PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE
ESCUELA DE INGENIERÍA

REAL-TIME ROBUST ECONOMIC DISPATCH WITH DATA-DRIVEN UNCERTAINTY SETS

ENRIQUE EDUARDO VÉLIZ SANZANA

Thesis submitted to the Office of Research and Graduate Studies
in partial fulfillment of the requirements for the degree of
Master of Science in Engineering

Advisor:
MATÍAS NEGRETE-PINCETIC

Santiago de Chile, July 2018

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Gratefully to my family

ACKNOWLEDGMENTS

I would like to thank through these words to my mother Patricia and my brothers Guillermo and Fernando for their unconditional support and great patience along this long journey, even in the most difficult times. This work is dedicated to them and to my father who takes care of me from heaven since 2005.

I also want to express my gratitude to my professors Matías Negrete, Daniel Olivares and Álvaro Lorca who trusted me when I crossed the office door in early 2015, and they invited me to the group where I have met great people, Rodrigo Henríquez, George Wenzel, Alan Valenzuela, Pablo Gallegos, Benjamín Maluenda, Pablo Sandoval, Nicolás Lobos, Juan Carlos Chuncho, Samuel Córdova, Felipe Verástegui, Leonardo Gacitúa, Marcelo Salgado, Christian Villalobos, Altamiro Piña, Alberto Castro, Fredrik Blom and Philipp Staudt.

My professors also gave me the unforgettable opportunity of being an international visiting researcher in the University of Texas at Austin during 3 months, experience who helped me to grow not only academically but also personally.

I want to thank professor Ross Baldick for receiving me in his group, and for his great disposition to contribute in my research. This experience would have not been the same without Manuel, Rachel, Juan, Sam, Bowen, Bing and Mohammad. Finally, I appreciate enormously the support of my friends Rodrigo Bernal, Pablo Bravo, Claudia Aravena, Felipe Soto, Marie González, Sebastián Ramírez, Ignacio Rodríguez, Daniel Montoya, Álvaro Santibáñez and the guys from IEEE Student Branch, with whom I shared the experiences of very demanding seasons, but also the joy of the accomplished goals.

This work has been supported by the Institute in Complex Engineering Systems, Fondecyt Project N 11140621 and the Seed Fund CORFO 14ENI226862.

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ABSTRACT

The continuous growth in variable renewable penetration in power systems has led to the appearance of several operational challenges. The ability of dealing with them is known as power system flexibility. This feature is present to a greater or lesser extent in every element within a power system, either generation, load, networks or storage devices, among others. Although flexibility resources are scheduled in a day-ahead process, they are deployed when uncertainty is realized in real-time operation. A Look-Ahead Economic Dispatch with affine policies is proposed, where real-time operation is solved with traditional modeling and look-ahead horizon is addressed through these policies for dealing with short-term uncertainties. A comprehensive analysis which unveils the importance of the election methodology to model the uncertain sources is carried out, in which performance of the proposed model is compared to current industry practices, existing approaches in literature and other formulations that can come off the proposed model.

Keywords: Affine Policy, Adjustable Robust Optimization, Look-Ahead Economic Dispatch, Uncertainty Set.

RESUMEN

El continuo crecimiento de la penetración de energías renovables variables en los sistemas de potencia ha determinado la aparición de diversos desafíos en la operación de estos. El atributo de un sistema que le permite hacer frente a estos desafíos es conocido como flexibilidad. Esta característica se encuentra presente en mayor o menor medida en cada uno de los elementos de un sistema eléctrico, ya sea generación, demanda, transmisión o almacenamiento, entre otras. A pesar de que los recursos de flexibilidad son programados en el proceso del día anterior, estos son desplegados cuando la incertidumbre es develada durante la operación de tiempo real. Un Despacho Económico con Mirada hacia el Futuro es propuesto, donde la operación de tiempo real es resuelta mediante el modelamiento tradicional y el horizonte futuro se aborda con el uso de políticas afines para considerar la incertidumbre de corto plazo. Un exhaustivo análisis que muestra la importancia de la elección en la metodología de modelación de la incertidumbre es realizado, en el que el desempeño del modelo propuesto es comparado con prácticas actuales de la industria, propuestas de la literatura y otras formulaciones que pueden desprenderse de la modelación propuesta.

Palabras Clave: Política Afín, Optimización Robusta Ajustable, Despacho Económico con Mirada hacia el Futuro, Conjunto de Incertidumbre.

1. INTRODUCTION

1.1. Context

The continuous growth of greenhouse gas emissions to the atmosphere as a product of the intensive use of fossil fuel has set a big challenge among countries. Paris Agreement in 2015 has meant an important milestone in the struggle against climate change, aiming an increase on global temperatures not greater than 2 celsius degrees for 2050 (UN, 2015).

One of the instrumental paths to achieve the goals imposed has been the implementation of new technologies in the energy matrix, such as wind and solar generation. This has been harnessed in late years due to the progressive decrease of production costs. For instance, levelized costs of solar panels are lower than coal costs in countries as Germany and United States, and they are expected to diminish even an additional 66 % for 2040, wind follows this trend with an expectation of a 47 % decrease (BNEF, 2017).

Renewable shares in power systems has grown continuously as a result of the efforts previously mentioned. Towards the end of 2015, ten countries had overcome the barrier of double-digits shares of variable renewable generation, even noting values beyond 20 % in cases like Germany, Ireland and Denmark (IEA, 2017b).

1.2. Literature Review

1.2.1. Uncertainty, Variability and the need for Power System Flexibility

The increasing penetration of variable renewable energy (VRE), has led to the appearance of two operational problems produced for their non-controllable nature: variability and uncertainty.

Variability refers to the changes in power output that a system can experiment in a given period of time as a result of fluctuations of generation and/or demand. When the penetration of variable generation increases, variability becomes a challenge due to the

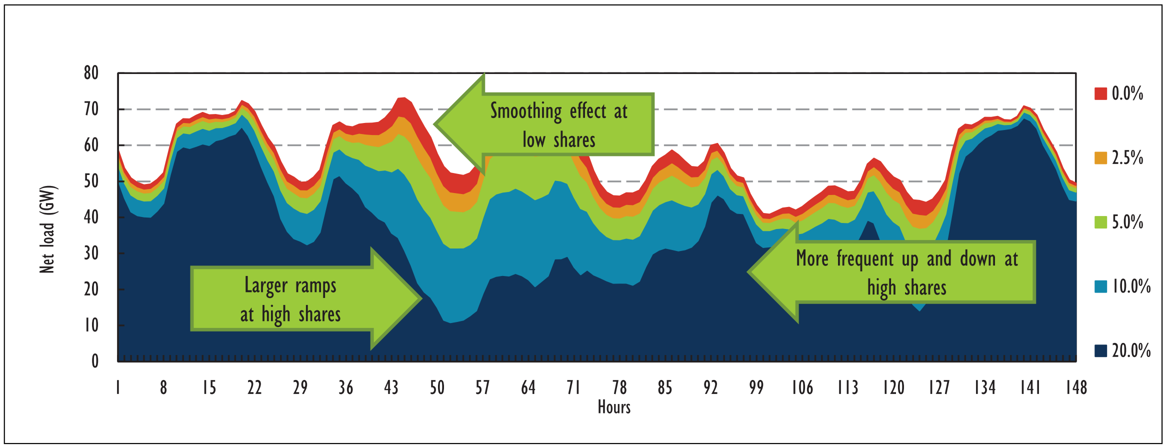


Figure 1.1. Effects on variability for one week operation in Germany given by hypothetical scaling on wind generation. Source IEA (2014)

major requirements imposed to the system. Figure (1.1) presents one week operation of Germany in 2010, figure shows the effect produced by the actual wind share (6.7 %) and by hypothetical scalings of this generation.

Other system operators who have experimented the variability proper of high shares of VRE are Bonneville Power Administration (BPA) and Electric Reliability Council of Texas (ERCOT). BPA has passed from hourly ramps of 1000 MW in 2008 (Kamath, 2010) to more than 1400 MW in 2016 (BPA, 2016), with its wind installed capacity varying from 1700 MW to 4000 MW in the same period (BPA, 2017). On the other hand, ERCOT being the power system with the highest amount of wind installed capacity, hit more than 20 GW wind installed capacity by the end of 2017 according to Matevosyan (2017), overcoming the total coal plants capacity across the state (19800 MW).

Figure (1.2) shows the distribution of wind power ramps in ERCOT during the first semester of 2016 in one specific hour of the day. Power ramps for duration of 25 minutes exceed 500 MW with frequency, which is a demanding operation condition.

The second operational problem is uncertainty, and is related with the difficulties to predict in an accurate manner the output of a non-controllable source. This situation complicates the decision of how many units turn on given that a scenario of excess generation

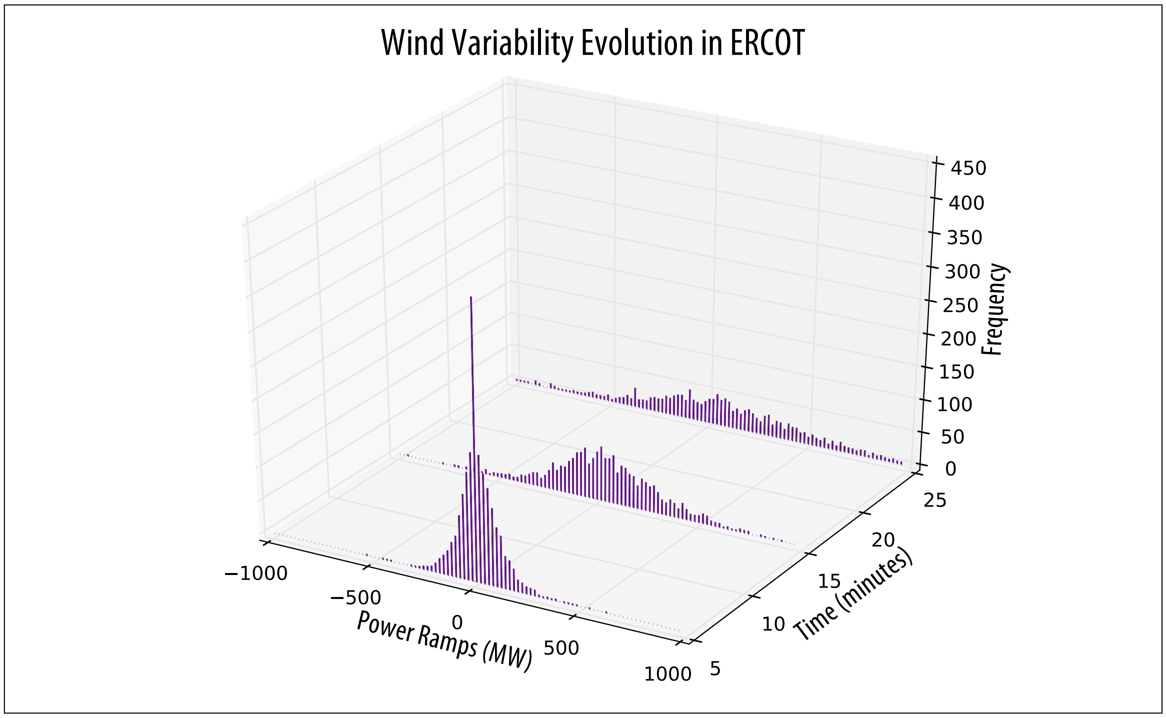


Figure 1.2. Histograms of wind power ramps of three different durations (5, 15 and 25 minutes) in ERCOT Power System. Source: ERCOT (2016)

may occur, or another scenario where the renewable generation was overestimated, leading to a need to turn emergency units or shed load.

The attribute which enables a power system to cope with variability and uncertainty has received the name of **flexibility**.

On one hand, power system flexibility has many definitions within literature, all of them quite similar:

- “The ability of a power system to keep a continuous service in presence of big and fast variations in load, i.e keep the stability in a cost-effective manner” (Papaefthymiou et al., 2014)
- “The capacity to cope with variability and uncertainty, while keeping a satisfactory performance temporally and spatially” (Lannoye et al., 2012)

- “The ability of a system to deploy its resources to respond to changes in net load” (Holttinen et al., 2013)

On the other hand, different strategies have been proposed to measure this attribute as a way to determine the sufficiency of it or to make it comparable with the flexibility of other system:

- Flexibility Charts: Graphs which allocates values to different attributes such as interconnections, CCGT or Hydro Generation with the purpose to compare amounts of flexibility between different systems (Yasuda et al., 2013).
- Flexibility Assessment Tool (FAST, FAST2): It is a measure of the total ramping capacity given different time frames and the resources available (IEA, 2011).
- Polytopes: 3d plot which represent feasible operation regions for generators (Ulbig et al., 2017), interconnections (Bucher et al., 2016) and zones (Bucher et al., 2015).
- Do-Not-Exceed Limits: Feasible region where a non-controllable generator can vary without jeopardizing the grid (Zhao et al., 2015)

From the definitions of flexibility is possible to conclude that it is closely related with the balance of quick and unexpected changes in net load (load minus renewable generation), meanwhile from the ways of measuring flexibility it can be noticed that a system utilizes different **flexible resources** (either generation, storage or transmission devices) to deploy this attribute. In effect, flexibility is present everywhere in a power system. However, a key aspect of flexibility is that as important to account with flexible resources is to have the efficient procedures to deploy them (Cochran et al., 2014). The most acknowledge operational procedures in power systems, where flexibility has to be managed, are the Unit Commitment and the Economic Dispatch. They will be revised on next section.

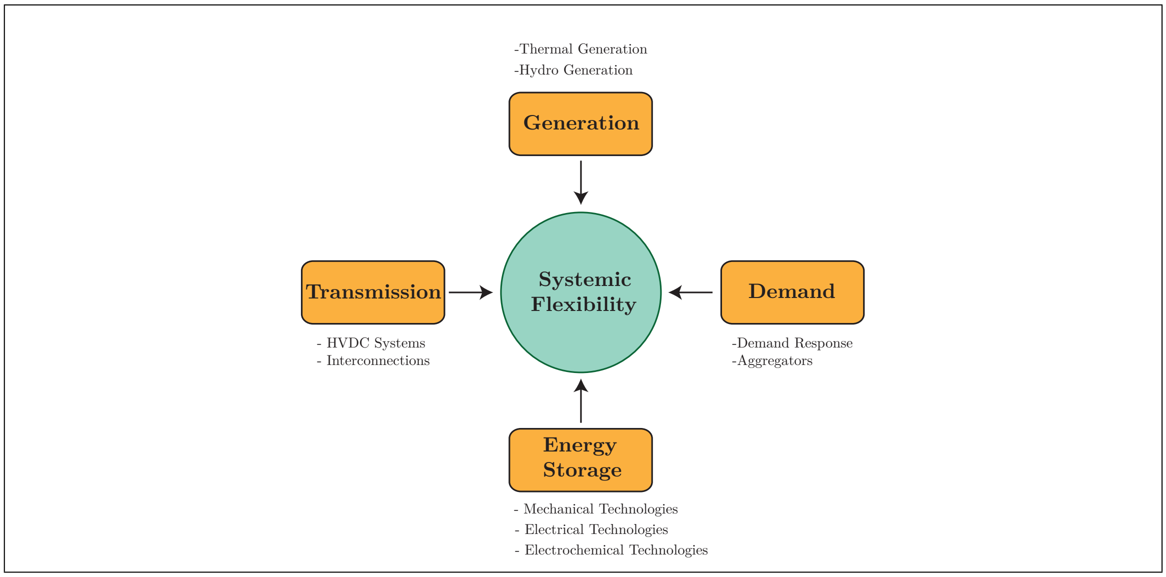


Figure 1.3. Flexibility is everywhere in a power system

1.2.2. The Economic Dispatch Problem

As it was mentioned above, flexibility needs to be modeled in the Unit Commitment and Economic Dispatch problems in order to consider the flexibility requirements given by the uncertainty and variability.

The Unit Commitment (UC) problem consists of deciding which units are going to be turned on during a day, and also defines the times when units that are offline will enter on operation. This procedure is made one day-ahead, so the flexibility requirements are included here as scheduled reserves, which then have to be deployed in Economic Dispatch (ED) when more accurate information is available.

Economic Dispatch consists of deciding the power output of the units which are already online in the power system. This problem is commonly solved with a time resolution between 5 and 30 minutes. The following optimization model represents the compact formulation of an ED problem.

$$\min_{\mathbf{P_g}} \sum_{g \in \mathcal{G}} C(P_g)$$
$$s.t \sum_{g \in \mathcal{G}} P_g = P^D$$
$$P_g^{min} \leq P_g \leq P_g^{max} \quad \forall g \in \mathcal{G}$$

Hedging the system against uncertainty is critical in ED because given the time frame, the option of committing an additional base or load following unit is not available, leaving as only options the commitment of a quick start unit and the load shedding, which are very expensive and not desirable solutions. This determines that management of the flexibility during real-time operation is key.

1.2.3. Uncertainty Management in Economic Dispatch

Management of reserves in real-time markets is being widely studied not only in academia but also in industry.

Traditional procedure to perform real-time operation has been the use of ED with spinning reserves (SR), which are scheduled in day-ahead markets and deployed according to Automatic Generation Control participation factors during operation (Wood & Wollenberg, 2012). In recent years, some System Operators, such as MISO (2016) and CAISO (n.d.), have proposed new products for the real-time operations, called Flexible Ramping Products (FRP). They act as an additional reserve for unexpected variations of net load. FRP are intended to cover a statistical range of values for net load ramps, given by the confidence interval of histograms or gaussian-sigma rules (Wang et al., 2017), which then are implemented through additional constraints in the operation model. Another mechanism which has been recently implemented in some systems such as PJM (2011) and MISO (2017) is the Look-Ahead Economic Dispatch (LAED). This variation of the traditional Myopic Economic Dispatch is an application of model predictive control in power systems, and consists of solving a receding horizon optimization problem where only the solutions correspondent to current time are implemented, whereas the finite look-ahead horizon is utilized to hedge against short-term uncertainties (Xie & Ilic, 2008).

In academia, introduction of uncertainty and variability into ED models has been mostly made through the utilization of stochastic and robust optimization models. Stochastic optimization (SO) addresses the uncertainty problem by representing it in a group of scenarios. For instance, a stochastic LAED with flexible ramping products is proposed in (Zhang & McCalley, 2015).

When the number of scenarios is large, strategies for keeping tractability are needed in order to apply SP in ED. For instance, a LAED decomposed into a deterministic and a stochastic horizon is presented in Gu & Xie (2017), whereas a multi-time scale LAED for modeling slow and fast generators is developed in Gangammanavar et al. (2016). Other decomposition techniques such as optimality condition decomposition are applied to diminish the computational burden and thus allow the optimal dispatch of dispatchable units and energy storage devices under a stochastic framework (Zhu & Hug, 2014).

Robust optimization (RO) appears as a solution to the tractability issue, since the problem considers a reduced amount of scenarios obtained by the column and constraint generation (C&CG) algorithm, thus obtaining a set with the worst case realizations of uncertainty. This technique has been applied to both UC and ED. A fully adaptive robust model for the security constrained UC is presented by Bertsimas et al. (2013). Thatte & Xie (2016) developed a Robust LAED with zonal reserve requirements that allows the interchange of power flows within areas while keeping a simple grid representation. A robust LAED with conditional value-at-risk (CVaR) to evaluate the risk of wind power accommodation is presented in (P. Li et al., 2018). The adjustability of uncertainty sets has also been a research line within robust optimization, in Z. Li et al. (2015b) the conservativeness of the uncertainty sets is allowed to be updated varying the confidence level.

Main challenge of robust programming is the design of the uncertainty set, which is usually build using budgets or cardinality constraints (Bertsimas et al., 2011), and how to consider correlations. A way to account for it is the use of dynamic uncertainty sets as it is shown in the multi-stage robust economic dispatch proposed in Lorca & Sun (2015).

Robustness also can be considered in power system operations by generating envelopes or single scenarios which encloses all the possible realizations of the uncertainty Nosair & Bouffard (2015a), thus protecting system against worst realizations of uncertain source. According to this strategy, a dispatch can be considered adequate if flexibility envelope of resources covers envelopes defined by net load requirements. This approach has also been extended to introduce a dynamic representation more complete for flexibility resources and requirements (Nosair & Bouffard, 2015b), to consider the energy limitations of demand response and energy storage through the implementation of energy-based envelopes constraints (Nosair & Bouffard, 2016) and to consider tree-scenario structures by using probabilistic envelopes (Nosair & Bouffard, 2017). Another proposal in the literature proposed by Dvorkin et al. (2014) develops a methodology to obtain non-parametric or distribution free reserve requirements, through the solution of a MILP that has a complexity dependent of the amount of the historical data to analyze.

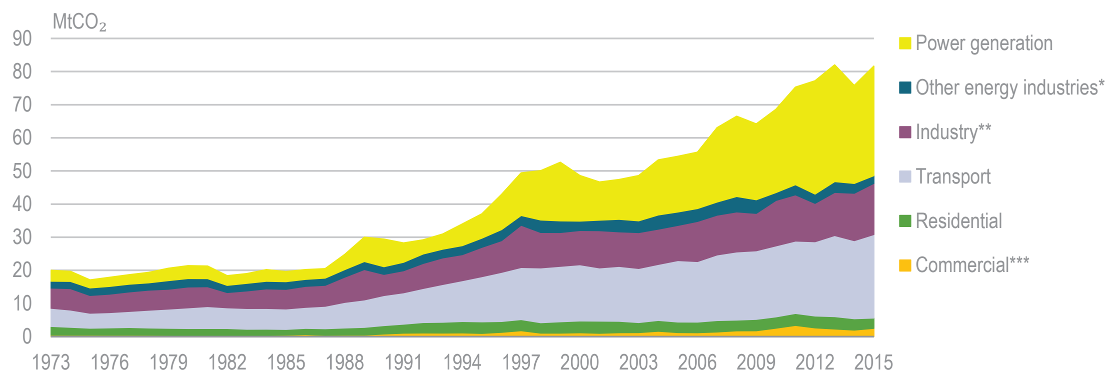
1.2.4. State-of-the-art on Affine Policies Modeling

Within RO framework, there exists a modeling approach named Affinely Adjustable Robust Optimization (AARO), where decision variables are forced to be linear functions of the uncertain parameter,instead of being fully adaptive. AARO has gained attention since the work of Ben-Tal et al. (2004), and has been extensively applied recently because of its simplicity to allocate uncertainties amongst generators using affine policies (AP). This accompanied by the closeness with traditional operation procedures such as the AGC participation factors in secondary control.

Some contributions within AARO framework have been made in the field of ED: Jabr (2013) proposed AP to change the fixed nature of participation factors in OPF. Z. Li et al. (2015a) solved an adjustable robust dispatch differentiating AGC from non AGC units. Warrington et al. (2013) developed a high resolution LAED with AP and set prices for these products. An extension which allows to consider scheduling of quick-start units is presented in (Warrington et al., 2016). Ye & Li (2018) addressed the congestion issue in existing formulation of FRP by introducing an Adjustable Robust Model, which ensures deliverability of ramp capacity.

1.3. The Chilean Case

Chile is no unrelated to the phenomena that has been generated around renewable energy. Acording to IEA (2018), carbon emissions in Chile increased from 54.4 $MtCO_2$ in 2005 to 81.6 $MtCO_2$ in 2015, where almost the 40 % was produced by power generation, as it is presented in figure (1.4).



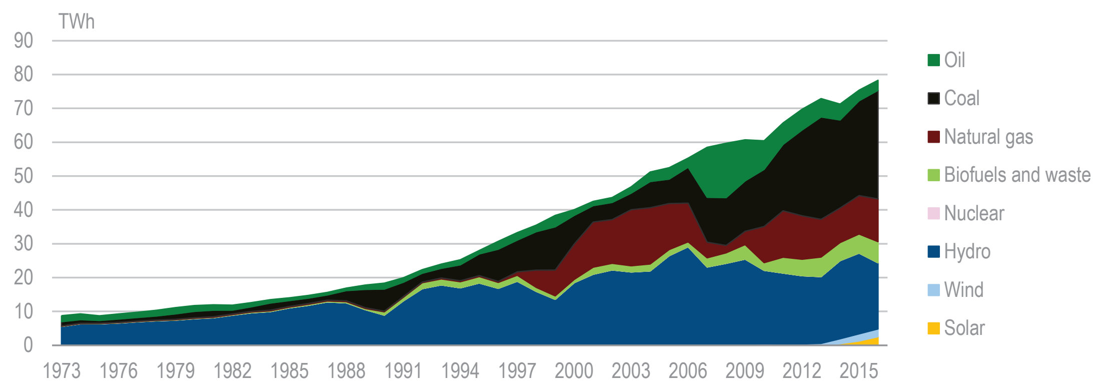
* *Other energy industries* includes other transformations and energy own-use.

** *Industry* includes CO_2 emissions from combustion at construction and manufacturing industries.

*** *Commercial* includes commercial and public services, agriculture/forestry and fishing.

Figure 1.4. Energy-related CO_2. Source: IEA (2017a)

Figure (1.5) shows the evolution of the electricity generation for the period 1973-2015, where coal generated the greatest amount of energy during 2015, more than one-third of the total energy.



Note: Data are estimated for 2016.

Figure 1.5. Electricity generation by type. Source: IEA (2017a)

In 2015, the Ministry of Energy developed joint with industries the Energy Policy 2050, a long-term road map which aims to achieve a secure and clean energy supply towards 2050. According to de Energía (2015), the four pillars of the documents are:

- Security and quality of the supply
- Energy as a motor of development
- Environmentally friendly energy
- Energy efficiency and energy education

The third main objective involves the task of generating the 70 % of the energy with renewable sources (including hydro). Simultaneously with the implementation of this agenda, many changes in auction processes have been made in order to make the market more competitive by simplifying the rules for renewable generators.

Currently, 8 % of the installed capacity is solar, whereas 6 % is wind, varying the renewable penetration in the system from 1 % in 2011 to 10 % in 2017 (Asociación de Generadoras, 2018).

As a result of this, the amount of renewable capacity present in the system has increased dramatically during the last years, which has impacted on the levels of variability and uncertainty. A study realized in 2018 by PSR-Moray (2018) concluded that flexibility costs given by cycling and load following will increase up to 30 % due to the flexibility requirements.

The Independent System Operator from Chile, named *Coordinador Eléctrico Nacional*, currently has realized studies to determine flexibility requirements and strategies to cope with them. These studies have been developed independently for the two interconnected systems, *Sistema Interconectado del Norte Grande* (SING) (CDEC-SING, 2016) and *Sistema Interconectado Central* (SIC). Meanwhile SING is mainly composed by thermal generation such as coal and combined cycles, SIC has hydro reservoirs. This feature implies, given the flexibility differences between these technologies, that the procedures in SING must be more stringent. For instance, the proposed measures for AGC in SING were the following (CDEC-SING, 2016):

- The ramp capacity for the AGC must be $8\frac{MW}{min}$.
- AGC must be supplied at least for 3 units.
- No unit can provide more than half of the AGC.

1.4. Contributions

Current approaches for quantifying reserves utilize histograms or distributions, and use up and down reserves to allocate requirements. The objective of this work is to study the impacts of using more complex representations of uncertainty, and implement them in a LAED model within AARO framework, given that it is easier to define responsibilities when uncertainty set has more than one dimension.

Main contributions of this work are the following:

- A new design methodology to build an uncertainty set based on net load power data is proposed, to reflect in an accurate way its sub-hourly behavior. This uncertainty set will be used to capture the potential variability in the future steps of power system operation. Methodology can also be applied to build the uncertainty set by only considering wind power.

- A LAED model based on AARO is proposed for allocating reserve requirements given by the uncertainty set, allowing generators to have sufficient reserve for any of the possible operation conditions given their own flexibility attributes.
- Performance of proposed model is evaluated in terms of costs and other metrics in real-time operation in comparison to existing approaches in literature and traditional industry practice. A comparison with other uncertainty sets that can come off the proposed formulation is also carried out, unveiling the importance of selecting an efficient methodology to use the sub-hourly information in order to prepare the system against the uncertainties.

1.5. Document Organization

The work has the following structure: **Chapter 2** explains robust nature of the approach, including the compact formulation of an AARO, the methodology to design the uncertainty set is presented, and the functioning of affine policies in power system operation is explained. **Chapter 3** presents the complete model formulation for the Look-Ahead Economic Dispatch with Affine Policies. **Chapter 4** details the study cases to test the performance of the proposed model, present and discuss the obtained results. Finally, **Chapter 5** concludes the work and presents different possible future directions for research.

2. AFFINELY ADJUSTABLE NATURE OF A ROBUST OPIMIZATION MODEL

2.1. Robust Optimization

Economic Dispatch presented in the introduction is called deterministic because all the parameters of the problem are known. In reality, many input parameters in an optimization model are unknown. Therefore, the nature of these inputs must be incorporated within the model.

In economic dispatch models and power system problems in general, one of the most uncertain parameters is net load, composed by load and variable renewable generation.

The most exploited techniques in literature to hedge a system against uncertainty have been stochastic and robust optimization.

Stochastic optimization aims to minimize the expected value of a finite number of realizations of the uncertain parameter. Taking net load as uncertain, it would be possible to formulate a stochastic economic dispatch as follows:

$$\min_{\mathbf{P}} \sum_{g\in G} \mathbb{E}[C(P_{g,s})]$$

$$s.t \sum_{g\in\mathcal{G}} P_{g,s} = P^D_s \quad \forall s \in \mathcal{S}$$

$$P^{min}_g \leq P_{g,s} \leq P^{max}_g \quad \forall g \in \mathcal{G}, s \in \mathcal{S}$$

Robust Optimization is based on getting an optimal solution for the worst-case scenario within a pre-defined uncertainty set.

$$\min_{\mathbf{P}} \max_{P^D\in\mathcal{D}} \sum_{g\in G} C(P_g)$$

$$s.t \sum_{g\in\mathcal{G}} P_g = P^D \quad \forall P^D \in \mathcal{D}$$

$$P_g^{min} \leq P_g \leq P_g^{max} \quad \forall g \in \mathcal{G}, P^D \in \mathcal{D}$$

Many parameters can be actually modelled as uncertain: parameters of units, outages and reserve requirements, among others. Consider the following compact formulation for an economic dispatch problem. This formulation is fully adaptive since dispatch is a function of the uncertain parameter, no matter what parameter is.

$$\min_{\mathbf{P(u)}} \max_{\mathbf{u}\in\mathcal{U}} \mathbf{c^T P(u)}$$

$$\alpha_{\mathbf{m}}^{\mathbf{T}} \mathbf{P(u)} + \beta_{\mathbf{m}}^{\mathbf{T}} \mathbf{u} \leq \mathbf{f_m} \quad \forall \mathbf{u} \in \mathcal{U}, \forall m \in \mathcal{M}$$

Where $\mathcal{U}$ and $\mathcal{M}$ are the set of uncertainties and constraints, respectively. It can be proved that under a polyhedral uncertainty set, the optimal solution must be in an extreme point of it, we refer to (Lorca & Sun, 2014) for the complete demonstration.

2.2. Compact Formulation of the Affinely Adjustable Counterpart

If $\mathbf{P(u)}$ is restricted to be an affine function of the uncertainty, the model becomes the Affinely Adjustable Counterpart of the Fully Adaptive Robust Model.

Call $\mathbf{x} = \begin{pmatrix} \mathbf{P^0} \\ \lambda \end{pmatrix}$

$$\min_{\mathbf{x}} \max_{\mathbf{u}} \mathbf{x^T \widetilde{C} u}$$

$$\widetilde{\alpha}_{\mathbf{m}}^{\mathbf{T}} \mathbf{x} + \widetilde{\beta}_{\mathbf{m}}^{\mathbf{T}} \mathbf{u} + \mathbf{x^T R_m u} \leq \widetilde{\mathbf{f}}_{\mathbf{m}} \quad \mathbf{u} \in \mathcal{U}, \forall m \in \mathcal{M}$$

Even though decisions variables are restricted to be affine functions of uncertainty, affinely adjustable counterpart has the same structure than the fully adaptive model. This means that regardless of the feasible space of $\mathbf{P(u)}$, the worst-case realization of uncertainty always takes place on the extreme points of $\mathcal{U}$. Moreover, as long as the uncertainty is polyhedral and it has low dimensions, the affinely adjustable counterpart is more likely to be solved by enumerating the extreme points.

2.3. Design Methodology for the Uncertainty Set

Previous section showed why finding the extreme points is enough to characterize a polyhedral uncertainty set in RO frameworks. In order to take advantage of these properties for capturing sub-hourly behaviors through this technique, it is necessary to design an uncertainty set which complies with the property of being polyhedral.

For that, we consider the profile of 1 hour net load generation shown in figure 2.1. The 12 power values of each time period can be reformulated as 12 coordinates, where **x** represents the deviation with respect to the average and **y** is the consecutive power ramp.

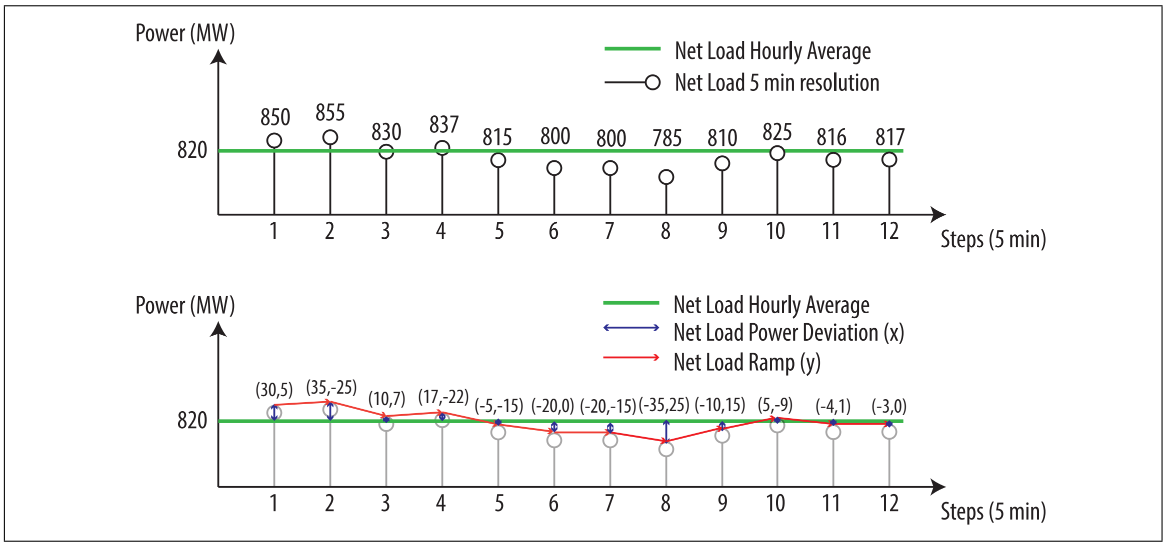
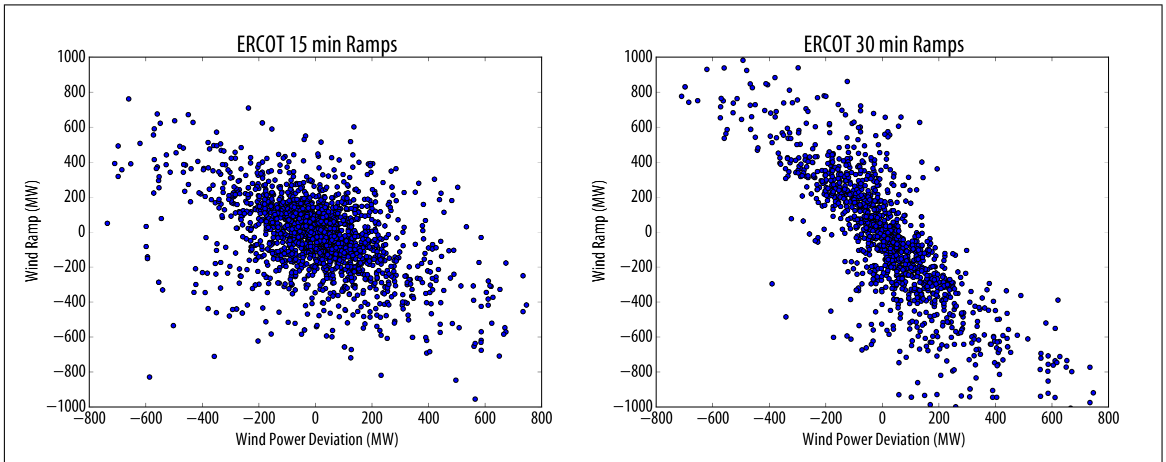


Figure 2.1. Net load profile and reformulation in power deviations and ramps

These coordinates can also be mapped in a X-Y plot, where x axis represents the power deviations and y the consecutive ramps. By collecting more historical data in the plot, it is possible to generate a more robust modeling of the uncertain parameter. For instance, figures 2.2a and 2.2b show the regions for wind system wide generation in ERCOT during the period January-June 2016.



(a) 15 min (b) 30 min

Figure 2.2. Deviation-Ramp Plot for ERCOT. Source: ERCOT (2016)

In order to generate a region with a finite number of extreme points which allow us to exploit the properties studied in last section, we propose an algorithm to enclose a certain percentage of the scatter plot with six extreme points as much.

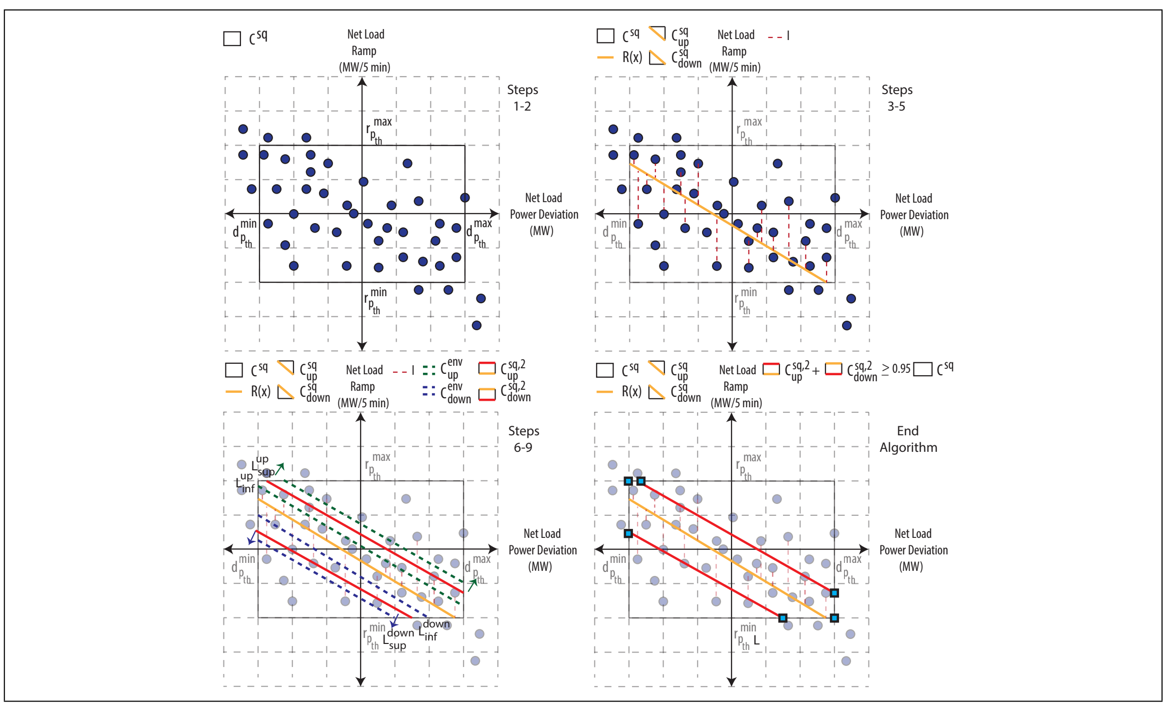


Figure 2.3. Algorithm

This algorithm needs as inputs the set of coordinates x, upper and lower percentiles for power deviations and ramps ($p_{dev}^{min}, p_{dev}^{max}, p_r^{min}, p_r^{max}$) and upper and lower percentiles for distance from upper and lower coordinates to the linear regression of scatter plot ($p_{dist}^{sup}, p_{dist}^{inf}$) for enclosing the region, the function of these last inputs will be explained in the algorithm. Figure 2.3 illustrates each step explained below.

Algorithm 1 Proposed Uncertainty Set

Input: Coordinates (x,y), percentiles ($p_{dev}^{min}, p_{dev}^{max}, p_r^{min}, p_r^{max}$), percentiles ($p_{dist}^{sup}, p_{dist}^{inf}$).

1: Given $p_{dev}^{min}, p_{dev}^{max}, p_r^{min}, p_r^{max}$, obtain power and ramp requirements $d_{p_{th}}^{min}, d_{p_{th}}^{max}, r_{p_{th}}^{min}, r_{p_{th}}^{max}$.

2: Define coordinates inside the box $x \in C^{sq}$, where $C^{sq} : [d_{p_{th}}^{min}, d_{p_{th}}^{max}] \times [r_{p_{th}}^{min}, r_{p_{th}}^{max}]$

3: Compute regression $\mathcal{R}(x)$ of coordinates $(x, y) \in C^{sq}$

4: Separate:

$$C^{sq} := \begin{cases} C_{up}^{sq} \ \ if \ \ y \geq R(x) \\ C_{down}^{sq} \ \ if \ \ y \leq R(x) \end{cases}$$

5: Calculate distance l as: $\|y - \mathcal{R}(x)\|$

6: Given (x,y),p_{dist}^{up} and p_{dist}^{inf}:

$$\begin{aligned} L_{sup}^{up} &= p_{dist}^{up}(l^{up}) \quad L_{inf}^{up} = p_{dist}^{down}(l^{up}) \\ L_{sup}^{down} &= p_{dist}^{sup}(l^{down}) \quad L_{inf}^{down} = p_{dist}^{inf}(l^{down}) \end{aligned}$$

7:

$$\begin{aligned} C_{up}^{env} &\subset C_{up}^{sq} \ \ if \ \ L_{inf}^{up} \leq \|y - R(x)\| \leq L_{sup}^{up} \\ C_{down}^{env} &\subset C_{down}^{sq} \ \ if \ \ L_{inf}^{down} \leq \|y - R(x)\| \leq L_{sup}^{down} \end{aligned}$$

8: Compute regressions $\mathcal{R}_2(x)^{up}$ from C_{up}^{env} and $\mathcal{R}_2(x)^{down}$ from C_{down}^{env}, respectively.

9: Get points inside rhomboid as:

$$\begin{aligned} C_{up,2}^{sq} &\subset C_{up}^{sq} \ \ if \ \ \|y\| \leq \mathcal{R}_2(x)^{up} \\ C_{down,2}^{sq} &\subset C_{down}^{sq} \ \ if \ \ \|y\| \geq \mathcal{R}_2(x)^{down} \end{aligned}$$

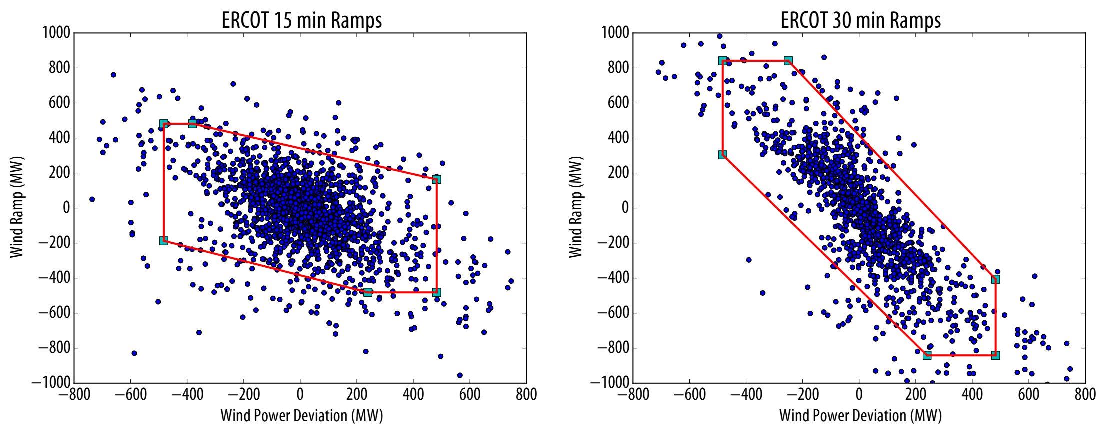
10: $z = (card(C_{up,2}^{sq}) + card(C_{down,2}^{sq}))/card(C^{sq})$

11: **while** $z \leq 0.95$ **do**

12: $\quad p_{dist}^{up} += \epsilon$

13: $\quad$ Repeat 6-10

14: **end while**



(a) 15 min (b) 30 min

Figure 2.4. Deviation-Ramp Plot for ERCOT. Source: ERCOT (2016)

The outcome of the presented algorithm is shown in figures 2.4a and 2.4b. As it can be noticed from the algorithm, distance percentiles from coordinates to the regression are the same for upper and lower coordinates, which leads to symmetrical steps in both directions. A more accurate algorithm to iterate regressions is left to future work.

From now on, we will refer to the coordinates of the extreme points as follow:

(i) Δd_h^k : power deviation for hour h and extreme point k

(ii) $r_{h,p}^k$: net load ramp for hour h, duration p and extreme point k

These parameters compose the reserve requirements and are introduced as inputs into the model presented in section V. It is worth mentioning that classification of power and ramping reserves have already been studied in a Unit Commitment context. In Morales-España et al. (2016) these reserves are hourly-based and are included in a Deterministic Power-Based UC, whereas a Stochastic UC with this type of reserves is presented in Marneris et al. (2017). Although the classification of reserves has already been made, the methodology to obtain them is different.

If the scatter plots for different ramp durations are shown together along with their uncertainty models the increase on the slope of the clouds of points becomes more evident, as it is presented in figure (2.5)

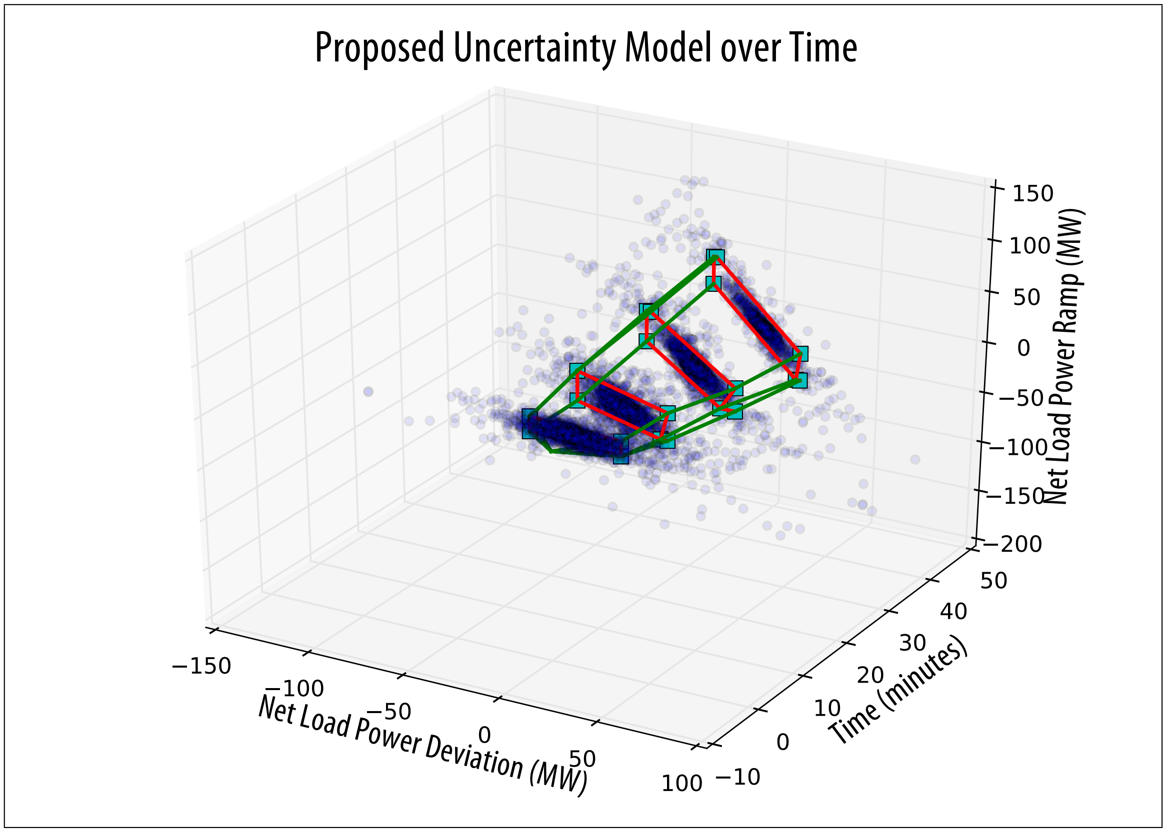


Figure 2.5. Evolution of the Proposed Uncertainty Model

2.4. Affine Policies in Power System Operations

After reserve requirements are quantified, a mechanism for distributing them amongst generators is needed. A simple rule to perform this task is the use of affine policies, which consist on defining the generation as a linear function of the scheduled generation and the uncertain load.

$$P_g = P_g^0 + \lambda_g \Delta d$$

$$\sum_{g \in \mathcal{G}} P_g^0 = d$$

$$\sum_{g \in \mathcal{G}} \lambda_g = 1$$

Second equation means that the forecast load profile must be satisfied, whereas third equation enforces the balance of deviations. For instance, consider 2 generators producing 100 MW each to balance a load profile of 200 MW. Unit 1 has a $\lambda_1 = 0.2$ and unit 2 $\lambda_2 = 0.8$, if load results to be 120 MW, the rule will lead to the following dispatches:

$$P_1 = P_1^0 + \lambda_1 \Delta d = 100 + 0.2 \cdot 20 = 104 \; MW$$

$$P_2 = P_2^0 + \lambda_2 \Delta d = 100 + 0.8 \cdot 20 = 116 \; MW$$

To solve a problem with affine policies two inputs are needed: Δd and λ. The first one can be obtained through an algorithm as the one presented previously, whereas policies need to be optimized in a dispatch model.

When affine policies are going to be used as hourly decision variables to model sub-hourly behaviors, it is necessary to model them adequately in order to not violate physical constraints of the units.

For instance, consider a 1-bus system with 2 generators whose features are detailed in Table 2.1. Suppose $C(P_1) \leq C(P_2)$.

Table 2.1. Features

Gen	$P^{min}\ (MW)$	$P^{max}\ (MW)$	$R \frac{MW}{5\ min}$
1	125	500	10
2	125	500	15

Suppose the we want to solve the economic dispatch for 1 hour load profile from figure (2.1). Then the problem can be solved using a 5-min resolution ED, or utilize another strategy. As it was mentioned, a dispatch based on affine policies would need to find a Δd. We can incorporate this by reformulating the hourly profile in 12 coordinates as in subsection 2.3, where **x** will be the deviation with respect to the average and **y** will be the power ramp, and mapping them in a X-Y plot shown in figure (2.6). As the number of points in the cloud is low, we will utilize the entire data instead of defining the polyhedral uncertainty set to show how the policy dispatch works.

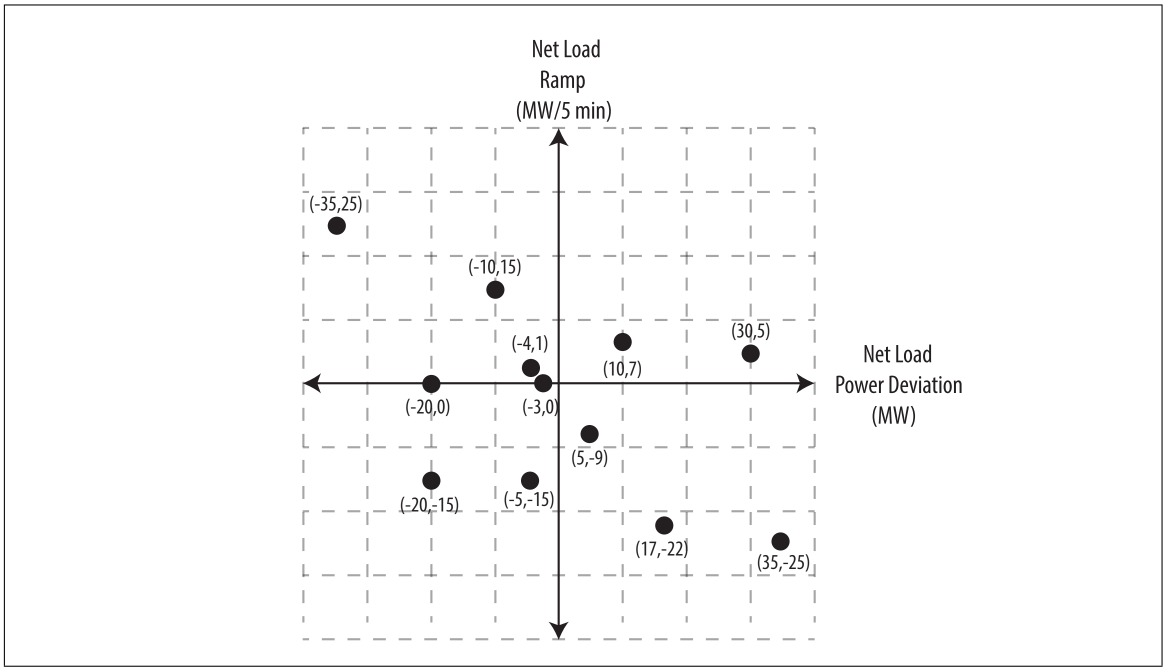


Figure 2.6. X-Y Plot

Consider d the net load, m the index for intra-hour steps and $\overline{d}$ the average.

$$\min_{\mathbf{P^0},\lambda} \; C(P_1) + C(P_2)$$

$$P_1^0 + P_2^0 = 820 \tag{2.1}$$

$$\lambda_1 + \lambda_2 = 1 \tag{2.2}$$

$$P_g^0 + \lambda_g(d^m - \overline{d}) \leq P_g^{max} \quad g = 1, 2, m = 1, ..., 12 \tag{2.3}$$

$$P_g^0 + \lambda_g(d^m - \overline{d}) \geq P_g^{min} \quad g = 1, 2, m = 1, ..., 12 \tag{2.4}$$

$$(P_g^0 + \lambda_g(d^{m+1} - \overline{d})) - (P_g^0 + \lambda_g(d^m - \overline{d}))$$
$$\leq R_g^{up} \quad g = 1,2,\ m = 1,...,11 \tag{2.5}$$
$$(P_g^0 + \lambda_g(d^{m+1} - \overline{d})) - (P_g^0 + \lambda_g(d^m - \overline{d}))$$
$$\geq R_g^{down} \quad g = 1,2,\ m = 1,...,11 \tag{2.6}$$
$$(P_g^0 + \lambda_g(d^{m+1} - \overline{d})) - (P_g^0 + \lambda_g(d^m - \overline{d}))$$
$$\leq P_g^{max} - (P_g^0 + \lambda_g(d^m - \overline{d})) \quad g = 1,2,\ m = 1,...,11 \tag{2.7}$$
$$(P_g^0 + \lambda_g(d^{m+1} - \overline{d})) - (P_g^0 + \lambda_g(d^m - \overline{d}))$$
$$\geq P_g^{min} - (P_g^0 + \lambda_g(d^m - \overline{d})) \quad g = 1,2,\ m = 1,...,11 \tag{2.8}$$

Since the load is the same within the hour, constraints (2.5)-(2.8) can be simplified to:

$$\lambda_g(d^{m+1} - d^m) \leq R_g^{up} \quad g = 1,2,\ m = 1,...,11 \tag{2.9}$$
$$\lambda_g(d^{m+1} - d^m) \geq R_g^{down} \quad g = 1,2,\ m = 1,...,11 \tag{2.10}$$
$$P_g^0 + \lambda_g((d^m - \overline{d}) + (d_{m+1} - d_m)) \leq P_g^{max} \quad g = 1,2,\ m = 1,...,11 \tag{2.11}$$
$$P_g^0 + \lambda_g((d^m - \overline{d}) + (d_{m+1} - d_m)) \geq P_g^{min} \quad g = 1,2,\ m = 1,...,11 \tag{2.12}$$

The way to solve this problem is by replacing the coordinates $(d^m - \overline{d}, d^{m+1} - d^m)$, or by finding the coordinates which generate the most binding constraints: $(-35, 25)$, $(35, -25)$, $(30, 5)$ and $(-20, -15)$.

$$\lambda_1 \cdot 25 \leq 10 \tag{2.13}$$
$$\lambda_2 \cdot 25 \leq 15 \tag{2.14}$$
$$\lambda_1 \cdot -25 \geq -10 \tag{2.15}$$
$$\lambda_2 \cdot -25 \geq -15 \tag{2.16}$$
$$P_1 + \lambda_1 \cdot (30 + 5) \leq 500 \tag{2.17}$$

$$P_2 + \lambda_2 \cdot (30 + 5) \leq 500 \tag{2.18}$$

$$P_1 + \lambda_1 \cdot (-15 - 20) \geq 125 \tag{2.19}$$

$$P_2 + \lambda_2 \cdot (-15 - 20) \geq 125 \tag{2.20}$$

The policy solution for this problem is $\lambda_1 = 0.4$ and $\lambda_2 = 0.6$,whereas the dispatch solution is $P_1 = 486\ MW$, $P_2 = 334\ MW$. The intra-hour trajectory of each generator is shown in figure (2.7).

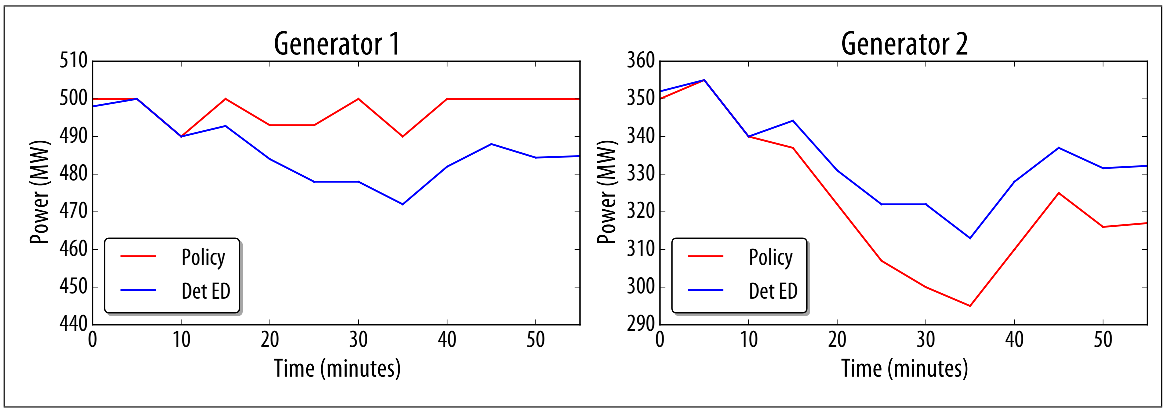


Figure 2.7. Intra-hour trajectories for Generators 1 and 2

It is worth mentioning that this problem is possible to be solved by enumerating all the points because the number is very low. In case of the information available is similar to the ERCOT database presented in previous section, it is necessary to develop a strategy to enclose them. The complete policy formulation in the dispatch model can be obtained by replacing $(d^m - \overline{d}, d^{m+1} - d^m)$ by $(\Delta d_h^k, r_{h,p}^k)$.

There are several ways to implement affine policies to solve economic dispatch problems. One could be to dispatch the system only using policies. This approach might be significantly expensive though, because it implies the development of boundary conditions between hours to connect hourly variables on a consistent way. Another drawback is that a model with hourly resolution presents more difficulties to curtail wind. Another option would be to apply the traditional practices in industry, where the most traditional is myopic dispatch with spinning reserves. In recent years, the addition of look-ahead time periods to prepare the system for the future has been implemented in some System Operators. We propose to include policy modeling into the look-ahead framework as a forecast tool, hedging the system against uncertainty. Complete formulation for the two periods look-ahead dispatch with policies is presented in following section.

3. MODEL FORMULATION

This chapter details the nomenclature and the complete formulation to model the Look-Ahead Economic Dispatch with Affine Policies.

3.1. Nomenclature

3.1.1. Sets and Indexes

g:	Index of Generators, $g \in G$.
t:	Index of Time Steps, $t \in T$
h:	Index of Hours, $h \in H$
k:	Index of Extreme Points of the Uncertainty Set for Net Load, $k \in K$
p:	Index of ramp duration (1 represents the interval 0-5, whereas the second 0-10)

3.1.2. Parameters

FC_g:	Fixed cost of generator g [US $]
VC_g:	Variable cost of generator g [US $/MWh]
P_g^{min}:	Minimum power output of generator g [MW]
P_g^{max}:	Maximum power output of generator g [MW]
R_g^{up}:	Upward 5 min ramp capability of generator g [MW]
R_g^{down}:	Downward 5 min ramp capability of generator g [MW]
Δd_h^k:	Net load power deviation for hour h and extreme point k [MW]
$r_{h,p}^k$:	Net load ramp for hour h, duration p and extreme point k [MW]
$r5_h^{up}$:	Upward reserve requirement for 5 minutes given by Gaussian-sigma rule (2σ) [MW]
$r5_h^{down}$:	Downward reserve requirement for 5 minutes given by Gaussian-sigma rule (2σ) [MW]
d_t:	Net load for time step t [MW]

d_h: Net load for the hourly look-ahead horizon h [MW]

3.1.3. Decision Variables

$p_{g,t}$: Power output of unit g for time step t [MW]

$r_{g,t}^{up}$: Upward reserve capacity of unit g for time step t [MW]

$r_{g,t}^{down}$: Downward reserve capacity of unit g for time step t [MW]

$P_{g,h}^{0}$: Scheduled power output of unit g in hour h for look-ahead policy dispatch [MW]

$\lambda_{g,h}$: Affine policy for power deviation for unit g in hour h for look-ahead policy dispatch

3.2. Optimization Problem

$$\min_{\mathbf{p},\mathbf{P^0},\lambda} \sum_{g\in\mathcal{G}} \sum_{t\in T} \frac{FC_g}{12} + \frac{VC_g}{12} \cdot p_{g,t} + \sum_{g\in\mathcal{G}} \sum_{h\in\mathcal{H}} FC_g + VC_g \cdot P_{g,h}^0 + \eta \tag{3.1}$$

$$\eta \geq \sum_{g\in\mathcal{G}} VC_g \lambda_{g,h} \Delta d_h^k \qquad \forall h, k \tag{3.2}$$

$$\sum_{g\in\mathcal{G}} p_{g,t} = d_t \qquad \forall t \tag{3.3}$$

$$\sum_{g\in\mathcal{G}} P_{g,h}^0 = d_h \qquad \forall h \tag{3.4}$$

$$\sum_{g\in\mathcal{G}} \lambda_{g,h} = 1 \qquad \forall h \tag{3.5}$$

$$p_{g,t} + r_{g,t}^{up} \leq P_g^{max} \qquad \forall g, t \tag{3.6}$$

$$p_{g,t} - r_{g,t}^{down} \leq P_g^{min} \qquad \forall g, t \tag{3.7}$$

$$P_{g,h}^0 + \lambda_{g,h} \cdot \Delta d_h^k \geq P_g^{min} \qquad \forall g, h, k \tag{3.8}$$

$$P_{g,h}^0 + \lambda_{g,h} \cdot \Delta d_h^k \leq P_g^{max} \qquad \forall g, h, k \tag{3.9}$$

$$p_{g,t} - p_{g,t-1} \leq R_g^{up} \qquad \forall g, t = 2 \tag{3.10}$$

$$p_{g,t} - p_{g,t-1} \geq R_g^{down} \qquad \forall g, t = 2 \tag{3.11}$$

$$P_{g,h}^0 + \lambda_{g,h} \cdot (\Delta d_h^k + r_{h,p}^k) \leq P_g^{max} \qquad \forall g, h, p, k \tag{3.12}$$

$$\lambda_{g,h} \cdot r_{h,p}^k \leq p \cdot R_g^{up} \qquad \forall g, h, p, k \tag{3.13}$$

$$P_{g,h}^0 + \lambda_{g,h} \cdot (\Delta d_h^k + r_{h,p}^k) \geq P_g^{min} \qquad \forall g, h, p, k \tag{3.14}$$

$$\lambda_{g,h} \cdot r_{h,p}^k \geq p \cdot R_g^{down} \qquad \forall g, h, p, k \tag{3.15}$$

$$P_{g,h}^0 - p_{g,t} \leq R_g^{up} \qquad \forall g, t, h \tag{3.16}$$

$$P_{g,h}^0 - p_{g,t} \geq R_g^{down} \qquad \forall g, t, h \tag{3.17}$$

$$r_{g,t}^{up} \leq R_g^{up} \qquad \forall g, t \tag{3.18}$$

$$r_{g,t}^{down} \leq R_g^{down} \qquad \forall g, t \tag{3.19}$$

$$\sum_{g \in \mathcal{G}} r_{g,t}^{up} \geq r5_h^{up} \qquad \forall g, t \tag{3.20}$$

$$\sum_{g \in \mathcal{G}} r_{g,t}^{down} \geq -r5_h^{down} \qquad \forall g, t \tag{3.21}$$

(3.1) is the objective function, which comprises the dispatch costs, (3.2) is the cost of the policy reserves. (3.3) is the power balance constraint for deterministic horizon, whereas (3.4) ensures hourly balance of look-ahead, intra-hourly balance is given by (3.5). (3.6)-(3.7) limit maximum and minimum power output for all deterministic set-points and (3.8)-(3.9) for policy dispatch, (3.10)-(3.11) and (3.12)-(3.15) are the ramp constraints for set-points and policy dispatch respectively. Constraints (3.16)-(3.17) impose continuity between deterministic and look-ahead horizons. Maximum up and down reserves are addressed in (3.18)-(3.19), and coverage of requirements is modeled in (3.20)-(3.21).

4. SIMULATIONS AND RESULTS

4.1. Definition of Study Cases

In order to assess the proposed formulation, two analysis were carried out over three different study cases:

- Performance analysis: The performance is evaluated in terms of costs and other metrics such as expected energy not served for the proposed model, using $T = 2$ and $H = 1$ in the model, and two benchmarks, one from literature and one representing current practice:
  - Literature: Flexibility envelopes Nosair & Bouffard (2015a) are adapted to replace the proposed uncertainty model, envelopes are ramping constraints defined by a certain confidence interval of a Laplace Distribution. This distribution is obtained from the historical data available, and its parameters are obtained for different ramp durations, some of them are presented in figure (4.1). This benchmark uses $T = 2$ and $H = 1$.
  - Traditional practice: Two periods Look-Ahead Dispatch. This model is obtained by setting $T = 2$ and $H = 0$.
- Uncertainty modeling analysis: In this analysis, 3 additional modeling approaches for the uncertain source were developed in order to compare the proposed model with other bidimensional approaches that result in regions of different sizes. Two of these approaches use a new enclosure technique called **convex hull**, a method of computational geometry that consists of enclose a set of points with the convex figure of lowest perimeter. Formulations are shown in figure 4.2. In this analysis, all the models use $T = 2$ and $H = 1$.
  - Policy Sq: Region formed by Step 1 of Algorithm, corresponding to a square delimited by the upper and lower percentiles defined.
  - Policy Sq CH: Convex hull of Policy Sq region.
  - Policy CH: Convex hull of the proposed Policy region.

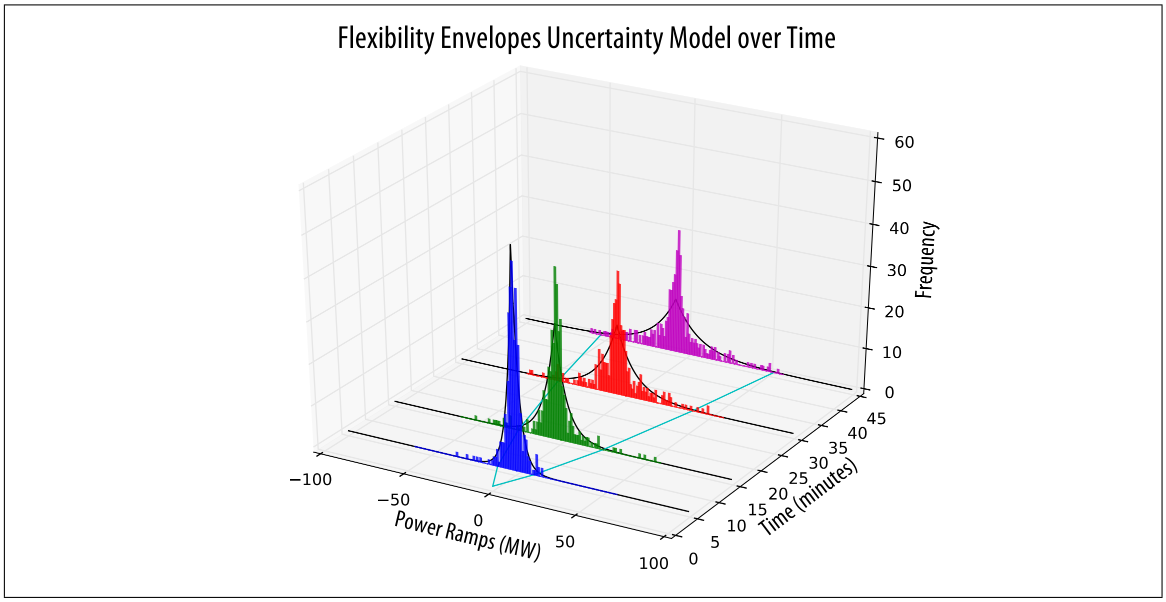


Figure 4.1. Flexibility Envelopes

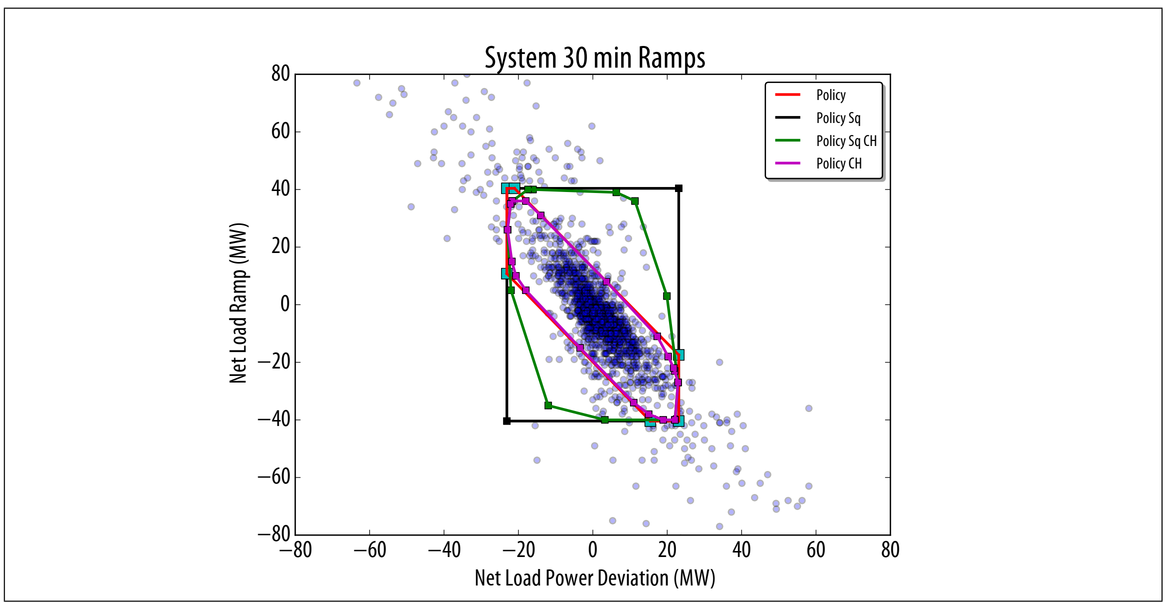


Figure 4.2. Benchmarks for Uncertainty Modeling Analysis

To measure performance, both analysis utilize an oracle model, which is a full deterministic economic dispatch with 5 min resolution. The proposed model uses ramp constraints with durations of 5, 15, 30 and 45 minutes. Percentiles $p_{dev}^{min}, p_{dev}^{max}, p_r^{min}, p_r^{max}$

were selected using a Laplace Distribution in order to enclose the 95 % of the deviations and the consecutive ramps. Percentiles ($p_{dist}^{sup}, p_{dist}^{inf}$) were initialized as 96 and 93.

Cases 1 and 2 utilizes 300 daily wind power scenarios obtained from NREL Wind Database and 1 load scenario for BPA replicated 300 times, whereas Case 3 analyses 140 days. Penetration levels of renewable energy achieves roughly 20 % in cases 1 and 2, whereas in case 3 it reaches 35 %. Simulations were carried out using a Dell PowerEdge R360 server with an Intel Xeon CPU E5-2630 v4 processor running at 2.20GHz, and 64 GB of RAM.

Although models were parallelized to diminish simulation time, they were registered to compute the required time to perform scenarios sequentially. Case 1 uses glpk and cases 2 and 3 uses gurobi solver. Shedding cost is defined as 5000 ($\frac{US\$}{MWh}$) while the cost of violating a flexibility constraint is set to 3000 ($\frac{US\$}{MWh}$).

4.2. Use of Scenario Data for Simulations

The information of the 300 scenarios must be used respecting the model formulation previously presented. Therefore, in each step of the simulation, each model takes the first two time steps for dispatch, and the following 12 points are averaged as it is shown in figure (4.3). In this manner, the structure of $T = 2$ and $H = 1$ is respected. As it was mentioned, in the case of two periods look-ahead dispatch only the information of the two time steps is utilized. When the simulation advances to the next step in order to solve dispatch for the new conditions, the average of net load is updated for the points between minutes 15 and 70.

4.3. Case 1

Case 1 consists of two identical generators whose features are shown in Table 4.1. Maximum load for the 300 scenarios is 270 MW while the maximum wind generation is 215 MW.

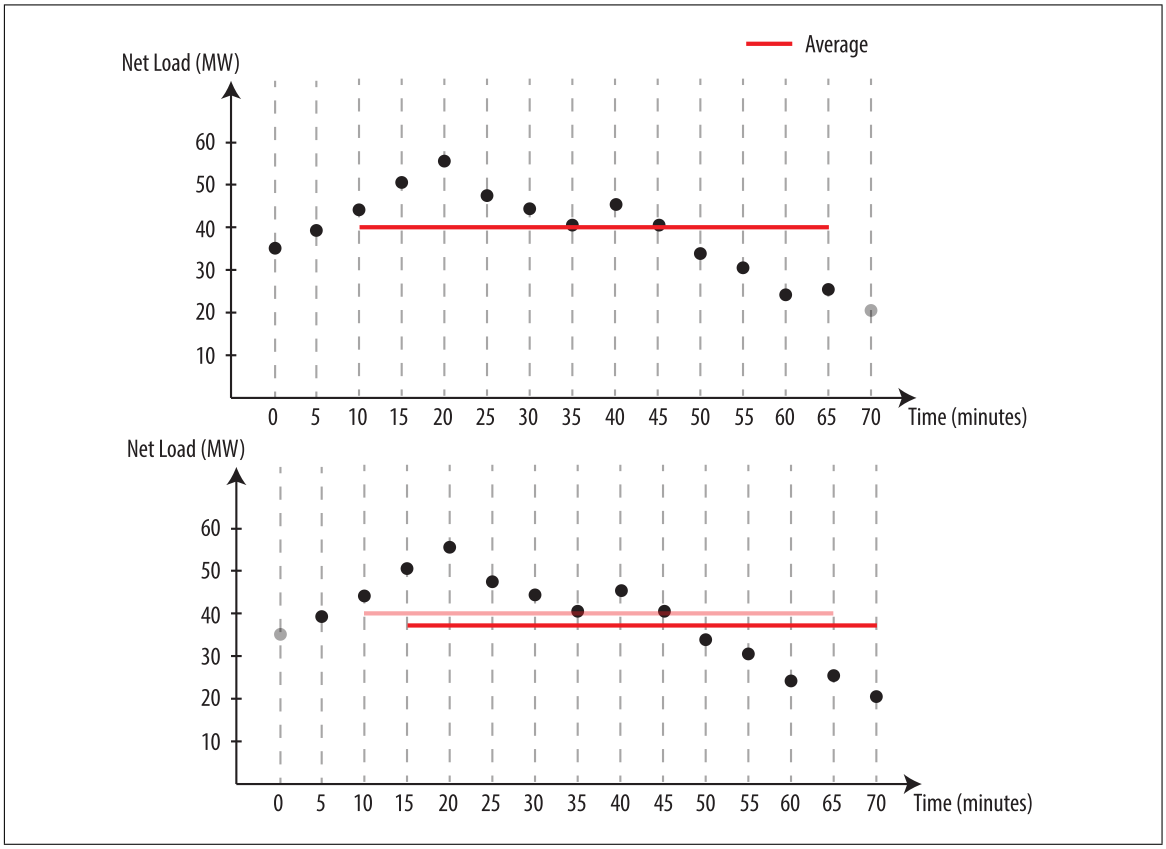


Figure 4.3. Net Load Evolution during Simulation

Table 4.1. Features Case 1

Gen	FC (US \$)	VC ($\frac{US\$}{MWh}$)	P^{min}	P^{max}	$R\frac{MW}{5\,min}$
1	0	20	50	150	6
2	0	40	50	150	6

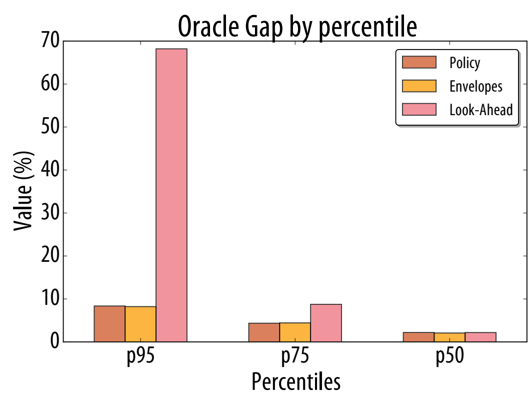
4.3.1. Performance Analysis

The outcome of performance analysis for case 1 is summarized in Table 4.2. The results show that the lowest operational costs are achieved by the envelopes model, whereas the highest are obtained by the look-ahead dispatch. This is mainly explained in the expected energy not served caused for the lack of a forecast tool.

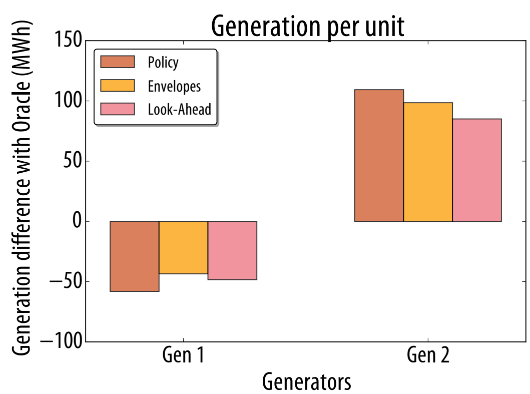
Table 4.2. Summary performance metrics case 1

Model	Oracle Gap	EENS (MWh)	CPU Time (s)
Policy	3.01 %	0.11	10073
Envelopes	2.95 %	0.12	9814
Look-Ahead	12.04 %	2.54	8056

Figure (4.4a) shows the oracle gap for different percentiles of the cost distribution, the results for p_{95} reaffirm the load shedding as the cause of the costs of look-ahead. Figure (4.4b) shows the energy generated by the 2 generators in the system, it can be seen that policy model is the one saving more generator for the cheapest generator in order to have more reserves. It can be also noticed that Look-Ahead generates less with unit 1 than envelopes, despite of it requires less reserve. This occurs because when the model with forecast see that wind is increasing but later it will decrease dramatically, the operator can curtail some generation in order to soften the downward ramp of wind generation. This additional generation is taken by unit 1, given that it is the cheapest of the 2 generators.



(a) Oracle Gap by percentile



(b) Generation

Figure 4.4. Results performance analysis case 1

Total costs of operating with envelopes based constraints in comparison to policy model are barely lesser, and they occur due to the dispatch formulation of that model, where the reserves are decoupled according direction (up and down reserves) and the duration (5, 15 min, etc). This feature allows to manage flexibility in a more efficient manner.

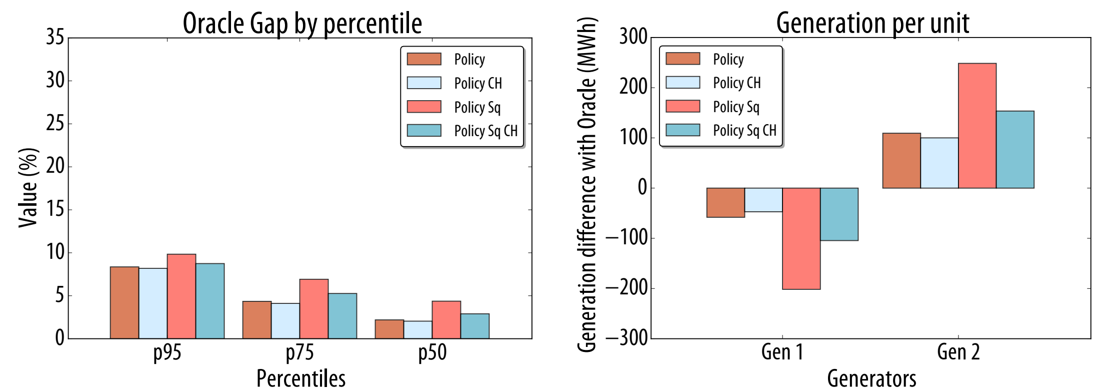
4.3.2. Uncertainty Modeling Analysis

Table 4.3 presents the results for the uncertainty modeling analysis. The results show that Policy Sq and Policy Sq CH formulations have operational costs significantly higher than the other models. From the table it is possible to observe that this influence of load shedding in the difference is very weak.

Table 4.3. Summary uncertainty modeling metrics case 1

Model	Oracle Gap	EENS (MWh)	Sim Time (s)
Policy	3.01 %	0.11	10073
Policy CH	2.86 %	0.10	23847
Policy Sq	5.31 %	0.15	10367
Policy Sq CH	3.73 %	0.12	20482

The source of the difference in costs appear from the results presented by Figures (4.5a) and (4.5b). It can be observed that differences in costs exists in all the percentiles analyzed, whereas the energy generated by unit 1 is noticeably lower in the last two models. This is related with the amount of reserve required by Policy Sq and Policy Sq CH, which defines larger regions of uncertainty than the other formulations. As the policy is a symmetrical reserve, if unit 1 has scheduled a big amount of upward reserve, it will have to provide downward reserve as well, operating further than the technical minimum.



(a) Oracle Gap by percentile

(b) Generation

Figure 4.5. Results uncertainty modeling analysis case 1

4.4. Case 2

Case 2 consists of the two generators from case 1 with their minimum output diminished to 45 MW and their maximum output to 120 MW each. A third unit with the ability of being committed during the real-time operation is also available, this generator has a start up cost of 100 US \$. The LAED needs to be modified to allow the real-time commitment of the additional unit, the assumptions for the provision of reserve by the quick start unit and the formulation for this dispatch model are available in Appendix C and D, respectively. New features are shown in Table 4.4. Load and wind data remain the same with respect to case 1.

Table 4.4. Features Case 2

Gen	FC (US \$)	VC ($\frac{US\$}{MWh}$)	P^{min}	P^{max}	$R\frac{MW}{5\,min}$	Type
1	0	20	45	120	6	Base
2	0	40	45	120	6	Base
3	0	60	10	60	8	QSU

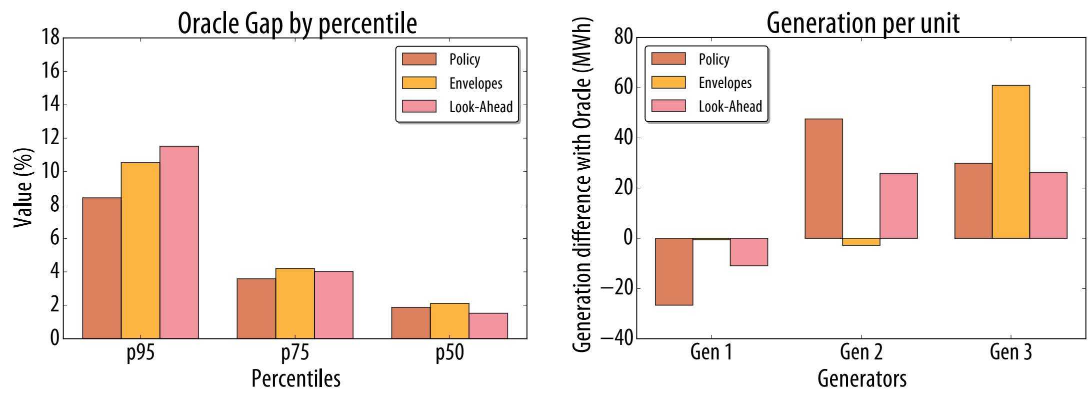
4.4.1. Performance Analysis

Main results of case 2 are presented in Table 4.5. They show that envelopes model has higher operation costs than the policy model, whereas look-ahead continues to obtain the more expensive performance due to the shed load.

Table 4.5. Summary performance metrics case 2

Model	Oracle Gap	EENS (MWh)	Comm U3	Sim Time (s)
Policy	2.48 %	0.033	1.49	22884
Envelopes	2.83 %	0.030	2.64	20186
Look-Ahead	3.47 %	0.440	2.27	16516

The expected real-time commitments realized by unit 3 are also shown as Comm U3 in the table. The results show that envelopes formulations lead to a more often schedule of this unit due to the amount of reserve required. Policy model has the closest expected number of commitments in comparison with the optimal operation, which is 1.5. The effects of the different reserve schemes on the net energy generated with respect to the Oracle are shown in Figure (4.6b), where the difference in the energy generated by unit 3 is relevant. This is produced by the extra upward reserves required in envelopes model. The energy generated by unit 3 significantly impacts the costs in more expensive scenarios, as shown in Figure (4.6a). Costs are increased in a lesser extent because of the additional start ups that the model realize in the case of envelopes and look-ahead dispatch.



(a) Oracle Gap by percentile

(b) Generation

Figure 4.6. Results performance analysis case 2

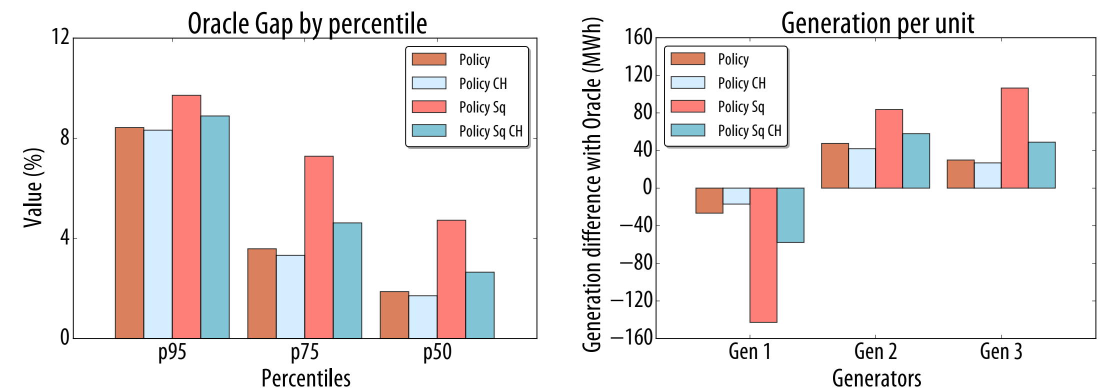
4.4.2. Uncertainty Modeling Analysis

The experiment of performing the dispatch using different uncertainty sets were repeated including the start up unit, whose results are depicted in Table 4.6.

Table 4.6. Summary uncertainty modeling metrics case 2

Model	Oracle Gap	EENS (MWh)	Comm U3	Sim Time (s)
Policy	2.48 %	0.033	1.49	22884
Policy CH	2.32 %	0.033	1.5	44049
Policy Sq	5.26 %	0.032	2.26	22418
Policy Sq CH	3.21 %	0.032	2.11	39039

Although expected energy not served is low in all models, it is possible to see the trade off that exists between the amount of reserve scheduled and the energy not served. Policy and Policy CH models have the greatest values of shedding whereas they schedule the lowest amount of reserve. Other interesting result is that the outcomes of these models are very similar, this means the model of 6 extreme points approximates with accuracy the convex hull. The resemblance in the operation can also be seen in figures (4.7a) and (4.7b) which presents the oracle gap by percentile and the generation per unit, respectively. Differences in oracle gap among the models remain similar in all the percentiles under study, this difference is mostly explained by the energy generated with more expensive units in the case of Policy Sq and Policy Sq CH models.



(a) Oracle Gap by percentile

(b) Generation

Figure 4.7. Results uncertainty modeling analysis case 2

4.5. Case 3: Modified IEEE 118-Buses System

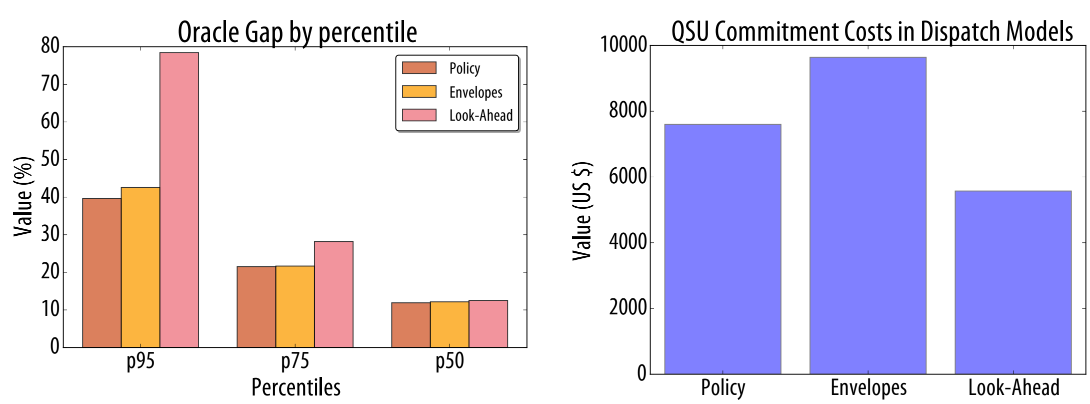
The Modified IEEE 118-Buses System consists of using the 54 generators of the original system in only 1 bus. This allows us to isolate from the analysis the effects of network congestions. Data of the IEEE 118-Buses System was obtained from (Morales-España et al., 2016) and is available in Appendix D. In order to simulate a real-time operation with this system, a Unit Commitment is solved for each day under study. The UC has a reserve constraint of 10 % of the load of the hour. Then, the operation is carried out allowing the commit of quick start units, in the same way than previous case.

4.5.1. Performance Analysis

The results for the performance analysis are summarized in Table 4.7, they show that the operation with Policy model is slightly cheaper than the envelopes based dispatch. This difference comes from the generation costs, given that EENS is greater in the case of policies. With respect to computation time, Policy formulation has more burden due to the larger number of constraints and the need to couple all the reserves in only one variable. Despite the above, as each day is solved in approximately 400 seconds, each dispatch period it is solved within 2 seconds. Therefore, under a scheme of 5 minutes resolution, the model achieves a good performance in terms of simulation time.

Table 4.7. Summary performance metrics case 3

Model	Oracle Gap	EENS (MWh)	Sim Time (s)
Policy	13.5 %	1.11	63605
Envelopes	14.0 %	0.96	41905
Look-Ahead	21.5 %	17.32	13203



(a) Oracle Gap by percentile

(b) Total RT start up costs

Figure 4.8. Results uncertainty modeling analysis case 3

Figures (4.8a) and (4.8b) give information about the costs by percentile and the cost of committing resources during real time. From the first figure it can be observed that the difference between policy and envelopes models become noticeable for the higher percentiles of costs, because of the need of accounting with more quick reserve, which also elevates the generation costs and is the other factor that explains the differences in operation costs.

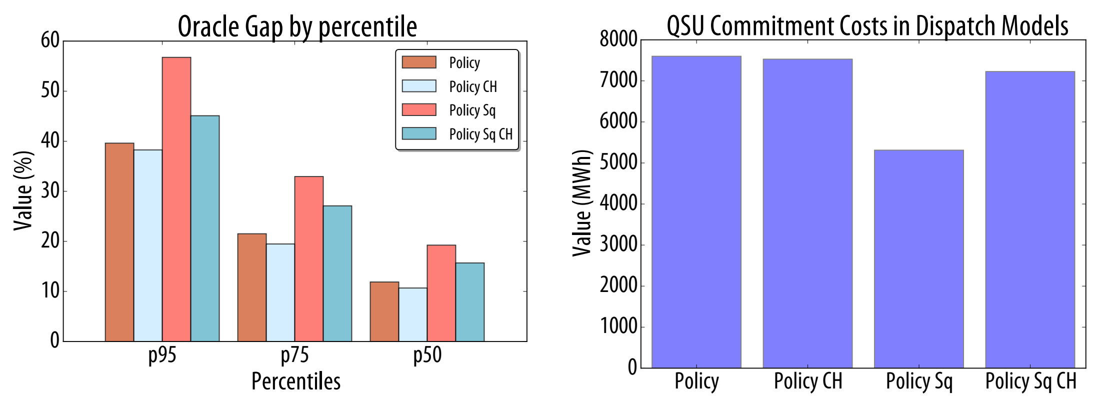
4.5.2. Uncertainty Modeling Analysis

Results of the uncertainty modeling analysis for the modified IEEE 118 Buses are presented in Table 4.8. The oracle gap of models with larger regions of uncertainty achieve the highest operation costs. This is occasioned by the amount of reserve required. Another interesting result of the simulation is in the difference between oracle gaps of Policy and Policy CH models. This means that the uncertainty set of the first model does not approximate in a very accurate way the second set. The difference in operation costs with respect to models Policy and Policy CH is present in all the percentiles of the cost distribution, as it is shown in Figure (4.9a).

Table 4.8. Summary uncertainty modeling metrics case 3

Model	Oracle Gap	EENS (MWh)	Sim Time (s)
Policy	13.5%	1.11	63605
Policy CH	12.3 %	0.67	256807
Policy Sq	21.4 %	1.61	48144
Policy Sq CH	17.5 %	1.71	229168

Figure (4.9b) shows the costs of incurring in commitment of quick start units during the real-time operation. It can be noticed that Policy Sq and Policy Sq CH models obtained lower costs than the other models. This occurs because the large amount of reserve required forces the system to keep some quick start units committed, whereas the other models only commit those generators when their reserve requirements determine it or it is necessary to balance an episode of upward ramp. This situation also determines that the EENS is superior in those cases, because the ramp constraint of QSU has an additional component given by the start-up process which can only be seized by the models whose units are off.



(a) Oracle Gap by percentile

(b) Total RT start up costs

Figure 4.9. Results uncertainty modeling analysis case 3

5. CONCLUSIONS AND FUTURE WORK

The increasing penetration of variable renewable generation is posing several challenges in real-time operation due to its uncertain behavior. This work presented a novel design methodology to represent the potential sub-hourly variations through a polyhedral uncertainty set based on historical data of wind generation and load. The uncertainty set was implemented in a Look-Ahead Economic Dispatch under the Affinely Adjustable Robust Optimization Framework. Therefore, the reserve responsibilities of each generator are established according to the uncertainty set previously designed. Performance of the proposed approach was tested under several days of operation in three different systems, and compared to other methodologies to size reserves available in literature, industry practices and other proposed formulations that can come off the proposed modeling. Results showed that under high amounts of scheduled reserves the operation costs may be less efficient due to either the distribution of generation between units and the need to commit additional units which are not needed and increase the total operation costs. This determines that an accurate modeling for uncertain sources is critical to ensure a secure and cost-efficient operation.

Many directions of future work are open. In relation with the uncertainty modeling, results demonstrated that keeping a reduced number of extreme points under a polyhedral uncertainty set would be desirable. Therefore, it could be possible to test new methodologies to enclose the historical data. For instance, using a technique of computational geometry called rotating calipers. It consists of enclosing a convex hull with the smallest parallelogram. Another option would be to implement non-linear designs such as 2 or 3 order regressions. This last option, however, would need a modification in the way the economic dispatch is being currently solved, because the enumeration of the extreme points is not a feasible option when the uncertainty set is not linear, given that the number of extreme points is infinite.

Another possible extension would be the use of piece-wise linear cost functions for generators. This is a challenge in AARO frameworks since implies to model piece-wise affine policies as well. The methodology to define the cost of the affine policy, either linear or piece-wise, is another interesting research line. The cost of providing reserves through affine policies could also be set as an offer in a market, which would be a new design to remunerate flexibility.

Uncertainty models could also be used to generate a market for wind offers. In that market, a wind producer could present its uncertainty model, and if the behavior does not comply with the margins, the generator could be penalized. This design would favor the offers of less uncertainty, and would be an incentive to keep it an a low level.

An additional analysis that would be possible to realize is to adjust the size of the uncertainty set based on the information available, this adjustment would be made automatically during the day and could diminish operational costs related with scheduled reserves.

Finally, it would be desirable to develop a policy-based dispatch where the entire dispatch is defined by the linear decision rule. This model would allow to develop novel market designs, but it needs improvements in order to achieve competitive costs. One option under analysis would be the reformulation of the dispatch model into a power-based dispatch, using trajectories instead of energy blocks.

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APPENDICES

A. UNIT COMMITMENT FORMULATION

Unit Commitment is deterministic and considers a 10 % of reserve given the load of the correspondent hour:

A.1. Sets and Indexes

g: Index of Generators, $g \in G$.

h: Index of Hours, $h \in H$

B: Set of Base Units $\{4,5,10,11,27,28,36,39,43,44,45\}$

A.2. Sets and Parameters

$Base$: Set of Base Units

LSU: Set of Low Start Units

QSU: Set of Quick Start Units

FC_g: Fixed cost of generator g [US $]

VC_g: Variable cost of generator g [US $/MWh]

SU_g: Start up cost of generator g [US $]

SD_g: Shut down cost of generator g [US $]

SD_g: Shut down cost of generator g [US $]

Min_g^{up}: Minimum up time of generator g in hours

Min_g^{down}: Minimum down time of generator g in hours

P_g^{min}: Minimum power output of generator g [MW]

P_g^{max}: Maximum power output of generator g [MW]

R_g^{up}: Upward 5 min camp capability of generator g [MW]

R_g^{down}: Downward 5 min ramp capability of generator g [MW]

d_h: Load for hour h

A.3. Decision Variables

$P^0_{g,h}$: Scheduled power output of unit g in hour h [MW]

$u_{g,h}$: Start up variable of unit g in hour h

$v_{g,h}$: Shut down variable of unit g in hour h

$w_{g,h}$: On/off status of unit g in hour h

$$\min_{\mathbf{u},\mathbf{v},\mathbf{w},\mathbf{P^0}} \sum_{g\in\mathcal{G}} \sum_{h\in\mathcal{H}} u_{g,h} \cdot SU_g + v_{g,h} \cdot SD_g$$

$$+ \sum_{g\in\mathcal{G}} \sum_{h\in\mathcal{H}} w_{g,h} \cdot FC_g + VC_g \cdot P^0_{g,h} \tag{A.1}$$

$$\sum_{g\in\mathcal{G}} P^0_{g,h} = d_h \qquad \forall h \tag{A.2}$$

$$P^0_{g,h} \geq w_{g,h} \cdot P^{min}_g \qquad \forall g, h \tag{A.3}$$

$$P^0_{g,h} \leq w_{g,h} \cdot P^{max}_g \qquad \forall g, h \tag{A.4}$$

$$P^0_{g,h} - P_{g,h-1} \leq 12 \cdot R^{up}_g \qquad \forall g, h > 0 \tag{A.5}$$

$$P^0_{g,h} - P_{g,h-1} \geq 12 \cdot R^{down}_g \qquad \forall g, h > 0 \tag{A.6}$$

$$\sum_{g\in\mathcal{G}} w_{g,h} \cdot P^{max}_g - P^0_{g,h} \geq 0.1 \cdot d_h \qquad \forall h \tag{A.7}$$

$$u_{g,h} - v_{g,h} = w_{g,h} - w_{g,h-1} \qquad g, h > 0 \tag{A.8}$$

$$u_{g,h} + v_{g,h} \leq 1 \qquad \forall g, h \tag{A.9}$$

$$\sum_{n=0,h-n\geq 0}^{Min^{up}_g} w_{g,h-n} \geq Min^{up}_g \cdot v_{g,h} \qquad \forall g, h \tag{A.10}$$

$$Min^{down}_g - \sum_{n=0,h-n\geq 0}^{Min^{down}_g} w_{g,h-n} \geq Min^{down}_g \cdot u_{g,h} \qquad \forall g, h \tag{A.11}$$

$$w_{g,h} = 1 \qquad \forall g \text{ if } g \in Base, h \tag{A.12}$$

$$w_{g,h} = 0 \qquad \forall g \text{ if } g \in QSU, h \tag{A.13}$$

$$w_{g,h}, u_{g,h}, v_{g,h} \in \{0, 1\} \qquad \forall g, h \tag{A.14}$$

A.1 is the objective function, which minimizes start up, shut down, fixed and variable costs. A.2 is the power balance, A.3 and A.4 set the technical limits for generators, A.5 and A.6 are the upward and downward ramping constraints. A.7 is the reserve requirement. A.8 and A.9 are the logical constraints for the binary variables, A.10 and A.11 are the Minimum Up and Down Time limits of the units. A.12 enforces that all the base units must be turned on, whereas A.13 determines that quick start units can not be committed in day-ahead unit commitment. A.14 is the constraint of nature of variables.

B. BOUNDARY CONDITION BETWEEN TWO PERIOD DISPATCH AND POLICIES

Consider w_1 and w_2 as the commitment solutions for the on/off status of a unit for intra-hourly periods 1 and 2, respectively. Then, it is possible to express the on/off status parameter $wpol$ for the policy horizon of the unit as:

$$wpol = \begin{cases} 1, & \text{if } w_1 = 1 \text{ and } w_2 = 1 \\ 0, & \text{if } w_1 = 1 \text{ and } w_2 = 0 \\ 1, & \text{if } w_1 = 0 \text{ and } w_2 = 1 \\ 0, & \text{if } w_1 = 0 \text{ and } w_2 = 0 \end{cases}$$

C. LOOK-AHEAD ECONOMIC DISPATCH WITH QUICK START UNITS

g: Index of Generators, $g \in G$.

t: Index of Time Steps, $t \in T$

h: Index of Hours, $h \in H$

k: Index of Extreme Points of the Uncertainty Set for Net Load, $k \in K$

p: Index of ramp duration (1 represents the interval 0-5, whereas the second 0-10)

C.1. Sets and Parameters

$Base$: Set of Base Units

LSU: Set of Low Start Units

QSU: Set of Quick Start Units

FC_g: Fixed cost of generator g [US $]

VC_g: Variable cost of generator g [US $/MWh]

SUC_g: Start up cost of generator g [US $]

SDC_g: Shut down cost of generator g [US $]

P_g^{min}: Minimum power output of generator g [MW]

P_g^{max}: Maximum power output of generator g [MW]

R_g^{up}: Upward 5 min ramp capability of generator g [MW]

R_g^{down}: Downward 5 min ramp capability of generator g [MW]

Δd_h^k: Net load power deviation for hour h and extreme point k [MW]

$r_{h,p}^k$: Net load ramp for hour h, duration p and extreme point k [MW]

$r5_h^{up}$: Upward reserve requirement for 5 minutes given by Gaussian-sigma rule (2σ) [MW]

$r5_h^{down}$: Downward reserve requirement for 5 minutes given by Gaussian-sigma rule (2σ) [MW]

d_t: Net load for time step t [MW]

d_h: Net load for the hourly look-ahead horizon h [MW]

$w_{g,\overline{h}}$: UC Solution for on/off status of the generator g in hour $\overline{h}$

$u_{g,\overline{h}}$: UC Solution for start-up of the generator g in hour $\overline{h}$

$v_{g,\overline{h}}$: UC Solution for shut down of the generator g in hour $\overline{h}$

C.2. Decision Variables

$p_{g,t}$: Power output of unit g for time step t [MW]

$r^{up}_{g,t}$: Upward reserve capacity of unit g for time step t [MW]

$r^{down}_{g,t}$: Downward reserve capacity of unit g for time step t [MW]

$P^0_{g,h}$: Scheduled power output of unit g in hour h for look-ahead policy dispatch [MW]

$\lambda_{g,h}$: Affine policy for power deviation for unit g in hour h for look-ahead policy dispatch

$w_{g,t}$: On/Off status of the generator g in time step t

$u_{g,t}$: Start-up of the generator g in time step t

$v_{g,t}$: Shut down status of the generator g in time step t

$wpol_{g,h}$: On/Off status of the generator g in look-ahead horizon h

$$\begin{aligned}\min_{\mathbf{p},\mathbf{P^0},\lambda} & \sum_{g\in\mathcal{G}}\sum_{t\in T}\frac{w_{g,t}\cdot FC_g}{12}+\frac{VC_g}{12}\cdot p_{g,t}\\ &+\sum_{g\in QSU}\sum_{t\in T}SUC_g\cdot u_{g,t}+SUD_g\cdot v_{g,t}\\ &+\sum_{g\in\mathcal{G}}\sum_{h\in\mathcal{H}}wpol_{g,h}\cdot FC_g+VC_g\cdot P^0_{g,h}+\eta \end{aligned} \tag{C.1}$$

$$\eta\geq\sum_{g\in\mathcal{G}}VC_g\lambda_{g,h}\Delta d^k_h \qquad \forall h,k \tag{C.2}$$

$$\sum_{g\in\mathcal{G}}p_{g,t}=d_t \qquad \forall t \tag{C.3}$$

$$\sum_{g\in\mathcal{G}}P^0_{g,h}=d_h \qquad \forall h \tag{C.4}$$

$$\sum_{g \in \mathcal{G}} \lambda_{g,h} = 1 \qquad \forall h \qquad \text{(C.5)}$$

$$\lambda_{g,h} \leq wpol_{g,h} \qquad \forall g, h \qquad \text{(C.6)}$$

$$p_{g,t} + r^{up}_{g,t} \leq w_{g,t} \cdot P^{max}_{g} \qquad \forall g, t \qquad \text{(C.7)}$$

$$p_{g,t} - r^{down}_{g,t} \leq w_{g,t} \cdot P^{min}_{g} \qquad \forall g, t \qquad \text{(C.8)}$$

$$P^{0}_{g,h} + \lambda_{g,h} \cdot \Delta d^{k}_{h} \geq wpol_{g,h} \cdot P^{min}_{g} \qquad \forall g, h, k \qquad \text{(C.9)}$$

$$P^{0}_{g,h} + \lambda_{g,h} \cdot \Delta d^{k}_{h} \leq wpol_{g,h} \cdot P^{max}_{g} \qquad \forall g, h, k \qquad \text{(C.10)}$$

$$p_{g,t} - p_{g,t-1} \leq R^{up}_{g} \qquad \forall g, t = 2 \qquad \text{(C.11)}$$

$$p_{g,t} - p_{g,t-1} \geq R^{down}_{g} \qquad \forall g, t = 2 \qquad \text{(C.12)}$$

$$P^{0}_{g,h} + \lambda_{g,h} \cdot (\Delta d^{k}_{h} + r^{k}_{h,p}) \leq wpol_{g,h} \cdot P^{max}_{g} \qquad \forall g, h, p, k \qquad \text{(C.13)}$$

$$\lambda_{g,h} \cdot r^{k}_{h,p} \leq p \cdot wpol_{g,h} \cdot R^{up}_{g} \qquad \forall g, h, p, k \qquad \text{(C.14)}$$

$$P^{0}_{g,h} + \lambda_{g,h} \cdot (\Delta d^{k}_{h} + r^{k}_{h,p}) \geq wpol_{g,h} \cdot P^{min}_{g} \qquad \forall g, h, p, k \qquad \text{(C.15)}$$

$$\lambda_{g,h} \cdot r^{k}_{h,p} \geq p \cdot wpol_{g,h} \cdot R^{down}_{g} \qquad \forall g, h, p, k \qquad \text{(C.16)}$$

$$P^{0}_{g,h} - p_{g,t} \leq R^{up}_{g} \qquad \forall g, t, h \qquad \text{(C.17)}$$

$$P^{0}_{g,h} - p_{g,t} \geq R^{down}_{g} \qquad \forall g, t, h \qquad \text{(C.18)}$$

$$r^{up}_{g,t} \leq w_{g,t} \cdot R^{up}_{g} \qquad \forall g, t \qquad \text{(C.19)}$$

$$r^{down}_{g,t} \leq w_{g,t} \cdot R^{down}_{g} \qquad \forall g, t \qquad \text{(C.20)}$$

$$\sum_{g \in \mathcal{G}} r^{up}_{g,t} \geq r5^{up}_{h} \qquad \forall g, t \qquad \text{(C.21)}$$

$$\sum_{g \in \mathcal{G}} r^{down}_{g,t} \geq -r5^{down}_{h} \qquad \forall g, t \qquad \text{(C.22)}$$

$$u_{g,t} - v_{g,t} = w_{g,t} - w_{g,t-1} \qquad g \in QSU, h > 0 \qquad \text{(C.23)}$$

$$u_{g,t} + v_{g,t} \leq 1 \qquad \forall g \in QSU, h \qquad \text{(C.24)}$$

$$w_{g,t} = w_{g,\overline{h}} \qquad \forall g \in LSU, t \qquad \text{(C.25)}$$

$$u_{g,t} = u_{g,\overline{h}} \qquad \forall g \in LSU, t \qquad \text{(C.26)}$$

$$v_{g,t} = v_{g,\bar{h}} \qquad \forall g \in LSU, t \tag{C.27}$$

$$w_{g,t}, u_{g,t}, v_{g,t} \in \{0,1\} \qquad \forall g, t \tag{C.28}$$

(C.1) is the objective function, which comprises the dispatch costs and the costs of commit and shut down quick start units, (C.2) is the cost of the policy reserves. (C.3) is the power balance constraint for deterministic horizon, whereas (C.4) ensures hourly balance of look-ahead, intra-hourly balance is given by (C.5). limits the provision of reserves to the units that are active during the look-ahead horizon. (C.7)-(C.8) limit maximum and minimum power output for all deterministic set-points and (C.9)-(C.10) for policy dispatch, (C.11)-(C.12) and (C.13)-(C.16) are the ramp constraints for set-points and policy dispatch respectively. Constraints (C.17)-(C.18) impose continuity between deterministic and look-ahead horizons. Maximum up and down reserves are addressed in (C.19)-(C.20), and coverage of requirements is modeled in (C.21)-(C.22). (C.23)-(C.24) are the logical constraints for commitment variables. (C.25)-(C.27) ensures the commitment status of a LSU is consistent with its UC Solution. Finally, (C.28) is the constraint of the nature of variables.

D. IEEE 118 BUSES DATABASE

Table D.1. Generator Data IEEE 118 Buses

-	P^{max}	P^{min}	R^{up}	R^{down}	FC	VC	MinUp	MinDw	SDCost	SUCCost
-	[MW]	[MW]	[MW/h]	[MW/h]	[$/h]	[$/MWh]	[h]	[h]	[$]	[$]
G1	30	5	25	25	26.55	27.08	1	1	0	120
G2	30	5	25	25	25.85	31.30	1	1	0	120
G3	30	5	25	25	26.10	27.90	1	1	0	120
G4	300	150	60	60	8.05	12.06	8	8	0	1320
G5	300	100	60	60	7.82	11.04	8	8	0	330
G6	30	10	25	25	28.87	28.51	1	1	0	120
G7	100	25	20	20	12.26	14.64	5	5	0	150
G8	30	5	25	25	28.51	30.45	1	1	0	120
G9	30	5	25	25	26.38	26.44	1	1	0	120
G10	300	100	60	60	7.12	11.72	8	8	0	300
G11	350	100	70	70	35.59	10.11	8	8	0	300
G12	30	8	25	25	29.49	29.17	1	1	0	120
G13	30	8	25	25	27.62	30.89	1	1	0	120
G14	100	25	20	20	11.96	14.13	5	5	0	150
G15	30	8	25	25	27.95	29.76	1	1	0	120
G16	100	25	20	20	11.61	16.76	5	5	0	150
G17	30	8	25	25	29.17	26.76	1	1	0	120
G18	30	8	25	25	27.25	28.10	1	1	0	120
G19	100	25	20	20	10.64	14.85	5	5	0	177
G20	250	50	50	50	30.48	10.83	8	8	0	300
G21	250	50	50	50	30.74	10.60	8	8	0	300
G22	100	25	20	20	12.59	15.37	5	5	0	150
G23	100	25	20	20	11.87	15.19	5	5	0	150
G24	200	50	40	40	43.01	11.31	8	8	0	300
G25	200	50	40	40	39.49	13.01	8	8	0	300
G26	100	25	20	20	12.12	15.34	5	5	0	150
G27	420	100	84	84	72.78	7.93	10	10	0	750
G28	420	100	84	84	69.33	8.28	10	10	0	750

G29	300	80	60	60	7.91	10.99	8	8	0	300
G30	80	30	66.7	66.7	66.83	17.83	4	4	0	135
G31	30	10	25	25	29.35	29.59	1	1	0	120
G32	30	5	25	25	27.59	30.83	1	1	0	120
G33	20	5	16.7	16.7	15.75	43.75	1	1	0	90
G34	100	25	20	20	11.94	15.09	5	5	0	150
G35	100	25	20	20	11.93	15.18	5	5	0	150
G36	300	150	60	60	8.22	12.28	8	8	0	1320
G37	100	25	20	20	11.73	14.73	5	5	0	150
G38	30	10	25	25	29.17	29.44	1	1	0	120
G39	300	100	60	60	35.29	10.17	8	8	0	1320
G40	200	50	40	40	7.73	11.14	8	8	0	1200
G41	20	8	16.7	16.7	15.22	44.87	1	1	0	90
G42	50	20	41.7	41.7	48.05	23.87	1	1	0	135
G43	300	100	60	60	7.28	12.65	8	8	0	300
G44	300	100	60	60	7.92	11.17	8	8	0	300
G45	300	100	60	60	7.41	12.10	8	8	0	330
G46	20	8	16.7	16.7	16.74	40.36	1	1	0	90
G47	100	25	20	20	11.24	14.73	5	5	0	150
G48	100	25	20	20	11.25	15.41	5	5	0	150
G49	20	8	16.7	16.7	15.77	40.55	1	1	0	90
G50	50	25	41.7	41.7	48.88	25.28	2	2	0	135
G51	100	25	20	20	11.18	15.01	5	5	0	150
G52	100	25	20	20	10.93	15.01	5	5	0	150
G53	100	25	20	20	12.04	16.22	5	5	0	150
G54	50	25	41.7	41.7	50.68	26.73	2	2	0	135