmission and distribution losses, and increasing overall energy efficiency.

- ❏ Higher Integration of Renewable Energy: Microgrids make it easier to incorporate renewable energy sources, which lowers greenhouse gas emissions and the dependency on fossil fuels.

- ❏ Enhanced Grid Stability: Microgrids contribute to the overall stability of the electricity grid by offering ancillary services like voltage and frequency support.

- ❏ Economic Benefits: The usage of microgrids can reduce costs for both operators and end users by enabling energy trading, demand response, and peak shaving.

Disadvantages of Microgrids

Despite their advantages, microgrids also present certain challenges[100, 118]:

- ❏ High Initial Capital Costs: Microgrid projects may have substantial initial investment costs due to the integration of sophisticated control systems, communication infrastructure, and DERs.

- ❏ Complex Control and Management: A complex control and management system is needed to operate a microgrid, one that can handle the variety of DERs and the dynamic interactions among them.

- ❏ Interconnection Challenges: It can be technically difficult and may require additional tools and safety measures to ensure smooth and secure transitions between grid-connected and island modes of operation.

Impact on Power System Optimization and Stability

Microgrids may significantly affect the stability and optimization of the electricity system. They offer the best foundation for DERs optimization, enabling effective usage of local resources for demand-side management, generation, and storage [100, 101]. They can contribute to lowering overall power losses, enhancing voltage profiles, and boosting system reliability [119].

Additionally, by offering ancillary services like voltage and frequency support, microgrids contribute to the overall stability of the power system [120]. Microgrids can adapt swiftly to small disturbances, modify their operation to maintain stability, and even help the main grid recover after significant outages due to the employment of cutting-edge control and communication systems [120, 121]. The integration of several DERs and microgrids, however, might also pose new difficulties for the stability and optimization of the power system [100, 118]. To maintain the dependable operation of both individual microgrids and the wider power grid, more sophisticated optimization algorithms and control strategies may need to be developed due to the increased fluctuation and uncertainty associated with renewable energy sources [116, 122]. likewise it can be technically difficult to provide smooth and secure transitions between grid-connected and islanded modes of operation, and it could be necessary to use additional tools and safety measures [116, 122, 123].

2.4.2.2 Nanogrids

Nanogrids are comparable to microgrids but on a smaller size, generally servicing a single building or a small group of buildings. They can use a range of energy sources, including non-renewable and renewable technologies, and are built to run independently or in in combination with the main grid [102]. The characteristics, advantages, and challenges of nanogrids, along with their influence on power system optimization and stability, are outlined below.

Characteristics of Nanogrids

Nanogrid systems exhibit the following features [102, 105, 124, 106]:

- ❏ Small-Scale Systems: Nanogrids are primarily used to serve single buildings, houses, or small networks of loads with power ratings less than 100 kW.
- ❏ Higher Granularity: Nanogrids work on a smaller scale, controlling energy consumption, generation, and storage at the appliance or device level.
- ❏ Plug-and-Play Capability: Nanogrid systems frequently provide plug-and-play capability to facilitate the integration and scaling of DERs and loads.
- ❏ Local Energy Management: Nanogrids are designed to optimize local energy output, consumption, and storage in order to reduce energy costs and assure consistent operation.

Advantages of Nanogrids

Nanogrid systems offer numerous benefits, including [102, 105, 124, 106, 125]:

❏ Enhanced Energy Efficiency: Nanogrids provide enable smooth management and monitoring of energy usage, resulting in increased energy efficiency and potential cost savings.

❏ Increased Resilience: Nanogrids can provide greater stability during grid breakdowns by providing local energy control, guaranteeing uninterrupted operation of essential loads.

❏ Ease of Deployment: Due to their compact size, plug-and-play operation, and comparatively low initial investment costs, nanogrids can be readily deployed and expanded.

❏ Demand Side Management: Advanced demand-side management techniques like demand response, load shedding, and peak shaving can be supported by nanogrids, further improving total energy efficiency.

Disadvantages of Nanogrids

Despite their advantages, nanogrids also present certain challenges [102, 125, 126]:

❏ Limited Economies of Scale: Nanogrids might not experience the same economies of scale as bigger microgrids or utility-scale power systems because of their small size.

❏ Complex Control and Coordination: The operations of several nanogrids within a larger power system may require complex control and coordination systems to keep optimal functioning and prevent conflicts.

❏ Interoperability: It can be difficult to ensure the compatibility of different parts, technology, and communication protocols within a nanogrid; this may need the creation of new standards and rules.

Impact on Power System Optimization and Stability

The improvement and stabilization of power networks are significantly impacted by nanogrids. Nanogrids can considerably improve the overall efficiency and stability of the power system by enabling rigorous control and supervision over energy use, production, and storage [126, 127]. They enable more effective demand-side management techniques like demand response, load shifting, and peak chopping by enabling the capacity to be adjusted for the loads and DERs [128, 129]. These tactics are helpful for restoring the electrical system's equilibrium and decreasing the burden on the grid's infrastructure [129, 130]. On the other hand, including multiple nanogrids into the power system may present special difficulties. Complex optimization techniques may be required for the control and management of numerous interconnected nanogrids [131]. Thus, while nanogrids offer compelling alternatives for power system optimization and stability, their integration demands careful analysis and advanced planning [106, 126, 131].

2.4.2.3 Hybrid Power Systems

A hybrid power system is an energy solution that integrates multiple energy sources, including non-renewable and renewable technologies and works alongside or independently from the primary power grid to deliver power. It does this by utilizing the strengths of various energy sources [108]. The key objectives are to improve system performance, minimize cost of energy, and have less of an adverse effect on the environment. The following are the unique characteristics, advantages, and disadvantages tied to hybrid power systems, as well as their role in enhancing the efficiency and stability of the overall power grid [78, 106, 132].

Characteristics of Hybrid Power Systems

Hybrid power systems exhibit the following features [108, 109, 110]:

❏ Integration of Multiple Energy Sources: To provide a more stable and efficient energy supply, hybrid power systems combine renewable energy (solar, wind, hydro), conventional generating (diesel, gas), and energy storage devices (batteries, flywheels).

❏ Improved Energy Management: Advanced control strategies and energy management techniques are used by hybrid power systems to optimize the utilization of available resources. This strikes a balance between economic viability and sustainability by ensuring that the energy sources used are not only cost-effective but also have the least negative impact on the environment.

❏ Enhanced Reliability and Resilience: Hybrid power systems can offer increased dependability and stability by mixing different energy sources and storage technologies, allowing for continuous operation during times of low renewable energy availability or equipment breakdown.

❏ Scalability and Flexibility: When required, new energy sources can be integrated into hybrid power systems because they have the ability to scale up or down in size to satisfy varying requirements for energy.

Advantages of Hybrid Power Systems

Hybrid power systems offer numerous benefits, including [108, 109, 110, 111, 112, 133]:

- ❏ Increased Energy Efficiency: By integrating and regulating various sources of energy, hybrid power systems can achieve higher overall energy efficiency than single-source systems.

- ❏ Higher Use of Renewable Energy: Hybrid systems make it easy to incorporate RERs, cutting the production of greenhouse gases and dependency on fossil fuels.

- ❏ Enhanced System Reliability: Mixing diverse energy sources and storage devices provides stability and variety, strengthening total power supply security.

- ❏ Cost Savings: By reducing fuel consumption, lowering operation and maintenance costs, and enabling load management techniques like peak shaving and DR, hybrid power systems can result in cost savings.

Disadvantages of Hybrid Power Systems

Despite their advantages, hybrid power systems also present certain challenges [113, 114]:

- ❏ High initial capital costs: The simultaneous deployment of numerous energy sources, storage devices, and advanced control systems might result in high initial investment costs for hybrid power system projects.

- ❏ Complex design and integration: A thorough understanding of the dynamics and interactions of the system is necessary for designing and integrating the various parts of a hybrid power system.

- ❏ Operational complexity: Operating a hybrid power system necessitates complex control and management systems to optimize resource utilization and ensure system stability.

Impact on Power System Optimization and Stability

Hybrid power systems have a significant impact on power system optimization and stability given that they combine numerous energy sources and storage options [108]. The combination produces a power supply that is not only more flexible but also more reliable, sustaining stability even when renewable energy is scarce or equipment fails [134]. Their innovative control techniques and energy management strategies result in better utilization of resources, reduced power losses, enhanced voltage profiles, and increased system reliability [114]. However, integrating several energy sources and storage devices introduces new complications. As renewable energy is unpredictable and uncertain, more advanced optimization algorithms and control strategies are required to ensure the reliable operation of both individual hybrid power systems and the broader power grid [135].

To summarize, hybrid power systems provide prospective possibilities for power system optimization and stability. Nevertheless, their successful deployment also demands resolving the challenges of uncertainties, integration complexities, and the requirement for advanced control methods [110].

Focus of this study is on standalone power systems, particularly hybrid power systems. Combining renewable and non-renewable energy sources, these systems run independently from the main grid. In order to design optimization techniques to increase their efficiency and security, the research is looking to better understand their special attributes, benefits, and limitations. Hybrid power systems provide savings and minimizes the environmental effects through the integration of multiple energy sources. The research results in helping to create reliable and sustainable energy solutions.

2.4.3 Comparison of Grid-connected and Standalone Systems

Standalone and grid-connected systems are two different strategies for producing and distributing electricity in the context of power systems. Grid-connected systems are connected to the main power grid, whereas standalone systems function independently of the main grid, relying on local generation and energy storage devices to meet their energy needs. The Table 8 provides a comparison of grid-connected and standalone systems, highlighting the key differences and trade-offs between the two approaches.

In the conclusion, both grid-connected and standalone systems offer benefits and drawbacks. Grid-connected systems provide higher reliability and cheaper initial capital costs since they may draw power from the main grid, when generator unit fails or renewable energy is scarce. On the other hand, standalone systems provide better scalability and flexibility, since they may be designed to suit varying energy requirements and integrate additional energy sources as needed. The decision between grid-connected and standalone systems is influenced by a number of factors, including resource availability, local restrictions, and the project's specific requirements. Power system research and development will continue to improve the performance and cost-effectiveness of both grid-connected and standalone systems, allowing for the wider adoption of sustainable and reliable energy solutions.

2.5 Standalone Power System of Oil and Gas (OG) Platform

OG sites are located in distant and harsh areas, and require a reliable and continuous power source to meet their energy requirements. Typical power sources for these platforms include GTs, DGs, and Combined Heat and Power (CHP) systems. However, due to the benefits of cost reductions, emissions reduction, and fuel diversity, there is a growing interest in incorporating renewable energy sources in OG platforms [139, 140, 141, 142].

Table 8 – Comparison of Grid-connected and Standalone Systems

Criteria	**Grid-connected Systems [84, 83, 86, 136, 137, 138]**	**Standalone Systems [104, 100, 102, 108, 109, 110, 111, 112]**
Reliability	High, given that they can take electricity from the main grid in the event of equipment failure or a lack of renewable energy supply.	Lower, because they rely on on-site generation and energy storage equipment, which may not always be adequate.
Cost	Lower initial capital costs, as there is no need for energy storage devices or backup generation systems.	Higher initial capital costs, as energy storage devices and backup generation systems are required.
Energy Efficiency	Can achieve great energy efficiency by maximizing local generation and taking power from the main grid when necessary.	High energy efficiency can be achieved by maximizing the usage of local generating and ESSs, however this may be limited by resource availability.
Integration of Renewable Energy	It is simpler as the main grid can offer backup power when renewable energy sources are unavailable.	More difficult, as energy storage devices and backup generation systems are necessary to maintain stability during periods of low renewable energy availability.
Maintenance	Lower maintenance requirements, as the main grid can compensate for local equipment failures.	Higher maintenance requirements, as local equipment failures can directly impact the stability and reliability of the system.
Scalability	Scalable, but may require additional grid infrastructure for larger systems.	Highly scalable, as additional generation and storage capacity can be added to the system as needed.

The incorporation of renewable energy sources in OG platforms involves various issues, including intermittency, unpredictability, and uncertainty, which may negatively impact the power system's reliability and stability. ESSs can help to mitigate these problems and enable the integration of renewable energy sources in OG platforms [142, 143].

This section examines the conventional power sources utilized in OG platforms, the problems and opportunities associated with incorporating renewable energy sources, and the significance of ESSs in OG platforms.

2.5.1 Conventional Power Sources in OG Platforms

These platforms have primarily used conventional power sources, such as:

- *Gas turbines:* OG platforms frequently employ GTs because of their high efficiency, small size, and capacity for consuming associated gas from the platform as fuel. They can generate vast amounts of power and successfully handle changes in load demand. However, they have substantial capital and maintenance expenses, as well as significant greenhouse gas emissions [76, 144, 145, 146].

- *Diesel generators:* DGs are another prominent source of power for OG platforms, especially in smaller installations or as backup power. They are quite cheap to install and maintain, but they emit a lot of pollutants and make a lot of noise, and their efficiency degrades with age [78, 147, 148].

- *CHP systems:* CHP systems generate both electricity and useful heat by absorbing waste heat from power-producing operations, improving overall energy efficiency [149]. These systems can use GTs or reciprocating engines as prime movers, decreasing pollutants and fuel consumption. It might nevertheless demand complicated control systems and have greater initial capital expenses [150, 151].

These conventional power sources have provided reliable energy to OG platforms for decades. However, there is now more interest in incorporating renewable energy sources into OG platforms due to growing worries about climate change, the depletion of fossil fuel reserves, cost reductions, and fuel diversification [152, 153]. The challenges, opportunities, and technologies associated with incorporating renewable energy sources, energy storage technologies, and floating WTs into OG platform power systems will be covered in the sections that follow.

2.5.2 Integrating Renewable Energy Sources

Reducing emissions, diversifying fuel sources, and reducing expenses are just a few of the possible advantages of incorporating renewable energy into OG platforms [142, 147, 150, 151, 152]. The various renewable energy resources that can be integrated into OG platforms and the linked challenges and opportunities are discussed below.

2.5.2.1 Challenges and Opportunities

- ***Solar power:*** Solar energy can be captured and used by PVs systems to produce electricity for OG platforms. However, due to the limitations of space on platforms and solar power's inconsistent nature, its overall contribution to the platform's energy mix may be restricted. Opportunities for greater adoption of solar power on OG platforms are presented by improvements in PV technology and declining solar panel prices [149, 154, 155].

- ***Wind power:*** Offshore wind energy is a compelling option for OG platforms due to the accessibility of rich wind resources in various offshore sites. WTs, both fixed and floating, can be integrated into OG platforms. The main problem with wind energy is that it is unpredictable and variable, which might compromise the stability and dependability of the power system. Nevertheless, advances in floating wind turbine technology and the potential for hybrid power systems with energy storage can assist in overcoming these difficulties [78, 132, 152, 153, 156].

- ***Ocean energy:*** Tidal, wave, and ocean thermal energy are examples of ocean energy resources that can be used to produce electricity for OG platforms. These technologies offer a dependable and predictable power source that may complement other renewable energy sources even if they are still in the early phases of development and may require a greater initial investment [154, 157, 158, 159].

  Whereas, the Power system stability, grid connections, and control techniques are only a few of the technical issues that must be resolved in order to integrate renewable energy sources into OG platforms [160]. Furthermore, the harsh offshore climate might place restrictions on the development and management of renewable energy installations [161].

2.5.3 Energy Storage Systems in OG Platforms

ESSs have become an important components of OG platforms due to their capacity to provide a consistent power supply, mitigate renewable energy intermittency, and improve power quality [162]. The role and technologies of ESSs in OG platforms, as well as their integration and optimization [132, 163, 164], are addressed below.

2.5.3.1 Role and Technologies

- *Role:* ESS may store surplus energy that comes from renewable energy sources and distribute it when required enhancing the power system's reliability and stability [165, 166]. Furthermore, ESS can provide ancillary services such as frequency control, voltage support, and spinning reserves, ensuring the OG platform's power grid's power quality and stability [162].

- *Technologies:* Electrochemical (e.g., batteries), mechanical (e.g., flywheels), and thermal ESSs are among the energy storage technologies suited for OG platforms. Owing to their high energy density, long cycle duration, and lower price, lithium-ion batteries are the most frequently used of them [148, 167, 168]. However, depending on the platform requirements and environmental conditions, various technologies like flow batteries [159] and Compressed Air Energy Storage (CAES) [169] may be considered.

2.5.3.2 Integration and Optimization

- *Integration:* Integrating ESS into OG platforms involves an in-depth review of the power system, including the energy storage system's sizing, site, and control mechanisms. The compatibility of ESS with current power generation infrastructure and renewable energy sources should also be considered throughout the implementation phase [168].

- *Optimization:* Optimization approaches can be used to determine the suitable sizing and operation of ESSs in order to best utilize the benefits of ESS. This comprises the development of mathematical models and algorithms that take into account a variety of elements such as energy demand, renewable energy generation profiles, and storage depletion. Furthermore, advanced control algorithms can be employed to efficiently regulate the charging and discharging of the ESS, assuring optimal utilization of stored energy and overall system flexibility [162, 166, 168].

Hence Energy storage system integration and optimization in OG platforms are crucial for enabling the integration of RERs, enhancing power system stability, and lowering the negative environmental impacts.

2.5.4 Floating Wind Turbines

Floating WTs are a novel and potential renewable energy solution for OG installations, particularly in deep-sea conditions where traditional fixed-bottom WTs are impractical [152, 153, 170, 171]. This section explores into the technologies and designs of floating WTs, as well as their operations and maintenance.

2.5.4.1 Technologies and Design

- *Technologies:* Floating WTs are made up of a wind turbine generator positioned on a floating support structure that is attached to the seabed by mooring lines and anchors. Semi-submersible, spar buoy and Tension-Leg Platform (TLP) are the three most frequent types of floating support structures. Each type has benefits and drawbacks, and the choice is determined by criteria like water depth, ambient conditions, and installation issues [172, 173, 27].

- *Design:* The design of floating WTs calls for an in-depth investigation of a number of factors, such as hydrodynamic and aerodynamic stresses, stability, and structural integrity [170]. Furthermore, the dynamic interactions between the wind turbine, support structure, mooring system, and environmental factors like wind, waves, and currents should be considered during the design process. To optimize the design and ensure the performance and safety of the floating wind turbine system, advanced simulation tools, and methodologies are employed [170, 171, 173, 27].

2.5.4.2 Operations and Maintenance

- *Operations:* The operation of floating WTs requires frequent control and observation of the system in order to guarantee successful operation and minimal downtime [153, 162]. This comprises controlling the wind turbine generator, pitch and yaw systems, mooring lines, and other components. Advanced control algorithms can be implemented to maximize energy harvesting while minimizing structural loads and ensuring the floating system's stability [170, 174].

- *Maintenance:* Maintenance of floating WTs is more complicated than maintenance of fixed-bottom WTs since the procedure involves not only the wind turbine components but also the floating support structure and mooring mechanism. Periodic inspections, condition monitoring, and preventative maintenance are all essential for ensuring the system's dependability and lifespan [175]. To reduce maintenance costs and downtime, remote monitoring and diagnostics, as well as autonomous and robotic maintenance systems, are being developed and adopted [176, 177].

Overall, floating WTs offer a promising renewable energy solution for offshore oil and gas sites. They can help to develop hybrid power systems for OG platforms when combined with ESSs and other renewable energy sources [178, 179].

2.5.5 Hybrid Power Systems for OG Platforms

Hybrid power systems combine several energy sources, such as conventional generators, renewable energy sources, and ESSs, to offer OG platforms with reliable, effective, and environmentally friendly power solutions [146, 179, 180, 181]. This section will go into hybrid power system design and control, as well as their economic and environmental implications.

2.5.5.1 System Design and Control

- *System Design:* The design of a hybrid power system for an OG platform must take into account a number of factors, including available energy resources, power consumption on the platform, and environmental constraints. The ideal system setup and sizing should strike an equilibrium between capital expenses, operational costs, and performance requirements [180]. For determining the best possible combination of energy sources and storage devices, broad optimization techniques such as LP, GA, and multi-objective optimization are carried out [179, 181].

- *Control:* The control of a hybrid power system entails the coordinated management of the various energy sources and storage devices to ensure reliable and effective operation [153, 180, 182]. This consists of real-time control strategies for power dispatch, load management, and storage system usage, as well as predictive control based on predicting renewable energy generation and platform load. The performance of the system can be optimized and it can adapt to dynamic circumstances by using advanced control algorithms like model predictive control and artificial intelligence approaches [183].

2.5.5.2 Economic and Environmental Impacts

- *Economic Impacts:* Integrating renewable energy sources and ESSs into OG platforms can result in substantial cost reductions by lowering fuel consumption and operational expenses [179]. Furthermore, less reliance on conventional sources of power can improve the platform's energy security and mitigate the risks associated with fuel price fluctuation. A thorough economic study should examine the hybrid power system's overall lifecycle costs, including capital expenditures, operational and maintenance costs, and possible savings from reduced emissions [176, 177, 184].

❏ *Environmental Impacts:* Hybrid power systems may greatly decrease the environmental impact of OG platforms by lowering greenhouse gas emissions, air pollution, and noise pollution. Incorporating renewable energy sources, like floating WTs and solar PVs, can help establish a more environmentally friendly power mix and aid the energy sector in its move to a low-carbon future. Environmental impact assessments should take into account not only emissions from power generation, but also the environmental implications of the manufacture, installation, and decommissioning of renewable energy systems [142, 184, 185].

2.5.5.3 Role of FPSO in Hybrid Power Systems

In the offshore oil and gas sector, Floating Production Storage and Offloading (FPSO) units are essential. The principal purposes of FPSOs, which are the extraction, processing, storage, and offloading of petroleum products as illustrated in Figure 4, make them complicated and energy-intensive activities in the offshore oil and gas industry [186].

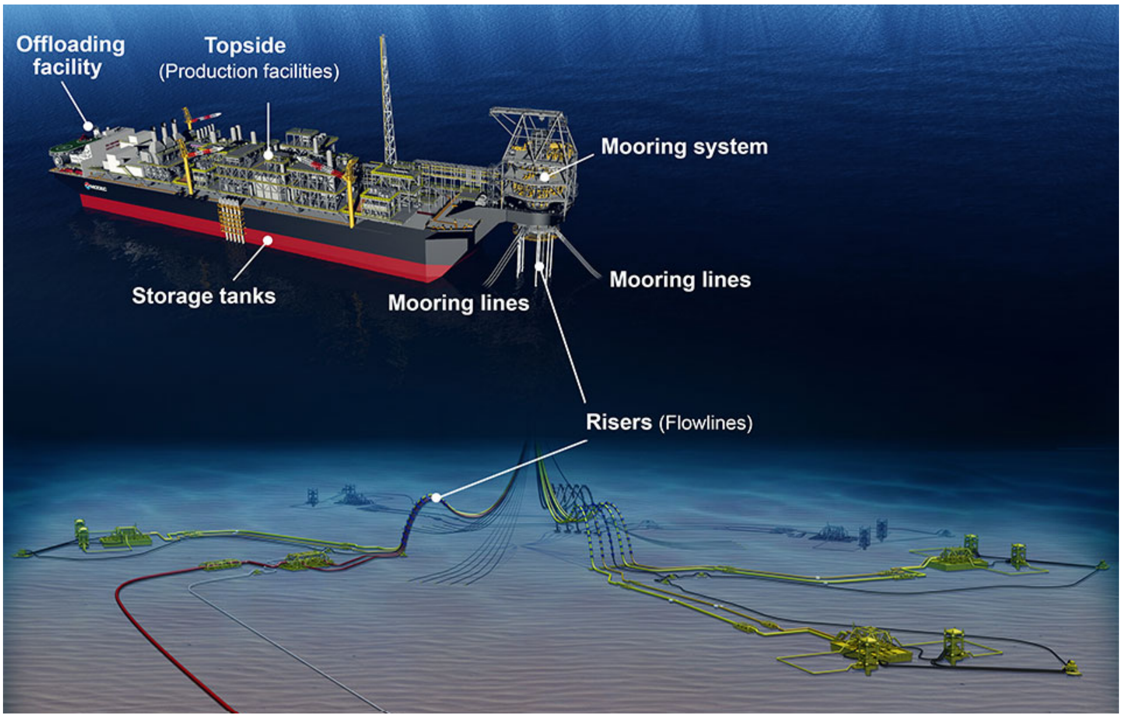


Figure 4 – Floating Production Storage and Offloading (FPSO) operation's illustration at the offshore deep-water OG extraction site. [186]

Integrating RE into FPSO hybrid power systems is becoming more important due to the demand for sustainability and the need for reducing greenhouse gas emissions. Alternative options for this integration may include wave energy converters, solar PVs, and WTs but these options are influenced by the FPSO's location and environmental factors [187].

The power system of FPSO needs a consistent and dependable energy source to run its production instruments, safety measures, and crew quarters [188]. Utilizing REin place of the conventional fossil fuels not only significantly reduces carbon emissions but may also result in long-term economic savings [187, 189]. However, it is crucial to guarantee the reliability and security of an FPSO's power supply [146], especially when incorporating RE sources [190]. The unpredictable nature of many RE sources makes the adoption of modern power management systems and energy storage technologies essential for maintaining continuous operations[191, 192].

In conclusion, hybrid power systems are essential for OG platforms to increase performance and reliability. These systems utilize RE sources, such as offshore wind, to reduce greenhouse emissions and minimize the reliance on the fossil fuels. By optimizing these resources, it promotes operational performance and cost savings. A greener and more robust oil and gas sector is produced via energy storage integration, which also enhances power management and grid stability. Additionally, the power systems of FPSOs have a lot of opportunity to evolve due to RE integration, enabling the OG platform more sustainable. However, it is essential to properly tackle the difficulties in preserving system stability and security in these new hybrid systems. [142, 146, 162, 164, 187, 193].

2.5.6 Case Studies and Implementations

Various case studies and real-world applications of hybrid power systems in OG platforms indicate the feasibility and benefits of bringing together RERs and ESSs. This section discusses some important cases as well as the lessons learned from their execution.

1. **Gullfaks Offshore Platform, Norway:** Equinor, a Norwegian multinational energy corporation, constructed a Hywind floating wind turbine at its Gullfaks offshore base in the North Sea [194]. The project sought to assess the viability of deploying floating WTs to power offshore OG platforms, thereby reducing the production of greenhouse gases and operational costs. The Hywind turbine's successful implementation highlighted the potential of floating wind technology as a sustainable and cost-effective power source for OG platforms [195, 196].

2. **DolWin3 Offshore Wind Farm, Germany:** A hybrid power system known as DolWin3 connects an offshore wind farm to an OG platform in the German North Sea. The system transfers power from the wind farm to the platform via a high-voltage direct current (HVDC) transmission system, which lowers power losses and assures a reliable power

supply [197]. The incorporation of the wind farm with the OG platform has resulted in considerable reductions in greenhouse gas emissions as well as an increase in the overall efficiency of the platform's power supply [198].

3. **Elk Hills Solar Project, California, USA:** The Elk Hills Solar Project consists of a large-scale PVs solar farm integrated into the Elk Hills OG plant of California Resources Corporation [199]. The 50 MW solar farm delivers clean, renewable power to the plant, reducing its reliance on traditional power sources and minimizing greenhouse gas emissions [200]. This project demonstrates the feasibility of integrating solar energy with OG operations on a large-scale, utility-connected scale [201].

4. **Gazprom Neft's OG Platform, Russia:** Gazprom Neft, a Russian energy firm, installed a hybrid power system at one of its Arctic OG platforms [202]. To reduce the platform's dependency on DGs, the design includes WTs, solar PVs, and battery storage [203]. The research has yielded encouraging results in terms of energy savings, lower emissions, and better power supply security, paving the path for greater use of hybrid power systems in the Arctic region [204].

5. **FPSO Cidade de Santos MV20:** In the case of the FPSO Cidade de Santos MV20, operated by MODEC off the coast of Brazil, a successful transition towards a hybrid power system was observed. In 2022, MODEC incorporated a compact wind turbine on the FPSO's deck to supplement traditional power sources, successfully reducing fuel consumption and emissions during periods of high wind. This initiative was further enhanced by incorporating energy storage solutions, providing continuous power supply irrespective of wind conditions. The success of the project, while signaling the potential of renewable energy in FPSOs, also highlighted the importance of a well-designed power management system, robust safety mechanisms, and strategic planning [205, 206].

These case studies and implementations highlight the potential of hybrid power systems for OG platforms, highlighting the advantages of combining renewable energy sources and ESSs. More OG platforms are anticipated to use hybrid power systems to improve their energy efficiency and lessen their environmental effect as technology develops and the demand for sustainable energy solutions rises.

CHAPTER 3

Methodology for Economic Dispatch and Flexibility in Standalone Hybrid Systems

This chapter presents the newly developed method to economically dispatch and analyse the flexibility of the standalone hybrid power system, with the consideration of efficiency curve of the Open Cycle Gas Turbine (OCGT)s and maximum ROCOF restrictions. The novel method is adopted in the python based environment, called LGridPy tool. The LGridPy tool (python-based) is for the power system analysis, developed by the LGrid of the University of Sao Paulo, to bridge the gap between the available power system analysis tools. The incorporation of renewable energy and the energy storage systems with the conventional power system of OG platform can result in significant reduction in operational cost and greenhouse gas emissions. Various tools are available in the market to model the electrical power system but not many, to analyse the flexibility of the power system, with the consideration of efficiency curve of the power system. In this chapter, the newly developed method will be discussed alone with the mathematical model, comparative analysis and simulations. The developed method considers various constraints (like ramp rates, minimum generator load, minimum uptime & downtime, startup & shutdown costs) and also incorporates the efficiency curve of the GTs that determine the least-cost strategy for the power system and the consideration ROCOF limit constraint ensures the power system security. The LGridPy tool is tested and compared with the PyPSA tool to validate the performance and robustness of the tool, resulting in a negligible average mean deviation for the power dispatch and operational cost. A case study is performed on **(a)**. Conventional OCGTs and **(b)**. State-of-the-Art OCGTs, based on the literature, for the OG platform. The case study shows the importance of efficiency curve consideration over the constant value of efficiency, to achieve more realistic and robust results. The results of the state-of-the-art OCGTs were significantly better, as the system was accommodating 34% of load variation, whereas, the conventional OCGT was able to accommodate the variation of only

7%. Therefore, the flexibility of the conventional power system should be assessed before, to accommodate and compensate the the variations of renewable resource.

3.1 Introduction

The flexibility of a power system is defined as the capability of the power system to incorporate the higher fluctuations of load and the higher share of power from the variable energy resources while ensuring the system's reliability and system operation at a low cost at any time series. From the generation perspective, power generation flexibility can be defined as the ability of the power plant to adjust the generation upon the deviation in the intentional or unintentional demand variation, within the constrained area of operation [20, 21]. As depicted in Figure 5, the flexibility options can be categorized into 5 key areas of the overall power system, i.e. **a.** System (power markets and operational structure of the power system), **b.** Supply (generation side flexibility), **c.** Demand (user side flexibility), **d.** Network (transmission side flexibility), and **e.** Energy Storage. [23, 22, 21]

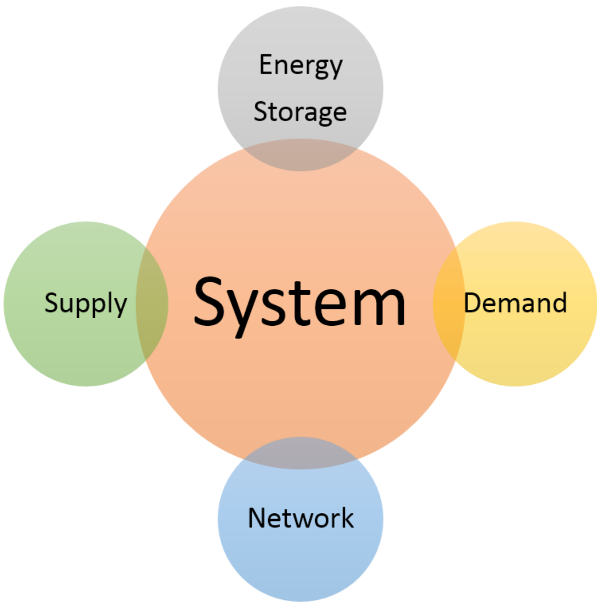


Figure 5 – Five key areas for the flexibility analysis of the power system [23]

From the generation side, there are some important flexibility attributes of generator as illustrated in Figure 6 that can be altered to increase the power system flexibility [207, 22, 208]:

- Ramp Rate: The ramp rate of the generators can be defined as the rate at which the generating unit can increase or decrease the output power, to meet the demand. It is generally calculated in percentage of the nominal power of the unit over minutes (% P_{nom}/min). For the conventional OCGTs, the ramp rate is considered at around 8-12%.

- ❏ Minimum Generator Load: The minimum generator loading or minimum generating level can be defined as the minimum allowable load on the generator unit, calculated as the percentage of nominal power of the unit ($\%\ P_{nom}$). The typical minimum loading value of the OCGTs are considered as 40-50%.

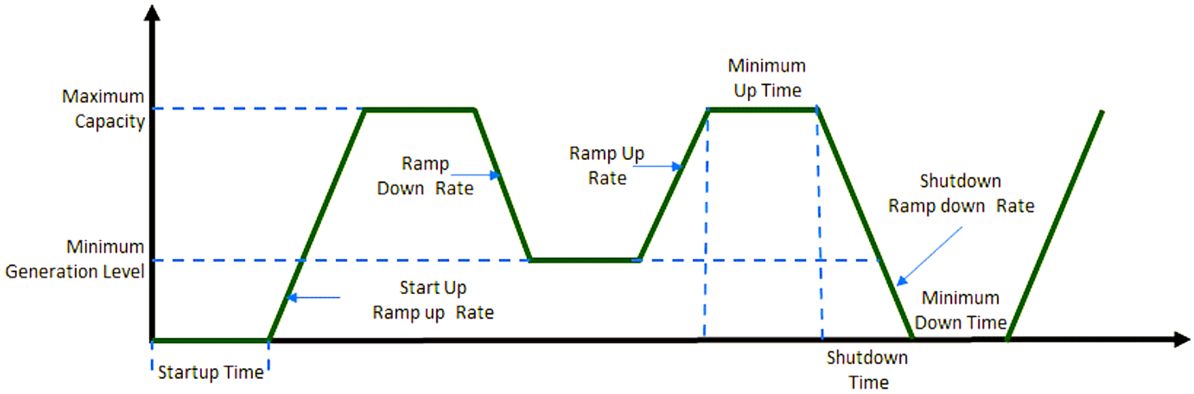


Figure 6 – Various flexibility attributes of generator. [207]

- ❏ Minimum uptime and downtime: The uptime and downtime of the generator is the minimum duration of time, for which the generator must be functional, before going offline and vice versa. The conventional uptime and downtime values are 10-30 minutes and 30-60 minutes, respectively.

- ❏ Startup and shutdown cost: There are some costs associated with the starting-up and shutting-down of the generator unit and it is usually considered in dollars per MW (USD/MW), with the typical value of 1-70 USD/MW for the OCGTs.

- ❏ Contingency Analysis: This relates to determining the stability of a power system in the event of a major failure or loss of power generating unit, such as the loss of a biggest gas turbine. This is known as an N-1 scenario, where N represents the usual state of the system and -1 represents the loss of a single component. This study assesses the system's ability to adapt to unexpected events or contingencies, helping in planning and operational decisions of the power system. Moreover, the "time to contingency"specifically refers to the duration left before the system breaches the frequency limit or threshold, after the N-1 scenario.

Whereas, the benefits of flexibilization are multifaceted and extend across the key areas of the power system as highlighted in Figure 7, which include system operation, CO_2 emissions, and power plant performance. In terms of system operation, flexibilization introduces optimized start-up procedures, enhances ramp rate capabilities, facilitates rapid turn-on and turn-off of generation units, and widens the overall operating range. These enhancements not only make the grid more adaptable to changes in demand and variable energy resources but also foster more reliable and cost-effective system operations [21].

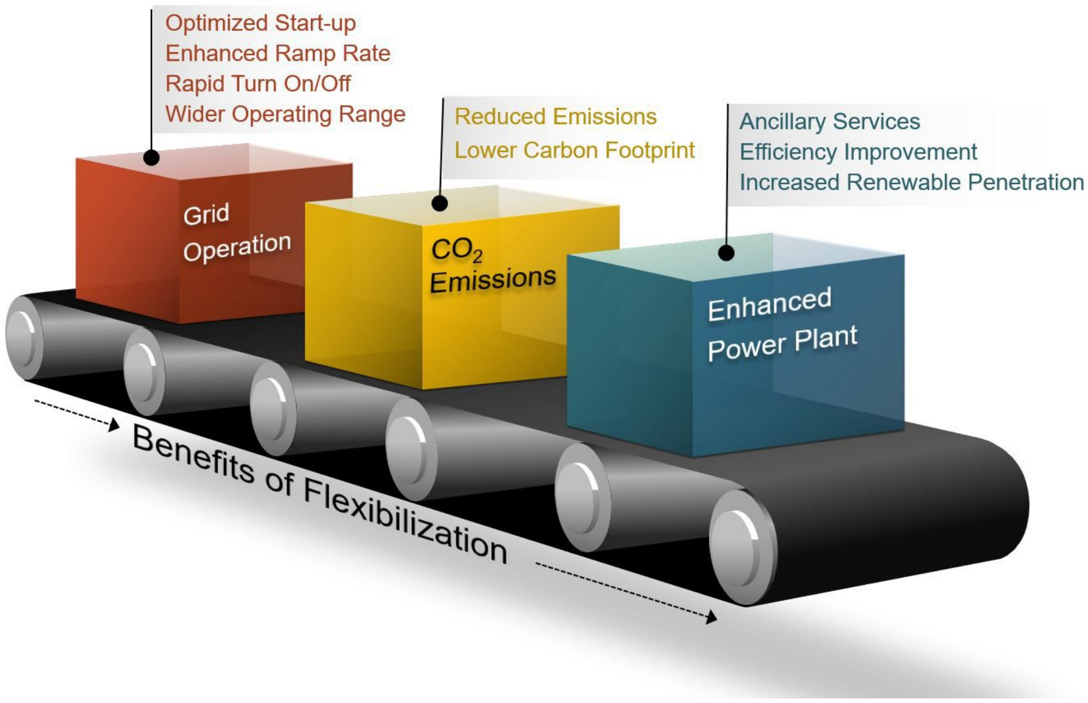


Figure 7 – The benefits of flexibilization for the electrical power system.

Moreover, flexibilization significantly contributes to the environmental aspects of power generation, leading to reduced CO_2 emissions and a lower carbon footprint. This is achieved through increased efficiency and a higher share of power from renewable energy sources, fostering sustainable energy practices and aligning with global decarbonization goals [22]. Lastly, flexibilization results in an enhanced power plant by supporting ancillary services, improving efficiency, and promoting increased renewable penetration. Ancillary services ensure grid stability, while efficiency improvements contribute to economic savings. The increased integration of renewables, on the other hand, mitigates the risks associated with the reliance on fossil fuels and supports the grid's resilience against regulatory risks associated with carbon emissions [23]. Consequently, the benefits of flexibilization manifest in the form of a more reliable, efficient, and sustainable power system.

Therefore, the novel methodology, adopted by the python-based LGridPy tool is presented in this chapter to bridge the gap between the power system analysis tools. LGridPy can model the economic dispatch and analyse the flexibility of the standalone hybrid power system, with the consideration of efficiency curve of the OCGTs and maximum ROCOF restrictions. Whereas, the Figure 8 illustrates the novelty of the newly developed tool in comparison with the other available software/tools. In addition, LGridPy is a free, transparent, and user-extendable software thus the source code is available for revisions and improvements for all users and the motivation of the tool is the limitation of an other open source software called PyPSA [26].

SOFTWARE	VERSION	FIRST RELEASE	LAST UPDATE	OPEN-SOFTWARE	TIMESERIES	OPTIMAL DISPATCH	UNIT COMMITMENT	ECONOMIC DISPATCH	FLEXIBILITY ANALISYS	GENERATOR MODEL	WIND TURBINE MODEL	ENERGY STORAGE SYSTEM MODEL	EFICIENCY CURVE CONSIDERATION	ROCOF LIMIT CONSTRAINT	OPERATING RESERVES CONSTRAINT	TIME TO CONTINGENCY ANALYSIS
FESTIV Model	1.0.0	Jun. 2014	Sep. 2022	✓	✓	☐	✓	✓	✓	✓	☐	✓	☐	✓	✓	☐
Oemof	0.4.0	Nov. 2015	Oct. 2022	✓	✓	✓	✓	☐	☐	✓	✓	☐	☐	☐	✓	☐
Power GAMA	1.1.0	Dec. 2014	Fev. 2017	✓	✓	✓	✓	☐	☐	✓	✓	✓	☐	☐	✓	☐
PyPSA	0.21.2	Jan. 2016	Nov 2022	✓	✓	✓	✓	✓	✓	✓	✓	✓	☐	✓	✓	✓
Switch 2.0	2.0.7	Aug. 2018	Mar. 2021	✓	✓	✓	✓	✓	☐	✓	✓	✓	✓	✓	✓	☐
URBS	1.0.0	Dec. 2014	Feb. 2022	✓	✓	✓	✓	☐	☐	✓	✓	☐	☐	☐	✓	☐
LGrid-Py	--	--	--	✓	✓	☐	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Figure 8 – LGridPy features comparison with the selected software and tools.

3.2 Model Design

In this section, the LGridPy methodology is described, including the models of generator, wind turbine, and energy system, along with the constraints and the objective function. The main variables along with units and descriptions can be found in Table 9.

3.2.1 Efficiency Curve Fitting

In order to calculate the parameters of the efficiency curve fitting, LGridPy considers the efficiency of the generators at different dispatches. The parameters are fitted according to the equation:

$$ef(p) = a \cdot p^2 + b \cdot p \tag{21}$$

Here, $ef(p)$ represents the efficiency at dispatch p (in per unit), and a and b are the quadratic and linear parameters of the efficiency curve fitting, respectively.

3.2.2 Objective Function

After calculating the efficiency curve parameters, LGridPy minimizes the total system costs, including generators' fuel cost, start-up cost, shut-down cost, and maintenance cost. The objective function is given by:

$$minimize \sum_{g} \sum_{t} (FuelCost_{g,t} + SUC_{g,t} + SDC_{g,t} + MC_{g,t}) \tag{22}$$

The $FuelCost_{g,t}$, $SUC_{g,t}$, $SDC_{g,t}$, and $MC_{g,t}$ represent the fuel cost, start-up cost, shut-down cost, and maintenance cost of generator g at snapshot t, respectively. The fuel cost for a generator is calculated by multiplying the power consumed by the generator with the fuel price.

$$FuelCost = P_{fuel} \cdot FuelPrice \tag{23}$$

P_{fuel} is calculated using the efficiency curve:

$$P_{fuel} = P_{nom}/b \cdot [a/b \cdot p + 1]^{-1} \tag{24}$$

In the above equation, P_{nom} is the nominal power, and a and b are the parameters of the efficiency curve fitting. The term p represents the power dispatch of the generator.

According to Newton's Binomial theorem, the equation can be re-written as:

$$P_{fuel} = P_{nom}/b \cdot (1 - x + x^2 - x^3) \tag{25}$$

To avoid the presence of fuel power when the dispatch is zero, we multiply the equation by the gas generator status u:

$$P_{fuel} = P_{nom}/b \cdot [1 - x + x^2 - x^3] \cdot u \tag{26}$$

In this equation, x is the variable calculated as $a/b \cdot p$, which represents the power dispatch of the generator.

Thus, this model design aims at optimizing the total system cost under several constraints, giving us an efficient and economical dispatch for the generators.

3.2.3 Constraints

The generators' operations are submitted to several dynamic constraints such as, minimum and maximum power dispatch, ramp up and ramp down limits, minimum uptime and downtime. Each generator has its own independent constraints, which depends exclusively on its own parameters. LGridPy also implements energy storage units, which are submitted to maximum charge and discharge constraints, a state of charge constraint, and two auxiliary constraints: cyclic storage and exclusive behaviour. The tool also consider the required spinning reserve constraint and ROCOF limit constraint. Finally, a power balance equation is set as a constraint of the network.

3.2.3.1 Minimum and Maximum Power Dispatches

At each snapshot of simulation, if the generator is off ($u_{g,t} = 0$) both minimum and maximum power dispatches are set to zero. Otherwise, when the generator is On, i.e. $u_{g,t} = 1$, the dispatches lower and upper bounds are set to $Pmin_g$ and $Pmax_g$ respectively. Thus the constraints are as follows:

$$\begin{aligned} -P_{g,t} + Pmin_g \cdot u_{g,t} \leq 0 \\ P_{g,t} - Pmax_g \cdot u_{g,t} \leq 0 \end{aligned} \tag{27}$$

Whereas, the $P_{g,t}$ represents the dispatch of generator g at snapshot t, $Pmin_g$ and $Pmax_g$ are the minimum and maximum power dispatch of generator g, and $u_{g,t}$ is the generator g status at snapshot t.

For the wind turbines, a special maximum power dispatch constraint is implemented considering the maximum allowed wind penetration, power curve, electromechanical conversion efficiency and wind speed.

For the wind turbines, a special maximum power dispatch constraint is implemented considering the maximum allowed wind penetration, power curve, electromechanical conversion efficiency, and wind speed. The maximum dispatch for wind turbines is given by:

$$P_{w,t} \leq \min(pc_w(ws_t) \cdot \eta_{emc}, wp \cdot P_{L,t}) \tag{28}$$

Whereas, the $P_{w,t}$ is the power dispatch of wind turbine w at instant t, pc_w is the power curve of wind turbine w, ws_t is the wind speed at instant t, η_{emc} is the electromechanical conversion efficiency, wp is the allowed wind penetration, and $P_{L,t}$ is the load demand at instant t.

3.2.3.2 Ramp-up and Ramp-down Limits

The ramp-up and ramp-down constraints limit the generator's dispatch maximum up and down variation between two consecutive snapshots. Besides for the first snapshot, the model considers the ramping limits for each snapshot of the simulation:

$$\begin{aligned} P_{g,t} - P_{g,t-1} \leq rul_g \cdot u_{g,t} \\ -P_{g,t} + P_{g,t-1} \leq rdl_g \cdot u_{g,t} \end{aligned} \tag{29}$$

Whereas, the $P_{g,t}$ represents the dispatch of generator g at snapshot t and $P_{g,t-1}$ is the dispatch for the same generator on the previous snapshot, rul_g and rud_g are the ramp-up limit and ramp-down limit for generator g respectively, $u_{g,t}$ is the generator g status at snapshot t.

3.2.3.3 Minimum Uptime and Downtime

To implement both minimum uptime and downtime, LGridPy assumes all the dispatches must be non-negative. Thus, the constraints are written as follows:

For minimum uptime:

$$\sum_{t'=t}^{t+mut_g} u_{g,t'} \geq mut_g \cdot (u_{g,t} - u_{g,t-1}) \tag{30}$$

Here, mut_g is the minimum uptime of generator g, $u_{g,t}$ is the generator g status at snapshot t and $u_{g,t-1}$ is the status of the same generator on the previous snapshot.

For minimum downtime:

$$\sum_{t'=t}^{t+mdt_g} u_{g,t'} \leq mdt_g \cdot (u_{g,t} - u_{g,t-1} + 1) \tag{31}$$

In this equation, mdt_g is the minimum downtime of generator g. Assuming t_{len} is the snapshots data length, if $t + mdt_g > t_{len}$, LGridPy replaces the sums upper limits by t_{len}. The same replacement is done to the minimum up time constraint.

3.2.3.4 Storage Maximum Charge and Discharge

The maximum charge and discharge constraints limit the power consumed and provided by the storage units in the system. Thus, for each snapshot, the expressions are:

$$\begin{aligned} c_{s,t} &\leq uc_{s,t} \cdot Pnom_s \\ d_{s,t} &\leq ud_{s,t} \cdot Pnom_s \end{aligned} \tag{32}$$

Whereas, $c_{s,t}$ and $d_{s,t}$ are the charge and discharge power of storage s at snapshot t, $uc_{s,t}$ and $ud_{s,t}$ are the storage s charge and discharge statuses, respectively, at snapshot t, i.e. $uc_{s,t} = 1$ if the storage is charging or $ud_{s,t} = 1$ if it is discharging. $Pnom_s$ is the nominal power of the storage s.

3.2.3.5 Storage State of Charge

LGridPy implements the state of charge for the storages in each snapshot considering the charging and discharging efficiencies, as well as the self-losses:

$$soc_{s,t} = \eta_{sl} \cdot soc_{s,t-1} - \eta_d^{-1} \cdot d_{s,t} + \eta_c \cdot c_{s,t} \tag{33}$$

Whereas, $soc_{s,t}$ is the state of charge of storage s at snapshot t, and $soc_{s,t-1}$ is the state of charge of the same storage in the previous snapshot. The $c_{s,t}$ and $d_{s,t}$ variables are the charge and discharge power of storage s at snapshot t. The efficiencies η_{sl}, η_d and η_c stand for self losses, discharging and charging respectively.

Furthermore, two special equations are considered for the first snapshot regarding if the storage is cyclic or not. If the storage is not cyclic, a initial state of charge $soc_{s,-1}$ must be provided by the user:

$$soc_{s,0} = \eta_{sl} \cdot soc_{s,-1} - \eta_d^{-1} \cdot d_{s,0} + \eta_c \cdot c_{s,0} \tag{34}$$

Otherwise, if the storage is cyclic, the state of charge of the last snapshot $soc_{s,T}$ is considered:

$$soc_{s,0} = \eta_{sl} \cdot soc_{s,T} - \eta_d^{-1} \cdot d_{s,0} + \eta_c \cdot c_{s,0} \tag{35}$$

3.2.3.6 Cyclic Storage

An auxiliary constraint is set in the case of a cyclic storage. The state of charge in the final snapshot must be equal to the state of charge in the first snapshot:

$$soc_{s,T} = soc_{s,0} \tag{36}$$

In the case of a non-cyclic storage, a final state of charge $soc_{s,final}$ can be set:

$$soc_{s,T} = soc_{s,final} \tag{37}$$

Nevertheless, if the storage is not cyclic and no final state of charge is passed, this constraint is ignored.

3.2.3.7 Storage Exclusive Behaviour

In order to prevent a storage unit of charging and discharging in the same snapshot, an exclusive behaviour constraint is implemented in the model for each snapshot:

$$uc_{s,t} + ud_{s,t} \leq 1 \tag{38}$$

Whereas, $uc_{s,t}$ is the charging status of storage s at snapshot t, and $ud_{s,t}$ is the discharging status of the same storage in the same snapshot. The statuses variables are considered binary, i.e. $uc_{s,t} = 1$ if the storage is charging or $uc_{s,t} = 0$ if it is not charging. Similarly, $ud_{s,t} = 1$ if the storage is discharging, or $ud_{s,t} = 0$ when the storage is not discharging. According to the equation above, the model allows a storage to not charge nor discharge in a given snapshot ($uc_{s,t} + ud_{s,t} = 0$), but charging and discharging simultaneously is forbidden ($uc_{s,t} + ud_{s,t} = 2$).

3.2.3.8 Spinning Reserve Constraint

LGridPy implements a required spinning reserve variable in the model that must be satisfied at each snapshot:

$$SR_t = \sum_g^{GT} [u_{g,t} \cdot (Pmax_g - P_{g,t}) \cdot v_{g,t}] \geq RSR \tag{39}$$

Whereas, $u_{g,t}$, and $P_{g,t}$ are the status and the power dispatch respectively of gas generator g at snapshot t. $Pmax_g$ is the maximum power dispatch of the gas generator g. The value $v_{g,t}$ is a parameter of the generator unit and represents its availability at snapshot t, modeling, for example, a case where the generator is suddenly shut down by a defect.

RSR stands for Required Spinning Reserve and to simulate the N-1 strategy, it is calculated by considering the maximum power output generator among the maximum power outputs of the active gas generators:

$$RSR = max(Pmax_g) \tag{40}$$

3.2.3.9 Minimum ROCOF Constraint

In order to model the frequency response of the network, the minimum ROCOF constraints is implemented to restrict the power system to a certain value of ROCOF limit (RL) and can be written as:

$$\frac{f_0}{2H_{eq}} \cdot \frac{\left(\sum_g^{GT} P_{g,t}\right) - max(Pmax_g) + \sum_w^{WT} P_{w,t} + \sum_s^{ST} P_{s,t} - P_{L,t}}{S_{rated,t}} \geq RL \tag{41}$$

Whereas, $P_{g,t}$, $P_{w,t}$ and $P_{s,t}$, respectively, are the power dispatch of gas generator g, wind generator w and storage unit s at snapshot t. $max(Pmax_g)$ is the maximum power dispatch among the maximum power dispatches of the active gas generators. $P_{L,t}$ is the power demand at snapshot t, f_0 is the natural frequency of the network, $S_{rated,t}$ is the sum of nominal powers of all active gas generators at snapshot t and RL is the ROCOF limit, a parameter of the network.

H_{eq} stands for equivalent constant of inertia. For the coherent GTs in the power system with all the active gas generators have the same constant of inertia H_g, H_{eq} is calculated as following:

$$H_{eq} = \sum_g^{GT} H_g \tag{42}$$

For non-coherent generators, the equivalent inertia is calculated differently. Each generator has its own speed, and thus its own inertia contributes differently to the system. The equivalent inertia, H_{eq}, for non-coherent generators can be calculated using the following equation:

$$H_{eq} = \sum_g^{GT} \frac{P_{g,t}}{P_{total,t}} H_g \tag{43}$$

In this equation, $P_{g,t}$ is the power output of generator g at time t, $P_{total,t}$ is the total power output of the system at time t, and H_g is the inertia constant of generator g. The summation is over all active gas generators in the system. This equation essentially calculates a weighted sum of the inertia constants of all generators, where the weights are the fractions of total power output contributed by each generator.

Likewise, the minimum spinning reserve constraint considers the spinning reserve SR_t in the equation:

$$\frac{f_0}{2H_{eq}} \cdot \frac{\left(\sum_g^{GT} P_{g,t}\right) - max(Pmax_g) + SR_t + \sum_w^{WT} P_{w,t} + \sum_s^{ST} P_{s,t} - P_{L,t}}{S_{rated,t}} \geq RL \tag{44}$$

3.2.3.10 Power Balance

Finally, a power balance equation is modeled in order to assure the total generation follows the demand in each snapshot:

$$\sum_g^{GT} P_{g,t} + \sum_w^{WT} P_{w,t} + \sum_s^{ST} P_{s,t} = P_{L,t} \tag{45}$$

Whereas, $P_{g,t}$, $P_{w,t}$ and $P_{s,t}$, respectively, are the power dispatch of gas generator g, wind generator w and storage unit s at snapshot t. $P_{L,t}$ is the power demand at snapshot t. The power dispatched by a storage s at snapshot t ($P_{s,t}$) is calculated as:

$$P_{s,t} = -c_{s,t} + d_{s,t} \tag{46}$$

With $c_{s,t}$ and $d_{s,t}$ representing the storage's charging and discharging power respectively.

3.2.4 Solution Method

Firstly, the LGridPy simulates the power system operation by considering the effect of the relevant dynamic parameters that characterize the power system. LGridPy is modelled to make the generated power to follow the load demand and maintain the power balance. Along with that, the total cost of the system is calculated by taking into account the (a). Marginal fuel cost (represented as the quadratic equation), (b). Start-up costs, (c). Shut-down costs, and (d) Maintenance cost. Lastly, the above-mentioned constraint must be met and satisfied in order to guarantee system feasibility and the system economic dispatch solution must respect all constraints of all generating units. On the other hand, when the any of the constraint is violated, the LGridPy will flag the infeasible solution as the model is unable to calculate a solution that respects the constraint. In addition to that, the Figure 9 shows the flow chart for the tool.

Furthermore, to simulate the above-mentioned model, the LGridPy adopts the Mixed-Integer Nonlinear Programming (MINLP). The MindtPy solver, which is an open source software package, is used to solve the MINLP. The MindtPy algorithm decomposes the MINLP in two minor problems: (a). Mixed-Integer Linear Programming (MILP) and (b). Nonlinear Problem (NLP). The MILP solves the model's constraints that are linear, while, NLP solves the non-linear quadratic objective function with power dispatch, start-up, shut-down costs, and maintenance cost variables. In order to solve the minor problems, MindtPy makes use of the Gurobi solver for the MILP and IPOPT for the NLP. Finally, MindtPy merges the results, checks the solution feasibility, and if all constraints are respected, results the optimal solution for the problem. The decomposition routine implemented by MindtPy relies on the Outer Approximation (OA) and Extended Cutting Plane (ECP) algorithms [209].

3.2.5 Limitations of the Method

- **Objective Function:** The objective function may not account for all possible costs or factors, such as environmental impact, regulatory compliance, or unexpected breakdowns. Also, the WTs and STs costs are considered zero.

- **Solution Method:** The use of the Mixed Integer Nonlinear Programming (MINLP) technique and the MindtPy solver may not be the most efficient or accurate methods for all types of problems.

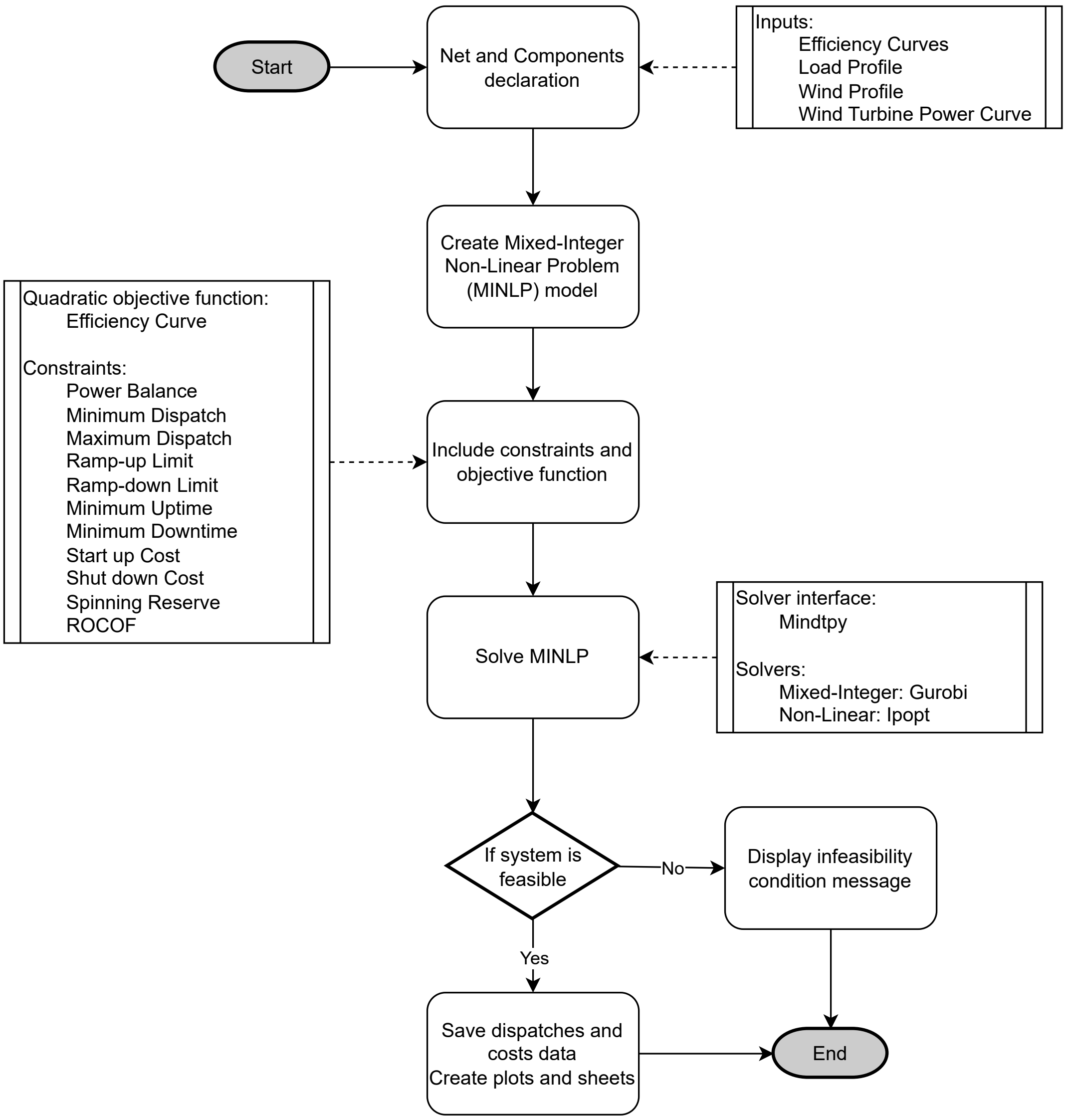


Figure 9 – The Flow Chart of LGridPy tool.

- **System Model:** The model does not account for transmission losses and assumes a single bus to connect all the generating units, which may not be representative of real-world power systems.

- **Problem Scope:** The model focuses only on the ED and UC problems, but does not consider other important aspects such as optimal power flow or optimal dispatch, which could limit its applicability in certain scenarios.

- **Simulation Time:** The simulation time can be slow and varies for different configurations. For configurations with only GTs, the LGridPy takes around 10 seconds. However, for configurations with GTs, WTs, and STs along with all the constraints, it takes between 1

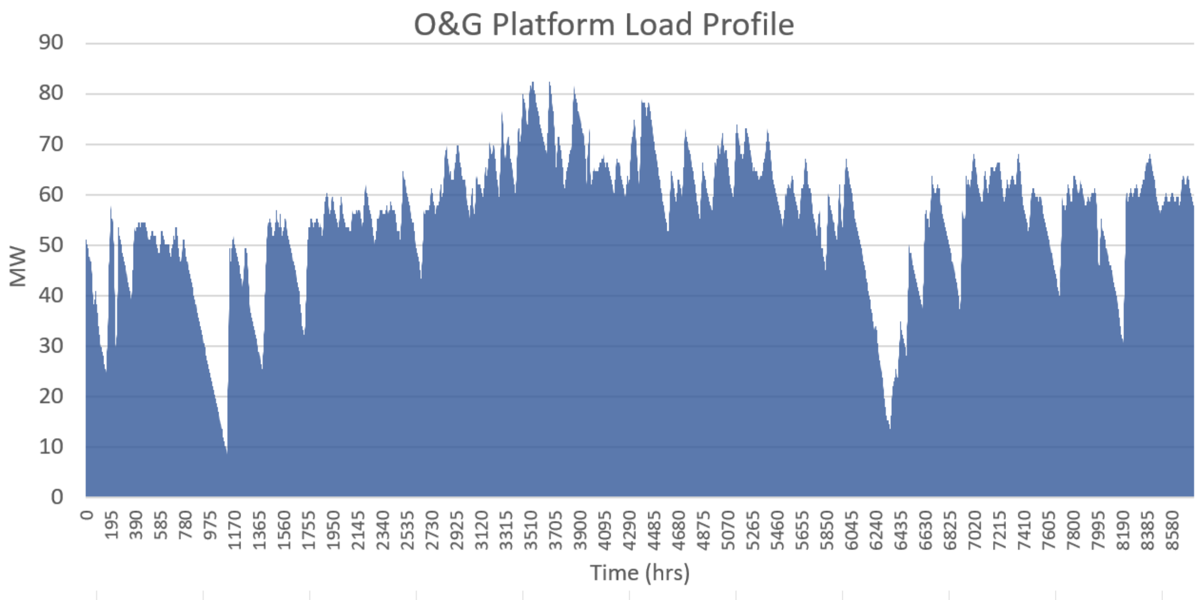


Figure 10 – OG Platform Load Profile with the resolution of 1 hour. [139]

to 2 minutes for 100 hours of simulations. This could limit the model's efficiency in larger or more complex scenarios.

3.3 LGridPy Test

The LGridPy is implemented to signifies the novelty of the tool and analyse the case studies to assess the robustness and effectiveness of the tool. In this section, the LGridPy is authenticated and implemented under different scenarios.

3.3.1 Power System Model

To to test the performance of the tool, various parameters are being considered:

3.3.1.1 Load Profile of Oil and Gas Platform

The load profile illustrated in Figure 10, corresponds to the realistic data from an OG platform's standalone power system, located at the North Sea, Norway. The OG platform load profile is relatively constant for a lengthy period of time as most of the consumption on the platform is dominated by large electrical loads like water injection systems and drilling equipment. However, the other spikes in the load curve are contributed by the other installed equipment like compressors, thermal processing equipment, and cranes, etc. [139].

3.3.1.2 Generators Detail

For this study, 4 similar GTs are considered with identical efficiency curves and quadratic fuel equations. As tabulated in the Table 9 for the LGridPy, the nominal power of all 4 GTs are considered 33.3 MW (as of GT LM2500+PJ) [210], and the minimum power (Pmin) and the maximum power (Pmax) of the gas turbine is selected as 40% (Pmin =13.32) of the nominal power and 100% (Pmax=33.3MW) of the nominal power, respectively.

Table 9 – Parameters of LGridPy and PyPSA for the comparative analysis. [16, 25, 26, 208]

Parameters	LGridPy	PyPSA
Load Profile	Figure 10	Figure 10
Nominal Power (P_{nom})	33.3MW	33.3MW
Minimum Power	13.32MW	13.32MW
Maximum Power	33.3MW	33.3MW
Minimum Up-time	10 minutes	10 minutes
Minimum Down-time	30 minutes	30 minutes
Ramp Up-limit	4MW	4MW
Ramp Down-limit	4MW	4MW
Ramp Limit Start-up	-	4MW
Ramp Limit Shut-down	-	4MW
Startup Cost	70 $	70.00 $
Shutdown Cost	70 $	70.00 $
Fuel Price	200 $/MW	-
Marginal Cost of GT1 Marginal Cost of GT2 Marginal Cost of GT3 Marginal Cost of GT4	- - - -	540.54 $/MW 600.00 $/MW 689.66 $/MW 740.74 $/MW
Efficiency Value of GT1 Efficiency Value of GT2 Efficiency Value of GT3 Efficiency Value of GT4	0.37 0.333 0.29 0.27	100% 100% 100% 100%
Objective Function	$\sum_{g,t} b_g \cdot \lambda \cdot P_{g,t} + suc_{g,t} + sdc_{g,t}$	$\sum_{g,t} marginalcost_g \cdot p_g + suc_{g,t} + sdc_{g,t}$

3.3.2 LGridPy Validation

The performance and authenticity of the LGridPy can be validated by testing the developed tool with a well-known software like PyPSA [26, 25]. PyPSA simulates, optimizes, and models the power system, including the unit commitment of conventional generator model, renewable generation model, energy storage model, etc. Therefore, the LGridPy is put in comparison with the PyPSA to validate the performance of the developed tool model and prove the reliability of the LGridPy tool.

As can be seen from the Figure 10, the LGridPy and PyPSA are simulated to analyze the unit commitment and economic dispatch for the given case study. The case study utilizes the load profile of sections 3.3.1.1, but with the consideration of 100 hours to validate the performance of the LGridPy. The key parameters that are considered for the simulation are tabulated in the Table 9. The key considerations assumed for the comparative study are as under:

- The load profile for the analysis is considered only 100 hours.

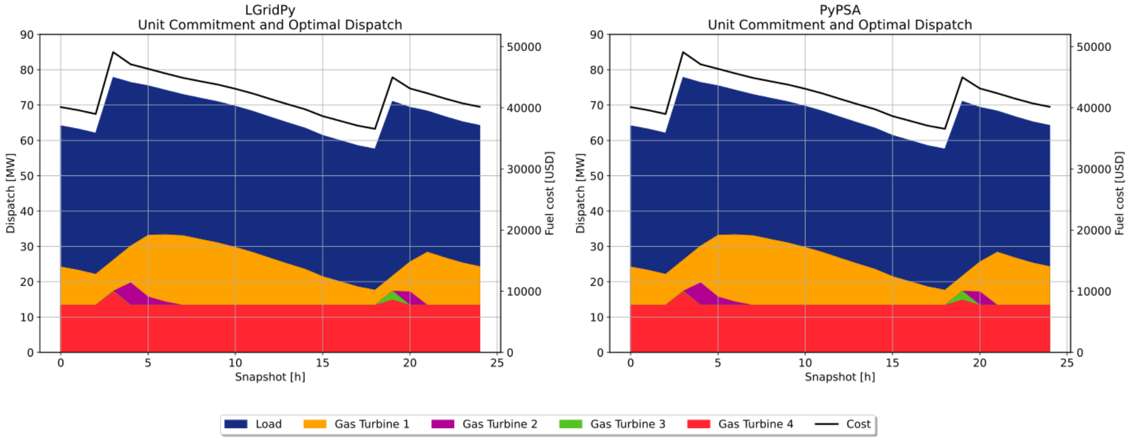


Figure 11 – Comparative study of LGridPy and PyPSA results, depicting negligible deviation

- Since the PyPSA tool only accepts the single efficiency value, instead of the efficiency curve (which is the main feature of the LGridPy tool), the LGridPy generator model is modified to accommodate the single value of efficiency.

- The generators efficiencies are considered as 37%, 33.3%, 29% and 27%, respectively.

- Since both simulations must have the exact same objective functions, the marginal costs of PyPSA GTs are calculated as following:

$$marginalcost_g = \frac{\pi}{efficiencyvalue_g} \tag{47}$$

Whereas, the π represents the fuel price and the $efficiencyvalue_g$ is the provided efficiency values for the generator g .

The Figure 11 illustrates the LGridPy and PyPSA comparative study results and both the tools simulate the case study with almost similar results. The power dispatch mean deviation and mean cost deviation of all the GTs are observed negligible. From the results, it is concluded that the LGridPy performs accurately as the PyPSA. Hence, this validates and authenticates the performance of LGridPy tool.

3.3.3 Efficiency Curve vs Constant Efficiency Value

The special feature of the newly developed tool is the incorporation of the efficiency curve of the OCGTs, rather than the constant value to efficiency. For the power system analysis, the market has the freely available and paid tools/softwares to simulate the power system, but the majority of the tools considers the constant value of efficiency for the OCGTs. Therefore, it is important to analyze the effects of both, efficiency curve and constant efficiency value for the OCGT model and assess the outcomes, especially for the standalone power systems.

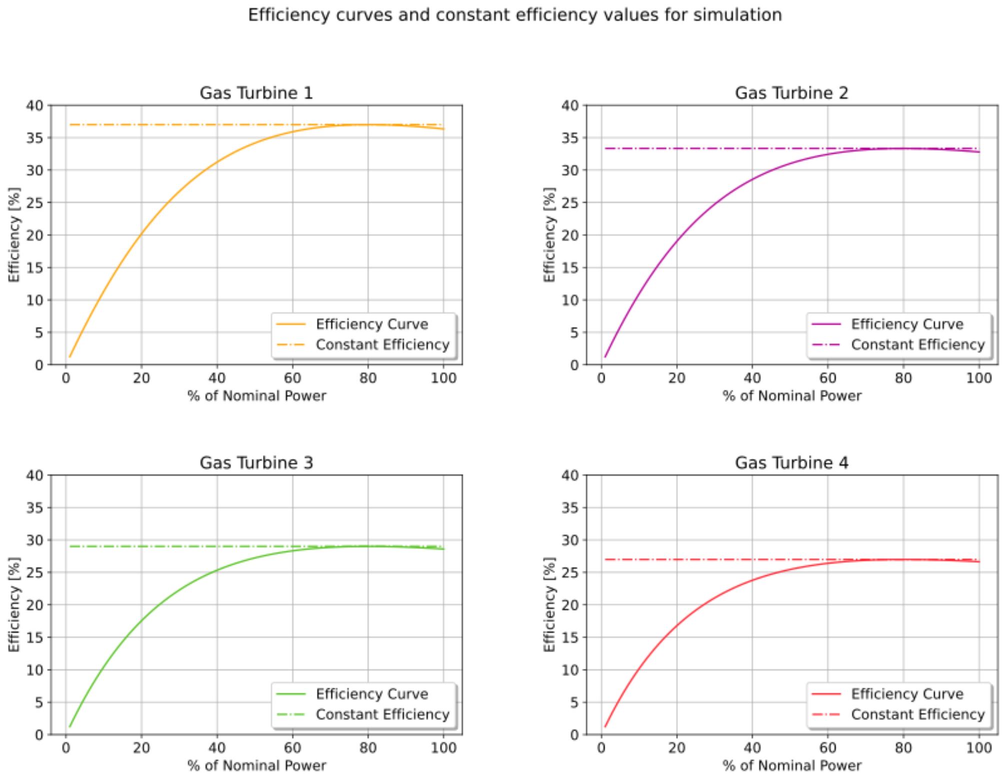


Figure 12 – Efficiency Curves and constant value efficiency of 4 different gas turbines, considered for the analysis.

This analysis is vital to show the impact of constant efficiency value over the efficiency curve of the OCGT for simulating the isolated power system response. The Figure 12 illustrates the different values of constant efficiency and the efficiency curves for the 4 different OCGTs, which are assumed to conduct the study.

The standalone power system of OG platform is simulated for both the constant value of efficiency and the efficiency curve with the 4 OCGTs with there corresponding dynamic constraints like, ramp rates, minimum load value, and the minimum up and down time as tabulated in Table 9. Also, it is to be noted that for this analysis, the maintenance cost, the ROCOF and spinning reserves constraints are not considered.

As can be seen from Figure 13, there is a notable change in the optimal dispatches of the power system. Since, the OCGTs tend to perform efficiently near to their maximum capacity, the OCGT with the efficiency curve tends to take time to reach the maximum efficiency, resulting in a different dispatch with higher fuel cost, and higher CO_2 emissions. The figure 13(a) illustrates the variation in power dispatch of the 4 OCGTs (considering the efficiency curve over the constant efficiency value).

While the Figure 13(b) illustrates the percentage change in the cost of the power system with consideration of efficiency curve over the constant value of efficiency, peaking the change at 15%, due to the inefficient performance and high fuel consumption of the OCGTs at the

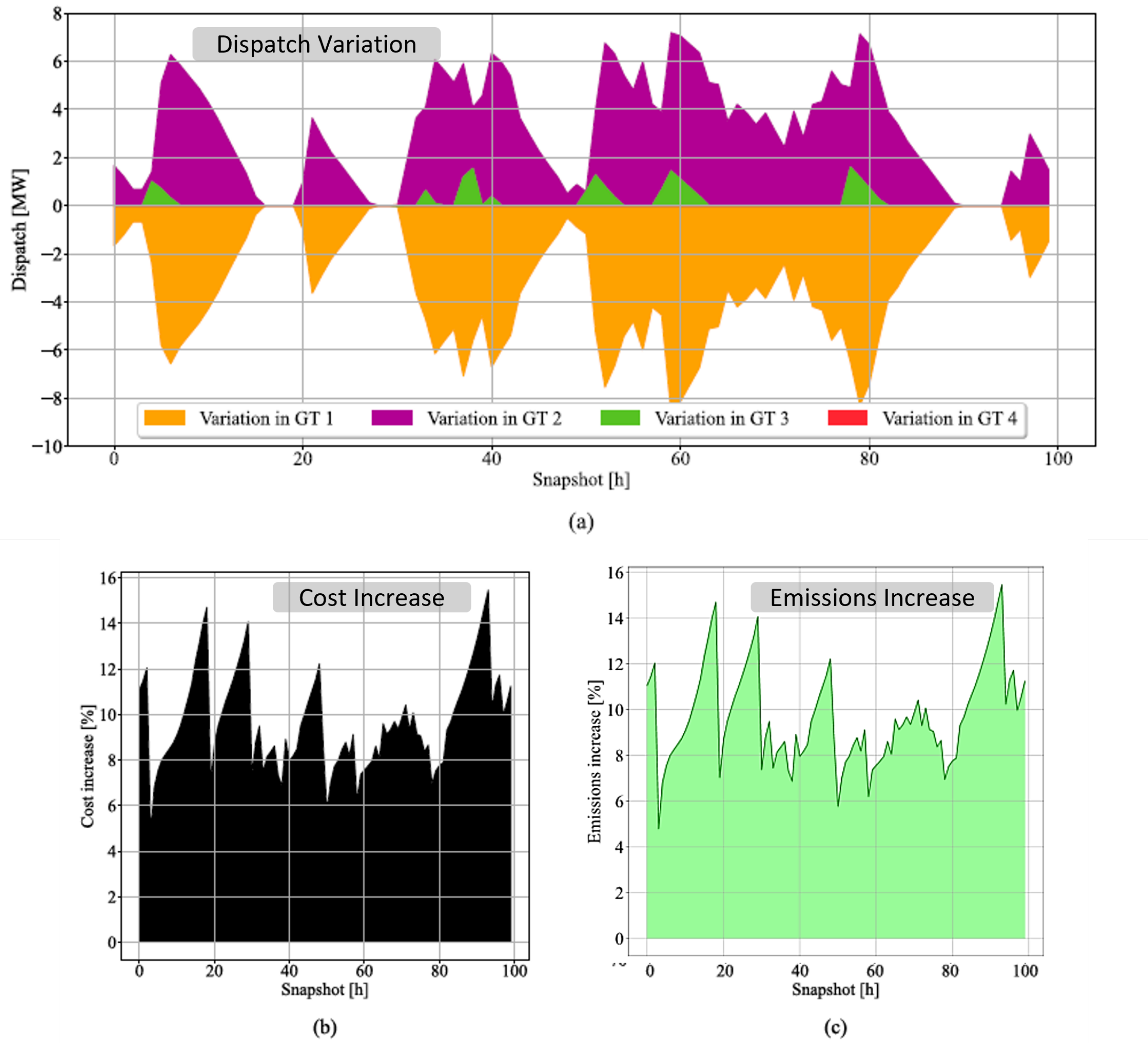


Figure 13 – System Response for the Efficiency Curve over the Constant Efficiency Value: (a). Optimal dispatch variation of the considered efficiency curve over the constant efficiency value of the 4 OCGTs. The difference in the dispatch is due to the efficiency curve of the OCGT, since it takes time to reach to the maximum power over the constant efficiency value, as the OCGT is already delivering power at maximum level. (b). The percentage cost increase for the considered efficiency curve OCGTs over the constant efficiency value OCGTs due to the high consumption of fuel at lower level of efficiency. (c). The percentage CO_2 emissions increase for the considered efficiency curve OCGTs over the constant efficiency value OCGTs due to the high consumption of fuel at lower level of efficiency.

lower efficiency values. Similarly, variation in the CO_2 emissions can be seen from figure 13(c), portraying the significant change in CO_2 emissions. For the initial snapshot[1], the difference of 10 tons of CO_2 emission can be seen and this huge variation signifies the importance of the implementation for the efficiency curve instead of a single value of efficiency in the power system analysis to achieve the realistic results.

[1] "snapshot"refers to each discrete time step in the simulation, allowing for detailed analysis of the system's behavior at specific intervals.

3.4 Case Studies: Operational Capabilities Analysis

The case studies are performed on the conventional and state-of-the-art OCGTs for the offshore standalone power system of OG platform, without the consideration of spinning reserve margins and the ROCOF constraints. The study will demonstrate the operational capabilities of both the systems under different load variations. The results will provide the insights into the feasibility of the power system and the amount of flexibility required to coup with the variations of demand and supply at the platform, highlighting the importance of flexibility analysis before the incorporation of RERs.

Table 10 – Parameters of conventional OCGT and state-of-the-art OCGTs of the standalone power system of OG platform based on the [16, 208].

Parameters	Conventional OCGT	State-of-the-Art OCGT
Load Profile	Figure 10	Figure 10
Efficiency Curve	Figure 12	Figure 12
Nominal Power (P_{nom})	33.3MW	33.3MW
Minimum Power	13.32MW (40% of P_{nom})	6.66MW (20% of P_{nom})
Maximum Power	33.3MW (100% of P_{nom})	33.3MW (100% of P_{nom})
Minimum Up-time	10 minutes	10 minutes
Minimum Down-time	30 minutes	30 minutes
Ramp Up-limit	4MW (12% of P_{nom})	5MW (15% of P_{nom})
Ramp Down-limit	4MW (12% of P_{nom})	5MW (15% of P_{nom})
Startup Cost	70.00 $	70.00 $
Shutdown Cost	70.00 $	70.00 $
Fuel Price of OCGT1 Fuel Price of OCGT2 Fuel Price of OCGT3 Fuel Price of OCGT4	100 $/MW 140 $/MW 180 $/MW 220 $/MW	100 $/MW 140 $/MW 180 $/MW 220 $/MW

3.4.1 Case Study of Conventional Power System

The flexibility analysis is crucial to analyse any existing standalone power system operation capabilities under the pressure of any variation, either from the user side or variable power production from the renewable energy resources (incorporated in the power system). The analysis will enable the power system developers to model the system accurately by keeping the flexibility indicators (like ramp rates, minimum power of generators, minimum up and down time, start-up and shut-down cost etc.) in consideration, before the incorporation of the further floating wind turbine in the OG platform. The system has to be analysed to confirm the ability of the system to withstand any possible high fluctuation of power generated from the floating wind turbines and its viable counter control. Since the power produced from the floating wind turbines is variable, it will force the power system to compensate for the variations by the installed OCGTs to ensure the reliable supply of the power to the consumers. To follow and satisfy the above-mentioned variations of power, the OCGTs must be equipped with state-of-the-art technology, like for the steeper ramps, the OCGTs must be capable enough to follow and satisfy the steep variations, as described in the [22]. Since, the load demand of the OG platform majorly consists of heavy loads like water injection system, pumps, compressors etc., so any variation (turning on and off of heavy loads) can pose a viable threat to the security and stability of the whole power system.

Therefore, a case study is conducted based on the tabulated parameters in the table 10 to analyse the operational capabilities of the installed conventional generators at the OG platform using the LGridPy tool, to analyse the amount of change a system can withstand without compromising the security of the power system. Firstly, the demand load of the OG platform is increased gradually, till the point where the system is not feasible anymore. As can be seen from the depicted Figure14(a), the initial load demand (Figure 10) is satisfied by the four OCGTs (of 33.3MW each). The overall load is then increased for the whole time period, by 1%, 2%, 3%, 4%, 5%, 6%, 7% (to see the capability of the architecture to absorb the changes in the load demand) using the LGridPy tool for simulating the feasible solutions. The Figure 14(a) also tabulated the average load, average power dispatched from the 4 OCGTs, and the average total cost for the give time series of 100 hours for each percent increase. As can be seen, with the increase in load of 8%, the system was not feasible for the conventional OCGTs due to the fact that the load variation was high enough to cause the mismatch in the demand and generation or compromise any of the considered constraints of OCGTs.

Whereas, the Figure 14(b) explains the cause of infeasibility due to the power mismatch, when the load is increased from 7% to 8%. The Figure 14(b) is the combination of two datas: (a). The load profile of 8% increased (blue) and (b). The OCGT dispatch of 7%. As depicted, the combined power generation of all the 4 OCGTs are not enough to satisfy the power demand and hence causing the mismatch in the demand and generation. Also, the dynamic constraints of OCGT are not able to cope with the sudden increase in the variation in the load at different snapshots and due to that, the generators are not capable of compensating for the load increase. Therefore, the LGridPy tool gives an infeasible solution for the 8% increase of load. Also in the Figure 14(c), the load derivative along with the ramp-up and down constraints for the whole simulation is illustrated, showing the ramp-up constraint is violated by the 8% increased load, resulting in the infeasible solution.

3.4.2 Case Study of State-of-the-art Power System

Since, the system after 8% load increase was not feasible, based on the conventional OCGTs, the new flexible constraints and OCGTs, based on [211] are analysed in this case study. To welcome higher share of renewable energy incorporation, more flexible and state-of-the-art OCGTs needs to be considered. In this case study, the load is further increased from 8% (based on the flexible constraints) to the point where the power system is no longer feasible based on the tabulated parameters in the Table 10.

As can be seen from the Figure 14(a), the load is further increased from 8% to 34%, resulting the feasible solution due to the more flexible constraints. The state-of-the-art OCGTs with the improved constraints can compensate and respond to the variations up to 34%. Whereas, when the load is increased to 35%, it causes the demand and generation mismatch and compromises the power system stability. Along with that, the high variation also compromises the ramp rate constraint of the OCGTs, as the system was not capable enough to cope with the abrupt change in the load.

3.4.3 Considerations

This chapter study aims to give a broad overview of the importance of assessing the conventional power system ability, to accommodate the demand load fluctuations and also to compensate for the intermittent renewable energy, integrated into the power system. The conventional power systems that are based on the non-flexible OCGTs, can not cope with the variation of the renewable energy resource, as they are dependent on the environmental conditions like wind speed, solar radiation etc. Therefore, the flexibility analysis is vital to assess the flexibility of the power system to ensure the constant supply of energy to the standalone OG platform, without compromising the power system stability under the steep change in the load demand or variation in the injected power from the renewable energy resources.

Firstly, the tool is validated and authenticated by comparing the results of a case study with the well renowned PyPSA tool. As expected, the new tool simulated the case study with the negligible results deviation. Secondly, the chapter discussed the importance of efficiency curve consideration over the constant value, by implementing the LGridPy for a case study with generators considering efficiency curve and constant value. The results were quite significant as the efficiency curve was producing more realistic results over the other. Thirdly, the LGridPy tool was tested to analyse 2 case studies to perform the flexibility analysis on the: (a). Conventional OCGTs and (b). State-of-the-art OCGTs. To analyse the power system ability to absorb the demand load variation, the load of 90MW is increased gradually to the point where the power system cannot cope with the variation and the solution of the model is infeasible. For the conventional OCGTs, the system accommodated the variation of load (90MW) increase of 7%. Whereas, for the State-of-the-art OCGTs with more flexible constraints, the load was increased from 7% to 34% but the system was able to tune with the variations, showing the ability of the system to adjust accordingly and compensate for the variations by countering the change with OCGT better state-of-the-art flexible attributes.

The following main conclusions can be drawn from our quantitative results:

- ❏ It is vital to perform the flexibility analysis on the already installed power system to assess the ability to accommodate the fluctuation caused by the load variations.

- The consideration of the OCGTs efficiency curve in the LGridPy tool, provides the more quantitative results.
- The state-of-the-art OCGTs can accommodated higher load variations as compared to the conventional OCGTs.
- Consideration of different OCGTs (size and dynamic constraints) can also increase the flexibility of the OG power system.

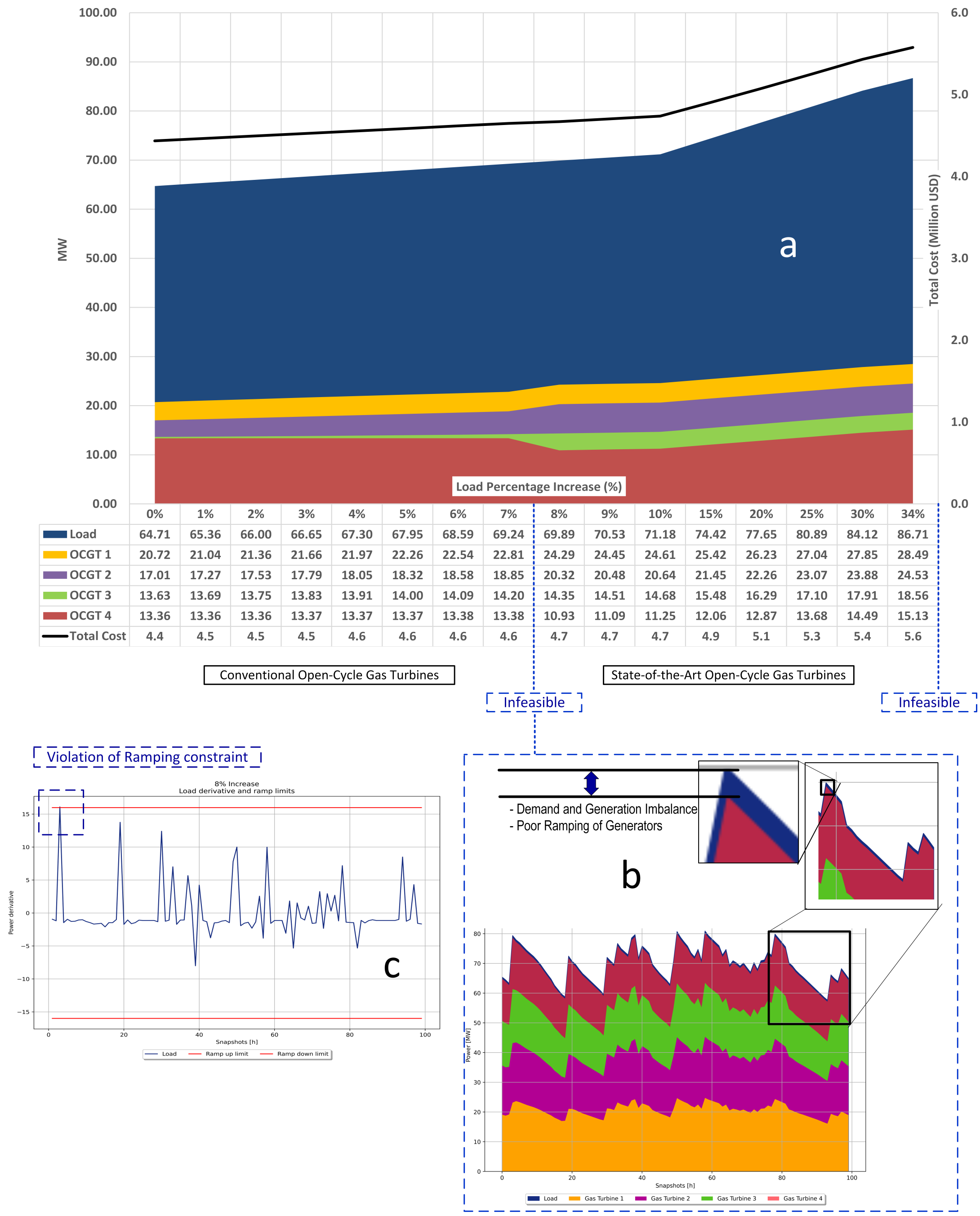


Figure 14 – Conventional and State-of-the-Art OCGTs response to the percentage load increase with the average dispatch values of each OCGT: (a) Illustrating the average dispatch of 4 OCGTs when load of 90MW is increased from 0% to 7% for the conventional OCGTs, to observe the OG platform power system capabilities to compensate the variation in load. With the increase of 8%, the conventional OCGT was unable to satisfy the load. The State-of-the-Art OCGTs are introduced for further load increase and satisfying the demand load increase up to 34%. (b) The infeasibility of power dispatch is shown when the load is increased from 7% to 8%, causing the mismatch of demand load and generation. (c) Showing the violation of ramp-up constraint when the load is increased from 7% to 8%, resulting in the infeasible solution

CHAPTER 4

Power System Tradeoffs: Economic Operation vs. Security

The power industry is going through immense transitions as a result of the increasing penetration of renewable energy sources, rigorous environmental laws, and breakthroughs in energy storage technology. Integrating renewable energy sources, such as wind turbines, into power systems brings new problems and also possibilities for attaining both economic operation and power system security. It is critical that we find the right equilibrium between these two competing objectives in order to provide a reliable and efficient power system.

This chapter focuses on the tradeoff analysis between economic operation and power system security under various scenarios involving conventional power plants, WTs, and ST. By analyzing the performance of various configurations using key performance indicators, we aim to locate the most effective ways for achieving cost-efficient and secure power system operation.

This analysis breaks down the power system into four different scenarios. These scenarios are intended to reflect various combinations of spinning reserves and ROCOF constraints. The first scenario displays results without any reserves or ROCOF constraints, giving a baseline for comparison. The second scenario introduces ROCOF constraints into the system, allowing us to investigate the implications of these constraints on system performance. The third scenario takes it a step further by introducing both ROCOF and reserves limits. This stacked approach to constructing scenarios enables a deeper comprehension of the tradeoff between economic operation and power system security in the context of renewable energy integration.

In each scenario, we conduct a thorough examination conventional standalone hybrid power system, each with four OCGTs, as well as WTs and STs. The main purpose is to analyse the economic performance and power system security concerns when the system is subjected to contingency like the loss of biggest operational OCGT (N-1 scenario). Therefore, the economical operation and security analysis results will be illustrated with different heatmaps with relevant power system indicators. For the economical operation indicators, the power dispatch of gas turbines (GT1, GT2, GT3, GT4) and WTs will be illustrated. In addition, we calculate average

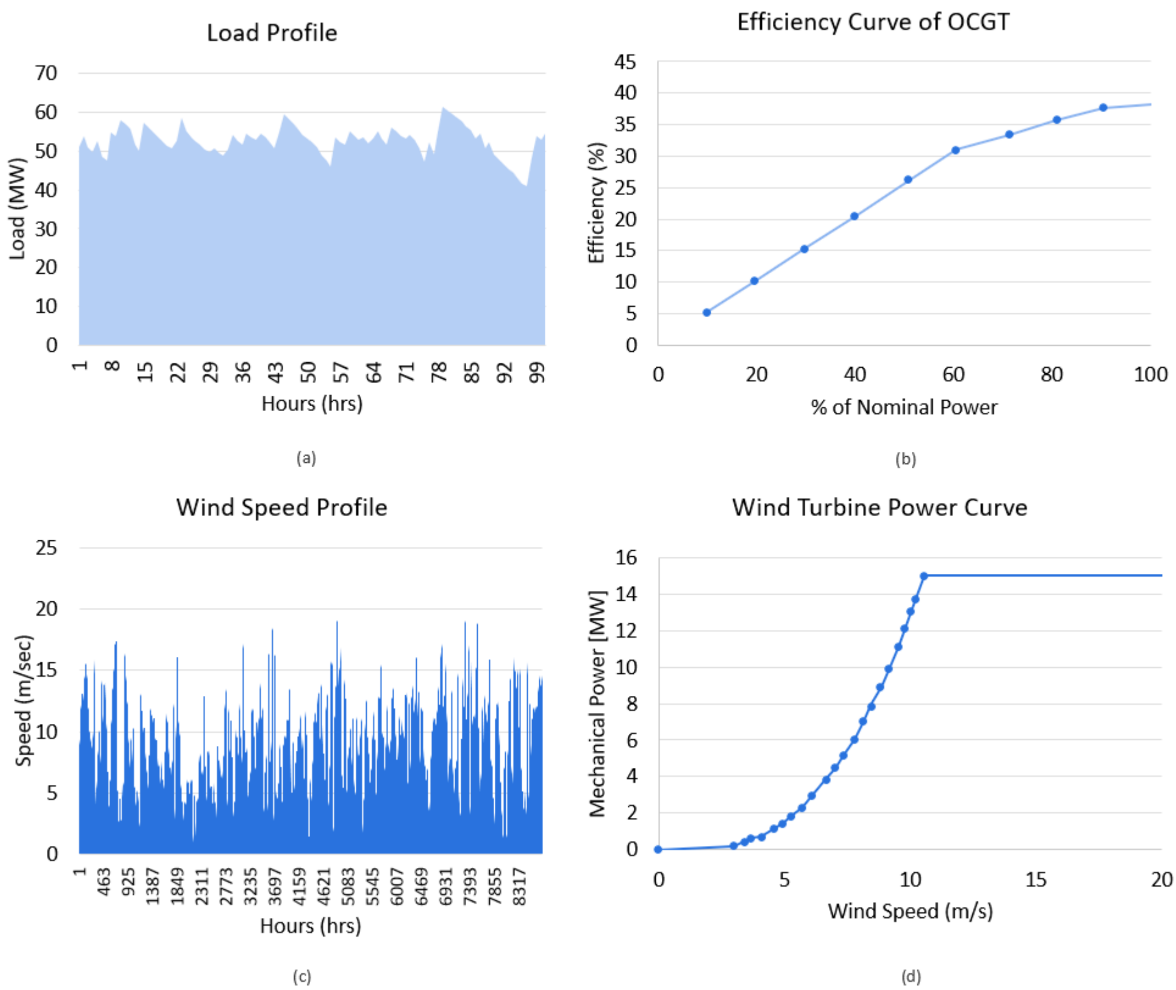


Figure 15 – Considered load profile and efficiency curve (of OCGTs) for the simulations. The Figure (a) depicts the load profile of 100 hours (taken from Figure 10), while the efficiency curve is illustrated in Figure (b). The wind speed profile is shown in (c) and the wind turbine power curve in (d).

values of the overall operational cost in US as Total cost [USD], total emissions in kg is shown as Total emission [kg], and total fuel consumption in tons as Total fuel [ton].

4.0.1 Key Performance Indicators

Simultaneously, various security indicator will assess the security aspect through the mean values of spinning reserves, which is the additional generation capacity available to handle unforeseen contingencies, such as a sudden generator loss, shown as Reserve [MW]. Also, the ROCOF [Hz/s] refers to the Rate of Change of Frequency, capturing the frequency change when the largest gas turbine is lost. In such scenarios, the power mismatch will be shown as delta P [MW] and the time to reach the threshold frequency value of 54Hz after the loss of biggest OCGT from the standalone hybrid power system without the controller action is shown as Time to Contingency [s]. The results will provide the in-depth insights into the trade-offs between economic operation and power system security through this comprehensive evaluation.

Table 11 – Simulation Parameters of Conventional Standalone Hybrid Power System of the OG Platform based on [22, 208]

Parameters	**Conventional Values**
Load Profile	Figure 15 (a)
Required Spinning Reserves	22.50MW (N-1 Scenario)
ROCOF Limit	-1.50 Hz/sec
Open-cycle Gas Turbines (OCGTs) Parameters	
Efficiency Curve	Figure 15 (b)
Nominal Power ($P_{nom_{GT}}$)	25.00MW
Minimum Power	10.00MW (40% of $P_{nom_{GT}}$)
Maximum Power	22.50MW (90% of $P_{nom_{GT}}$)
Minimum Up-time	10 minutes
Minimum Down-time	30 minutes
Ramp Up-limit	3.00MW (12% of $P_{nom_{GT}}$)
Ramp Down-limit	3.00MW (12% of $P_{nom_{GT}}$)
Startup Cost	70.00 $
Shutdown Cost	70.00 $
Maintenance Cost	1000 $
Inertia Constant	3.4 sec
Fuel Price of OCGT1 Fuel Price of OCGT2 Fuel Price of OCGT3 Fuel Price of OCGT4	100 $/MW 100 $/MW 100 $/MW 100 $/MW
Wind Turbine (WT) Parameters	
Nominal Power ($P_{nom_{WT}}$)	15.00MW
Wind Speed Profile	Figure 15 (c)
Wind Turbine Power Curve	Figure 15 (d)
Allowed Instantaneous Wind Penetration[0]	35% of Load (each snapshot)
Electromechanical Conversion Efficiency	96.5%
Energy Storage System (ST) Parameters	
Nominal Power ($P_{nom_{ESS}}$)	1.00MW
Minimum Capacity	20%
Standby Efficiency	99.997%
Discharge Efficiency	92%
Initial State of Charge	100%
Cyclic Charging	True

The simulation is performed on the various parameters and input data provided in the Figure 15 and the technical parameters for the cases studies are tabulated in Table 11.

4.0.2 Results with Base Case

In this section, we examine the base case, which neither consider the ROCOF nor the spinning reserves constraints. The simulation results are displayed as heatmaps for operational and security indicators.

[0] Allowed Instantaneous Wind Penetration refers to the maximum percentage of the load demand that can be reliably allocated to wind energy integration at each time instance, ensuring system stability.

According to Figure 16, the combination of WT and ST decreases the total cost, emissions, and fuel consumption of the standalone hybrid power system. When comparing configurations with conventional 4 GTs and 4 GTs with 5 WTs, there is a considerable reduction in overall cost (from 2531605.62 USD to 1470928.55 USD), total emission (from 8464.97 kg to 5599.23 kg), and total fuel consumption (from 1178.61 tons to 779.6 tons). This trend demonstrates the economic benefits of introducing renewable energy and energy storage into the power system.

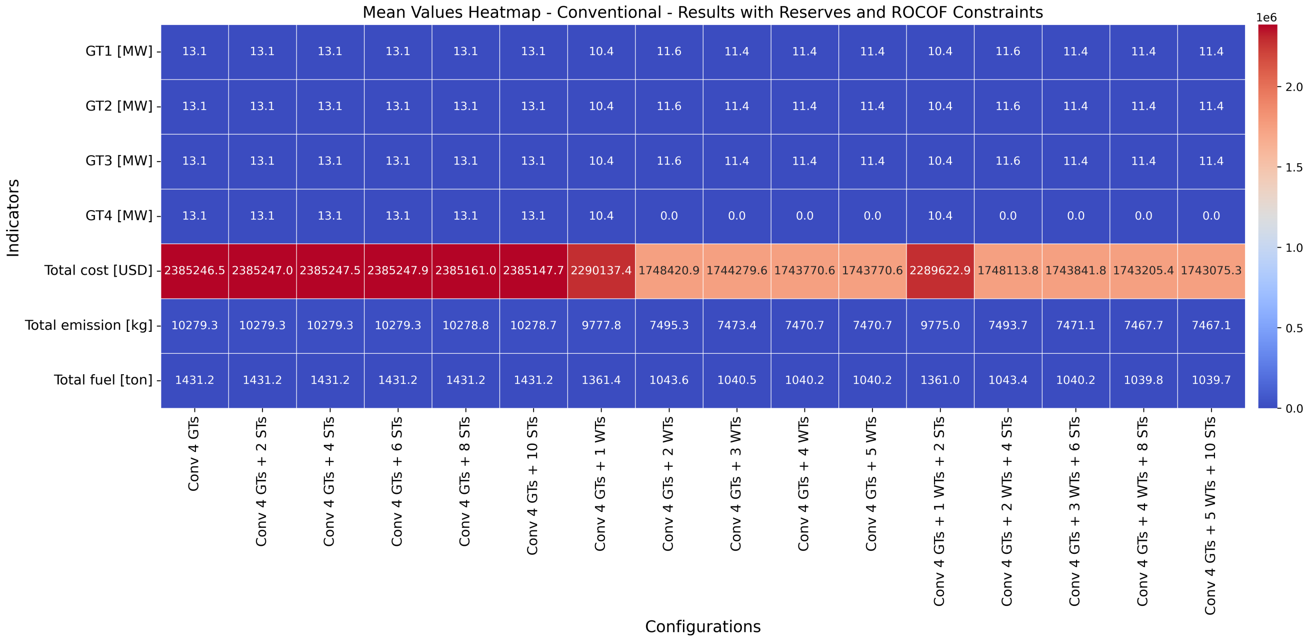


Figure 16 – Operational heatmap of the standalone hybrid power system **without** the consideration of Reserves and ROCOF constraints

However, when the ROCOF and spinning reserves constraints are not considered, the security heatmap Figure 17 exposes possible challenges. The ROCOF is substantially lower (less than -1.5 Hz/s) and the Time to Contingency is lower (approximately 2.84 seconds) in configurations with a greater number of wind turbines and storage systems. These findings suggest that, while the system reduces operational cost, the security is jeopardized since it is more prone to frequency fluctuations and has less time to respond to unforeseen contingencies.

Additionally, when there are more wind turbines, the output of the traditional gas turbines (GT1, GT2, and GT3) tends to decline, allowing the power system to rely more heavily on renewable energy. This is indicated by a decrease in gas turbine power production and an increase in wind turbine power output. However, because renewable energy sources are more variable and unpredictable than traditional generation units, and give essentially no inertia support to the system, this transition toward renewable energy also adds to decreased power system security.

In conclusion, the reduction in costs, emissions, and fuel consumption that results from the base case scenario shows the economic benefits of including wind turbines and storage system into the power system. In configurations with more renewable energy sources, there is a trade-off

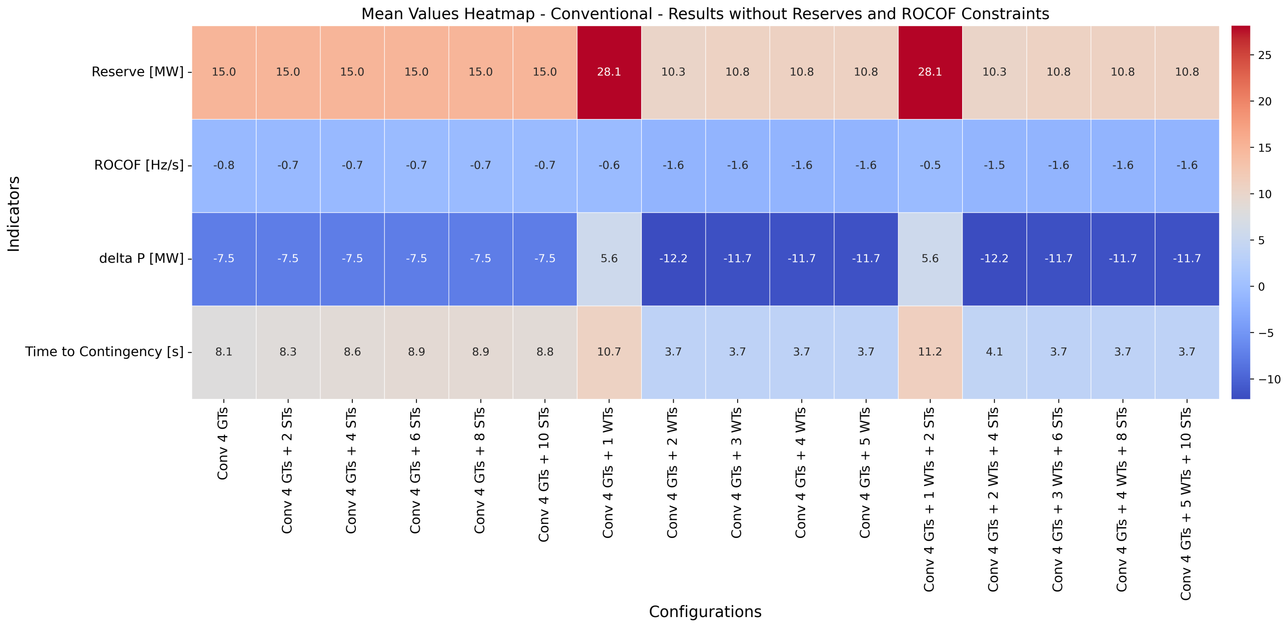


Figure 17 – Security heatmap of the standalone hybrid power system **without** the consideration of Reserves and ROCOF constraints

in terms of the compromised security of the overall power system. Additionally, the overall system's available inertia is decreased as a result of the additional generation in the form of wind turbines, which results in higher ROCOF values and shorter Time to Contingency.

By analyzing both the operational and security heatmaps (Figures 16 and 17), we can conclude that while operating a power system without ROCOF and spinning reserves restriction, it can result in economic and environmental advantages but can jeopardize the power system security. To guarantee a reliable power system operation, it is critical to find an equilibrium between economic operation and power system security by evaluating suitable constraints and implementing effective solutions.

In the next sections, we will examine the impact of implementing ROCOF and spinning reserves constraints on system performance in order to find a balance between economic operation and power system security.

4.0.3 Results with ROCOF Constraint

It was noted from the previous section that there is an economic benefit in terms of the total cost if the system is operated with no restrictions but the security of the system was compromised. In this section, the impact of ROCOF constraints on the system is examined. The ROCOF constraint restricts the rate of change of frequency in the system during the contingency.

By restricting the ROCOF to -1.5 Hz, simulation findings demonstrate that installing additional wind turbines and storage units improves the system's overall security. This can be observed by a reduction in ROCOF values under contingencies, which can be observed in Figure 19. For example, the improvement in the ROCOF from -0.9 Hz/s to -0.8 Hz/s indicates a slowing of the rate of frequency change, which implies an increase in system security.

In contrast, the existence of a negative delta P value (active power imbalance) indicates that the existing power generating capacity is insufficient to meet the demand for energy during the N-1 scenario. This scenario indicates that the system's spinning reserve is insufficient to deal with such unforeseen contingencies. As a result, considering the spinning reserves is critical to avoiding potential system outages. By ensuring the availability of adequate spinning reserve capacity, the system can retain operational stability even when the largest generator is lost.

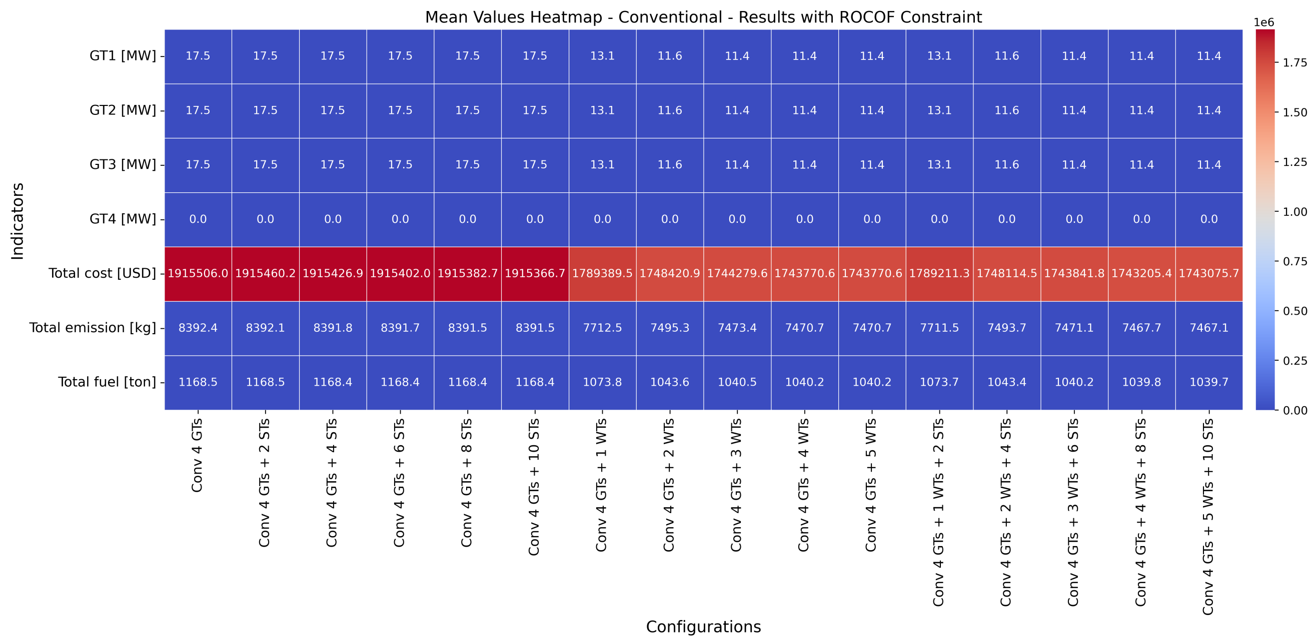


Figure 18 – Operational heatmap of the standalone hybrid power system with the consideration of ROCOF constraint

The operational heatmap for the system under ROCOF limitations is displayed in Figure 18. The heatmap depicts the total cost, total emissions, and total fuel consumption, as well as the power dispatch of each generator and wind turbine. The graph depicts the power dispatch of each OCGTs and WT rises, when more units are added to the system. The incorporation of ST lowers overall cost, total emissions, and total fuel consumption.

The security heatmap for the system with ROCOF constraints is shown in Figure 19. Indicators such as reserve capacity, delta P (active power imbalance), ROCOF, and time to contingency are represented in the heatmap. The results illustrates that With the addition of more WTs and STs, the reserve capacity and time to contingency rise, indicating that the system's security improves. Whereas, the delta P values drops significantly (negative value) for the first 6 configurations, shows the pressing need of spinning reserves to adequately balance the system during the contingency situations.

The Figure 20 depicts the percentage variation of the system parameters compared to the base case of system without ROCOF and spinning reserves constraints with the system only

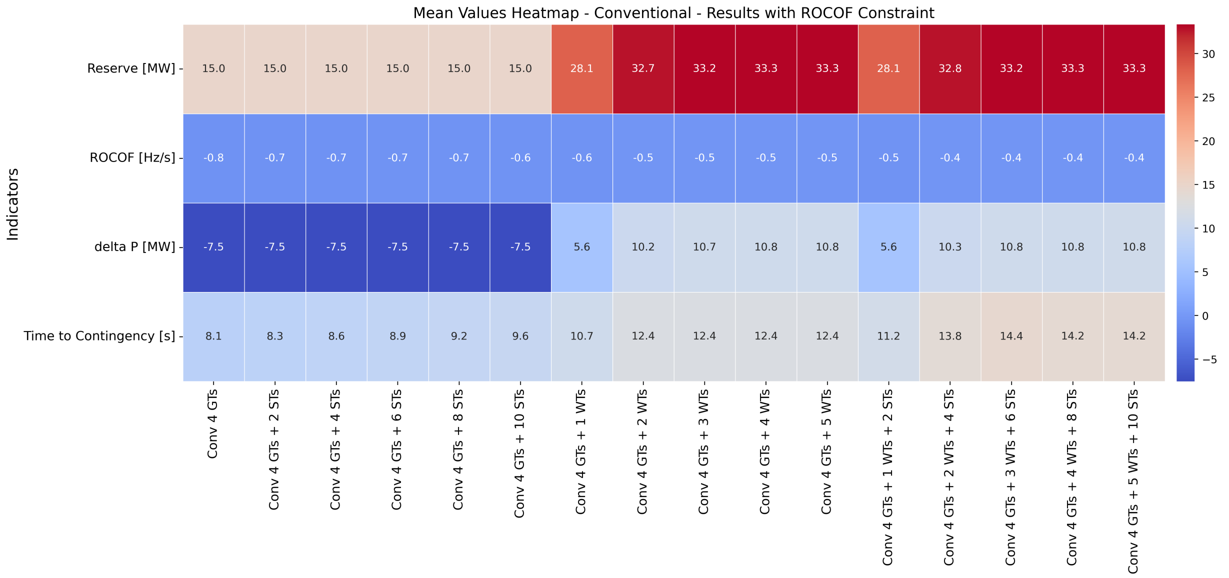


Figure 19 – Security heatmap of the standalone hybrid power system with the consideration of ROCOF constraint

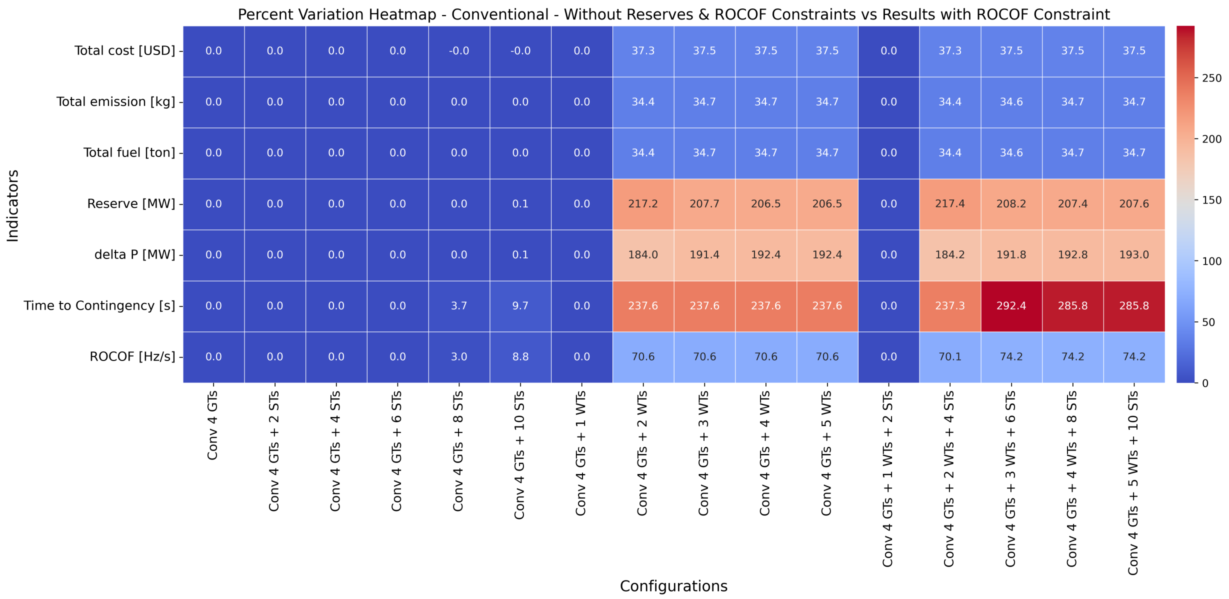


Figure 20 – Percent variation heatmap - System without reserves and ROCOF (base case) vs System with only ROCOF constraint

with ROCOF constraints. The figures show that the addition of WTs increases the total cost, total emissions, and total fuel consumption as the ROCOF limit of -1.5 Hz pushes the system to dispatch more generating units. In addition to that, the ROCOF constraint improves the spinning reserves, delta P, and time to contingency by nearly 200%. Whereas, with the ROCOF constraint, the ROCOF value improves up to 70% (value improved from -1.6 to -0.5 Hz/s), which indicates a significant improvement in system security during contingencies.

In conclusion, the addition of ROCOF constraint improved the system's security by improving the ROCOF, spinning reserve, and time to contingency values but the system's overall total cost, total emissions, and total fuel consumption increased. On the contrary, for the STs the ROCOF constraint does not maintains enough spinning reserves to avoid the negative active power mismatch (delta P), signifying the need to adequate spinning reserve in the system for the unforeseen emergency situations.

4.0.4 Results with ROCOF and Reserves Constraints

It can be seen from Figure 21 that incorporating the WTs and STs decreases the overall operational cost. The number of WTs was increased, which led to less fuel being used and less emissions being produced. From the operational point of view, the trend is decreasing with the addition of STs and WTs as compared to only 4 GT configuration.

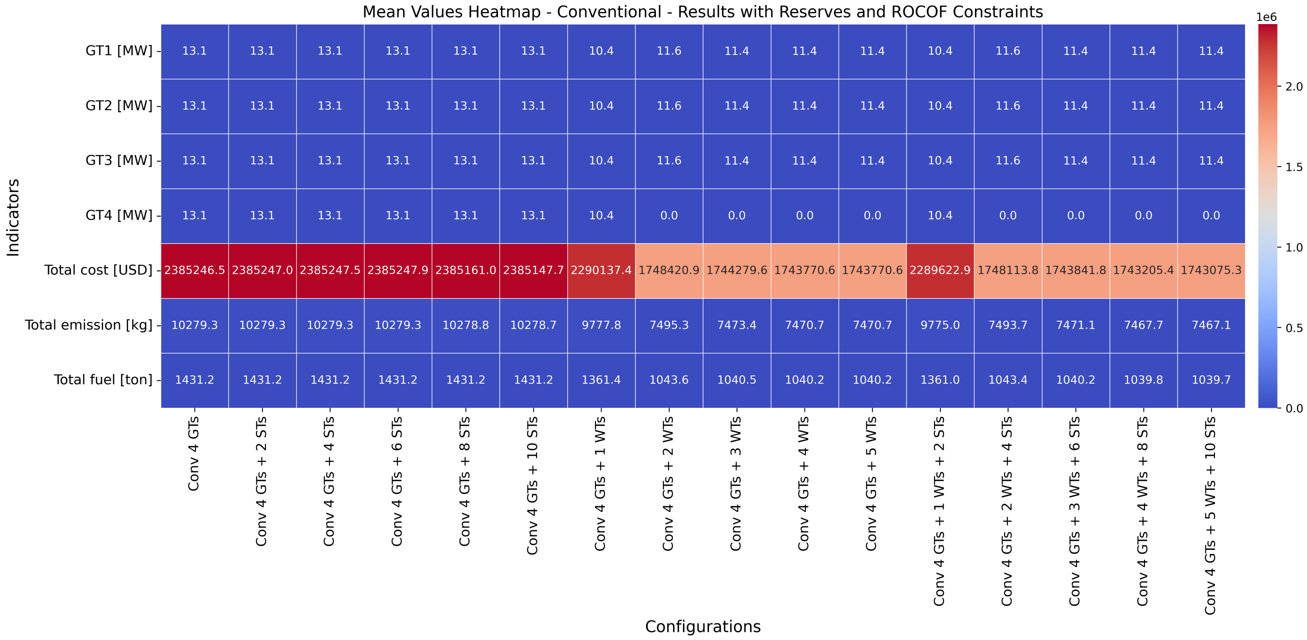


Figure 21 – Operational heatmap of the standalone hybrid power system with the consideration of ROCOF and spinning reserve constraint

The security heatmap of the hybrid power system is shown in Figure 22 and it displays the reserve, delta P, ROCOF, and time to contingency. The addition of WTs to the system has a good effect on the security of the system, shown in the heatmap. The incorporation of wind turbines resulted in an increase in both the reserve and delta P values. With the addition of wind turbines, the ROCOF value improved, suggesting a slower rate of frequency shift with spinning reserves. With the incorporation of wind turbines, the time to contingency escalated, suggesting a longer window of opportunity for the system operator to take necessary steps in the unfortunate event of a contingency.

Figure 23 illustrates the percentage variation among various indicators in comparison to the base case of system without ROCOF and reserves constraints verses the system with ROCOF

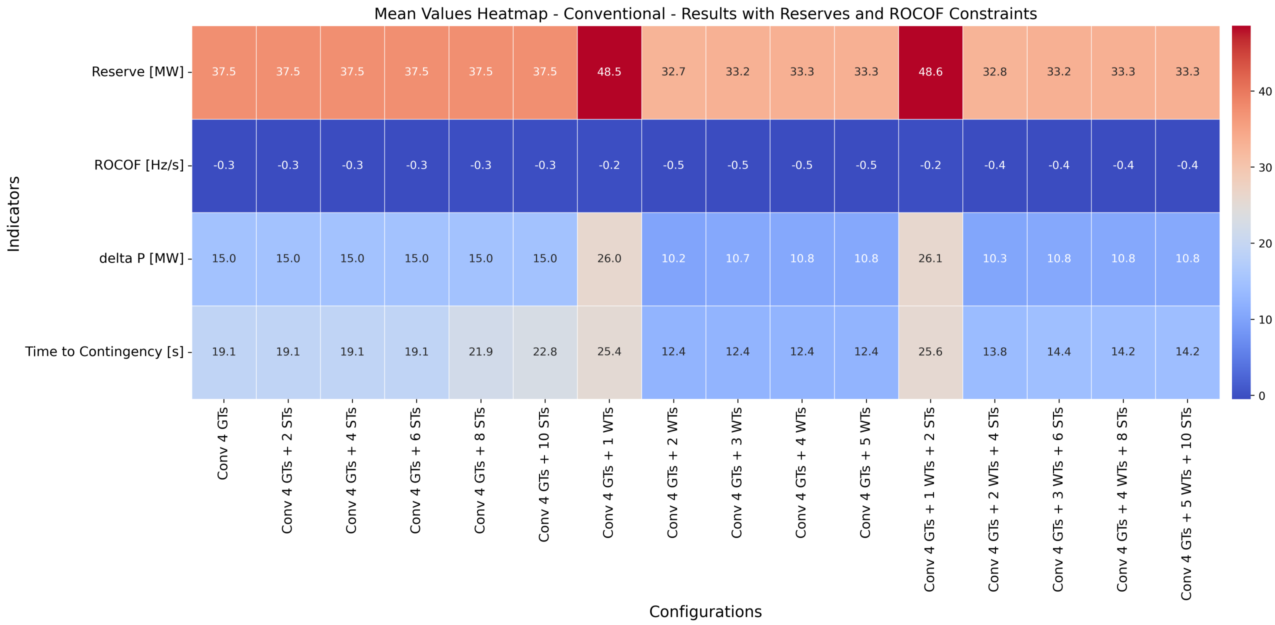


Figure 22 – Security heatmap of the standalone hybrid power system with the consideration of ROCOF and spinning reserve constraint

and reserves constraints. With the addition of the ROCOF and reserves constraints, the system operational cost, emissions, and fuel consumption increased. Whereas, the security of power system improved significantly due to the availability of adequate spinning reserves and restricted ROCOF, pushing the OCGTs to operate and dispatching the electrical power.

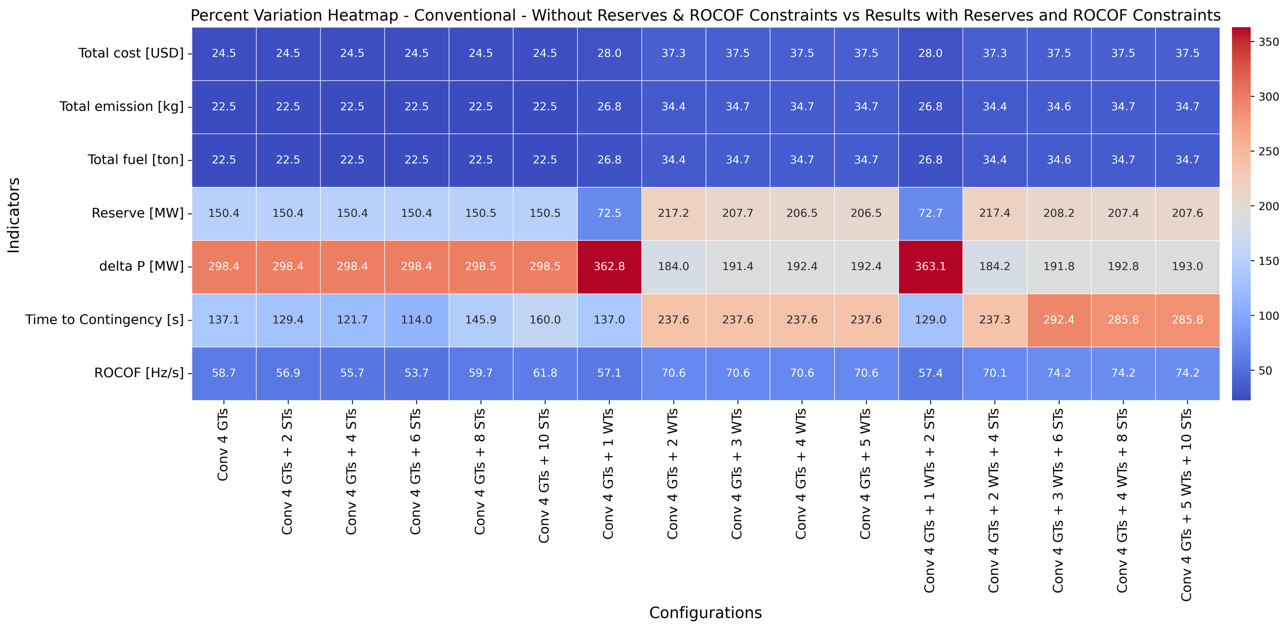


Figure 23 – Percent variation heatmap - System without reserves and ROCOF (base case) vs System with reserves and ROCOF constraint

Therefore, the simulation results and the comparative percentage variation, with the consideration of reserve and ROCOF constraints indicates that the power system could be operated at higher operation cost but with more reliable and secure scheme or vice verse. For this reason, the sensitivity analysis is performed to assist the power companies to select the best scheme to operate the power system in a efficient and reliable manner.

4.1 Sensitivity Analysis on Different Required Operating Reserve Levels

The ROCOF and Reserves Constraints sensitivity analysis for different Required Operating Reserves (RORs) levels is presented in this section. Understanding the system's behavior and performance under various RORs and evaluating the trade-offs between cost savings for the power system operator and maintaining system security are the primary objectives of this study.

4.1.1 100% Required Operating Reserves (RORs = 22.5MW)

The sensitivity analysis with 100% RORs (22.5 MW) is shown in Figure 24. This scenario acts as the baseline, giving a point of comparison for analyzing the results of other scenarios with lower RORs. It presents the greatest degree of system security as the most secure choice, but at a higher operating cost to the power system operator.

Figure 24 – Sensitivity analysis on the ROCOF and Reserves Constraints with the consideration of 100% Required Operating Reserves (RORs = 22.5MW)

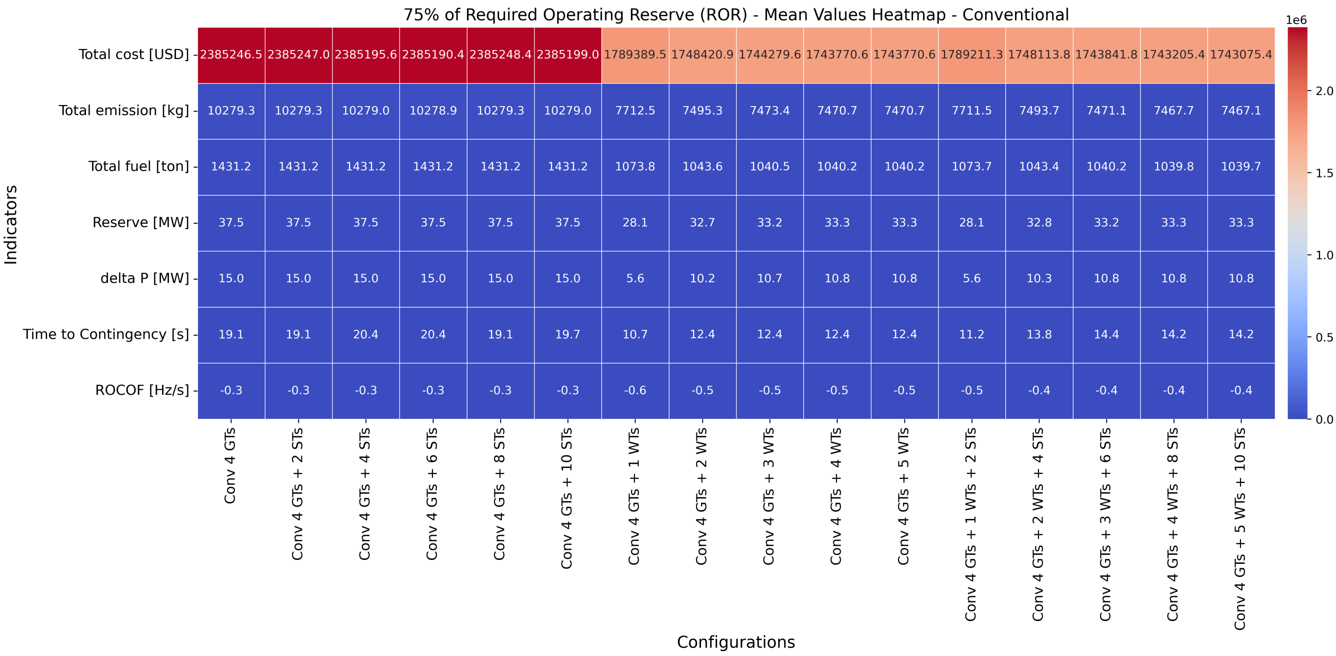


Figure 25 – Sensitivity analysis on the ROCOF and Reserves Constraints with the consideration of 75% Required Operating Reserves (RORs = 16.875MW)

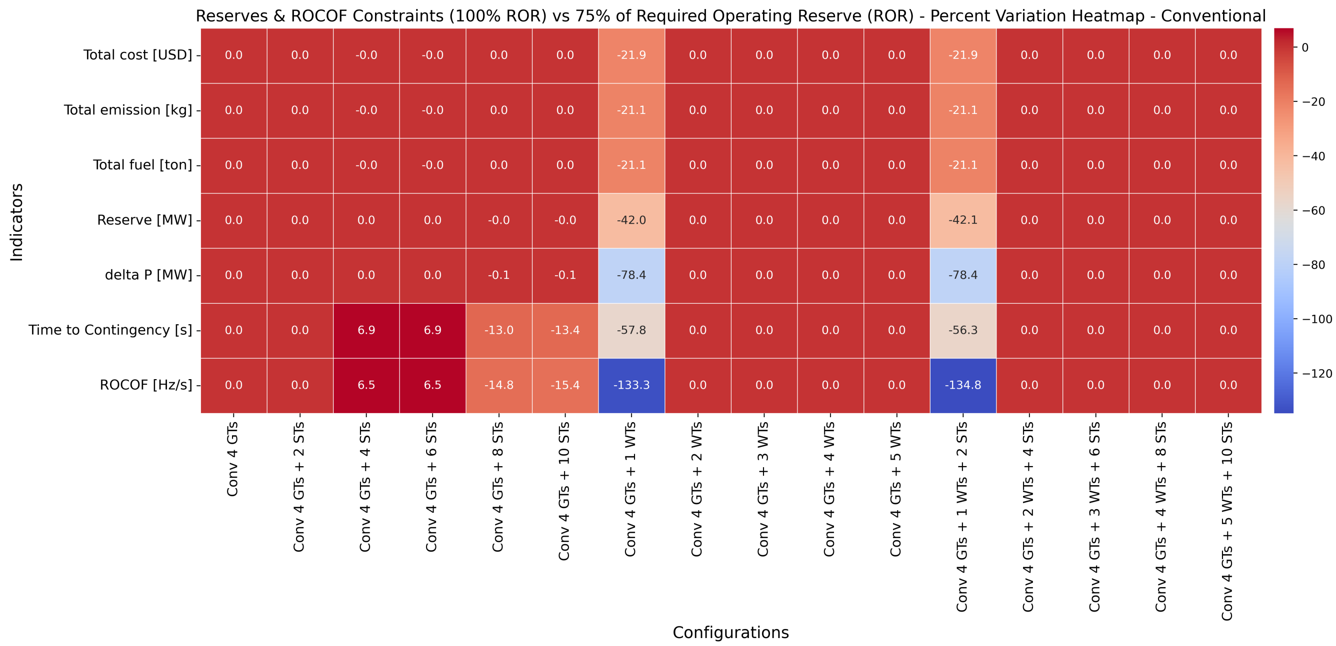


Figure 26 – Percentage variation between the ROCOF and Reserves Constraints with the consideration of RORs of 100% vs RORs of 75%

4.1.2 75% Required Operating Reserves (RORs = 16.875MW)

The sensitivity analysis with 75% required operating reserves (16.875 MW) is shown in Figure 25. The findings show a trade-off between cost savings and system security, with a consideration of RORs=75% causing significant shift in the ROCOF and Reserves Constraints. Figure 26 illustrates how a lower RORs level affects system performance by comparing the percentage variance between the 100% RORs and 75% RORs situations.

4.1.3 50% Required Operating Reserves (RORs = 11.255MW)

The sensitivity analysis with 50% required operating reserves (11.25 MW) is shown in Figure 27. The findings reveal a higher level of risk to power system security but with the reduction in the operational cost, when the RORs are reduced to 50%. This has an influence on the ROCOF and Reserves Constraints and the comparison between the 100% RORs and 50% RORs is illustrated in Figure 28. The comparative analysis highlights the system's heightened sensitivity to the RORs reduction, by displaying the percentage change between the 100% and 50% RORs results.

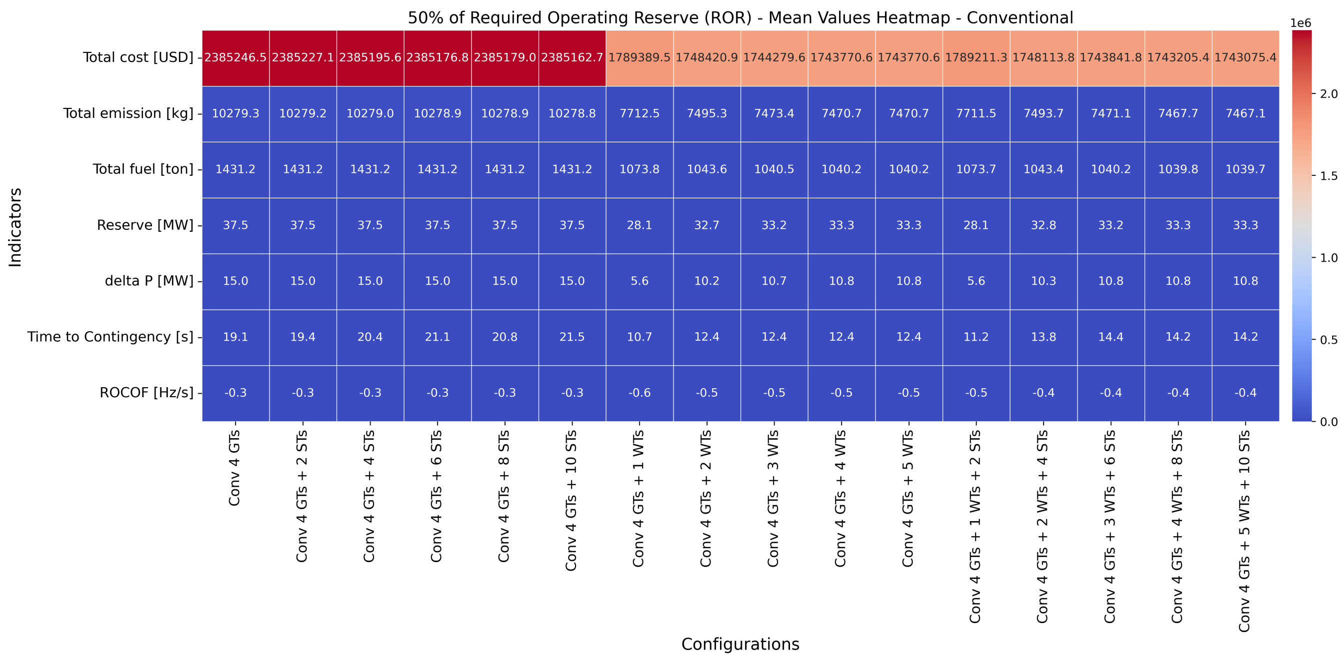


Figure 27 – Sensitivity analysis on the ROCOF and Reserves Constraints with the consideration of 50% Required Operating Reserves (RORs = 11.25MW)

4.1.4 25% Required Operating Reserves (RORs = 5.625MW)

The Figure 29 shows the sensitivity analysis with 25% Required Operating Reserves (of 5.625 MW). The findings demonstrate a more severe trade-off between cost savings and system security, with an even further drop in RORs to 25% leading to significant changes in the ROCOF and Reserves Constraints. The percentage difference between the 100 percent RORs and 25 percent RORs scenarios is shown in Figure 30, highlighting the system's increased vulnerability

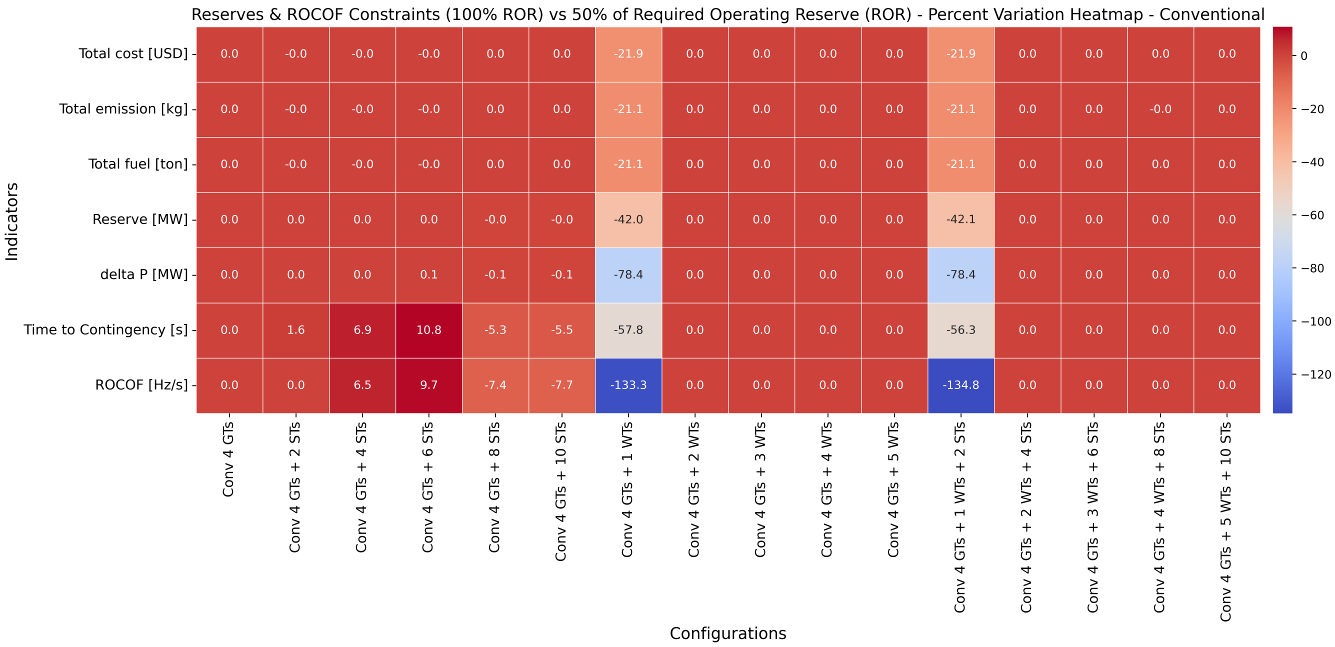


Figure 28 – Percentage variation between the ROCOF and Reserves Constraints with the consideration of RORs of 100% vs RORs of 50%

to such a drastic drop in RORs levels and the possible hazards associated with maintaining system stability.

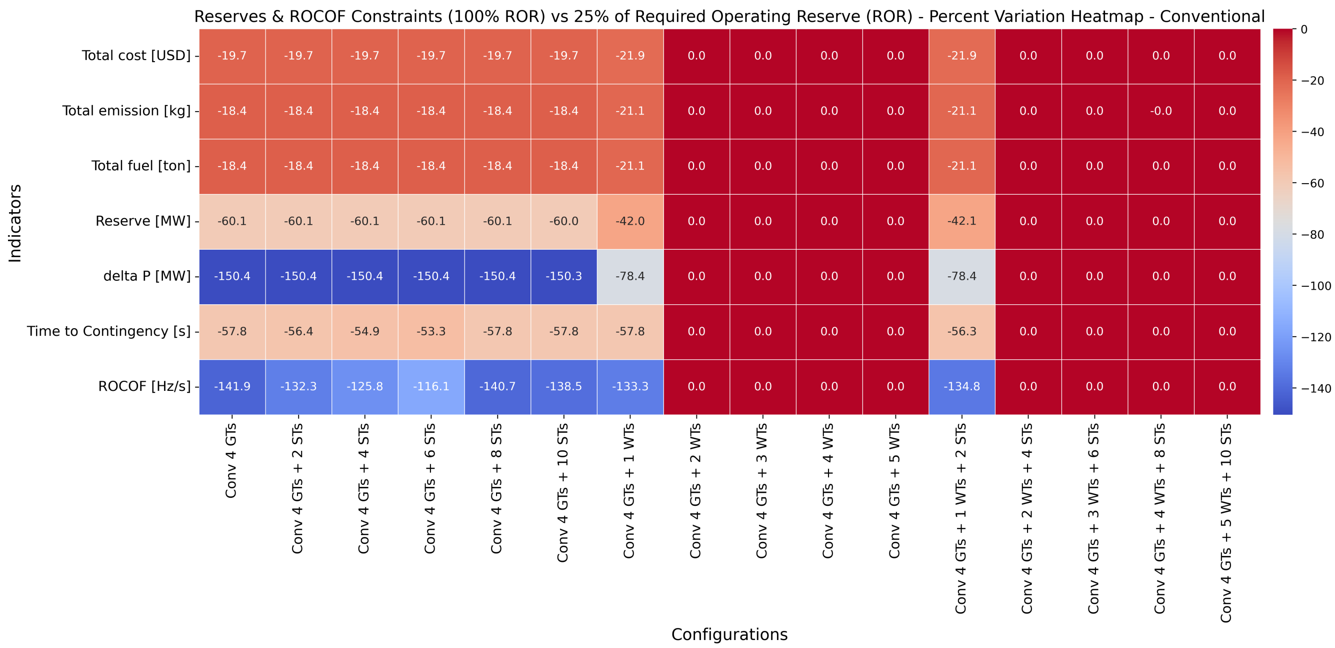


Figure 30 – Percentage variation between the ROCOF and Reserves Constraints with the consideration of RORs of 100% vs RORs of 25%

In conclusion, this sensitivity study aids in understanding how the system performs and behaves under various RORs levels, which is essential for developing successful methods for

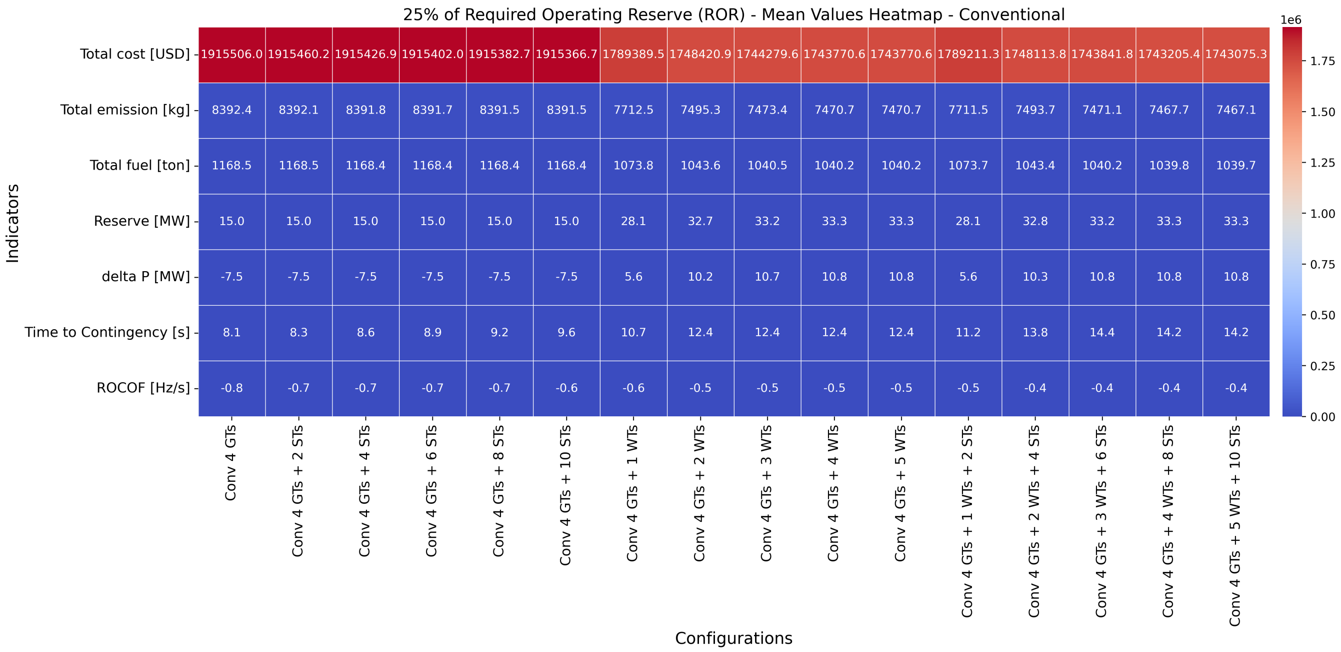


Figure 29 – Sensitivity analysis on the ROCOF and Reserves Constraints with the consideration of 25% Required Operating Reserves (RORs = 5.625MW)

preserving standalone hybrid power system security and guaranteeing a consistent supply of power. The outcomes highlight how crucial it is to carefully consider the right RORs values when designing and operating the power systems. Power system operators must assess the possible threats to system security against the cost savings associated with lower RORs, especially in cases when reserve levels are significantly lowered.

4.2 Considerations

The primary focus of this chapter was on the trade-off between power system security and economic operation in the context of incorporating renewable energy sources (WTs) and energy storage (ST) technologies into existing electrical grids. Utilizing key performance indicators, the study evaluated the performance of various scenarios and configurations.

The results illustrated in the chapter, emphasized on the economic advantages of incorporating renewable energy sources and energy storage into the power system, such as cost reductions, lower emissions, and reduced consumption of fuels. In addition to that, the further utilization of renewable energy sources might jeopardize the security of the power system, creating complications with frequency stability and contingency response.

The chapter also examine the effects of rate of change of frequency and spinning reserves constraints on the operation of the standalone power system. It was concluded that implementing these constraints increased system security by lowering the rate of change of frequency and providing greater reserves margins to address unforeseen contingencies. Whereas, the setup also increased the total cost for operating the power system.

A sensitivity analysis on various Required Operating Reserves (RORs) levels was also performed, highlighting the trade-off between cost savings and system security. Cost savings from lower RORs levels came at the expense of a higher security risk for the system.

Overall, this chapter highlighted the significance of finding an equilibrium between economic operation and power system security. To maintain a reliable and efficient operation for the power system, it emphasized the importance for careful assessment of constraints including ROCOF, spinning reserves, and RORs. Power system operators may determine a balance between economical operation and system security by assessing tradeoffs and implementing suitable solutions.

The knowledge gained from this chapter helps the power system operators and policymakers to make wise choices regarding the integration of renewable energy sources, energy storage systems, and the operational constraints, required for maintaining a sustainable and resilient power system.

CHAPTER 5

Flexibility Analysis and Comparison of Different Power System Configurations

The need for reliable, sustainable power sources is increasing, which is causing a fast transition of the energy sector. As the demand for electricity grows, power networks must become more flexible and robust in order to manage variable demands, integrate renewable energy supplies, and survive unanticipated contingencies. In this context, the Oil and Gas (OG) power system is crucial to global energy supply, and elevating its flexibility is vital.

This chapter provides a thorough examination of flexibility and comparison of various power system topologies/configurations with an emphasis on the OG power system. Our goal is to determine the best methods for increasing system flexibility while taking a variety of technical, environmental, and economic performance factors into consideration. We use the LGridPy simulation tool to accomplish the objective, which allows to simulate and evaluate various power system configurations that include models such as gas turbines (GTs), wind turbines (WTs), and energy storage systems (STs).

The chapter is organized as follows: In the first section, we give a thorough review of the simulation framework, input variables, and various configurations that we took into consideration in our study. Following that, we will go over the KPIs that will be used to analyze and compare the results of each configuration. After that, we provide the results of the simulations and examine the implications of various power system parameters on total flexibility. Finally, based on our research, we create a series of useful suggestions for boosting the OG power system's flexibility and ability to respond to changing energy needs and constraints.

5.1 Methodology

The flexibility analysis of the OG power system is simulated on the LGridPy simulation tool. Input parameters for the basic case (Table 13) and the input parameters, such as demand load, generator efficiency curves, and network settings, are tabulated in Table 12 to ensure realistic portrayal of real-world scenarios. The study will demonstrate the influence of various power system components, such as gas turbines (GTs), wind turbines (WTs), and energy storage systems (STs), on overall power system flexibility. This method allows us to examine the possible advantages and trade-offs associated with each configuration, directing our recommendations for increasing the flexibility of the OG power system.

Table 12 – Simulation Parameters of State-of-the-Art (SOA) Standalone Hybrid Power System based on [16, 208]

Parameters	**State-of-the-Art (SOA) Values**
Load Profile	Figure 15 (a)
Required Spinning Reserves	22.50MW (N-1 Scenario)
ROCOF Limit	-1.50 Hz/sec
Open-cycle Gas Turbines (OCGTs) Parameters	
Efficiency Curve	Figure 15 (b)
Nominal Power ($P_{nom_{GT}}$)	25.00MW
Minimum Power	5.00MW (20% of $P_{nom_{GT}}$)
Maximum Power	22.50MW (90% of $P_{nom_{GT}}$)
Minimum Up-time	10 minutes
Minimum Down-time	30 minutes
Ramp Up-limit	3.75MW (15% of $P_{nom_{GT}}$)
Ramp Down-limit	3.75MW (15% of $P_{nom_{GT}}$)
Startup Cost	70.00 $
Shutdown Cost	70.00 $
Maintenance Cost	1000 $
Inertia Constant	3.4 sec
Fuel Price of OCGT1 Fuel Price of OCGT2 Fuel Price of OCGT3 Fuel Price of OCGT4	100 $/MW 100 $/MW 100 $/MW 100 $/MW
Wind Turbine (WT) Parameters	
Nominal Power ($P_{nom_{WT}}$)	15.00MW
Wind Speed Profile	Figure 15 (c)
Wind Turbine Power Curve	Figure 15 (d)
Allowed Instantaneous Wind Penetration	35% of Load (each snapshot)
Electromechanical Conversion Efficiency	96.5%
Energy Storage System (ST) Parameters	
Nominal Power ($P_{nom_{ESS}}$)	1.00MW
Minimum Capacity	20%
Standby Efficiency	99.997%
Discharge Efficiency	92%
Initial State of Charge	100%
Cyclic Charging	True

5.1.1 Key Performance Indicators

To compare and evaluate the performance of the base case (as tabulated in Table 13 that is the already installed power system on the OG platform) with the alternative configurations, we considered the KPIs that cover a variety of power system flexibility parameters. The considered KPIs are:

- Total cost (USD): Operational expense of the power system,
- Total emissions (kg): Emitted greenhouse gases from the system,
- Total fuel consumption (ton): Fuel consumed by the system,
- Spinning Reserve capacity (MW): Dispatchable/available generator's capacity ,
- Rate of change of frequency (ROCOF) (Hz/s): Rate of frequency change,
- Power deviation (delta P) (MW): Difference between generation and demand,
- Available inertia (s): Resistance against ROCOF, and
- Time to contingency (s): Time to respond to unforeseen events.

These KPIs enable a thorough evaluation of the technical, economic, and environmental performance of any configuration, ensuring an in-depth understanding of the effects of various system changes in comparison with the base case as tabulated in the Table 13.

5.1.2 Simulation and Analysis

We perform a series of simulations using the LGridPy tool and the chosen KPIs to evaluate how each configuration performs under various operational conditions and contingencies. During the simulation process, variables such the system's total number of GTs, WTs, and STs are defined, as well as whether or not the GTs should operate with flexible or conventional parameters based on the defined parameters in Table 11 and Table 12, respectively.

5.2 Results

A number of alternative configurations with various numbers of GTs, WTs, and STs are compared with the conventional configuration (base case), tabulated in Table 13. Two different heatmaps are shown with the results, (a). One for Conventional (Conv) configurations and the other for State-of-the-Art (SOA) configurations. The percentage difference in the KPIs between the base case and each alternate configuration can be observed across the heatmap.

The heatmap of Figure 31 depicts the percentage variation of conventional configurations with the base case of Table 13. Similarly, the state-of-the-art power system configurations are examined and shown in the Figure 32. The figures and trends in the heatmaps are then used to compare the performance of the various configurations in terms of cost, emissions, fuel consumption, and importantly the security aspects of the standalone power system of OG platform.

Table 13 – Base Case Data - Mean Values of Conventional (4 GTs) Power System Configuration

Parameter	Value
Load [MW]	52.54
GT1 [MW]	13.13
GT2 [MW]	13.13
GT3 [MW]	13.13
GT4 [MW]	13.13
WT Total [MW]	0
ST Total [MW]	0
Total cost [USD]	2385246.55
Total emission [kg]	10279.3
Total fuel [ton]	1431.23
# Active GTs	4
Available Inertia [s]	12.8
Reserve [MW]	37.46
delta P [MW]	14.96
ROCOF [Hz/s]	-0.31
Time to Contingency [s]	19.09

5.2.1 Conventional Power System Configurations

Different trends and patterns may be seen in the KPIs, when comparing the base case with the alternative conventional configurations with the addition of STs and WTs from the Figure 31. The average total cost, total emissions, and total consumption of fuel reduces as the number of STs increases. With a reduction ranging from 26.7 to 26.92% from the base case. The configurations with WTs demonstrated the highest decrease in total cost as the cheapest source of energy is injected into the system. Similarly, the total emissions and total fuel consumption experienced the significant reductions in the same configuration, ranging from 27.1 to 27.4% when compared to the base case values. With the Conv 4GTs + 1 WT configuration, the reduction is not significant as all the 4 GTs are pushed to operate to satisfy the load and the constraints.

However, the power system security KPIs were also impacted by the installation of WTs and STs. As can be seen from the Figure 31, with the addition of one WT, resulted in the highest gain in spinning reserve capacity (29.5%), as some of the dispatched power came from the WT, without turning off the fourth GT. As the WTs incorporation increases from 2 to 5, it contributes more to load compensation and shuts off the 4th GT, which lowers the overall reserves, the ROCOF, and the value of the active power mismatch (delta P). In addition to that, the configuration with 4 GTs, (2 to 5) WTs, and no STs showed a significant decrease in time to contingency, resulting in a reduction of -35% from the base case.

In conclusion, the OG standalone power systems economic and environmental performance improved with the addition of STs and WTs as compared with the conventional power system with four GTs as a base case. On the other hand, the decline in the values of the spinning

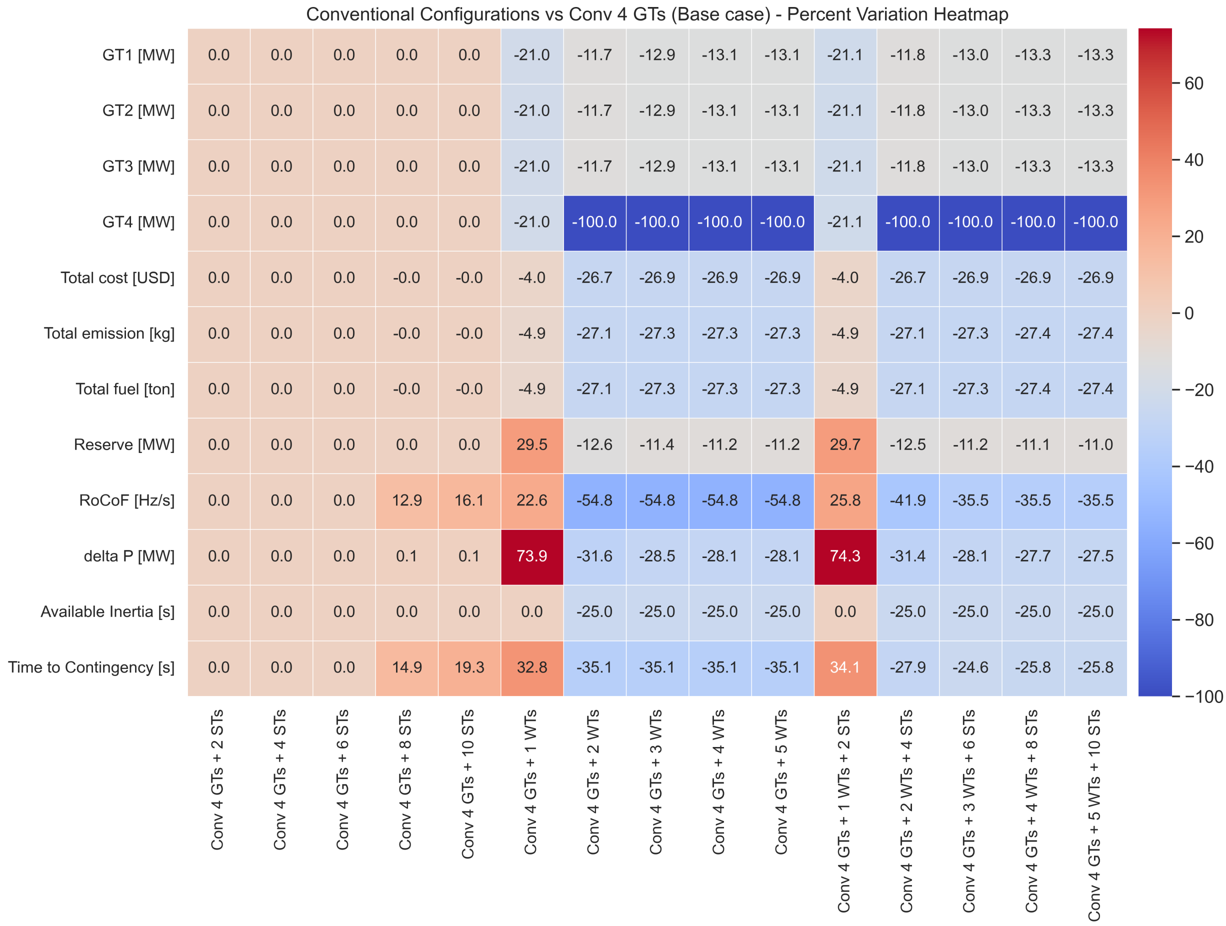


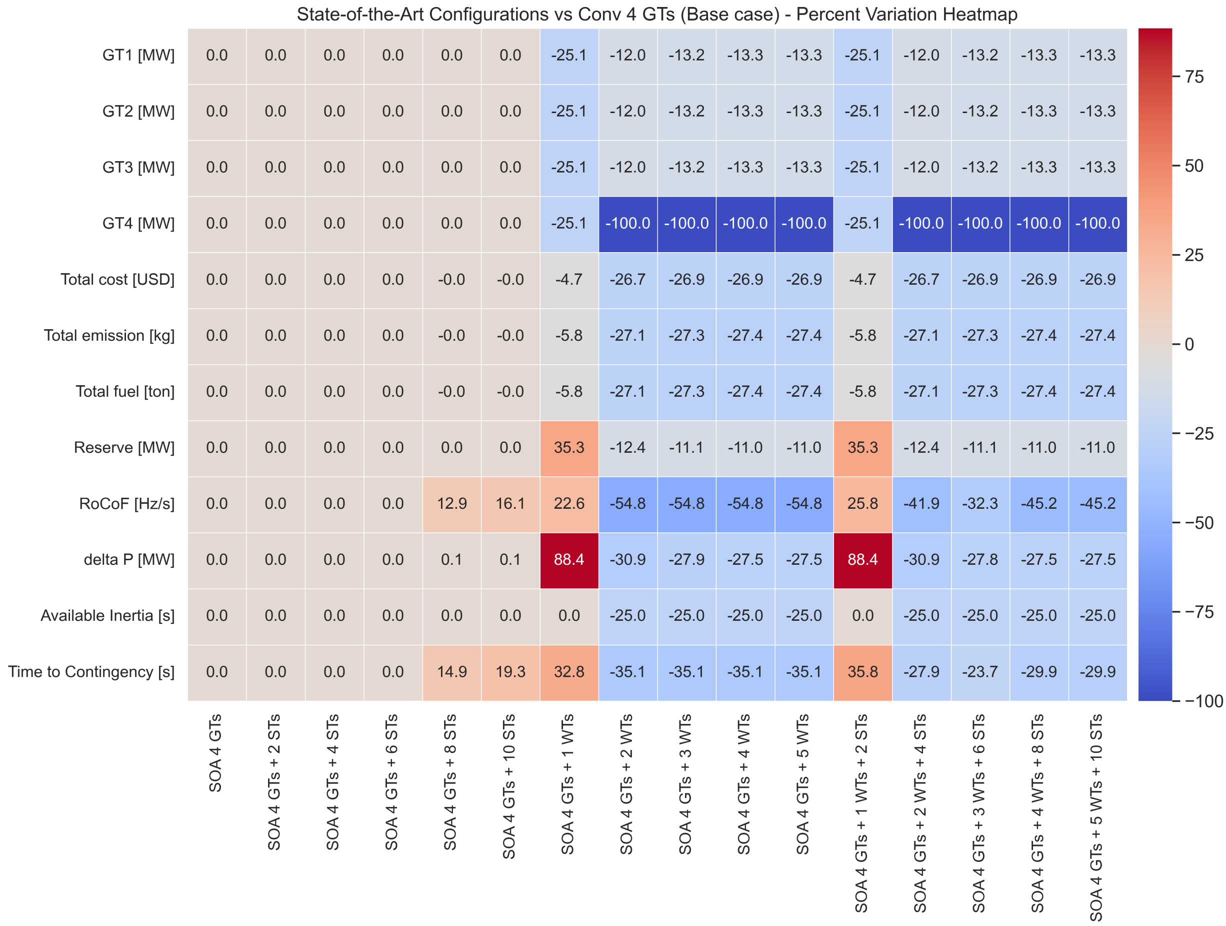
Figure 31 – Percentage Variation of the conventional power system configurations with the base case of conventional 4 Gas Turbines configuration

reserves, delta P, and ROCOF compromises the security performance.

5.2.2 State-of-the-Art Power System Configurations

There are clear trends and patterns across the KPIs as shown in Figure 32, when comparing the base case with other state-of-the-art configurations. As the number of STs increases, there is a hike in the total cost, total emissions, and total fuel consumption. In comparison, the setups with WTs showed the greatest percentage reduction in total cost, with a decrease ranging between 26.73% and 26.93%. Similarly, the total emissions and total fuel consumption experience the significant percentage decreases ranging from 27.12 to 27.37% from the base case values, for the same configuration. However, the SOA 4GTs + 1 WT configuration does not show a significant reduction since all four GTs are required to operate to meet the load demand and satisfy the constraints.

The system's security KPIs were also impacted with the addition of WTs and STs. When one WT was added, the capacity of the Spinning Reserve increased by almost 35.32%, since some of the WT's power contributed without turning off the fourth GT. By incorporating the



	SOA 4 GTs	SOA 4 GTs + 2 STs	SOA 4 GTs + 4 STs	SOA 4 GTs + 6 STs	SOA 4 GTs + 8 STs	SOA 4 GTs + 10 STs	SOA 4 GTs + 1 WTs	SOA 4 GTs + 2 WTs	SOA 4 GTs + 3 WTs	SOA 4 GTs + 4 WTs	SOA 4 GTs + 5 WTs	SOA 4 GTs + 1 WTs + 2 STs	SOA 4 GTs + 2 WTs + 4 STs	SOA 4 GTs + 3 WTs + 6 STs	SOA 4 GTs + 4 WTs + 8 STs	SOA 4 GTs + 5 WTs + 10 STs
GT1 [MW]	0.0	0.0	0.0	0.0	0.0	0.0	-25.1	-12.0	-13.2	-13.3	-13.3	-25.1	-12.0	-13.2	-13.3	-13.3
GT2 [MW]	0.0	0.0	0.0	0.0	0.0	0.0	-25.1	-12.0	-13.2	-13.3	-13.3	-25.1	-12.0	-13.2	-13.3	-13.3
GT3 [MW]	0.0	0.0	0.0	0.0	0.0	0.0	-25.1	-12.0	-13.2	-13.3	-13.3	-25.1	-12.0	-13.2	-13.3	-13.3
GT4 [MW]	0.0	0.0	0.0	0.0	0.0	0.0	-25.1	-100.0	-100.0	-100.0	-100.0	-25.1	-100.0	-100.0	-100.0	-100.0
Total cost [USD]	0.0	0.0	0.0	0.0	-0.0	-0.0	-4.7	-26.7	-26.9	-26.9	-26.9	-4.7	-26.7	-26.9	-26.9	-26.9
Total emission [kg]	0.0	0.0	0.0	0.0	-0.0	-0.0	-5.8	-27.1	-27.3	-27.4	-27.4	-5.8	-27.1	-27.3	-27.4	-27.4
Total fuel [ton]	0.0	0.0	0.0	0.0	-0.0	-0.0	-5.8	-27.1	-27.3	-27.4	-27.4	-5.8	-27.1	-27.3	-27.4	-27.4
Reserve [MW]	0.0	0.0	0.0	0.0	0.0	0.0	35.3	-12.4	-11.1	-11.0	-11.0	35.3	-12.4	-11.1	-11.0	-11.0
RoCoF [Hz/s]	0.0	0.0	0.0	0.0	12.9	16.1	22.6	-54.8	-54.8	-54.8	-54.8	25.8	-41.9	-32.3	-45.2	-45.2
delta P [MW]	0.0	0.0	0.0	0.0	0.1	0.1	88.4	-30.9	-27.9	-27.5	-27.5	88.4	-30.9	-27.8	-27.5	-27.5
Available Inertia [s]	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-25.0	-25.0	-25.0	-25.0	0.0	-25.0	-25.0	-25.0	-25.0
Time to Contingency [s]	0.0	0.0	0.0	0.0	14.9	19.3	32.8	-35.1	-35.1	-35.1	-35.1	35.8	-27.9	-23.7	-29.9	-29.9

Figure 32 – Percentage Variation of state-of-the-art power system configurations compared to the base case of conventional 4 Gas Turbines configuration

two to five WTs, the load compensation by the WTs contribution increases and hence, the fourth GT is turned off. Due to this reason, the spinning reserves, the ROCOF, and the value of the active power mismatch (delta P) dropped substantially. Furthermore, the time to contingency illustrates the increase in the configuration with four GTs, two to five WTs, and no STs, resulting in a -35% percentage drop as compared to the base case.

In conclusion, the integrating renewable energy sources like WTs with STs contributes to improve the economic operation of the conventional and state-of-the-power system configurations. The heatmaps of Figures 31 and 32 clearly demonstrate the trends of reduced costs, emissions, and fuel consumption with the incorporation of these technologies. However, impacts on security indicators like spinning reserves, delta P, and ROCOF values, shows the compromised security and effectiveness of the power systems.

5.3 Comparison of Conventional and State-of-the-Art Results

This section examines the differences between the conventional and state-of-the-art power system results, obtained in the section 5.2.1 and 5.2.2. The calculation is the subtraction of the percentage variation of the SOA (Figure 32) from the Conv (Figure 31) configuration. The section will discuss the importance of state-of-the-art configurations for the oil and gas industry by analyzing the heatmap, depicted as Figure 33.

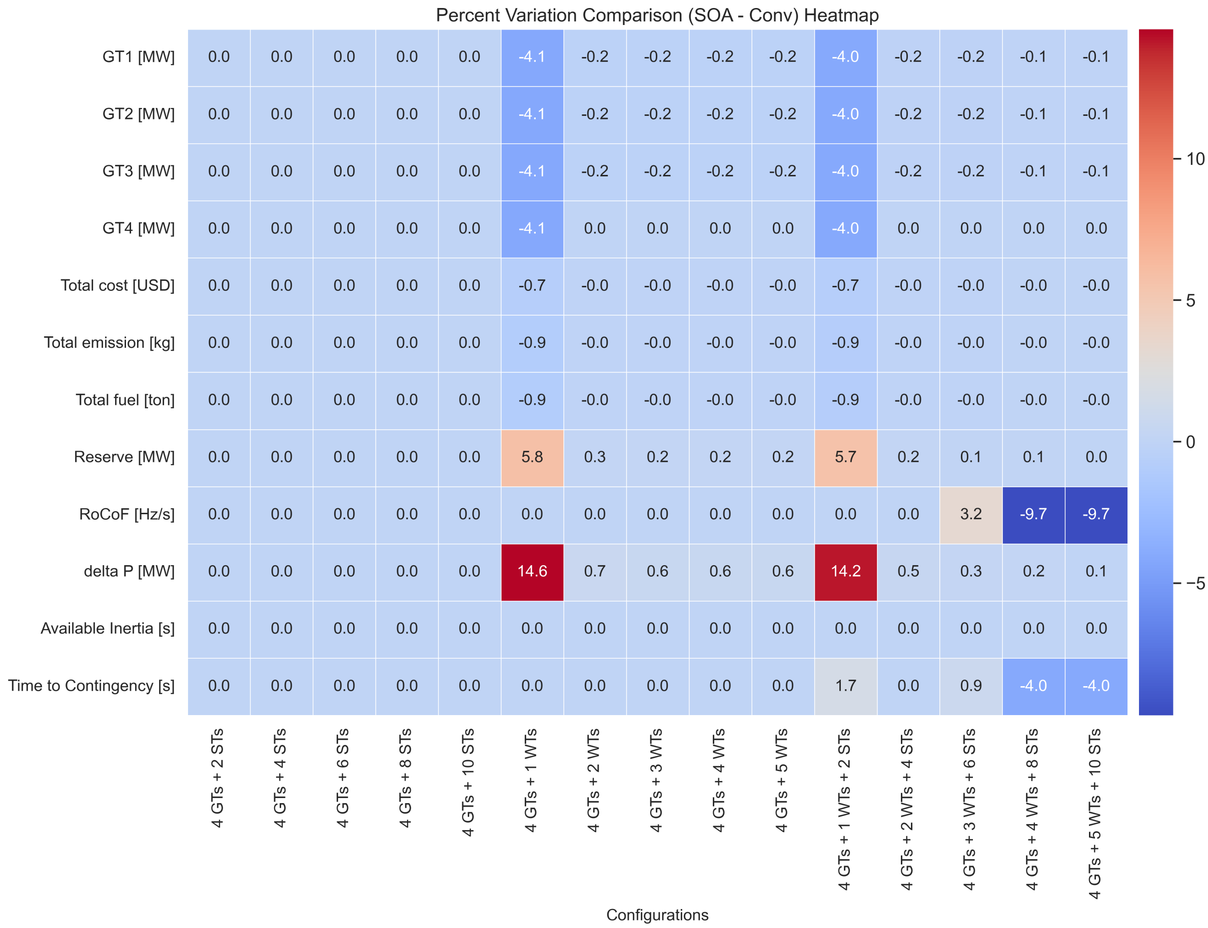


Figure 33 – Difference in the Percentage Variation of the flexible/state-of-the-art with the conventional power system configurations, taking 4 Gas Turbines configuration as a base case

The heatmap 33 clearly illustrates that a state-of-the-art power system integrated with WTs and STs offers significant cost, emissions, and fuel consumption savings over conventional power systems. With the incorporation of 1 WTs, the cost, emissions, and fuel consumption savings vary upto -0.7 to -0.9%. It is due to the fact that, the higher ramp rates satisfies the steeper ramps for the state-of-the-art configurations and hence pushes the 4th GT to dispatch less power, which helps the system economical operational.

Along with that, the security KPIs shows improvement for the state-of-the-art configurations as compare to the conventional configurations. With the help of flexible parameter of the

SOA configuration, the system shows the noticeable increase in the reserves, ROCOF, and the delta P, illustrating the reliable power system. Therefore, the consideration of state-of-the-art configurations for OG platforms is essential to balance the economic and environmental benefits with system security and reliability.

In conclusion, state-of-the-art configurations with WTs and STs provide considerable amount of cost, emissions, and fuel consumption savings. Furthermore, the approach enhances the security KPIs of the standalone power system of the OG platforms. This approach will help the OG sector transformation to more sustainable and environmentally friendly operations.

5.4 Comparison of Conventional and State-of-the-Art Results under Generators Prioritization

The same capacity GTs can be operated on a priority schemes by considering various factor like the fuel costs, efficiency at different load points, maintenance schedules, and emissions output. Fuel costs, which are determined by market variations, have an impact on each GT's economic viability. Whereas, efficiency at different load points defines optimal operation. Maintenance routines ensure consistent performance and eliminate potential disruptions. Also, consideration of emissions production in operational planning is important since it aligns with sustainable practices, supporting a cleaner energy mix.

In this section, we analyze the impact of prioritizing GTs based on different fuel prices, such as GT1=100, GT2=140, GT3=180, and GT4=220, to emulate the prioritization scenario in LGridPy tool. This approach pushes the generators to operate the cheaper ones first and subsequently the more expensive ones. However, this may cause the second or third GT to operate at lower efficiency, resulting in higher fuel consumption and emissions due to operating at a lower efficiency point.

The results of this study show that the proposed technique may not assist efficient operation of State-of-the-Art configurations. This inefficiency is caused by the SOA parameter setting, which sets the minimum power at 20% (5MW), implying that the gas turbines (GTs) can run at levels as low as 5MW. A low operating point forces the system to operate at a lower efficiency level, resulting in increased fuel consumption and emissions.

For this study, the new base case is selected based on the different fuel prices of the GTs (fuel price of GT1=100$/MW, GT2=140$/MW, GT3=180$/MW, and GT4=220$/MW) and the rest of parameters presented in the Table 12. Whereas, the input data utilized for the simulations are presented in the Figure 15. The base case results for the State-of-the-art (4 GTs) power system configuration is tabulated in Table 14, which will be used to find the percentage variation between the conventional and state-of-the-art power systems.

When examining the comparative results of percentage variation (SOA-Conv) shown in Figure 34, it is evident that for the flexible/state-of-the-art percentage variation from the base

Table 14 – Base Case Data for Different Fuel Prices- Mean Values of State-of-the-art (4 GTs) Power System Configuration

Parameter	**Value**
Load [MW]	52.54
GT1 [MW]	20.71
GT2 [MW]	11.73
GT3 [MW]	10.09
GT4 [MW]	10
WT Total [MW]	0
ST Total [MW]	0
Total cost [USD]	3531001.38
Total emission [kg]	10363.44
Total fuel [ton]	1442.94
Available Inertia [s]	12.8
Reserve [MW]	37.46
delta P [MW]	14.96
ROCOF [Hz/s]	-0.52
Time to Contingency [s]	11.49

case of Table 14 has the increase in both total fuel consumption and emissions, when compared with the percentage variation of the conventional configurations. There is an increase of 0.295 to 0.9% in the overall fuel consumption and for the overall CO_2 emissions, illustrated in the Figure 34.

The increase in overall fuel consumption and emissions can be related to the fact that prioritizing generators could result in some of GTs operated at lower efficiency values. Operating at lower efficiency points leads in increased fuel consumption and, as a result, higher CO_2 emissions. As a result, while the priority strategy appears to deliver savings in terms of the operational cost but it can result in higher fuel consumption and emissions, which subconsciously leads to a less greener power system.

In conclusion, this section highlights the significance of operating the state-of-the-art power systems efficiently in order to increase cost savings and reduce environmental effect. The results analysis shows that prioritizing generator dispatch may result in greater fuel consumption and emissions, negating the benefits of using state-of-the-art or flexible power system.

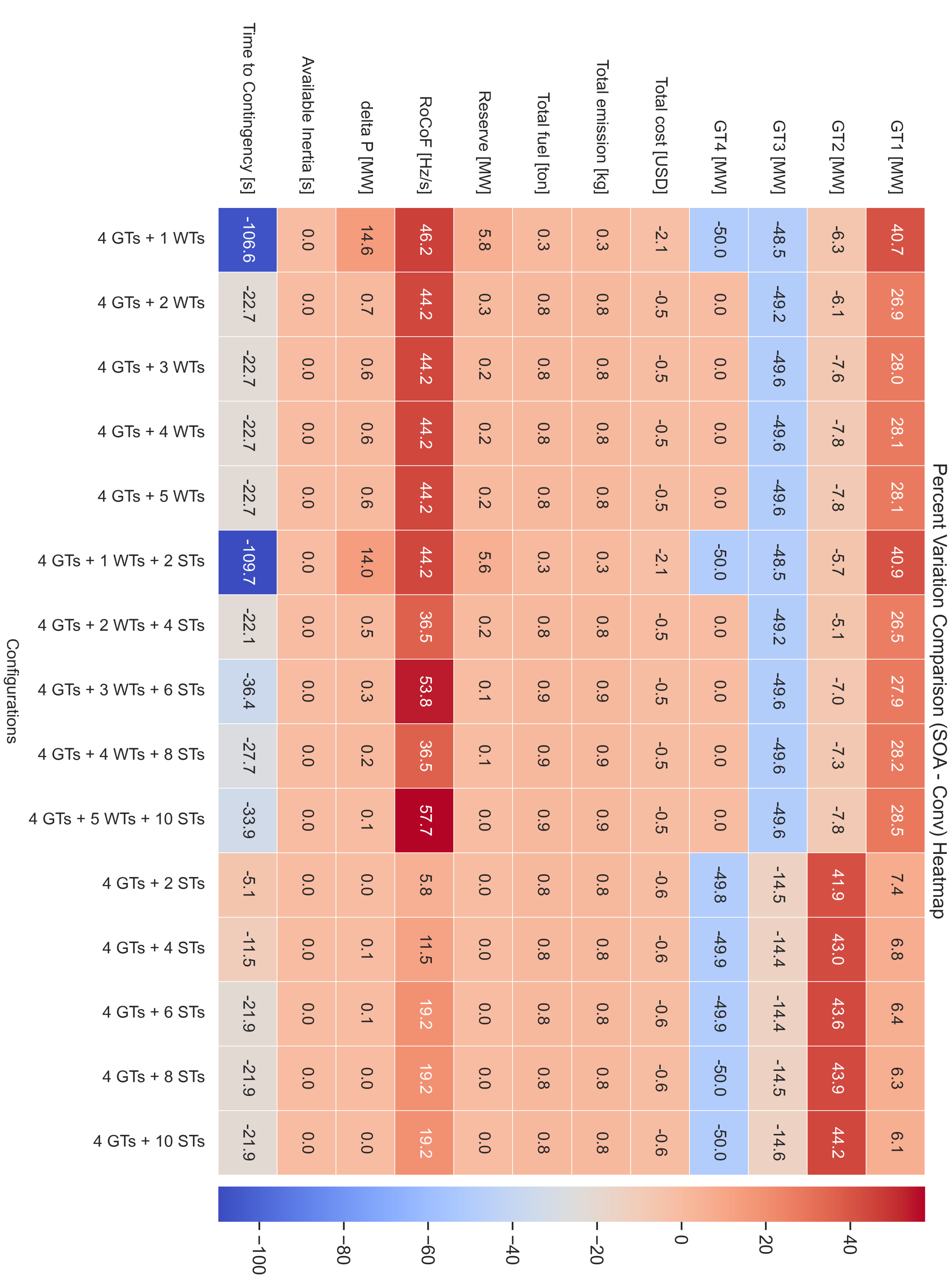


Figure 34 – Difference in the Percentage Variation of the flexible/state-of-the-art with the conventional power system configurations under prioritising the GT based on different fuel prices, taking 4 Gas Turbines configuration as a base case

Chapter 6

Conclusion

This thesis presents a novel methodology for the planning of standalone hybrid power systems. The novel method is implemented in a python based tool, called LGridPy, for the robust power system analysis. The LGridPy is based on the Mixed-Integer Nonlinear Programming (MINLP), which minimizes the total system costs, including generators' fuel, start-up, shut-down, and maintenance costs, using the IPOPT and Gurobi solvers. The main feature of method is the consideration of the generator's efficiency curve over the constant value and the consideration of the ROCOF constraint along with others, to gaurentee the relaible and realistic emulation of power system behavior. Furthermore, the comprehensive flexibility analysis is perform on the conventional and state-of-the-art OCGTs that offer insights into system dynamics under various system fluctuations and the cost benefits.

Firstly, the new method is validated and authenticated by comparing the results of a case study with the well renowned Python for Python for Power System Analysis (PyPSA) tool. As expected, the new tool simulated the case study with the negligible results deviation.

Secondly, it discusses the importance of efficiency curve consideration over the constant value, by implementing the LGridPy for a case study with generators considering efficiency curve and constant value. The results were quite significant as the efficiency curve was producing more realistic results over the other.

Thirdly, the LGridPy tool was tested to analyse 2 case studies to perform the flexibility analysis on the, (a). Conventional OCGTs and (b). State-of-the-art OCGTs. For the conventional OCGTs, to analyse the power system ability to absorb the demand load variation, the load of 90MW is increased gradually to the point where the power system cannot cope with the variation and the solution of the model is infeasible. For the conventional OCGTs, the system accommodated the variation of load (90MW) increase of 7%. Whereas, for the state-of-the-art OCGTs with more flexible constraints, the load was increased from 7% to 34% but the system was able to tune with the variations, showing the ability of the system to adjust accordingly and compensate for the variations by countering the change with OCGT better state-of-the-art flexible attributes.

Fourthly, the more robust constraint of ROCOF and spinning reserves been introduced to analyse the performance of the standalone power system. Initially, the ROCOF constraint limited the frequency drop to -1.5Hz, when subjected to any contingency situation, resulted in the a secure and reliable operation but with the increased cost of operation, compared to the base case of conventional 4 OCGTs, already installed at the OG platform. Whereas, the ROCOF limit does not ensure the enough spinning reserves in certain case studies, resulted in the negative active power mismatch during the loss of biggest generating unit, thus supported the need of required spinning reserve constraint. Finally, the combination of ROCOF limit and required spinning reserve constraints were introduce, that enhanced the power system security even further but at the cost of increase operational cost. The tradeoff between the economic operation and security of the power system is explained in detail with various key performance indicator, which gives a detail insight for the power system operator to find the equilibrium between both requirements.

The WTs and STs integration into the hybrid power systems encourages the sustainability by lowering the operational costs, emissions, and fuel consumption. However, establishing a balance between economics and system security is something to consider in this manner. The system security may be jeopardized due to the high-penetration of WTs and STs in the hybrid systems, if are not operated with robust constraints such as ROCOF and spinning reserves. Nonetheless, while applying these robust constraints may increase the operating costs but they considerably improve the security and reliability of hybrid systems.

Lastly, The flexibility analysis of the OG standalone power system in analysed with the consideration of robust ROCOF and spinning constraints. The based case of 4 GTs (operated with non-prioritized scheme of GTs) is compared with the conventional and state-of-the-art configurations, resulted in the percentage reduction in the overall cost, emission, and fuel consumption with the integration of WTs and STs in the hybrid standalone power system. Whereas, the security was compromised with the integration of WTs and STs due no inertial and spinning reserve support. Whereas, the state-of-the-art configurations promised improved results in the form of higher percentage reduction on the operational and environmental side (cost, emissions, and fuel consumption) but also, with the improved and enhanced security aspects of the system.

In addition to that, the flexibility analysis is also performed on the OG power system, operated on the prioritized GTs scheme. The comparative analysis of the conventional and state-of-the-art configuration (both compared the prioritize 4 GT configuration) resulted in the higher reduction in the operational cost for the state-of-the-art configuration but with the higher fuel consumption and emission. The results declared the flexible/state-of-the-art power system non-greener solution, when the GTs are operated on the prioritized scheme. Therefore, it is advised to dispatch the required GTs of flexible/state-of-the-art configurations equally to benefit more from the flexible attribute they offer.

6.1 Perspectives for Future Research

At this point, the LGridPy need to be upgraded to its best potential and the future topics to be addressed are:

- The detailed flexibility analysis needs to be performed on the power system to analyse the system behavior.
- The Automatic Under Frequency Load Shedding (AUFLS) strategy is under review, to be implemented on LGridPy tool to analyse more feasible solutions.
- The dynamic analysis could be perform in the future.

6.2 Publication

Main Publications

- Vieira, G. T., Pereira, D. F., Taheri, S. I., **Khan, K. S.**, Salles, M. B., Guerrero, J. M., & Carmo, B. S. (2022, June). Optimized Configuration of Diesel Engine-Fuel Cell-Battery Hybrid Power Systems in a Platform Supply Vessel to Reduce CO2 Emissions. In Energies (Vol. 15, No. 6, p. 2184). MDPI.
- **Khan, K. S.**, dos Santos, I. V., dos Santos, G. B., Salles, M. B., & Monaro, R. M. (2021, February). Evaluation of Deep-Water Floating Wind Turbine to Power an Isolated Water Injection System. In International Conference on Offshore Mechanics and Arctic Engineering (Vol. 84768, p. V001T01A002). American Society of Mechanical Engineers.
- **Khan, K. S.**, Sousa, M. L., Santos, G. B., Monaro, R. M., & Salles, M. B. (2022, November). Flexibility Analysis of O&G Platform Power System with Wind Energy Integration. In Journal of Physics: Conference Series (Vol. 2362, No. 1, p. 012021). IOP Publishing.
- Otremba, L., dos Santos, I. V. M., **Khan, K. S.**, Monaro, R. M., & Salles, M. B. C. (2022, November). Design of Stand-Alone O&G Water Injection System Fed by Wind Generation with Battery Support. In Journal of Physics: Conference Series (Vol. 2362, No. 1, p. 012027). IOP Publishing.

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