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A Matheuristic Approach for the Unit Commitment Problem in Electrical Power System Operations

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FINAL PROJECT SHEET

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Abstract

Electric power system is one of the most critical service systems that keep our society running, as it is responsible for generating, transmitting, and distributing electricity. Since a power system is an interconnected, large structure spread over a geographically wide network, its operation is complex. In power system operation and planning, the Unit Commitment (UC) is an optimization problem that consists of determining the optimal on/off state of the production units that meets the power demand at a minimum operating cost.

With the increase of the high renewable energy penetration level, the power system operators need to implement innovative power systems to accommodate the variability and uncertainty of renewable energy outputs. The conventional UC shows a lot of restrictions to keep up with increasing changes. Therefore, more advanced optimization approaches are required to solve the large-scale UC problem within a reasonable time.

In this study, a stochastic unit commitment problem is described and formulated where the wind uncertainty is captured by simulating a certain number of scenarios. Because the large number of scenarios dramatically increases computational complexity, this work proposes a matheuristic method to reduce the number of variables and the combinatorial search space of the UC. This hybrid method employs the greedy randomized adaptive search procedure (GRASP) to obtain a reduced UC before conducting a MILP algorithm. This search space reduction strategy will result in faster convergence of the MILP solver and potentially a better solution for the UC.

The case studies illustrate the validity and effectiveness of the proposed approach, and the simulation results show that the proposed methodology is able to find a high-quality solution of large-scale UC problem in less amount of computational time compared to the exact MIP solver.

Keywords: Unit commitment, Matheuristics, GRASP, MILP

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1 Introduction

1.1 Problem Statement

Optimization models have been widely used in the operations of electrical power industry, the system operators need to evaluate and plan-ahead the generation resources in order to ensure feasible and economical operation of the power system, in this context, variability and constraints are typically captured using Unit Commitment (UC) models. UC is one of the key and high priority decision processes performed by the system operator, it is employed to determine the operation schedule of the generating units at every hour interval with varying loads and generations and technical constraints. The UC problem is known to be NP-hard Mixed Integer Linear Programming (MILP), the application of mathematical models to solve this type of hard combinatorial optimization problems is not practical when the size of the instances increases since they spend high computational times. Therefore, researchers have been focusing on the development of an efficient, and near-optimal UC algorithms which can be applied to large-scale power systems. This work explores the necessity for alternative optimization approaches for UC solution, where the novelties of this study are summarized below:

1) A novel matheuristic algorithm is proposed to solve the UC problem improving its computational performance compared to the traditionally exact solution methods. Here, a GRASP algorithm is used to tighten the search space of the UC problem reducing the number of binary variables related to the status of the generation units without losing the optimum solution. The best solution overall GRASP iterations is considered to be the initial solution of the MILP. Once the search space has been reduced by the previous method, a MILP is used to solve the UC problem.

2) This study provides an extensive review of the different methodologies used to solve the UC problem that are available in the literature. This review allows us to extract general conclusions concerning the most suitable

techniques to solve the UC problem as well as guidelines for the selection of our proposed matheuristic approach.

3) A UC model considering wind uncertainty and transmission switching is described and formulated. The formulation includes limitations of the load shedding, wind power spillage, and spinning reserve calculation. Different scenarios represent the wind uncertainty.

1.2 Unit Commitment Solution Methods - Literature Review

Unit commitment is one of the classic optimization problems in power systems operation and control, various approaches to the solution of the UC problem have been proposed from simple to complicated methods. A comprehensive review of the main solution approaches implemented in UC problems is summarized in **Table 1-1**.

Table 1-1 Literature review UC solution methods – Summary

Year	References	Solution Methods UC	
Classical Methods			
1991-2013	[1]-[2]	Heuristic	Priority-list
1988-2012	[3]-[4]	Exact	Dynamic programming
1989-2005	[5]-[6]		Lagrange relaxation
2006-12	[7]-[8]		Mixed integer linear programming
2005-07-15-18	[9]-[10]-[11]-[12]	Stochastic	Stochastic programming
2015-17-18	[13]-[14]-[15]		Robust optimization
2015-17	[16]-[17]		Interval optimization
Metaheuristic Methods			
2002-04-17	[18]-[19]-[20]	Metaheuristics	Genetic algorithms
2002-17	[21]-[20]		Other evolutionary algorithms
2003-16	[22]-[23]		GRASP
2004-05	[24]-[25]		Tabu search
2007-11	[26]-[27]		Particle swarm optimization
Hybridizing Methods			
2001-18-19	[28]-[29]-[30]	Hybrid / new approaches	Hybrid metaheuristics
2014-17-18	[31]-[32]-[33]		Matheuristics
2018-19	[34]-[35]		Machine Learning

Most of the UC problems are formulated based on Lagrangian relaxation, dynamic programming or mixed-integer linear programming methods. Nevertheless, with the high penetration of renewable energy new UC models have been proposed to manage the uncertainty of this type of generation resources; therefore the next wave is focused on transitioning from traditional approaches to stochastic optimization for solving the UC problem. The following subsections of this chapter provide a brief description of the advantage and drawbacks of the main methods covered in **Table 1-1**.

1.2.1 Classical Methods

Based on **Table 1-1**, the simplest unit commitment solution method consists of creating a priority list of units, the most priority-list schemes are built around a simple shut-down algorithm where the units must be shut-down as the load goes down and then recommitted as it goes back [36]. The Dynamic Programming (DP) approach is focused on searching for the minimal cost solution and it has the ability to overcome the difficulty of non-convexity and non-linear systems. However, the DP method of solution of UC problem has many disadvantages for large power systems with many generating units, this is because of the necessity of forcing the DP solution to search over a small number of commitment states to reduce the number of combinations that must be tested in each time period. In the Lagrange Relaxation (LR) technique these disadvantages disappear, LR is based on a dual optimization approach where the dual procedure attempts to reach the constrained optimum by maximizing the Lagrangian concerning the Lagrange multipliers while minimizing with respect to the other variables.

Over the past decade, Mixed-integer linear programming (MILP) has become the preferential way to solve UC problem [2], where the main advantage is that MILP solver returns a feasible solution and the optimality level is known. However, the computational complexity of this method grows exponentially with increasing problem size. Different solution approaches have been proposed to solve the UC when the optimization models include uncertainties from the renewable generation and/or faults of the components of the power system, such as stochastic programming, robust and interval optimization, etc. In stochastic optimization, we assume known distributions to represent the uncertainties, and in robust optimization, we assume that uncertainties belong to a set. An academic review of Stochastic Unit Commitment is presented in [11].

1.2.2 Metaheuristic Methods

The use of heuristics and metaheuristics to solve real problems is widely accepted within the operation research community, [37]. A heuristic is a technique designed to solve a given problem, which ignores whether the final solutions can be proved to be optimal or not, and usually produces a sufficiently good quality solution at a reasonable computational cost. A metaheuristic is an iterative master process that guides and modifies the operations of subordinate heuristics to efficiently produce high-quality solutions [37]. Albeit the exact algorithms are the most successful methods proposed to solve the UC problem in recent literature, the use of metaheuristics has become popular to solve large scale UC optimization problems. According to **Table 1-1** the family of metaheuristics applied to UC problem includes genetic algorithms, tabu search, GRASP, particle swarm optimization, and other evolutionary algorithms. Fine-tuning is one of the main drawbacks faced by almost all heuristic-based methodologies, and their application is not yet widely accepted by the power system operators.

1.2.3 Hybridizing Methods

The application of hybrid methods in the UC problem has been advanced in recent literature, and it still represents a future trend in the power system operation research. Regarding **Table 1-1** few studies proposed hybrid approaches to solve the UC problem combining two or more metaheuristics, or using matheuristics (hybridizing metaheuristics and mathematical programming), and recent works have used machine learning techniques to improve the performance of the UC problem solution.

1.3 Approach and Method Followed

A summary of the key characteristics of the methodology implemented in this work is illustrated in **Table 1-2**. First, the process of introducing the data inputs into the optimization model are described. Then, the considerations for the problem formulation and the reduction search space strategy are detailed. Also, the corresponding case studies and the simulation tools for test the proposed UC problem are provided. Finally, this summary provides the possible applications of the proposed methodology.

Table 1-2 Key characteristics of the proposed methodology

Characteristic	Methodology
Data Requirements	Full parameters of the components of the power system to model a UC problem, including wind generation uncertainty. The scenario construction to represent the wind uncertainty is based on a normal distribution. See **sections 2.3 and 4.1**.
Problem Formulation	The MILP formulation for Unit Commitment proposed includes transmission switching operations, spinning reserve calculation, and uncertainty representation from wind generation. The objective function minimizes the total operation cost. The corresponding constraints are divided into two sets: pre-contingency constraints and wind scenario-based constraints. See sections 2.3 and 2.4.
Reducing the Problem Size	A matheuristic approach is applied to solve the UC model. Here, an algorithm based on GRASP is used to reduce the size of the problem and then the CPLEX MILP optimizer is employed to solve the UC problem in the reduced search space. **See section 3.5**.
Case Studies	The proposed approach will be applied IEEE RTS system. Where the performance of the proposed matheuristics method vs. the results of the exact algorithm will be evaluated. **See chapter 4**.
Simulation	The proposed model is coded in python version 3.7.4, and the MILP model was solved with IBM Decision Optimization CPLEX Modeling for Python v2.10.
Application	Power system operators and/or policymakers trying to improve the methodologies to solve the UC problem. The proposed method can be used to provide insights for reducing the search space of different power system optimization problems as transmission planning, optimal transmission switching, etc.

1.4 Organization of the Memory

This thesis includes five chapters. Chapter 1 introduces the problem statement. Moreover, an exhaustive literature review about the UC solution methods is presented. Chapter 2 provides a description and formulation of the UC mathematical model where a probabilistic reserve criterion, transmission switching, and wind uncertainty are considered. In Chapter 3, a matheuristic approach that combines the benefits of GRASP algorithm and MILP is proposed to solve the UC problem formulated in Chapter 2. Chapter 4 presents the results of the analysis that shows the performance of the methodology proposed. Chapter 5 summarizes the conclusions, the limitations of the study, and suggestions for further research.

2 Overview of the Unit Commitment Problem

2.1 Power System Fundamentals

Before introducing the Unit Commitment (UC) problem, it is useful to recall a general overview of the electric power system which is one of the most important service systems that keep our society running, as it is responsible for generating, transmitting and distributing electricity, which powers almost all aspects of our life. **Figure 2-1** shows the four subsystems of a power system: Generation, Transmission, Distribution, and Supply, each subsystem has a different nominal voltage level which is regulated and changed by transformers. In this study, we will concentrate on the generation and transmission subsystems. The generation incorporates the production facilities that generate electricity, i.e., nuclear power plants, oil, coal, and natural gas-fired power plants, or hydro, wind, solar and biomass power plants. On the other hand, the transmission subsystem is the network of electricity that allows moving bulk electrical energy from generation to consumption areas [38].

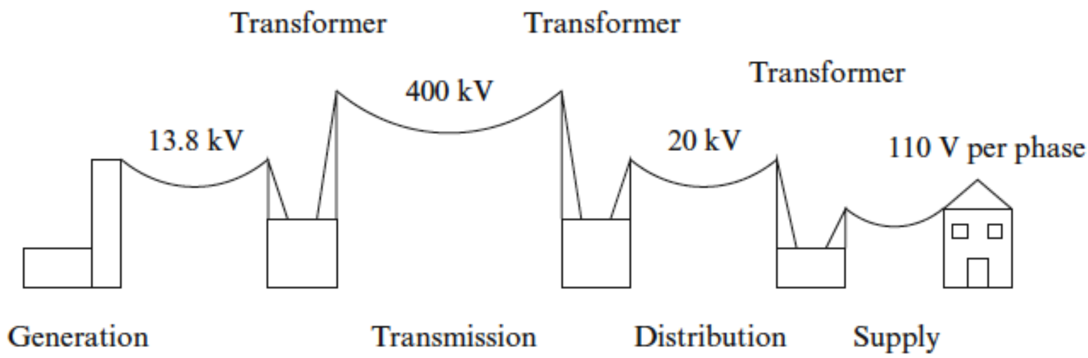

Figure 2-1 Power system general scheme [38]

2.2 Power System Operations

Electric energy systems are managed either in a centralized operation (optimal control) manner or through a market [38]. In the centralized approach a central operator has perfect knowledge of the entire power system, including both economic and technical information then makes appropriate decisions, and informs producers and consumers on how to proceed, i.e., the central operator plans and operates the system to supply the demand at minimum cost and the power producers are simply told when and how to operate their own generating units. A market operation incorporates both regulated and competitive activities where a market operator receives offers and bids from producers and consumers, respectively, clears the market using an auction, and informs producers and consumers of their assigned productions and consumptions, respectively.

Power system operations include decisions within a time frame of 1 month to minutes in advance to power delivery. Although there are different operation decisions, this thesis covers the Day-Ahead Operation where the decisions are made within 1 day of power delivery and include the scheduling of dispatchable generating units for production (Unit Commitment) and the procurement of reserves (backup power ready to take over if contingencies occur). Note that the term dispatchable is used for controllable generating units and the term non-dispatchable is employed to the weather-dependent renewable generating units whose cannot be scheduled with accuracy since their production is uncertain.

In a centralized approach, day-ahead operations are based on solving a UC algorithm by the central operator to identify the hourly on/off status of each generating unit, as well as the actual hourly energy production and the level of the reserve where the objective is to minimize the total production cost. In a market framework, day-ahead operations are based on a market-clearing algorithm that pursuing maximum social welfare allocates energy production and reserve levels to generating units. This chapter is focused on the description and formulation of the UC problem-based in a centralized approach, which will be solved by the strategies described in chapter 3.

2.3 Unit Commitment Problem - Description

This section describes the day-ahead Unit Commitment problem, which consists of determining, for a given planning horizon, the commitment of thermal generating units with the objective of minimizing the generation cost subject to energy demand, technical and security constraints. Note that to “commit” a generating unit is to “turn it on” that is, to bring the unit up to speed, synchronize it to the power system, and connect it so it can deliver power to the transmission network [36]. For the sake of clarity, a description of the main *ingredients* of the UC problem is presented in the following subsections, including planning horizon, power system components, power flow, spinning reserve and the integration of renewable energy into the UC problem.

2.3.1 Planning Horizon

In the day-ahead UC, a typical planning horizon is one day, and it divided into 24 hours. The time intervals are represented by the index t, where T is the number of time periods in the planning horizon, in this case, is equal to 24.

$$t = 1,2,.....,T \tag{2.1}$$

2.3.2 Power System Components

The most common components of power systems that are including in the UC problem are illustrated in **Figure 2-2** through a small size power system, the details are given below:

- **Generating Units**

The generating units are the key components of the power system they used to produce electrical energy, control the frequency, and regulate voltage levels. In this thesis, the case studies include thermal generating units and wind farms as energy production. The thermal units are indexed by i, where I is the number of thermal generating units, see (2.2). The wind farms are indexed by w, where W represents the number of wind farms, according to (2.3).

$$i = 1,2,.....,I \tag{2.2}$$

$$w = 1,2,.....,W \tag{2.3}$$

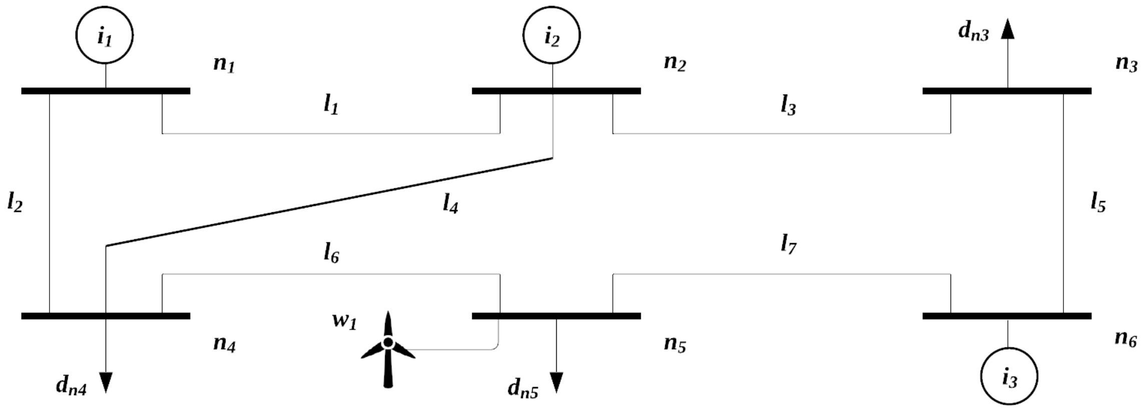

Figure 2-2 Power system diagram – 6 buses system example

◆ **Transmission Network**

The transmission network is modeled by a set of nodes or buses interconnected by transmission links. Generators units (i) and loads (d_n) connected to the busses inject and remove energy power flow from the transmission system. The buses are indexed by n, where N is the number of buses in the system, see (2.4). The transmission lines are indexed by l, where Λ represents the number of lines, according to (2.5).

$$n = 1,2,.....,N \tag{2.4}$$

$$l = 1,2,.....,\Lambda \tag{2.5}$$

2.3.3 Power Flow

In order to include the constraints on flows through the network elements, the power flow must be evaluated as an integral part of the UC problem. In [39], the power flow problem is defined as the computation of voltage magnitude (V_n) and phase angle (θ_n) at each bus in the power system under balanced three-phase steady-state conditions, where the real and reactive power flows in transmission assets (lines and transformers) can be obtained as a by-product of this calculation.

The non-linear equations (2.6) and (2.7) express the average active (P_{lnm}) and reactive power (Q_{lnm}) at each node respectively, these formulations correspond to the network flow problem for the AC transmission grid. Due to the difficulty with solving non-linear problems, the AC power flow can be further simplified neglecting the reactive power (2.7), and assuming that the bus voltages magnitudes are constant at 1.0 per unit. With these simplifications, the power flow is reduced to a completely linear problem referred to as the DC power flow according to the expression in (2.8). This last expression will be incorporated in the UC formulation of Section 2.4

$$P_{lnm} = V_n \sum_m V_m \left[G_{nm} \cos\left(\theta_n - \theta_m\right) + B_{nm} \sin(\theta_n - \theta_m\right)] \tag{2.6}$$

$$Q_{lnm} = V_n \sum_m V_m \left[G_{nm} \sin\left(\theta_n - \theta_m\right) - B_{nm} \cos(\theta_n - \theta_m\right)] \tag{2.7}$$

$$P_{lnm} = B_{nm}\left(\theta_n - \theta_m\right) \tag{2.8}$$

2.3.4 Spinning Reserve

Reserves compose the resources that enable the implementation of preventive and corrective security actions. Several types of reserves are definite into the electricity market context, this work focuses on the Spinning reserve (SR) which is the most critical resource used by the power system operators to respond to sudden generation outages and load variations. SR is known as the unused capacity of the power system to respond voluntarily to contingencies within a given period of time using the already synchronized devices [40]. When estimating the SR capacity, two different approaches can be adopted: deterministic and probabilistic. For the deterministic criterion, the SR is set to the capacity of the largest online generator or a fraction of load. However, this approach ignores the probability of occurrence of the components failures and/or the uncertainty from the renewable generation, [41]. A probabilistic reserve criterion is used in the UC formulation of this study.

2.3.5 Integrating Renewable Energy in Unit Commitment

Renewable energy is defined as the energy offered through natural resources, such as wind power, solar power, hydropower, among many others. These types of energy are desirable and sustainable because of "no" costs and/or no pollutant emissions, which well fits the current and future needs of the next-generation energy systems. Thus, their production will continue to grow during the next years, according to the statistics presented in [42]. However, its intermittent and uncertain nature brings a lot of challenges to the current and future operations of the power system. The wind generation is non-dispatchable, and the wind power uncertainty constitutes the main obstacle to the power systems operations [43]. Therefore, uncertainty from the wind generation forecast should be considered into the day-ahead UC problem due to its inherent randomness during the real-time operation.

◆ **Wind power uncertainty**

In this study, the wind uncertainty is considered, and it is assumed that it is modeled as a continuous normally distributed random variable with zero mean and a standard deviation σ_{wt}. In stochastic programming, the random variables are typically represented by a finite set of realizations or scenarios [43]. P_{wst} represents the realization of the random variable P_{wt} in the wind scenario *s*. According to the normal distribution of wind power uncertainty illustrated in **Figure 2-3** seven scenarios are considered in this case. The mean is the expected value of the random variable (*s4*, forecast), whereas the other scenarios represent the forecast error. Each scenario is associated with a probability of occurrence π_s, which is calculated based on the normal distribution curve shown in **Figure 2-3**. The summation of these probabilities over all scenarios is equal to one. The mid-value for each interval represents the value of the corresponding scenario.

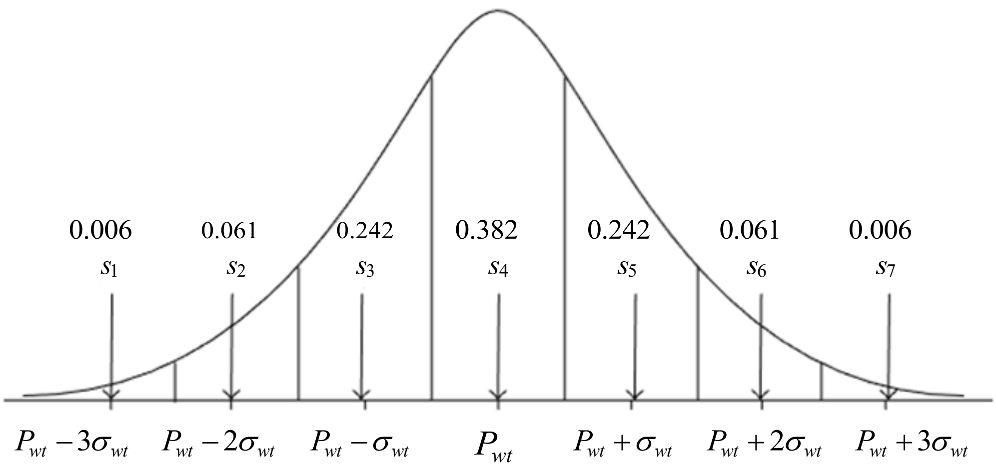

Figure 2-3 Seven-interval discretization of a normal distribution, No. of standard deviations from the mean (s4). Mean= forecast

2.3.6 Transmission Switching

The automatic adjustment of the transmission network topology known as Optimal Transmission Switching (OTS) integrates the control of transmission assets into the UC formulation to co-optimize the network topology simultaneously with the generation output [44]. OTS removes selected transmission lines from service or puts lines back into service, it can yield the generation cost reduction or reliability improvement. Note that the conventional transmission system is treated as a static asset in the network, and the current operation standards do not consider the grid topology as a decisive measure in the classical dispatch optimization models. However, in the recent literature of the UC models the OTS functionality is incorporated for enhancing the flexibility of the future power system, [45].

2.4 Unit Commitment Problem - Formulation

Considering the definitions of the previous subsection, a formulation of the Unit Commitment with OTS to deal with the wind power uncertainty is an extension of the formulation explained in [46]. In this section, a Unit Commitment model with wind uncertainty is formulated where the operation cost and the cost of the load shedding are included in the objective function. The Spinning reserve is calculated according to the largest deviation between the wind scenario and the pre-contingency generation level. To represent wind power uncertainty, a normal distribution is used to create wind scenarios. The limitations of the wind spillage and the load shedding under wind variability are considered. The algorithm employed to solve this model and the strategies to improve its computational performance are described in Chapter 3.

2.4.1 Objective Function

The objective function (2.9) consists of two main terms: i) The first term is the operation cost, which includes the running and the star-up costs. ii) The second term is the cost of load shedding under wind uncertainty, which is equal to load shedding LS_{nst} multiplied by the value of lost of load (VOLL) at bus n during the period t ($VOLL_{nt}$) and the probability of occurrence of each wind scenario π_s. VOLL is defined as the average value (cost) that the costumers attach to the loss of one kW of electricity for one hour [40]. This objective function is subject to the pre-contingency and post-contingency constraints.

$$Min_{\Xi}:\sum_{i\in I}\sum_{t\in T}\left[C_{it}\left(P_{it},u_{it}\right)+SUC_i v_{it}\right]+\pi_s\sum_{s\in\Omega}\sum_{n\in N}\sum_{t\in T}VOLL_{nt}LS_{nst} \tag{2.9}$$

2.4.2 Pre-contingency Constraints

The set of constraints (2.10) - (2.21) represents the pre-contingency state, i.e., the normal operation state of the UC problem. Constraint (2.10) represents the power balance in each bus n during the period t. Here, P_{wt} indicates the wind power forecast value. The DC power flow across the transmission lines are shown in (2.11) - (2.12), the key point of these constraints is the incorporation of the binary variable z_{lt} which represents the status of the transmission lines to be optimized using OTS ($z_{lt}=0$, line opened, i.e., out of service), ($z_{lt}=1$, line closed, i.e., in-service). M_l is referred to as the "Big M". When z_{lt} is one the value of M_l does not active, when the binary variable z_{lt} is zero, the value of M_l must be a large number greater than or equal to the expression described by (2.13).

In (2.14) the limits of the power flow across the transmission lines P_{lt} are multiplied by z_{lt}, so P_{lt} is equal to zero when the line l is out of service. The voltage angle in each bus should be bounded by (2.14). Equation (2.16) specifies the maximum number of open transmission element (J) allowed in each time period.

$$\sum_{i\in\phi_n^I} P_{it} + \sum_{w\in\phi_n^W} P_{wt} - \sum_{\substack{l\in\Lambda \\ FB(l)=n}} P_{lt} + \sum_{\substack{l\in\Lambda \\ TB(l)=m}} P_{lt} = D_{nt}, \forall n \in N, \forall t \in T \tag{2.10}$$

$$B_l\left(\theta_{FB(l)t} - \theta_{TB(l)t}\right) - P_{lt} + \left(1 - z_{lt}\right)M_l \geq 0, \forall l \in \Lambda, \forall t \in T \tag{2.11}$$

$$B_l\left(\theta_{FB(l)t} - \theta_{TB(l)t}\right) - P_{lt} - \left(1 - z_{lt}\right)M_l \leq 0, \forall l \in \Lambda, \forall t \in T \tag{2.12}$$

$$M_l \geq B_l\left|\theta^{\max} - \theta^{\min}\right|, \forall l \in \Lambda \tag{2.13}$$

$$-P_l^{\max} z_{lt} \leq P_{lt} \leq P_l^{\max} z_{lt}, \forall l \in \Lambda, \forall t \in T \tag{2.14}$$

$$\theta^{\min} \leq \theta_{nt} \leq \theta^{\max}, \forall n \in N, \forall t \in T \tag{2.15}$$

$$\sum_{l\in\Lambda}\left(1 - z_{lt}\right) \leq J, z_{lt} \in \left\{0,1\right\}, \forall l \in \Lambda, \forall t \in T \tag{2.16}$$

The following constraints are related to the variables that represent the unit commitment problem. Here, the restriction (2.17) limits the active power output of each generator. The startup variable satisfies (2.18). The block of constraints (2.19) includes initial conditions, ramp rates, and minimum-up and down-time constraints [47]. Constraints (2.20) and (2.21) are spinning reserve up and down restrictions where τ is the time required for units to deliver their reserve. RU_i and RD_i represent the ramp-up and the ramp-down rate limits of the unit i, respectively.

$$u_{it}P_i^{\min} \leq P_{it} \leq P_i^{\max} u_{it}, \forall i \in I, \forall t \in T \tag{2.17}$$

$$v_{it} \geq u_{it} - u_{i,t-1}, u_{it} \in \left\{0,1\right\}, v_{it} \geq 0, \forall i \in I, \forall t \in T \tag{2.18}$$

$$\left(u_{it}, P_{it}\right) \in \psi, \forall i \in I, \forall t \in T \tag{2.19}$$

$$R_{it}^{up} \leq P_i^{\max} u_{it} - P_{it}, R_{it}^{up} \leq \tau RU_i u_{it}, \forall i \in I, \forall t \in T \tag{2.20}$$

$$R_{it}^{dn} \leq P_{it} - P_i^{\min} u_{it}, R_{it}^{dn} \leq \tau RD_i u_{it}, \forall i \in I, \forall t \in T \tag{2.21}$$

2.4.3 Wind Scenario-Based Constraints

Constraints (2.22) - (2.30) model the UC problem with OTS under wind scenarios. In particular, equation (2.22) represents the mathematical expression of the power balance at the node. Here, the variable S_{wst} represents the wind power spillage (WPS) in period t and scenario s. The amount of WPS has to be smaller than or equal to the current wind production, and greater than or equal to zero according to (2.28). The DC power flow expressions are shown in (2.23) - (2.24), the transmission capacity constraint (2.25) and the voltage phase angle, and load shedding bounds (2.26) - (2.27) are also given. The amount of up and down reserve are determined by (2.29) and (2.30).

$$\sum_{i \in \phi_n^I} P_{ist} + \sum_{w \in \phi_n^W} (P_{wst} - S_{wst}) - \sum_{\substack{l \in \Lambda \\ FB(l)=n}} P_{lst} + \sum_{\substack{l \in \Lambda \\ TB(l)=m}} P_{lst} = D_{nt} - LS_{nst}, \forall n \in N, \forall t \in T, \forall s \in \Omega \tag{2.22}$$

$$B_l\left(\theta_{FB(l)st} - \theta_{TB(l)st}\right) - P_{lst} + \left(1 - zs_{lt}\right)M_l \geq 0, \forall l \in \Lambda, \forall t \in T, \forall s \in \Omega \tag{2.23}$$

$$B_l\left(\theta_{FB(l)st} - \theta_{TB(l)st}\right) - P_{lst} - \left(1 - zs_{lt}\right)M_l \leq 0, \forall l \in \Lambda, \forall t \in T, \forall s \in \Omega \tag{2.24}$$

$$-P_l^{\max} zs_{lt} \leq P_{lst} \leq P_l^{\max} zs_{lt}, \forall l \in \Lambda, \forall t \in T, \forall s \in \Omega \tag{2.25}$$

$$\theta^{\min} \leq \theta_{nst} \leq \theta^{\max}, \forall n \in N, \forall t \in T, \forall s \in \Omega \tag{2.26}$$

$$0 \leq LS_{nst} \leq D_{nt}, \forall n \in N, \forall t \in T, \forall s \in \Omega \tag{2.27}$$

$$0 \leq S_{wst} \leq P_{wst}, \forall w \in W, \forall t \in T, \forall s \in \Omega \tag{2.28}$$

$$R_{it}^{up} \leq P_{ist} - P_{it}, \forall i \in I, \forall t \in T, \forall s \in \Omega \tag{2.29}$$

$$R_{it}^{dn} \leq P_{it} - P_{ist}, \forall i \in I, \forall t \in T, \forall s \in \Omega \tag{2.30}$$

3 Matheuristics Approach to Solve the Unit Commitment Problem

3.1 Introduction

The UC problem formulated in the previous chapter is a mixed-integer linear programming (MILP) model, where the on/off status of each generation unit is modeled using binary variables for each time period. Exact MILP algorithms are known to be time and/or memory consuming, consequently, the problem complexity and the large system size make the UC intractable on a real power system. Therefore, new approaches are needed to improve the computational performance of the UC problem.

In particular, it is important to note that in MILP problems removing a binary variable reduces the search space by half. For example, there are around 2^{20} solutions in a MILP problem with 20 binary variables. Removing one variable will result in 2^{19} solutions ($2^{20}/2$). With this consideration, a search space reduction method for decreasing the size of the UC problem is proposed, where a metaheuristic is used to boost the performance of the MILP Unit Commitment problem. The following sub-sections provide an introduction about the matheuristics, Greedy Randomized Adaptive Search Procedure (GRASP), MILP, and the description of the matheuristics proposed solution strategy for the UC problem presented in Chapter 3.

3.2 Matheuristics

Matheuristics are methods that have recently begun to attract much research attention as a means to obtain good model-based feasible solutions for complex and large size optimization problems. The general idea underlying matheuristics is the exploitation of mathematical programming (MP) techniques in a (meta)heuristic framework, or the use of a heuristic or metaheuristic procedure to deal with non-feasible or non-optimal solutions yielded by an MP algorithm, [48]. To form a better understanding, extensive description, and implementation of different matheuristics approaches are included in [37]. This thesis explorer the concept of matheuristics to speed up the convergence of the UC problem.

3.3 General Description of GRASP

GRASP is a multi-start metaheuristic algorithm, where each iteration consists of two phases: constructing a feasible solution and improving it. Table **3-1** provides a pseudocode listing of the GRASP for minimizing a cost function. Here, the construction and local search phases are repeated interchangeably until a stopping criterion is satisfied. At each iteration of the construction phase, let the set of candidate elements be formed by all elements that can be incorporated into the partial solution under construction without destroying feasibility. The selection of the next element for incorporation is computed by the evaluation of all candidate elements according to a greedy function. This greedy function usually represents the incremental increase in the cost function due to the incorporation of this element into the solution. The evaluation of the elements by this function leads to the creation of a restricted candidate list (RCL) integrated by the best elements, i.e., those whose incorporation to the current partial solution results in the smallest incremental costs (this is the greedy aspect of the algorithm). The RCL may be constrained by an explicit size, or by using a threshold ($\alpha \in [0,1]$).

Table 3-1 Pseudocode General Description of GRASP

Algorithm 1: Pseudocode for the GRASP

```
Input: α
Output: S_best
S_best ← ConstructRandomSolution();
while ¬ StopCondition() do
   S_candidate ← GreedyRandomizedConstruction(α);
   S_candidate ← LocalSearch( S_candidate );
   if Cost( S_candidate ) < Cost( S_best ) then
      S_best ← S_candidate ;
   end
end
return S_best ;
```

The solutions generated by a greedy randomized construction are not necessarily optimal, even for simple neighborhoods. The local search phase usually improves the constructed solution. A local search algorithm works in an iterative fashion by successively replacing the current solution by a better solution in the neighborhood of the current solution. It terminates when no better solution is found in the neighborhood [49].

3.4 Mixed-Integer Linear Programming

A Mixed-Integer Linear Programming (MILP) problem is linear programming in which some of the optimization variables are not continuous but integer, [38]. MILP problems can be solved using branch-and-cut methods, also this type of problems can be solved using one of the many commercially available software tools. In this work, a CPLEX solver under IBM Decision Optimization CPLEX Modeling for Python [50], is used. The reader can find an introduction about CPLEX in [51].

3.5 Proposed Solution Strategy

This section describes the proposed matheuristics approach to solve the UC problem where the main aim is improving its computational performance. The matheuristics procedure is described as following and it is illustrated in **Figure 3-1**:

(i) The algorithm reads the input data of the case study: parameters of the generator, transmission lines, load, and wind generation forecast.

(ii) The algorithm reads the parameters related to the GRASP method, such as the number of iterations, etc.

(iii) The UC model presented in chapter 2 is solved by the GRASP procedure defined in Section 3.5.1.

(iv) The solutions obtained in the previous step will be evaluated by the variable fixing process defined in Section 3.5.2, the result will be a reduced UC problem.

(v) Finally, the reduced UC model that incorporates the uncertainty of the wind energy is solved using a MILP solver, CPLEX.

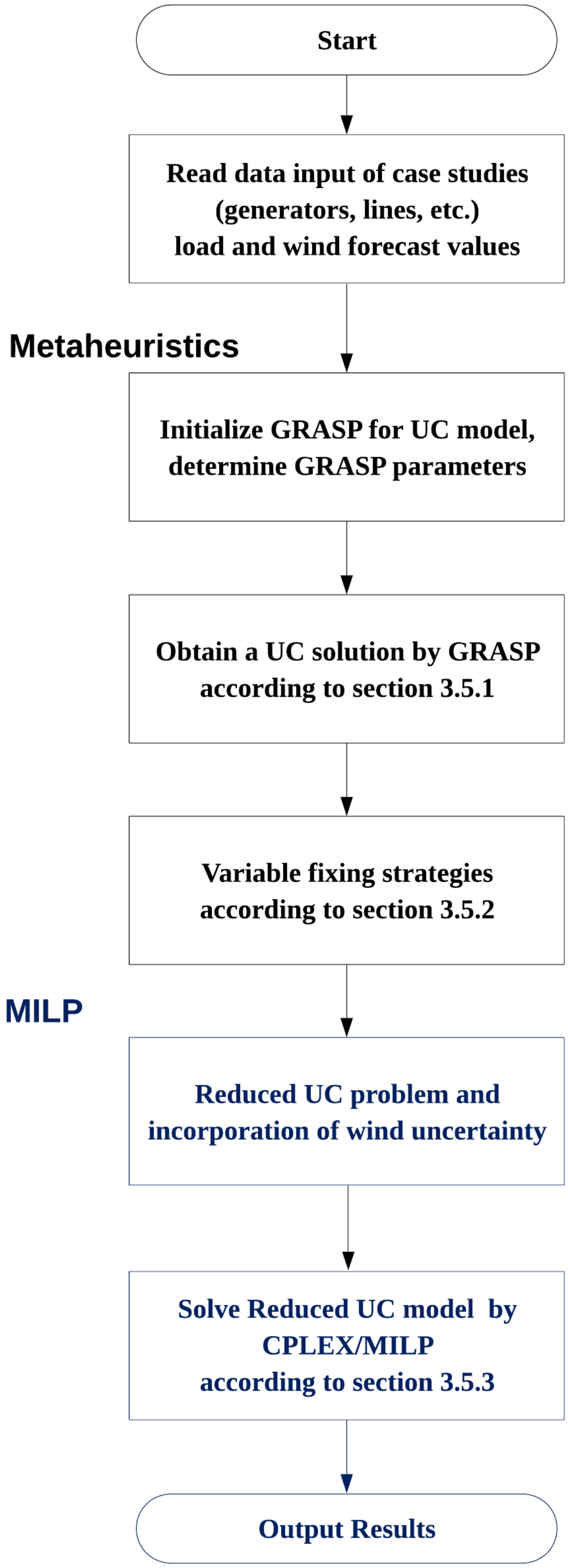

Figure 3-1 Flowchart proposed matheuristics approach to solving the UC model

3.5.1 GRASP for Reducing the UC Search Space

In this work, a GRASP procedure is used to reduce the search space of the UC problem. According to **Table 3-2** in the main procedure of the UC GRASP proposed the inputs are a random initial solution (***u_initial***) which includes UC status variable (u_{it}) for each generator in each time period, the maximum number of iterations (***max_iterations***) and the greediness factor (***alpha***). Here, the process ***ConstructGreedySolution*** is repeated until the maximum number of iterations is performed, and if the best solution found is better than the best solution found in the previous iteration of the algorithm, it is kept.

These solutions are compared in terms of their total operation cost in the UC problem, which is obtained by ***TotalCost*** in the function of the generator status variable obtained, generator fixed and variable costs, and the generator maximum production power. Note that in this work, the local search phase of the classical GRASP is not used because it is very time demanding and may tighten the search space by converging to local solutions.

Table 3-2 Main Procedure for GRASP UC Problem

Algorithm 2: Main Procedure GRASP UC Problem

```
Input: u_initial, max_iterations, alpha, Pimax
Output: S_best
S_best ← None;
while max_iterations > 0 do
  S_candidate ← ConstructGreedySolution(u_initial,alpha);
  if TotalCost(S_candidate,Pimax) < TotalCost(S_best,Pimax) then
      S_best ← S_candidate;
    end
end
return S_best;
```

The construction phase procedure is outlined in **Table 3-3**. Here for each period t, a set of all units ($St\_candidate$) that satisfy the technical constraints is selected for building the construction phase solution ($S_{candidate}$). In each iteration, the algorithm starts by ***Switch_on_Units***, this function forces to "on" ($u_{it} = 1$) the units that, due to constraint (2.19), that includes the initial conditions, minimum up time, minimum down time, must be "on" at period t, a set with the state of each generator status variables is returned. In line 4, the function ***Check_Balance_Max*** verifies if $St\_candidate$ meets the energy power balance considering the constraint (2.10), see Chapter 2. If the power balance is satisfied, then the candidate is added to the solution. If not, based on ***Built_RCL*** the algorithm sets additional units to “on” until the power balance is met. Note that in this procedure, the continuous variables of the UC problem take their maximum values; thus, some constraints and variables become inactive.

Table 3-3 Construction Phase Procedure for GRASP UC Problem

Algorithm 3: Construction Phase GRASP UC Problem

Input: `u_initial, alpha, utime, dtime, Pini, Pimax, Pwind`
Output: $S_{candidate}$

1 $S_{candidate}$ ← `None;`
2 **for** `t` **in** `T:`
3 $\quad St_{\_candidate}$ ← `Switch_on_Units(u_initial,utime,dtime,Pini,t);`
4 $\quad$ **if** `Check_Balance_Max(`$St_{\_candidate}$`,Pimax,Pwind) ==1` **then**
5 $\qquad S_{candidate}$ ← `append.`$St_{\_candidate}$`;`
6 $\quad$ **else**
7 $\qquad S_{candidate}$ ← `append.Built_RCL(`$St_{\_candidate}$`, alpha)`
8 $\quad$ **end**
9 **end**
10 **return** $S_{candidate}$;

Built_RCL forms the Restric Candidate List (RCL) according to the process described in **Figure 3-2**, where the RCL elements are chosen according to the impact in the UC cost when this element is turned on computed by ***GreedyCost*** using the greedy function defined in (3.1).

$$G(i,t) = \frac{CFixed_i + CVariable_i * P_i^{\max}}{P_i^{\max}} \quad (3.1)$$

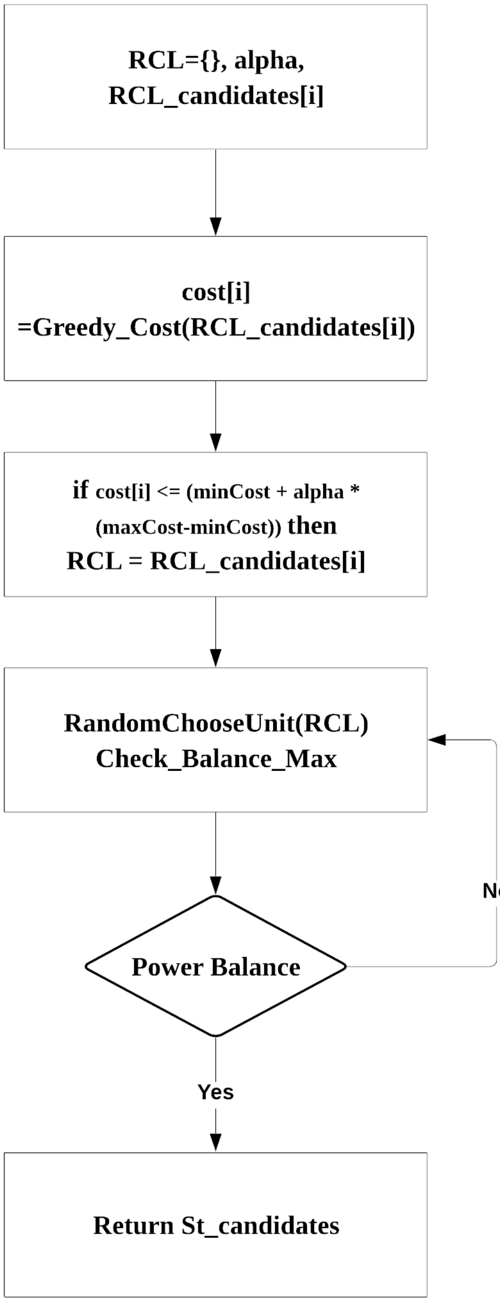

Figure 3-2 Flowchart Built RCL function

3.5.2 Variable Fixing Heuristic

The search space of the problems can be further reduced by fixing binary variables. In this work, a heuristic algorithm based on [23] is used to determine the likelihood of a UC status variable (u_{it}) to become equal to zero in the optimum solution. According to the process shown in **Figure 3-3** we should compare a number of different solutions obtained with the GRASP methodology of the previous section, then the status of a generator is forced to be “off” in period t if its status is “off” in the majority of the GRASP solutions, the percentage of majority is defined by a threshold value (80% in this thesis).

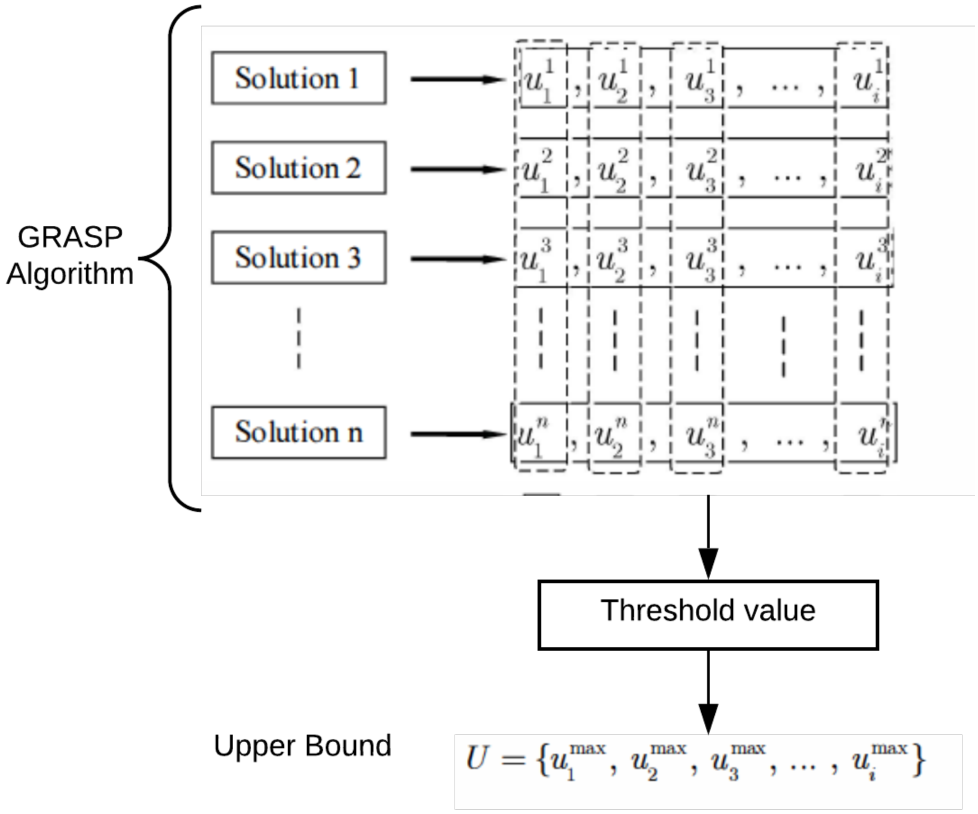

Figure 3-3 Variable fixing strategy using GRASP [23]

3.5.3 Exact MILP Solver

Considering the solution obtained in the previous section, when the value of the generator status variable is equal to zero, the corresponding binary variables u_{it} are fixed to "0" into the UC MILP optimization implementation. Finally, the reduced UC is solved by CPLEX under IBM Decision Optimization CPLEX Modeling for Python [50]. In the following illustrations, some important configurations of the UC problem into python platform are shown:

```
#.................................................
#OPTIMIZATION MODEL SETTINGS
# ................................................
#Modeling_Package: docplex
from docplex.mp.environment import Environment
env = Environment()
env.print_information()

#Create Model
from docplex.mp.model import Model
ucpm = Model("UCP")
```

Figure 3-4 MILP Model settings

```
#DECISION VARIABLES.....................................................

# u = status of thermal unit i at period t
u = ucpm.binary_var_matrix(keys1=I,keys2=T,name="u")
# v = startup variable of thermal unit i at period t
v = ucpm.binary_var_matrix(keys1=I,keys2=T,name="v")
# w = shutdown variable of thermal unit i at period t
wv = ucpm.continuous_var_matrix(keys1=I, keys2=T, lb=0, ub=1, name="wv")
# Pi = active power of thermal unit i at period t
Pi = ucpm.continuous_var_matrix(keys1=I,keys2=T,name="Pi")
# Rup = spinning reserve up of thermal unit i at period t
Rup = ucpm.continuous_var_matrix(keys1=I,keys2=T,name="Rup")
# Rdn = spinning reserve down of thermal unit i at period t
Rdn = ucpm.continuous_var_matrix(keys1=I,keys2=T,name="Rdn")
# Pl = active power of transmission line l at period t
Pl = ucpm.continuous_var_matrix(keys1=L,keys2=T,lb=-600,name="Pl")
# z = status of transmission line l at period t
```

```
#PRE-CONTINGENCY CONSTRAINTS.....................................................................

#Eq(2.10) Power Balance
Eq10 = ucpm.add_constraints((ucpm.sum(Pi[i,t] for i in I if n == pi_bus[i-1]) + ucpm.sum(wind_foreca
#Eq(2.11) Power Flow condition 1
Eq11 = ucpm.add_constraints((Bl[l-1]*(ucpm.sum(theta[n,t] for n in N if n == l_from[l-1]) - ucpm.sum
#Eq(2.12) Power Flow condition 2
Eq12 = ucpm.add_constraints((Bl[l-1]*(ucpm.sum(theta[n,t] for n in N if n == l_from[l-1]) - ucpm.sum
#Eq(2.14) Power flow limits
Eq14a = (ucpm.add_constraints(Pl[l,t] <= (pl_max[l-1]*z[l,t]) for l in L for t in T),'Pl_limit1')
Eq14b = (ucpm.add_constraints(Pl[l,t] >= (-pl_max[l-1]*z[l,t]) for l in L for t in T),'P_limit2')
```

Figure 3-5 MILP Variables and constraints declaration

```python
# minimize sum of all costs
ucpm.minimize(total_fixed_cost + total_variable_cost + total_startup_cost + ELNS_cost_0 + ELNS_cost_wind)
#Constraint model built
ucpm.print_information()
#print(ucpm.export_to_string())

import time
start = time.time()
solution = ucpm.solve(log_output = True)
duration = time.time() - start
print(solution)
ucpm.report()
print("Solve Time:  ",duration)
```

Figure 3-6 MILP Objective Function and Solver

4 Computational Experiments

4.1 Test case: IEEE RTS System

The algorithms were coded in python version 3.7.4 [52], and the MILP model was solved with IBM Decision Optimization CPLEX Modeling for Python v2.10, also known as DOcplex library [50]. A modified IEEE-RTS system is used to analyze the effectiveness of the proposed UC model with OTS to manage the wind uncertainty. The model was solved on a macOS High Sierra with Intel Core i5 CPU 2.7 GHz and 8GB memory RAM. The relative optimally gap of CPLEX is set to 0.1%. The time horizon is set to 24 hours.

The one area (24 buses) diagram from the IEEE three area RTS-96 system is taken from [53], and it is illustrated in the **Annex A**. This system consists of 26 units. The generation, transmission lines, load demand, and reliability data were obtained in [54], and the UC and ramp limits parameters are given in [55]. Nine wind power farms are added to buses 2, 14, 16, 17, 18, 19, 20, 21 and 22, respectively. For simplicity, the total daily wind power forecast of the nine wind farms follows the same pattern, and it is given in [53] and showed in **Figure 4-1**. The total wind power capacity is 267 MW, which corresponds to 10% of the total peak load.

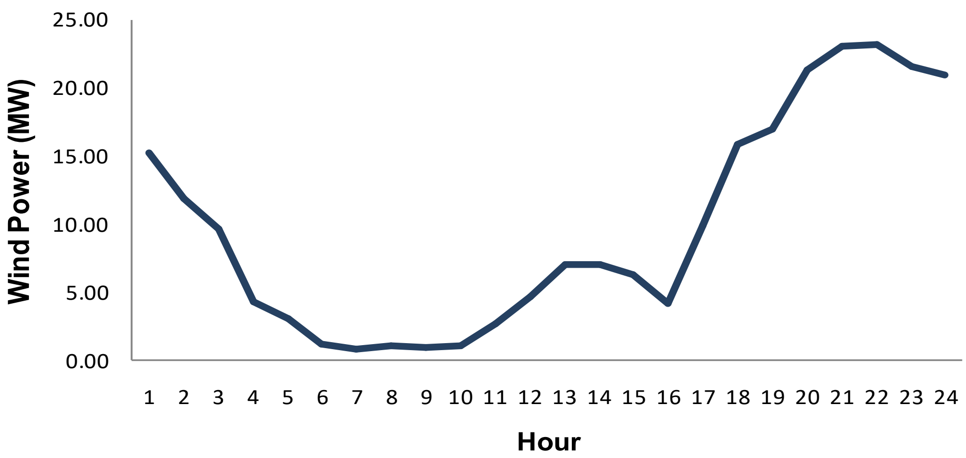

Figure 4-1 24-hour wind power generation forecast at IEEE RTS 96 system

According to Section 2.3.5, the uncertainty of wind power generation is modeled by possible scenarios with their corresponding probability. The wind uncertainty representation of the wind farms located at buses 2, 14, and 16 is shown in **Figure 4-2**, there are seven scenarios. In particular, scenario 4 (dark blue) represents the wind forecast value. To characterize the other scenarios (forecast errors), a standard deviation of ϭ=10% is used. Similarly, the wind scenarios regarding the wind farms at buses 17, 18, and 19 follow the same pattern of **Figure 4-2**, which is scaled by a factor of 1.5 (ϭ=15%). The wind scenarios of the remaining wind farms are scaled by a factor of 2.0 (ϭ=20%). The probability of each scenario is given in **Figure 2-3**. The numerical values for each scenario representing the wind farms are detailed in Appendix B.

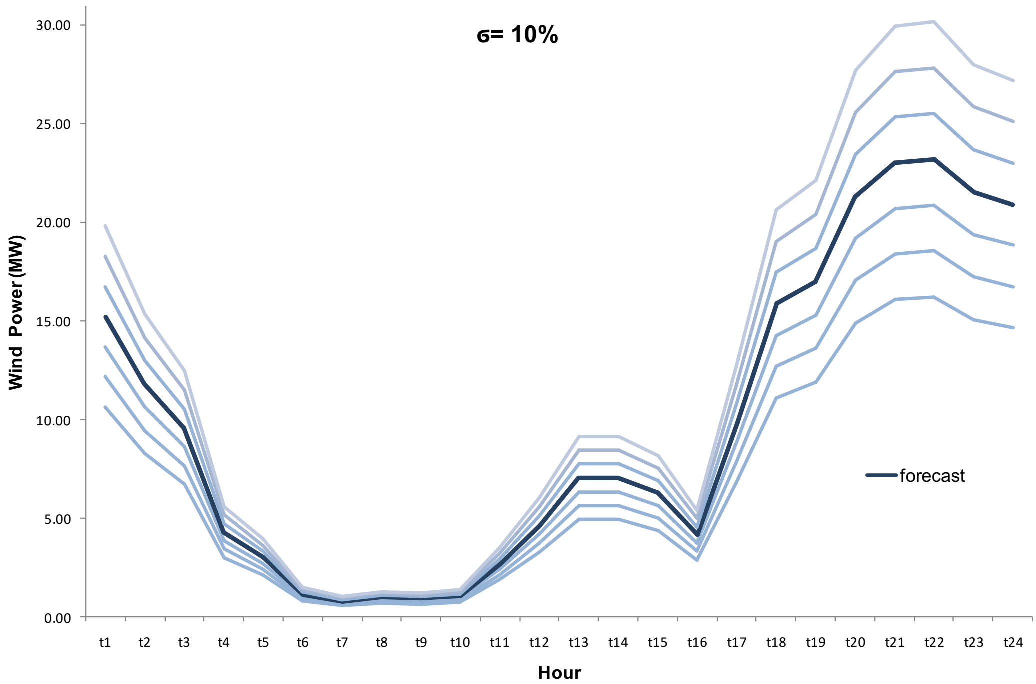

Figure 4-2 Wind power forecast and the generated scenarios at 24-h, with ϭ=10%

4.2 Results of UC by GRASP

Table 4-1 outlines the line schedule for the Reduced UC problem obtained from the GRASP and the Fixing Variables procedures according to Sections 3.5.1 y 3.5.2, respectively. Here, we can observe that “0” means that the binary variable

u_{it} will be fixed into the MILP, and "x" means that u_{it} remains included as a variable into the MILP implementation. Regarding the GRASP algorithm, the maximum number of iterations is set to 50, and the greediness factor is 0.3. In the fixing variables process, five GRASP solutions were considered.

Table 4-1 UC Schedule of IEEE RTS – Reduced Search Space

u_{it}	Hours (t1-t24)																						
i1	0	0	0	0	0	0	0	0	x	x	0	0	0	0	0	0	0	0	0	0	0	0	0	0
i2	0	0	0	0	0	0	0	0	x	x	0	0	0	0	0	0	0	0	0	0	0	0	0	0
i3	0	0	0	0	0	0	0	0	x	x	0	0	0	0	0	0	0	0	0	0	0	0	0	0
i4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
i5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
i6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
i7	x	0	0	0	0	0	x	x	0	0	0	0	0	0	0	0	0	x	x	x	x	0	0	0
i8	x	0	0	0	0	0	x	0	0	0	0	0	0	0	0	0	0	0	x	x	x	0	0	0
i9	0	0	0	0	0	0	x	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
i10	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i11	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i12	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i13	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i14	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i15	0	0	0	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i16	0	0	0	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i17	0	0	0	0	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	0	0	0
i18	0	0	0	0	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i19	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i20	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	x	x	x	x	0	0
i22	0	0	0	0	0	0	0	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	0	0
i23	0	0	0	0	0	0	0	x	x	x	x	x	x	x	x	x	x	0	0	0	0	0	0	0
i24	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i25	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
i26	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

4.3 Results of Reduced UC by MILP

Here, two examples are tested on the IEEE-RTS system where the results obtained using only CPLEX are referred to as “Exact MILP," and the results using the proposed matheuristic approach described in the previous chapter are named “Matheuristic."

Example 1, UC problem without OTS: In this example, the optimal transmission switching (OTS) is not considered into the MILP UC formulation with wind uncertainty, the results are summarized in **Table 4-2**. Clearly, the quality of the solution is kept using the Matheuristic approach, although the computational performance of both methodologies is similar. The computational performance of the UC problem using OTS will be treated in the next example, it will allow us to present a better analysis of the proposed model.

Table 4-2 Simulation Results of UC Problem - IEEE RTS system

Criterion	UC with Wind Uncertainty	
	Exact MILP	**Matheuristic**
Operation Cost ($)	676568,25	672612,71
Startup Cost ($)	2157,6	2544,96
Spinning Reserve (MW)	25919,86	25361,21
Wind Spillage (MW)	1504,256	1560,37
Comp. Time (seg)	17,14	8,23

Table 4-3 Simulation Results of UC Problem with OTS – IEEE RTS system

Criterion	UC with Wind Uncertainty and OTS	
	Exact MILP	**Matheuristic**
Operation Cost ($)	NA	602611,31
Startup Cost ($)	NA	2103,44
Spinning Reserve (MW)	NA	16361,21
Wind Spillage (MW)	NA	344,43
Comp. Time (min)	Out of Memory	42,20

Example 2, UC problem with OTS: In this example, the optimal transmission switching (OTS) is considered into the MILP UC formulation with wind uncertainty, the maximum number of transmission lines to be opened by period is set to 1. The results are summarized in Table 4-3. The results with the exact MILP algorithm are not reported here because it runs out of memory after more than four hours, which is not acceptable in power system operations. Clearly, the solution with the matheuristic approach results in better outcomes in terms of the computational performances. Also, the cost of the UC problem is improved with the OTS actions compared to the previous example.

5 Conclusions

5.1 Conclusions

This dissertation investigates the benefits of the use of a matheuristic approach to solve a UC problem. Specifically, a GRASP algorithm was used to tighten the search space of the UC problem reducing the number of binary variables related to the status of the generation units. Once the search space has been reduced, a CPLEX solver is used to solve the UC problem. The approach has been tested on two optimization models: the UC with wind uncertainty and the UC problem with wind uncertainty and transmission switching. The case studies show that this proposed matheuristic strategy can significantly enhance the computation efficiency without losing the quality of the solution.

5.2 Future Works

Further works can be focused on using the proposed matheuristic approach to reduce the search space solution using other binary variables. In this thesis, the generator status variable is employed. However, future research can include the status of the transmission lines z_{lt} as an input of the GRASP algorithm. Moreover, the proposed methodology should be applied to different power systems for better verification of its computational benefits.

Regarding the GRASP-UC procedure, future researches can be focused on methods to tunning its parameters, the maximum number of iterations, and the greediness factor.

6 Nomenclature

◆ List of indices and sets

i, j, I : indices and set for generators units;

w, W : index and set for wind farms;

n, m, N : indices and set for buses system;

l, Λ : index and set for transmission lines;

s, Ω :.. index and set for wind scenarios;

t, T : index and set for time periods;

Ψ : set of constraints for UC formulation;

◆ List of variables

$C_{it}()$: running cost of unit *i* at period *t*;

P_{it}, P_{ist} : active power output of thermal unit *i* at period *t* under normal state and wind scenario respectively;

u_{it} : status of thermal unit *i* at period *t*;

v_{it} : startup variable for unit *i* at period *t*;

R_{it}^{up}, R_{it}^{dn} : spinning reserve-up and down of unit *i* at period *t*;

P_{lt}, P_{lst} : active power flow in line *l* at period *t* under normal state and wind scenario respectively;

LS_{nt}, LS_{nst} : load shedding in the node *n* at period *t* under normal state and wind scenario respectively;

$\theta_{nt}, \theta_{nst}$: voltage phase angle in the node *n* at period *t* under normal state and wind scenario respectively;

z_{lt}, zs_{lt} : state of transmission line *l* at period *t* under normal state and wind scenario respectively;

S_{wst} : wind power spillage at wind farm *w* at period *t* and scenario *s*;

P_{wst} : random variable, wind power in the wind farm *w* at period *t* and scenario *s*;

◆ List of parameters

SUC_i :	startup cost of unit *i*;
$VOLL_{nt}$:	value of lost of load in the node *n* at period *t*;
D_{nt} :	active power demand in the node *n* at period *t*;
B_l :	susceptance of line *l*;
M_l :	big M value of line *l*;
$\theta^{\min}, \theta^{\max}$:	minimum and maximum voltage angle values;
J :	maximum number of switchable lines at period *t*;
$P_i^{\min}, P_i^{\max}$:	minimum and maximum active power values;
$P_l^{\max}$:	maximum active power on line *l*;
τ :	time required for generation units to delivery their reserve;
RD_i, RU_i :	ramp down and up rates limits of unit *i*;
π_s :	probability of wind scenario *s*;
P_{wt} :	wind power forecast in the wind farm *w* at period *t*;

◆ List of acronyms

AC	alternating current;
ACOPF	alternating current optimal power flow;
DC	direct current;
DCOPF	direct current optimal power flow;
FB	from bus;
GRASP	greedy randomized adaptive search procedure;
MIP	mixed-integer programming;
MILP	mixed-integer linear programming;
MINLP	mixed-integer nonlinear programming;
OPF	optimal power flow;
OTS	optimal transmission switching;
RCL	restricted candidate list;

SC	scheduled cost;
SCUC	security-constrained unit commitment;
SO	stochastic optimization;
SR	spinning reserve;
TB	to bus;
UC	unit commitment;
WPG	wind power generation;
WPS	wind power spillage;
VOLL	value of lost load;

7 References

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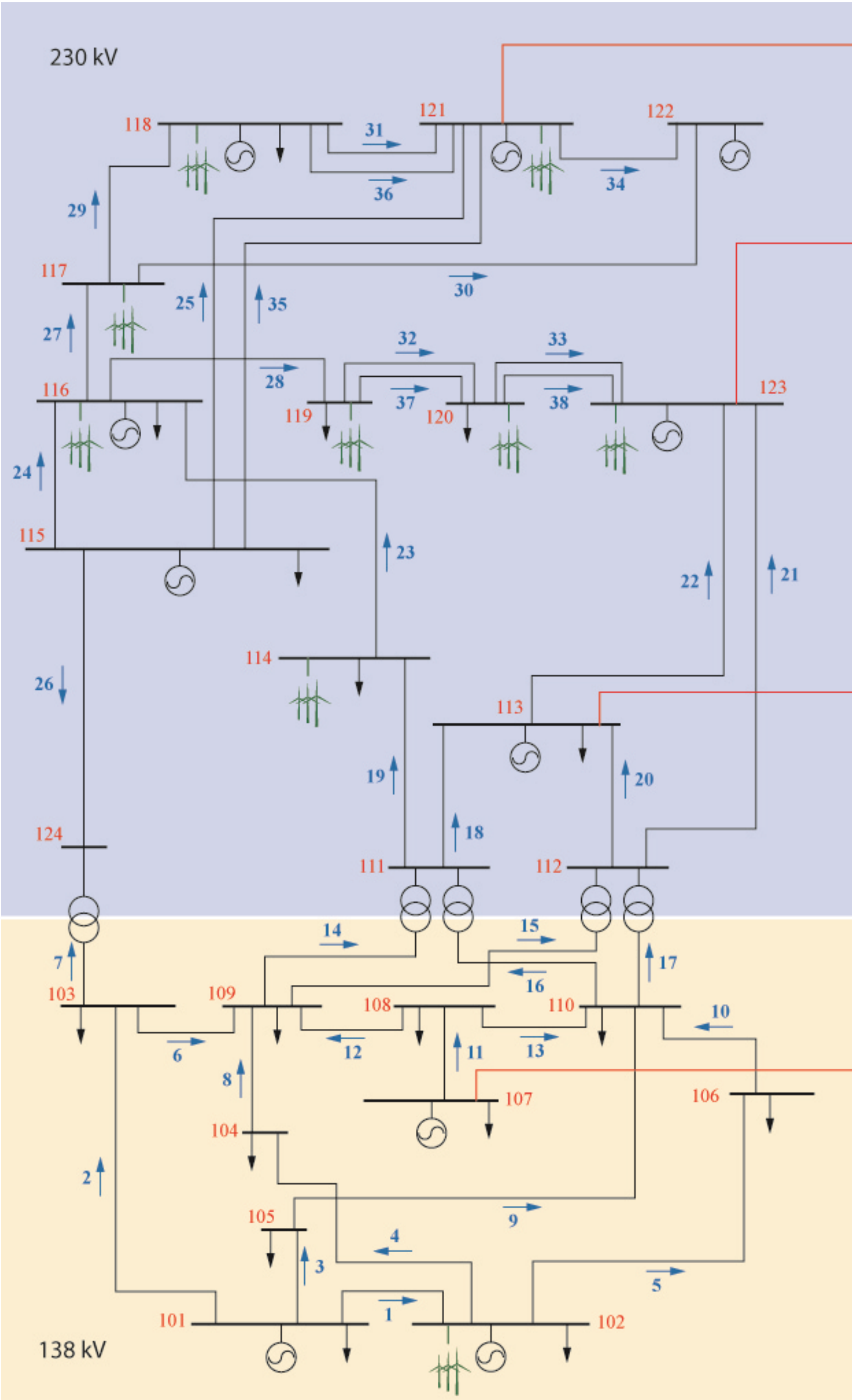
8 Annexes

A: One-Area IEEE RTS System Diagram with Wind Farms



B: Wind Power Data of IEEE (RTS96) System

Scenario Probability			0.0062	0.0606	0.2417	0.3829	0.2417	0.0606	0.0062
Wind Uncertainty			**scen1**	**scen2**	**scen3**	**forecast**	**scen5**	**scen6**	**scen7**
						σ=10%			
t1	.	w1	10.6650	12.1886	13.7122	15.2357	16.7593	18.2829	19.8065
t2	.	w1	8.2616	9.4418	10.6220	11.8023	12.9825	14.1627	15.3429
t3	.	w1	6.7071	7.6652	8.6234	9.5815	10.5397	11.4978	12.4560
t4	.	w1	3.0105	3.4405	3.8706	4.3006	4.7307	5.1608	5.5908
t5	.	w1	2.1301	2.4344	2.7387	3.0430	3.3473	3.6516	3.9559
t6	.	w1	0.7998	0.9141	1.0284	1.1426	1.2569	1.3711	1.4854
t7	.	w1	0.5681	0.6492	0.7304	0.8115	0.8927	0.9738	1.0550
t8	.	w1	0.6969	0.7965	0.8960	0.9956	1.0952	1.1947	1.2943
t9	.	w1	0.6596	0.7539	0.8481	0.9423	1.0366	1.1308	1.2250
t10	.	w1	0.7542	0.8620	0.9697	1.0775	1.1852	1.2930	1.4007
t11	.	w1	1.8820	2.1509	2.4198	2.6886	2.9575	3.2263	3.4952
t12	.	w1	3.2594	3.7250	4.1906	4.6562	5.1218	5.5875	6.0531
t13	.	w1	4.9269	5.6308	6.3346	7.0384	7.7423	8.4461	9.1500
t14	.	w1	4.9310	5.6354	6.3399	7.0443	7.7487	8.4531	9.1576
t15	.	w1	4.3987	5.0271	5.6555	6.2839	6.9122	7.5406	8.1690
t16	.	w1	2.9144	3.3307	3.7470	4.1634	4.5797	4.9960	5.4124
t17	.	w1	6.8747	7.8568	8.8388	9.8209	10.8030	11.7851	12.7672
t18	.	w1	11.1109	12.6982	14.2855	15.8728	17.4600	19.0473	20.6346
t19	.	w1	11.9048	13.6055	15.3062	17.0069	18.7076	20.4083	22.1090
t20	.	w1	14.9188	17.0501	19.1814	21.3126	23.4439	25.5751	27.7064
t21	.	w1	16.1171	18.4196	20.7220	23.0244	25.3269	27.6293	29.9318
t22	.	w1	16.2361	18.5556	20.8750	23.1945	25.5139	27.8334	30.1528
t23	.	w1	15.0722	17.2254	19.3786	21.5317	23.6849	25.8381	27.9912
t24	.	w1	14.6469	16.7393	18.8317	20.9242	23.0166	25.1090	27.2014

C: Thermal Generation Data: IEEE RTS System

GENERATORS	i1	i2	i3	i4	i5	i6	i7	i8	i9	i10	i11	i12	i13
Bus Number	115	115	115	115	115	101	101	102	102	101	101	102	102
Power Min (MW)	2.4	2.4	2.4	2.4	2.4	4	4	4	4	15.2	15.2	15.2	15.2
Power Max (MW)	12	12	12	12	12	20	20	20	20	76	76	76	76
Up Rate -RU	48	48	48	48	48	30.5	30.5	30.5	30.5	38.5	38.5	38.5	38.5
Down Rate - RD	60	60	60	60	60	70	70	70	70	80	80	80	80
Cost aP^2 ($/MW/MW)	0.03	0.03	0.03	0.03	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Cost bP ($/MW)	25.55	25.68	25.80	25.93	26.06	37.55	37.66	37.78	37.89	13.33	13.35	13.38	13.41
Cost ($)	24.39	24.41	24.64	24.76	24.89	117.76	118.11	118.46	118.82	81.14	81.30	81.46	81.63
Start Up Cost ($/MWh)	68	68	68	68	68	5	5	5	5	655.6	655.6	655.6	655.6
Up Spinning Reserve Cost ($/MWh)	5	3	2	6	4	5	7	6	5	3	2	6	5
Down Spinning Reserve Cost ($/MWh)	5	3	2	6	4	5	7	6	5	3	2	6	5
MIN Up time (s)	1	1	1	1	1	1	1	1	1	3	3	3	3
MIN Down Time (s)	1	1	1	1	1	1	1	1	1	2	2	2	2
Unit Initial Conditions	-1	-1	-1	-1	-1	-1	-1	-1	-1	3	3	3	3
Unit Initial Power (MW)	0	0	0	0	0	0	0	0	0	15.2	15.2	15.2	15.2

GENERATORS	i14	i15	i16	i17	i18	i19	i20	i21	i22	i23	i24	i25	i26
Bus Number	107	107	107	115	116	123	123	113	113	113	123	118	121
Power Min (MW)	25	25	25	54.25	54.25	54.25	54.25	68.95	68.95	68.95	140	100	100
Power Max (MW)	100	100	100	155	155	155	155	197	197	197	350	400	400
Up Rate -RU	51	51	51	55	55	55	55	55	55	55	70	50.5	50.5
Down Rate - RD	74	74	74	78	78	78	78	99	99	99	120	100	100
Cost aP^2 ($/MW/MW)	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cost bP ($/MW)	18.00	18.10	18.20	10.69	10.72	10.74	10.76	23.00	23.10	23.20	10.86	7.49	7.50
Cost ($)	217.90	218.34	218.78	142.73	143.03	143.32	143.60	259.13	259.65	260.18	177.06	310.00	311.91
Start Up Cost ($/MWh)	655.6	566	566	1048.3	1048.3	1048.3	1048.3	775	775	775	4468	0.01	0.01
Up Spinning Reserve Cost ($/MWh)	3	2	5	3	6	8	6	5	3	5	3	2	5
Down Spinning Reserve Cost ($/MWh)	3	2	5	3	6	8	6	5	3	5	3	2	5
MIN Up time (s)	4	4	4	5	5	5	5	5	5	5	8	8	8
MIN Down Time (s)	2	2	2	3	3	3	3	4	4	4	5	5	5
Unit Initial Conditions	-3	-3	-3	5	5	5	5	-4	-4	-4	10	10	10
Unit Initial Power (MW)	0	0	0	124.94	121.42	121.42	121.42	0	0	0	350	400	400