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OPERATING RESERVE DEMAND CURVES FOR THE INTEGRATION OF VARIABLE RENEWABLE ENERGIES INTO THE CHILEAN POWER SYSTEM

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Resumen

La incorporación de fuentes renovables no despachables afectará la definición óptima de las reservas de operación en un sistema eléctrico. Debido a esto, las señales de precios deben ser adecuadas para asegurar inversiones en nueva capacidad de generación, por lo cual deben ser efectivas en el corto y largo plazo. Los mecanismos que definen el precio óptimo de las nuevas capacidades asociadas a la reserva operacional deberán reflejar la temporalidad de la confiabilidad y seguridad del sistema eléctrico.

Por lo tanto, como el valor que la sociedad le asigna al consumo de energía eléctrica, por ejemplo, el Valor de Pérdida de Carga (VOLL), es mayor que cero, el valor incremental de las reservas que podría reducir la probabilidad de un evento de pérdida (Loss of Load Probability – LOLP), también debe ser mayor que cero cuando las reservas no son abundantes.

Las curvas de demanda de reservas operativas (ORDC) son un mecanismo administrativo dinámico explícito para evaluar los requerimientos de reservas adecuadas que necesita el sistema. Esto se debe a que son el resultado de considerar múltiples fuentes de incertidumbre en el sistema que provocan desequilibrios entre generación y demanda, fijando un precio dinámico en función de su contribución a mejorar la confiabilidad del sistema, entregando señales efectivas de la condición real del escenario. a través de su impacto en el costo marginal. En un mercado como el chileno, la introducción de esta estrategia permite a los operadores aumentar los precios durante eventos de escasez, ya que los precios están determinados por el costo marginal de la unidad de generación más cara que opera en el sistema.

El presente trabajo propone una metodología para incorporar de forma óptima fuentes renovables como el viento y el sol a sistemas con características hidrotérmicos como el chileno.

De hecho, la introducción de este mecanismo de escasez tendrá un impacto sustancial en los incentivos a la inversión, entregando señales apropiadas para alentar/apoyar nuevas tecnologías vinculadas al nuevo camino que Chile está avanzando.

Abstract

The optimal price of new capacities associated with operational reserves must reflect the temporality of the reliability and safety of the electric power system.

Society places a high value on electricity consumption, as evidenced by the Value of Lost Load (VOLL). Therefore, the incremental value of reserves that reduce the probability of a loss event (Loss of Load Probability - LOLP) must be greater than zero when reserves are not abundant.

To evaluate the adequate reserve requirements that a system needs, operating reserve demand curves (ORDC) are an explicit and dynamic administrative mechanism. They consider multiple sources of uncertainty in the system that cause imbalances between generation and demand, setting a dynamic price based on their contribution to improving the reliability of the system. This provides effective signals of the actual condition of the scenario through its impact on marginal cost. In a market such as the Chilean market, introducing this strategy allows operators to increase prices during scarcity events as prices are determined by the marginal cost of the most expensive generation unit operating in the system.

Introducing this scarcity mechanism will substantially impact investment incentives, delivering appropriate signals to encourage and support new technologies linked to the new path that Chile is advancing. This document proposes a methodology to optimally incorporate renewable sources such as wind and solar into systems with hydrothermal characteristics, such as the Chilean one.

KEYWORDS: ORDC, LOLP, VOLL, Capacity Payments, Economic Signals

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Chapter 1 Introduction

As renewable energy becomes increasingly integrated into the market, the income from energy sales in the spot market is expected to decrease due to the low variable costs of technologies like wind and solar. This means that large generators, mainly those fueled by fossil fuels, need to be replaced or reduced with renewable energies that have stochastic behavior. The goal is to ensure quality standards in the short and long term by providing effective economic signals.

To achieve effective short- and long-term signals, dynamic reserve curves can be utilized to generate additional energy revenues that reflect the backup supply shortage [1][2]. By using operating reserve demand curves (ORDCs), it can be established dynamic and non-static price signals based on the available capacity within the power system. This approach has already been applied in markets like ERCOT. By using ORDCs, it can be enhanced the economic viability of potential generators by compensating them based on the system's requirements linked to scarcity signals.

The proposed ORDC approach can be applied to the Chilean electricity system by using different curves linked to its subsystems. This is necessary due to the system's length, transmission congestion, and the variety of the electrical matrix. Additionally, operating reserve curves can incentivize the deployment of energy storage systems like batteries. By modifying marginal costs based on the need for greater reserve requirements, the integration of variable renewable energy can be improved.

To calculate the operating reserve demand curve, probabilistic methods will be employed to portray the value of available reserves that consumers or the system are willing to pay for a flexible resource. The operating demand curve will be calculated between the cost of energy not served and the expected load loss value. This calculation will consider uncertainties associated with generator contingencies, demand projections errors, and solar and wind generation.

The present work will integrate the resulting curves into a mathematical computational model of the Chilean electricity market. It is important for this study that the mathematical-computational models consider uncertainty on both the consumption and generation sides. Additionally, they must estimate the risk of unserved demand and integrate the associated cost into the price paid by the operator for the necessary operating reserve.

The structure of this document is as follows: section 2 provides introductory review of the topic, section 3 addresses the Value of Loss of Load (VOLL), and section 4 discusses operating reserves. Section 5 looks at the use of ORDC in systems primarily in Texas, and the following section explains the methodology developed and implemented in this work. Finally, section 8 presents the conclusion of the work.

1.1 Main objective

Design a methodology to value operational flexibility in the Chilean electricity system through Operating Reserve Demand Curves (ORDC).

1.1.1 Secondary objectives

- Develop and validate a mathematical-computational operating model that allows testing the use of operating reserve demand curves in an electricity market with the characteristics of Chile, testing various scenarios to evaluate its operation.

- Characterize the geographical areas of operational reserve of the Chilean electricity system to value the shortage price using ORCD.

- Develop a methodology for estimating the LOLP in a zonal manner, considering various generation and storage technologies available locally and the radiality of the Chilean transmission system.

1.2 Scope of work

The estimation of the operating reserve demand curve will be conducted through the use of probabilistic processes, enabling the representation of the energy value that consumers are willing to pay for this flexible resource. This calculation will involve the determination of the operating demand curve, which is derived from the cost of unserved energy and the expected load loss value. The calculation will incorporate uncertainties associated with generator contingencies, errors in demand projections, as well as solar and wind generation. As a result, the integration of non-conventional renewable energy sources can be improved, while simultaneously providing more accurate economic signals in valuing the resources associated with operating reserves in the Chilean electricity system.

The derived curves will be implemented in a mathematical computational model specifically designed for the Chilean electricity market. Given the system's radial structure and the significant hydroelectric generation capacity in the southern region, the model will divide the system into distinct zones to define the operating reserve demand curves. Each zone will exhibit a unique generation probability distribution.

The mathematical-computational models employed in this study should:

- Take into account uncertainties in both consumption and generation.

- Estimate the risk of unserved demand.

- Incorporate the cost associated with the risk of unserved demand into the price paid by the operator for the required operating reserve.

Chapter 2 Bibliographic Review

Electricity markets are designed with consideration for various factors, including political, social, and economic aspects. These markets can differ in their approach, with some focusing solely on trading energy and leaving the task of signal delivery for constructing new capacity entirely to the energy market (referred to as Energy-Only Markets, EOM). However, this can result in high electricity prices during periods of scarce available capacity. In response, regulators often impose limits on these signals. It is important for regulators to strike a balance by proving clear price signals, especially during scarcity, while also ensuring that prices remain reasonable [3].

Energy markets without [4] capacity payments offer advantages related to visualizing the need for capacity through high prices [5]. This approach avoids the need for additional metrics or regulations to ensure an adequate level of capacity. Through price signals that indicate resource scarcity at specific times, appropriate incentives for operation and investment can be created [6] [7] [8]. Examples of energy-only markets include NEM (Australia), New Zealand, Singapore, and ERCOT (USA). However, the notion of an "exclusive energy market" as a utopia has been suggested by Stoft due to existing market failures in the electricity sector [10-11]. For instance, in [12], it is argued that the presence of capacity markets stems from the inherent failures of the electricity market, particularly the limitations in demand flexibility.

The energy market provides real-time indications of pricing and supply dynamics. When energy resources are abundant, the market signals low prices. Conversely, if there is a shortage of a particular energy resource, such as electricity, the law of supply and demand dictates that high prices will reflect the scarcity. However, the significance and reliability of these signals may not always be straightforward. In situations of energy shortage, the market may signal high energy prices as an alarm.

However, economic and social factors in many energy markets limit the market's ability to deliver such signals entirely. The true market signal may be 100%, but due to these limitations, only 80% may be reflected, leading to questions about the remaining 20% [19]. Essentially, these limits modify the economic signal. Conversely, in markets where this issue can be overcome [20], implementing a capacity market through either a pricing mechanism (as done in Chile) or a quantity system (as in Colombia) [21-22] could potentially improve the accuracy of signals provided to investors.

Inadequate market designs with limitations on achievable prices lead to what is mentioned above and known as the "missing money problem" [13-18]. As these imperfections suppress the spot price signal, the incentives delivered through the spot market become inadequate. It is possible to explain the emergence of capacity remuneration based on this phenomenon. However, when this strategy falls short, other dynamics or guidelines are established to address the problem. The concept of "Resource Adequacy" gave rise to capacity markets in the United States in the late 1990s. These markets were created to enable investors to build generation capacity without being directly influenced by regulatory institutions [1],[23] with the goal of ensuring sufficient power generation to meet demand and prevent blackouts [24-26].

Unlike EOM markets [9], Chile's energy market is based on audited production costs, and administrative payments for capacity complement energy remuneration. In Chile and in other markets with capacity remuneration mechanisms, regular payments (usually proportional to the generation firm's capacity) are made. These capacity payments are separate from the energy market and cover at least the capital cost of new generation units, thereby incentivizing the availability of units that are rarely dispatched, except during peak hours. By increasing available capacity and promoting competition among various participants, conditions of scarcity are reduced. Regulators must strike a balance between the amount of capacity payments and maintaining reasonable prices, all while minimizing the likelihood of inadequate capacity.

In an effort to diversify the energy matrix, the Colombian government implemented a capacity market [27-28]. However, the market design had some flaws, particularly with the definition of scarcity prices, as discussed in [28]. As a result, certain generating plants have been forced to become unavailable due to their high variable costs, which exceed the regulatory scarcity price.

Capacity markets provide clear market signals to investors, reducing their risk levels and encouraging greater participation in the market. In the short term, socializing peak energy costs benefits risk-averse market participants, including consumers and generators [3]. However, in the long term, this may lead to a decrease in incentives for economically efficient behavior and potentially result in overinvestment in generation capacity and a lack of demand control from consumers utilizing technological devices. Despite these challenges, there is currently no consensus on the appropriate amount of money to allocate for capacity payments or the range of payments for installed capacity. Furthermore, determining the appropriate payment for each generator may present discrepancies. This issue is particularly evident when comparing thermal and hydro units, as they contribute differently to the system's reliability. During the dry season, the production of hydrological units may be limited, further complicating the payment calculation process.

Furthermore, there may be a discrepancy in determining the appropriate payment for each generator, particularly when comparing thermal and hydro units due to their distinct contributions to the reliability of the system. This discrepancy is further compounded during the dry season when the production of hydrological-type units may be limited, posing additional challenges in calculating payments.

It is still uncertain whether capacity payments, which are not tied to specific performance standards, effectively enhance reliability. A different approach has been adopted in England and Wales, where the central electrical energy price is determined for each period. This price can be augmented by a capacity element (CEt), calculated by multiplying the load loss value (VOLL) determined through surveys on an annual basis (adjusted for inflation) and the probability of load loss during the period (LOLP). LOLP relies on the margin between available capacity and the load, as well as the number of unit outages during the period. Consequently, the capacity element fluctuates from one period to another and can occasionally result in significant price spikes. The energy price is capped at the load loss value and the funds collected during the period are distributed among all generators that offered to supply the demand, even if they were not dispatched.

With the increasing emphasis on renewable energies, non-renewable units are likely to be utilized only during periods of extreme electricity scarcity, leading to higher prices. However, market price limiters may discourage new investments and hinder the recovery of fixed costs. Additionally, high demand and prices may incentivize consumers to reduce consumption, but price ceilings may not effectively motivate this behavior.

In regions where capacity markets are implemented, it is crucial for the scarcity price design to be integrated into the capacity market design [29]. This integration is evident in markets like ISO-NE and PJM [30], where the establishment of capacity and shortage price markets is linked to reserving margins to replace the number and severity of shortage events. This interaction helps create appropriate incentives. Furthermore, the co-optimization between energy markets and complementary services ensures that the price of these products accurately reflects their opportunity cost and value.

It is important to note that, unlike ERCOT, the mentioned markets in the preceding paragraph co-optimize the requirements for energy and ancillary services. In these markets, when scarcity arises, an administrative price may be implemented.

Chapter 3 Value of Lost Load (VoLL)

Electricity markets face two distinct market failures concerning real-time signals and instantaneous consumption, as discussed in a previous study [11]. Except for large industrial consumers, most end customers do not have access to real-time electricity prices, which contributes to the second market failure. The demand side experiences its first failure due to the absence of real-time metering and billing for end consumers, while the second flaw lies in the lack of real-time control over power flow to specific customers.

Although real-time metering is widely available, real-time electricity prices are not effectively integrated into real-time consumption, leading to a limited response to price signals. Consequently, there is a potential mismatch between supply and demand, and the system operator assumes the responsibility of determining the price.

From a societal perspective, load shedding is costly, and it becomes challenging to differentiate between customers who require or value electricity more than others. To address this issue, the Value of Load Loss (VOLL) is utilized as a real-time pricing approach, based on the valuation of uninterrupted power supply from the demand side [31]. VOLL allows for an assessment of the value that consumers are willing to pay to maintain continuous electricity supply without interruptions [11], [32]. Typically, VOLL is measured in Currency/MWh and plays a crucial role in evaluating resource adequacy regulations and developing scarcity pricing rules. A specific maximum price value can be referenced from [33] to interpret VOLL correctly.

Calculating the value of VOLL is intricate as it depends on various factors such as outage time, duration, and notification timing. Furthermore, the value of VOLL may differ among different consumer groups. Consequently, multiple estimates for its value are available, as discussed in [33].

Different jurisdictions adopt various approaches to measure VOLL within their administrative scarcity pricing systems, as indicated in [34]. For instance, MISO and ERCOT explicitly incorporate VOLL into their scarcity price calculations, with different estimates. ERCOT sets its VOLL at 9,000 [USD/MWh], while MISO sets it at 3,500 [USD/MWh]. In markets or jurisdictions with a centralized capacity market, ISO-NE and PJM implement performance-related capacity incentives that could reflect VOLL at $6,000/MWh during periods of low supply. However, disclosing these signals publicly may present political and social risks.

Chapter 4 Operating Reserves

There are multiple approaches to determining operating reserves, including the one outlined in [35]. This technique considers errors in wind generation predictions and load estimation to identify the optimal amount of spinning reserve that minimizes the total operating cost of the system. Monte Carlo modeling demonstrates that this approach is more cost-effective and leads to lower standard deviations in operating costs, thus reducing risk. The required reserve amount is also influenced by the Value of Lost Load (VOLL) of the system, whereby an increase in VOLL puts greater pressure on reserve requirements.

In Europe, reserves are traded separately from the energy market, resulting in exogenously computed reserve requirements. In order to address the dispatch problem in the face of uncertainty, [36] proposes a co-optimization of the energy and reserve markets to find the optimal solution. The proposed model optimizes at two levels, thereby enhancing coordination between energy and reserve.

To mitigate scarcity and uncertainty in the operation of renewable energy systems, [37] suggests the addition of operational reserves, ensuring system adequacy. This paper explores the economic and reliability implications of implementing dynamic operating reserves in an electrical power system.

[38] and [39] present a mathematical optimization model that examines the operating reserve demand curves and two price adders within exclusive energy markets, resulting in dispatch corrections. The technique employs Lagrange multipliers to construct the operating reserve curve and is validated using the ERCOT system.

In a comprehensive review of operating reserves, [40] discusses the concept, its interaction with the unit commitment problem, and how to incorporate it into models.

Operating Reserve Demand Curves

The concept of price adders through administrative methods is investigated in [41]. These methods are implemented to increase prices in the energy and ancillary services market when supply is scarce, in order to provide accurate market price signals that properly value resources such as fast ramps based on their importance and worth. These mechanisms have been adopted by numerous independent system operators with centralized markets. When all scheduled units have been dispatched, the system enters a shortage state, and the market begins utilizing operating reserves to meet demand. As reserves are depleted and the system approaches a point of load disconnection, alternative methods must be employed to reflect the increasing value of delivering supply services.

Based on this, there are two types of strategies for reflecting this value appreciation through administrative scarcity measures:

1) The ceiling price, which represents the maximum value indicating the willingness to pay for energy and additional services.
2) As scarcity conditions intensify, staggered prices will increase, accompanied by penalty factors or additional fees to indicate the depletion of reserves.

A comprehensive overview of administrative measures for managing scarcity pricing and delivery in various markets across the United States can be found in [41].

The concept of the Operating Reserve Demand Curve (ORDC) was first introduced by Hogan [5] and aims to enhance the determination of prices during scarcity conditions [43]. Operating reserves refer to generation resources that are readily available in the United States to address imbalances caused by changes in demand or the loss of generation units or transmission lines [1]. These reserves play a critical role in balancing load fluctuations and ensuring system reliability.

A dynamic operating demand curve, as suggested by [1], could provide a basis for scarcity pricing and improve overall economic dispatch. The ORDC is designed to increase the price as the available reserve decreases and serves as a markup to the energy price. In situations where there is excess capacity, the price is determined by the marginal unit during peak demand periods. However, when capacity becomes scarce, a demand curve is used to determine the price [5]. This ensures that the price accurately reflects the market signal.

The operation of the ORDC is based on the probability that the system operator will unintentionally disconnect the load and the value of load loss. Increasing the reserve reduces the probability of load shedding, which is reflected in a markup on the energy price. The Loss of Lost Probability (LOLP) curve represents this probability at different levels of reserve operation.

Under normal pricing conditions, excess capacity leads to competitive pressure, driving electricity market prices to offset the variable opportunity cost of the most expensive generator in operation [1]. However, when generation capacity becomes scarce, the price of operating reserve capacity should increase, and the corresponding energy price should rise to reflect the opportunity cost of the reserve shortage. This price scarcity could and should result in a significant increase in prices during scarcity conditions, ensuring the appropriate incentives when capacity is critically needed.

On Figure 1, the vertical axis represents the value of reserves, while the horizontal axis indicates their availability [1]. The Value of Lost Load (VOLL) is set at 10,000 USD/MWh, and a minimum reserve requirement of 500 MW is assumed. If the operating reserve falls below 500 MW, involuntary load shedding occurs, which leads to an adjustment in the VOLL to reflect this situation. The shape of the curve above 500 MW is determined by the Loss of Load Probability (LOLP) function. The discontinuity in the reserve level at 500 MW is due to a decrease in load, which reduces the likelihood of load shedding. In 2014, ERCOT [1] established the operating reserve demand curve to accurately capture the value of flexible resources in power prices. Fig. 1 illustrates that the VOLL value in the ERCOT area was 9,000 USD/MWh, and the minimum contingency reserve value was set at 2,000 MW for the year 2015.

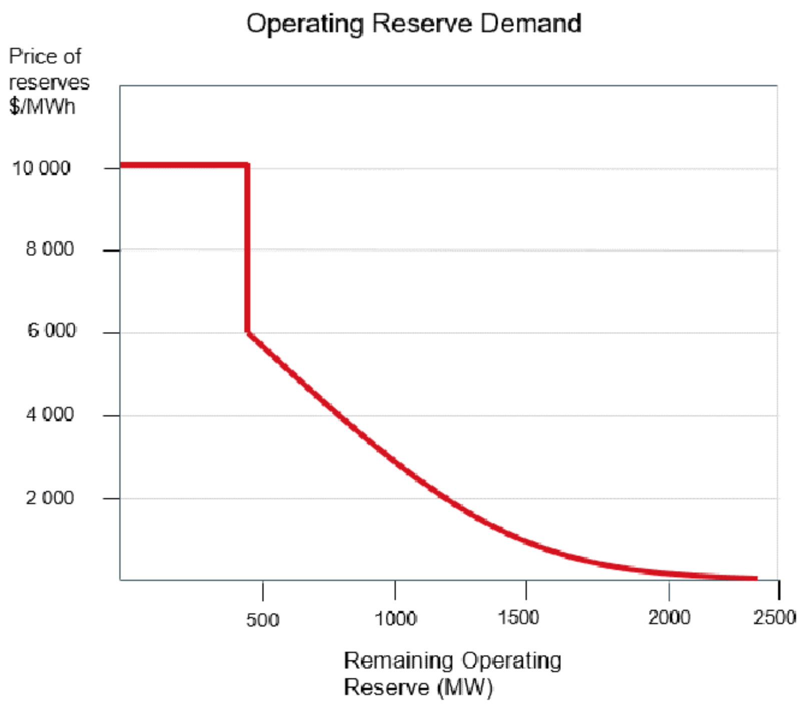

Fig. 1 Demand curve associated with operating reserves applied in ERCOT [1].

The Operating Reserve Demand Curve (ORDC) is a market design that is primarily used in exclusive energy markets. Its purpose is to facilitate arbitrage between the operational capacity in the energy market and the reserves that are set aside to handle uncertainties in actual operation. Payment in this market is directly tied to the ability to respond in real-time, regardless of the technology utilized. The ORDC performs these calculations in real-time, resolving a portion of the problem and enhancing the efficiency of the market in the short term [2].

ERCOT in the United States operates through a unique structure that focuses solely on energy trading [1],[29]. To ensure a reliable supply of energy, ERCOT employs the Operating Reserve Demand Curve for revolving and static reserves. The system generates six demand curves for each season, depending on the time of day. A price adder is then determined based on the Loss of Load Probability (LOLP) for each remaining reserve amount in the system, multiplied by the difference between the LOLP value and the energy price value. The system operator estimates the LOLP for the reserve quantity by conducting a system simulation to determine the shape and magnitude of the ORDC.

The ORDC methodology is founded on a probabilistic assessment of the LOLP for various reserve levels and an estimation of the Value of Lost Load (VOLL). While ideally the ORDC should be utilized in co-optimized power and reserve markets, ERCOT currently uses a post-calculation simulation to achieve market co-optimization, in order to derive prices for reserve and energy price addition.

The ORDC methodology relies on assessing the likelihood of Loss of Load Probability (LOLP) for different reserve levels and estimating the Value of Lost Load (VOLL) in a probabilistic manner. Ideally, it should be employed in co-optimized power and reserve markets. However, since ERCOT lacks real-time market co-optimization, a post-calculation simulation is utilized instead. This simulation replicates the co-optimization process and determines prices for reserve and energy price addition [45]:

1) To estimate the Loss of Load Probability (LOLP), it has been conducted an analysis of the historical deviations between the reserve dispatch one hour in advance and the actual reserve available in real-time. This estimation is performed for each of the four seasons and is further subdivided into six daily hourly blocks, resulting in a total of 24 distinct time segments. The resulting probability distribution is assumed to follow a standard form, taking into account potential forced disconnections, errors in renewable energy production forecasts, and discrepancies in load forecast across the 24 time slots.
2) A probability distribution of the LOLP, LOLP', is fitted, assuming that a certain reserve level is necessary to avoid disconnections.

In the referenced study [1], several advantages of using the Operating Reserve Demand Curve (ORDC) are presented. These advantages include:

1) Reliability: The implementation of the ORDC enables energy and reserve prices to align more closely with reliability requirements. Scarcity prices, by definition, will reflect immediate reliability conditions, while generators and load will benefit from appropriately responding to reliability needs. By focusing on the short term, the ORDC provides signals and incentives that are often challenging to capture in longer-term markets.

2) Consistent Design: The design of exclusive energy markets inherently aligns well with the ORDC. The study suggests that forward contracts may not be necessary when ORDCs are in place, as they can effectively deliver incentives for maintaining system adequacy. It is important to note that the author does not propose an either-or choice, but rather emphasizes the need to find the optimal signal for scarcity prices.

3) Demand Response: The ORDC facilitates better signals for modifying consumption patterns, allowing demand to interact more effectively by reflecting the opportunity cost associated with altering consumption behavior.

4) Efficient Operating Procedures: By optimizing reserves and economic dispatch operations, the application of ORDC principles can enhance the overall efficiency of system operations.

In England, the implementation of the Loss of Load Probability (LOLP) function and the Value of Lost Load (VOLL) has been observed [46][47]. The national regulatory authority, Ofgem, conducted a review of the balancing code in November 2015, leading to reforms concerning market imbalance. One significant issue regarding pricing was the utilization of pre-contracted standby products with fixed activation prices that did not accurately reflect the actual conditions of the power system. This discrepancy adversely affected the cash price of the imbalance. To address this issue, the scarcity reserve price was introduced as a means to incentivize appropriate behavior in the electricity markets. The scarcity reserve price also incorporates LOLP and VOLL, replacing the reservation price if it exceeds the original activation price. This adjustment allows the price to be determined based on the order of merit of the offers. However, if the price is deemed inadequate to reflect scarcity, the reserve scarcity price function will increase it. It is important to note that this scarcity adder only applies to the market imbalance price.

In Europe, the Operating Reserve Demand Curve (ORDC) is currently being evaluated, and some researchers are investigating its potential implementation. In a study [2], the Belgian market is analyzed as an "energy-only market," where the reserve is assigned value by adjusting the energy price in real-time to reflect the capacity's value under scarcity conditions [44]. This proposed system is validated through a 21-month historical comparison, demonstrating that the introduction of additional price components that accurately reflect the flexible capacity of power plants restores economic viability for the majority of these plants in the Belgian market. The authors conclude that the reintroduction of nuclear capacity in the Belgian system would reduce price adders to near-zero values. Further research is needed to assess how specific market designs influence the transmission of scarcity adders as long-term signaling mechanisms.

Despite the positive aspects of the scarcity price policy, some criticisms have been raised [47]. The ORDC emulates the reliability compromise unit calculation by employing six types of curves throughout the day. However, according to the author, ERCOT's methodology incorrectly applies its estimate of LOLP in calculating the ORDC. This argument is based on incorrect prediction values used in determining the curve. While the concept may be sound in theory, it is essential to analyze the level of error between the actual and predicted values to verify its validity.

Chapter 5 Methodology Applied: LOLP calculation.

In the traditional approach, the calculation of Loss of Load Probability (LOLP) for thermal generators in the system is based on their forced outage rate. However, in this study, the incorporation of renewable generation is considered in order to assess the behavior of LOLP in scenarios with high penetration of clean energy. This approach allows for the utilization of a LOLP curve for each hour, which takes into account the effects of renewable energy integration at any given moment.

To determine the probability distribution of the total available capacity of thermal units, the maximum capacity and respective forced outage rates (IFOR) of each plant in the system are considered. The distribution entails performing a convolution of the discrete variables of Capacity and IFOR for each plant within the studied time span (yearly). The procedure involves summing the forced outage probability based on the available capacity. This value, denoted as unit i, is a probability determined by the following expression:

$$c_i = Pmax_i * (1 - IFOR_i)$$

The loss probability distribution is derived by summing each of these values. To obtain the Loss of Load Probability (LOLP), an iterative process is employed. This process involves convolving the installed capacity with the forced output rates of the various conventional thermal generators within the system under analysis. The convolution procedure provides a table of load loss probabilities as a function of demand (Fig. 3 describes Demand and Reserves Curves used in the current document). The Cumulative Capacity Outage Probability Table formulated for the present work, for example, is described in Fig. 2 and it is the first step in the procedure implemented to obtain the LOLP for a demand requirement.

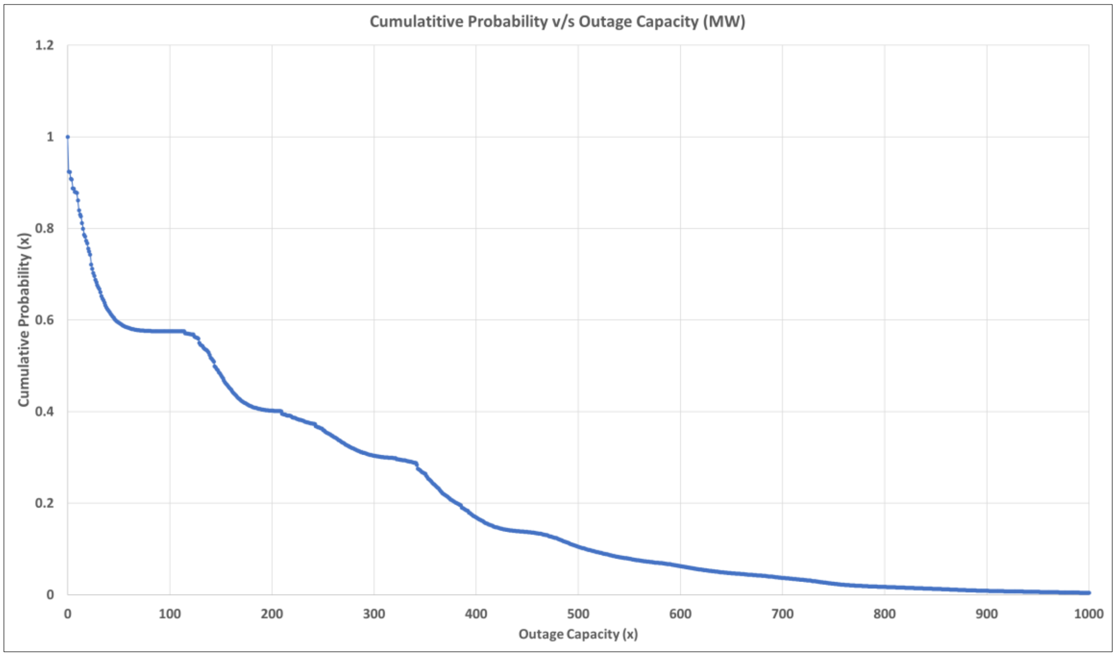

Fig. 2 Cumulative Probability v/s Outage Capacity for the System described in Appendix (Figure prepared by the authors).

Although each thermal power plant may have unique capacity and IFOR data, the number of capacity and probability vectors for the system will be equal to the number of hours in the analyzed time horizon. Consequently, a distinct LOLP curve will be obtained for each hour of analysis. For a one-year study period consisting of 8,760 hours, a total of 8,760 LOLP curves will be generated. Each curve represents the risk assessment of the system for a specific hour, with the first curve corresponding to the risk for the first hour, the second curve for the second hour, and so on.

To assess the impact of solar and wind availability, it is necessary to account for the capacity of conventional thermal generators as well as the available power from renewable sources. This involves considering both the forced output rates of the conventional generators and the generation capacities of the renewable generators. Fig. 4 provides an overview of the production vectors used for each renewable technology. These vectors serve as the basis for constructing the Operating Reserve Demand Curves (ORDCs) which is used in the present document.

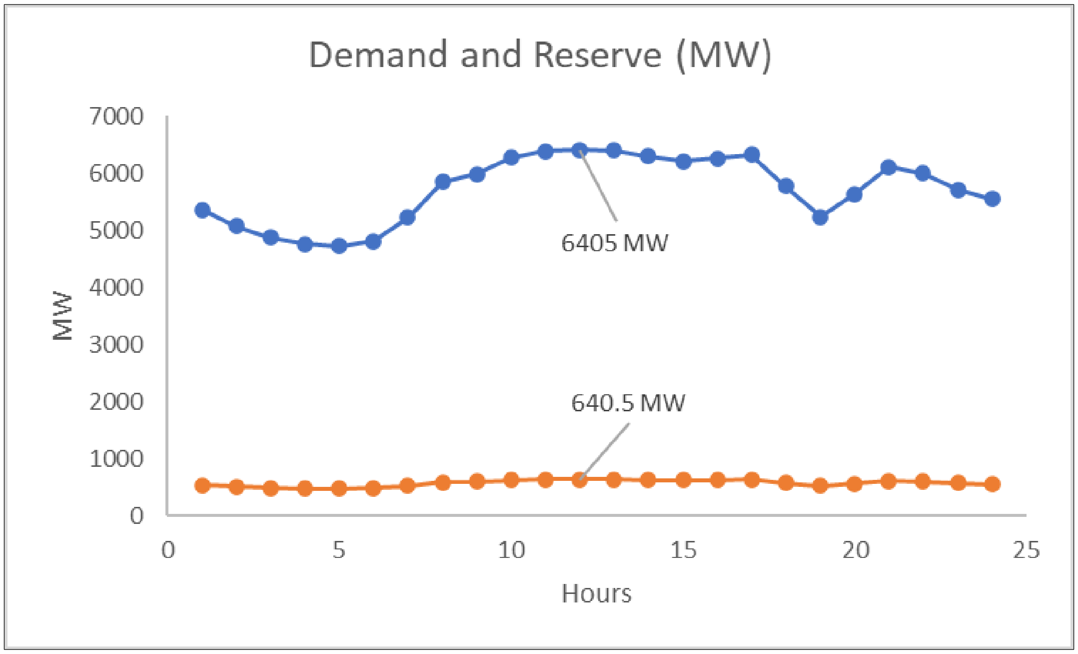

Fig. 3 Demand and Reserve Curves used for the system modelled (Figure prepared by the authors).

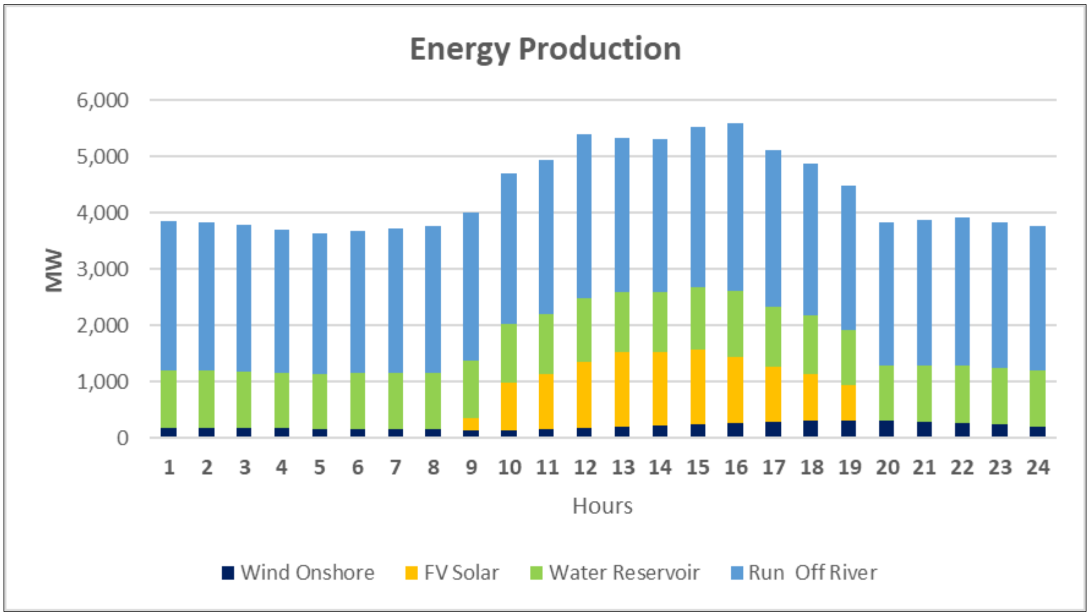

Fig. 4 Vector energy production for renewable technologies (Figure prepared by the authors).

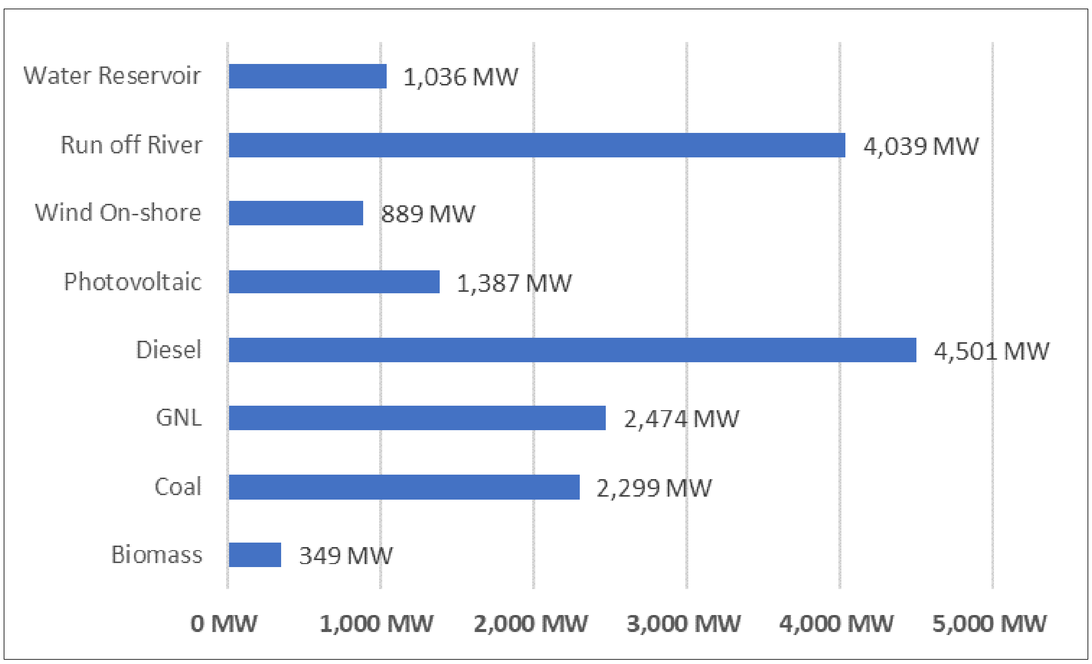

Fig. 5 Technology installed capacity of the modelled system (Figure prepared by the authors).

Using as inputs the accumulative probability presented in Fig. 2 and the production and demand vectors described in Fig. 3 and Fig. 4, the respective Operating Reserve

Demand Curves (ORDC) are obtained. The first sets of results for the system are depicted in Fig. 6, Fig. 7 and Fig. 8.

As LOLP (x) is the probability that real-time uncertainty exceeds reserve capacity x, to build the ORDC, a Value of Lost Load (VOLL) must be used. Chilean regulation, through the document "Costos de Falla" described this value for different levels of failure depth. For example, the last value calculated by the Energy National Commission (CNE) is defined for a depth between 0% to 5% of 314 USD/MWh [49]. Therefore, to calculate the ORDC, the following equation is used:

$$\left[VOLL - MC_h(P_g)\right] * LOLP_h(R) \quad (1)$$

$VOLL = Value\ of\ Lost\ Load = 314\ USD/MWh$

$MC = System\ Marginal\ Cost\ at\ hour\ h$

$LOLP_h\ (R)\ at\ different\ levels\ of\ Reserve$

The figures presented below illustrate how renewable technologies such as wind and solar contribute to the overall security of the Chilean power system. An interesting observation can be made when comparing the "LOLP + Thermic" curve for solar hour 14 in Figure 8. By incorporating PV and wind technology into the calculation of LOLP, the curve shifts to the left. This shift indicates that the inclusion of renewable generation reduces the need for reserves and decreases the associated risk to the system. Consequently, it can be inferred that the integration of renewable generation enhances the overall security and reliability of the power system.

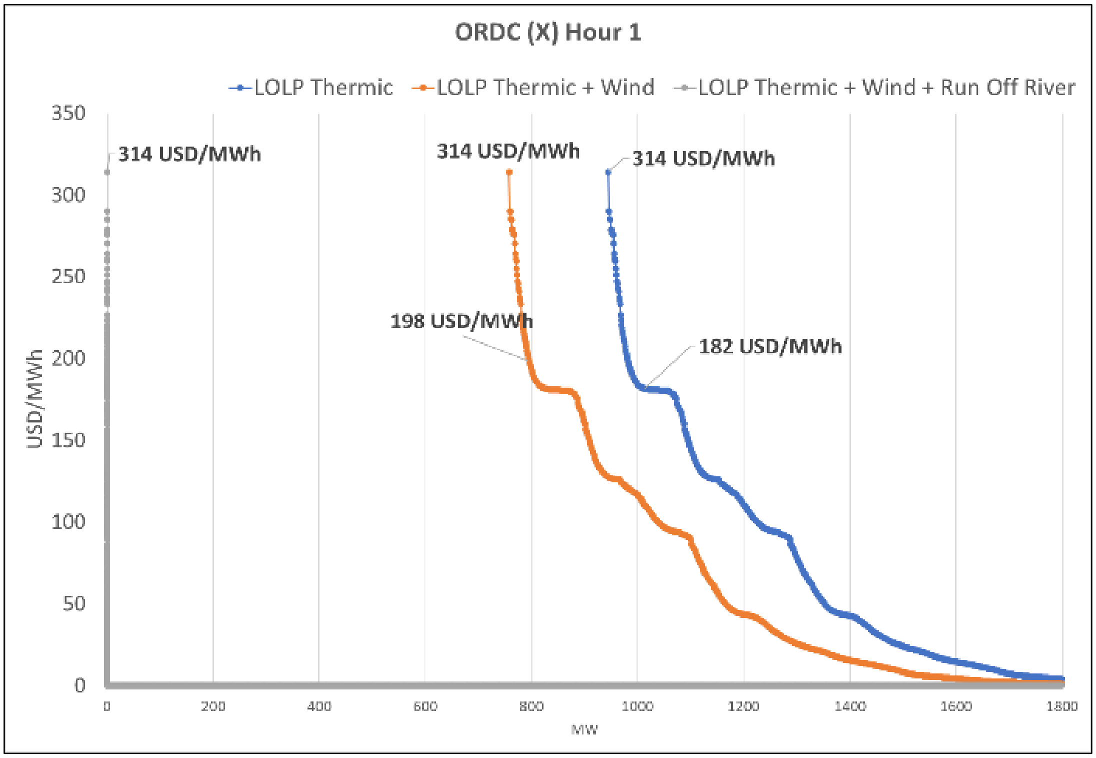

*Fig. 6. Evolution of the ORDC for **hour 1** in terms of the inclusion of renewable generation (Figure prepared by the authors).*

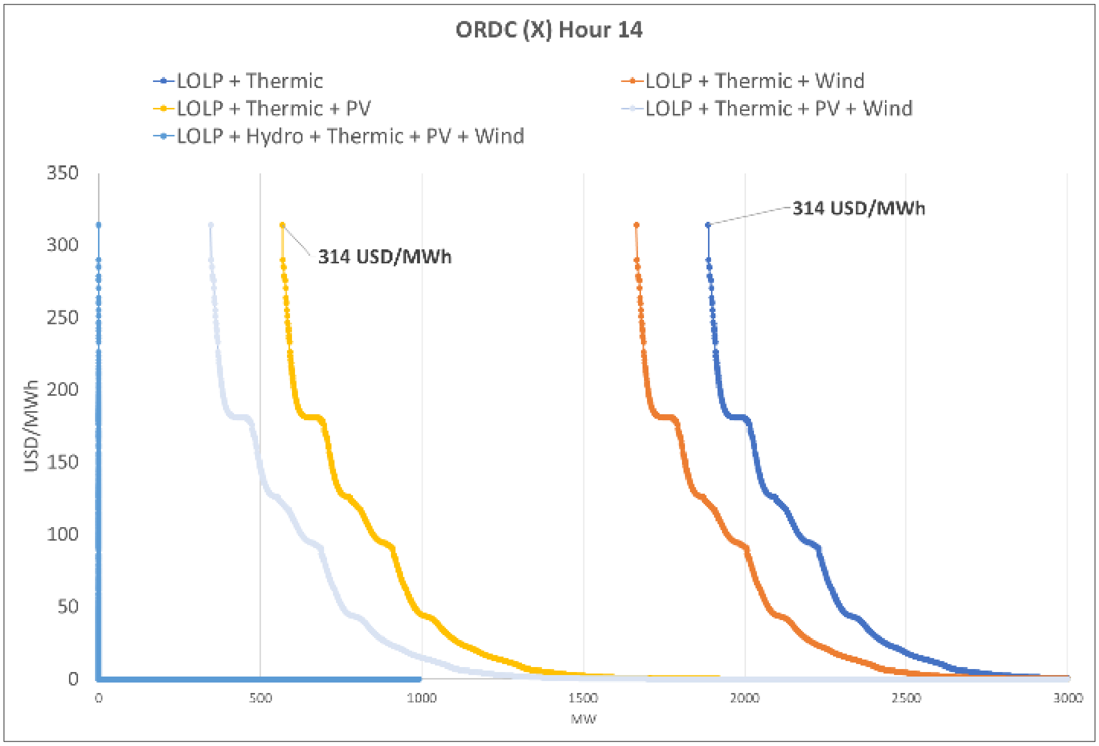

*Fig. 7 Evolution of the ORDC for **hour 14** in terms of the inclusion of renewable generation (Figure prepared by the authors).*

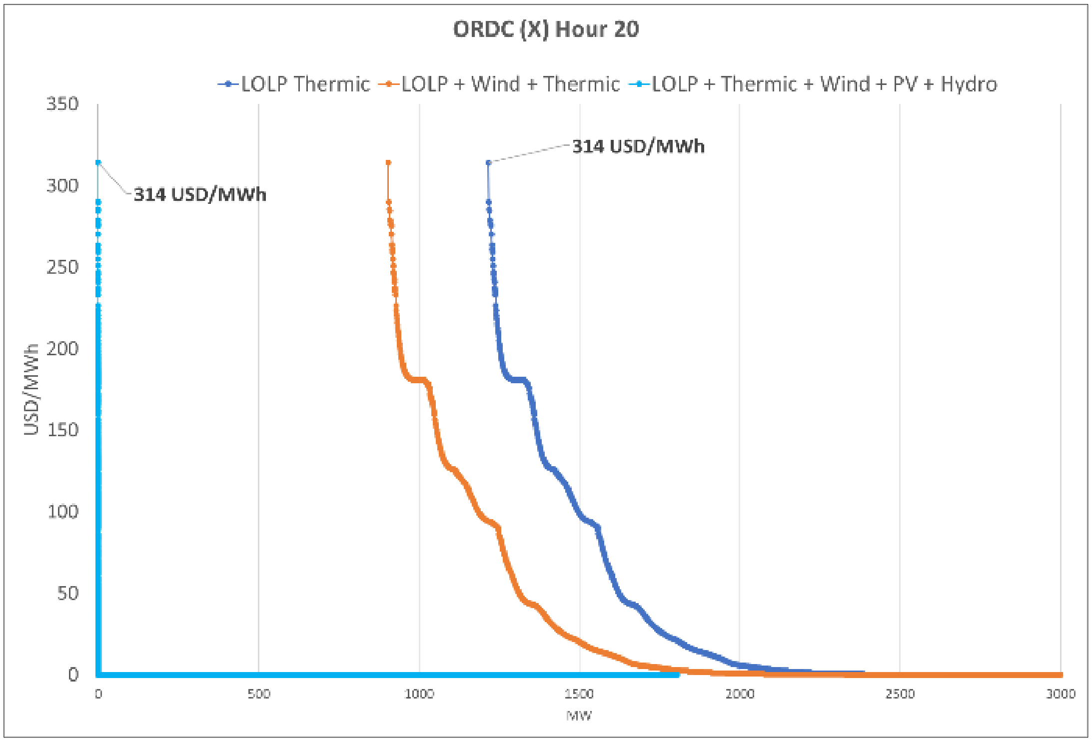

*Fig. 8. Evolution of the ORDC (x) for **hour 20** in terms of the inclusion of renewable generation (Figure prepared by the authors).*

Chapter 6: Unit Commitment Implementation

The proposal's implementation in this work is done by programming a unit commitment system that dispatches the units 24 hours in advance and the reserves to be used with that anticipation.

Based on this and taking into consideration a one-node system[1], the following objective function to be optimized is programmed[2] to obtain the comparison concerning using the price of the reserve delivered by the optimization algorithm or the use of the valuation curve of the reserve, which provides the effective price concerning the effective valuation of the reserve. Usually, the reserve takes the form of a percentage of the biggest unit[3].

The equation to use to implement the unit commitment is:

$VC = Variable\ Cost\ \left[\frac{USD}{MWh}\right]$

$Pg_{g,h} = Unit\ g\ Producction\ [MW] at\ hour\ h$

$ST\ C_g = Starting\ Cost\ unit\ g$

$SP\ C_g = Stoping\ Cost\ unit\ g$

$v_{g,h} = Unit\ g\ starts\ at\ hour\ h$

$z_{g,h} = Unit\ g\ stops\ at\ hour\ h$

[1] While the analytical approach considered a single-node system to convey the conceptual idea of the work, it is necessary for future research to consider a radial system in order to reflect the potential limitation of reserves when dispatched and the issues of transmission line congestion preventing their activation. Therefore, the problem should be addressed by defining operational zones according to the constraints of the transmission network.

[2] Programming is done using Julia Language.

[3] The current work considered that the scarcity of reserves is reflected in an increased valuation of the resource, for instance due to a lack of wind energy, in the case of a surplus of resources, the curve would precisely reflect an excess of reserves and therefore a lower valuation of the operation at that time.

$\beta = transmission\ losses$ %

$PHP = Producction\ Run\ of\ Rivers\ units$ [MW]

$PHE = Producction\ Water\ Storage\ units$ [MW]

$D_h = Demand\ at\ hour\ h$ [MW]

$R_h = Reserve\ at\ hour\ h$ [MW]

$\rho = Water\ density\ \left[\frac{Kg}{m^3}\right]$

$g = specific\ gravity\ \left[\frac{m}{s^2}\right]$

$\eta = efficiency$ %

$Q = flow\ \left[\frac{m^3}{s}\right]$

$H = height$ [m]

$S_h = Water\ stored\ at\ hour\ h$

$u_{g,h} = 1\ when\ unit\ g\ is\ on\ and\ 0\ when\ unit\ g\ is\ off$

$Pinst_g = Installed\ Capacity\ unit\ g$

$P_{\min g} = Minimum\ Capacity\ in\ unit\ g$

$coefDisp_{g,h} = Producction\ Pattern\ of\ wind\ and\ solar\ plants$

$$Total\ Cost = min\left\{\sum_{h=0}^{23}\sum_{g=1}^{G} VC_g * Pg_{g,h} + ST\ C_g * v_{g,h} + SP\ C_g * z_{g,h}\right\} \tag{2}$$

$$s.t.$$

$$(1-\beta) * \left(PHP + PHE + \sum_{g=1}^{G} Pg_{g,h}\right) = D_h\ \forall h \tag{3}$$

$$\sum_{g=1}^{G} Pg_{g,h} * u_{g,h} \geq D_h + R_h\ \forall h\quad \forall h \tag{4}$$

$$PHP[MW] = \frac{\rho\left[\frac{Kg}{m^3}\right]*g\left[\frac{m}{s^2}\right]*\eta*Q\left[\frac{m^3}{s}\right]*H[m]}{10^6} \tag{5}$$

$$PHE\ [MW] = S_{h-1} - S_h + \frac{\rho\left[\frac{Kg}{m^3}\right]*g\left[\frac{m}{s^2}\right]*\eta*Q\left[\frac{m^3}{s}\right]*H[m]}{10^6} \tag{6}$$

$$Pg_{g,h} \leq u_{g,h} * Pinst_g \quad \forall\ h, g\ thermic\ plant \tag{7}$$

$$Pg_{g,h} \geq u_{g,h} * P_{\min g} \quad \forall\ g\ thermic\ plant \tag{8}$$

$$Pg_{g,h} \leq coefDisp_{g,h} * Pint_g \tag{9}$$

$\forall\ h, g\ solar\ and\ wind\ plants$

$$S_h \leq S_{max} \tag{10}$$

$$S_0 = 0, S_{24} = 0 \tag{11}$$

$$v_{g,h} - z_{g,h} = u_{g,h} - u_{g,h-1} \tag{12}$$

$$u_{g,0} = 0, v_{g,0} = 0, z_{g,0} = 0, \forall g \tag{13}$$

Table 1. Thermal technology units committed by the algorithm.

Technology	Capacity MW
Biomass	329.78
Coal	2299.1
Gas	1036.25

Diesel	198.5
Total	**3863.63**

Table 2. Thermal units committed in a 24-hour program.

(Figure prepared by the authors).

		Hours																								
Central	**Resource**	**x1**	**x2**	**x3**	**x4**	**x5**	**x6**	**x7**	**x8**	**x9**	**x10**	**x11**	**x12**	**x13**	**x14**	**x15**	**x16**	**x17**	**x18**	**x19**	**x20**	**x21**	**x22**	**x23**	**x24**	**MW**
Arauco 01	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10
Arauco 02	Biomass	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10
Arauco 03	Biomass	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	4
Celco 01	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3
Celco 02	Biomass	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2
Celco 03	Biomass	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
Licantén 01	Biomass	0	0	0	1	0	0	0	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
Valdivia 02	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	21
Valdivia 03	Biomass	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	1	1	1	1	1	6
Valdivia 04	Biomass	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	23
Viñales 01	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	6
Viñales 02	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10
Viñales 03	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	6
Santa Fe 01	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	17
Santa Fe 02	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	17
Santa Fe 03	Biomass	1	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	16
Santa Fe 04	Biomass	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	11
Laja CMPC 02	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10
Pacífico CMPC 02	Biomass	1	1	0	0	0	0	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	1	1	1	11
Pacífico CMPC 03	Biomass	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11
Lautaro 01	Biomass	1	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	13
Lautaro 02	Biomass	1	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	1	1	1	1	1	9
Lautaro 03	Biomass	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	1	1	0	0	0	4
Lautaro 2 *	Biomass	1	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	1	1	1	22
Energía Pacífico	Biomass	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	14
Los Colorados 01	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
Los Colorados 02	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	17
Masisa	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	10
Escuadrón	Biomass	1	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	13
cholguan 00	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	9
Nueva Aldea 01	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	19
Santa Marta	Biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	16
Ventanas 01	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	113
Ventanas 02	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	209
Santa María	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	321
Nueva Ventanas	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	249
Campiche	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	242
Bocamina 01	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	122
Bocamina 02	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	342
Guacolda 01	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	143
Guacolda 02	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	143
Guacolda 03	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	137
Guacolda 04	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	139
Guacolda V	Coal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	139
Nehuenco 01 GNL	Gas GNL	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	340
Nehuenco 02 GNL	Gas GNL	1	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	384
Nueva Renca GNL	Gas GNL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	312
Los Guindos	Diesel	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	132
Doña Carmen	Diesel	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	67

Figures 10, 11, and 12 propose an approach for evaluating the risk of the system by directly considering the probabilities of wind and solar potential. This methodology enables the accurate representation of system risk and the determination of hourly[4] Operating Reserve Demand Curves (ORDCs) based on available resources and demand.

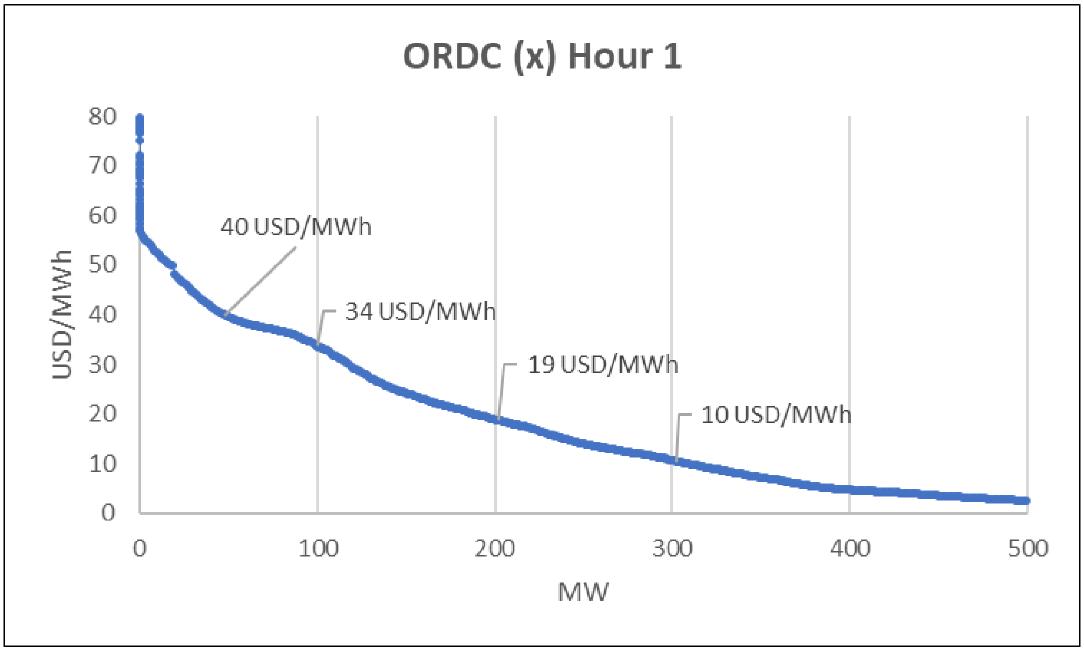

Fig. 9. ORDC (x) for hour 1 when 1400 MW are disconnected and a net demand of 2046 MW (Figure prepared by the authors).

To assess the optimal time for extra capacity through the hourly Operating Reserve Demand Curve (ORDC), the plan was evaluated 24 hours in advance, taking into consideration the risk associated with the available resources. As part of this evaluation, a disconnection of 1400 MW was simulated, which is equivalent to the outage of two 700 MW Coal plants. The following results depict the level of risks, as shown in the figures.

[4] The operation of the Chilean electric system is shifting from an hourly valuation of the marginal cost to a finer granularity every 15 minutes. This will allow for greater accuracy in the valuation of resources, mainly wind, thus reducing uncertainty in their valuation and reserve estimation. From the perspective of the current work, shifting from hourly curves to a more granular valuation will enable the valuation of other types of resources that can respond much faster to the system's needs.

To accurately determine the contribution of solar and wind plants in enhancing the system's adequacy at each hour, it is crucial to properly value the risks associated with generation. An adequate analysis of system adequacy should examine the plants' contributions on an hourly basis to effectively capture the relationship between generation and demand.

The proposed methodology utilizes an hourly resolution and considers the proximity between generation and demand by weighting their contributions. This approach grants greater recognition to generators that inject electricity into the network during periods of high system risk.

According to Figure 12, it is evident that system risk rises during nighttime primarily because solar generation is unavailable and demand levels remain high. This indicates a clear economic incentive to increase capacity during this specific hour. One potential solution to improve the risk profiles during hour 20 could be the implementation of battery energy storage systems (BESS).

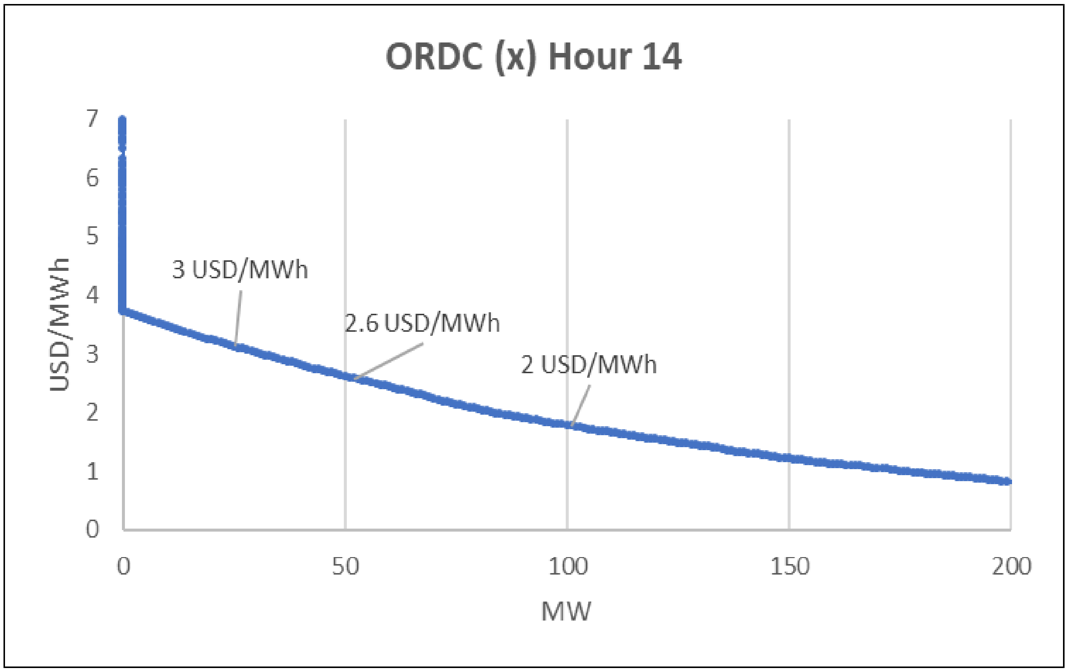

Fig. 10. ORDC (x) for hour 14 when 1400 MW are disconnected, and a net demand of 1610 MW is required (Figure prepared by the authors).

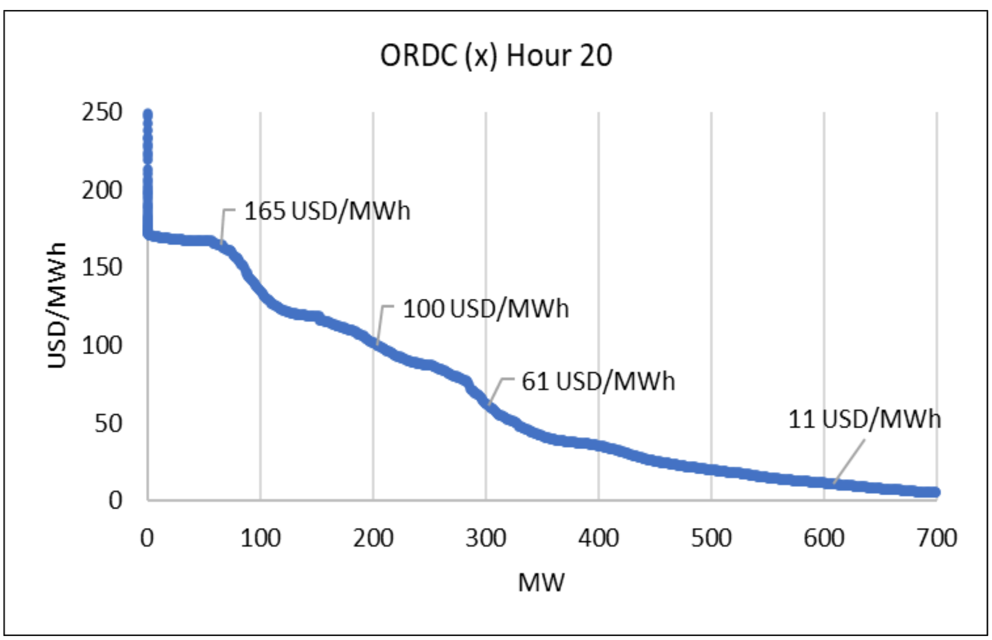

Fig. 11. ORDC (x) for hour 20 when 1400 MW are disconnected, and a net demand of 2356 MW is required (Figure prepared by the authors).

To explain the procedure how the ORDC works Fig. 11 will be used. At 8 PM, the marginal operating (*MC*) cost was calculated at *MC* [USD/MWh], meaning every power plant operating at that hour is receiving *MC* [USD/MWh] for the energy supplied. As depicted in Figure 11, if an event occurs at 8 PM where 1400 MW were disconnected, the values of the available reserve are appraised according to what is described by this figure. Then, for example, if there is 100 MW of reserve available, this operating reserve would be valued at 125 [USD/MWh], which means a plant that was operational at that time will receive an additional revenue for having this reserve available (125 [USD/MWh] - *MC* of the system at that hour).

In other words, the curve adds an additional revenue for having this reserve available at that time by valuing it according to the system's stress.

This is significant when considering a Battery Energy Storage System (BESS) with the available capacity to supply reserve according to its stored energy.

Chapter 7: Conclusions

In conclusion, the introduction of Operating Reserve Demand Curves (ORDC) as an explicit and dynamic administrative mechanism for evaluating reserve requirements in electricity systems has proven to be effective. The ORDC approach takes into account various sources of uncertainty that can cause imbalances between generation and demand, enabling the establishment of dynamic prices based on their contribution to system reliability. This not only provides accurate signals of the system's adequacy but also reflects its actual condition through the impact on marginal cost as for example was depicted in figures 11 and 12.

The implementation of the ORDC strategy in a market such as the Chilean electricity market allows operators to adjust prices during scarcity events. This is important because prices are determined by the marginal cost of the most expensive generation unit operating in the system. Consequently, this scarcity mechanism significantly impacts investment incentives, providing appropriate price signals that encourage and support the adoption of new technologies aligned with Chile's evolving energy transition.

In this document, we propose a methodology to effectively incorporate renewable sources, such as wind and solar, into hydrothermal systems like the Chilean electricity system. By considering the risk valuation of generation, we are able to accurately assess the contribution that solar and wind plants make to the system's adequacy on an hourly basis. This approach allows for a comprehensive analysis that captures the dynamic connection between generation and demand, leading to a more robust assessment of system adequacy.

Conventional approaches, such as calculating reserves as a percentage of available capacity, do not adequately account for the actual scarcity needs of the system. By contrast, the utilization of ORDCs provides explicit economic signals that optimize system operations based on real scarcity conditions.

In summary, this research highlights the effectiveness of ORDCs in evaluating reserve requirements and improving system reliability. The methodology presented demonstrates the importance of studying the hourly contribution of renewable plants and correctly valuing risk to capture the connection between generation and demand. By implementing these approaches, we can enhance the adequacy of the system and support the integration of renewable energy sources in electricity systems.

Appendix A: Conference Presentation

Related to the current work:

- **Sergio Díaz**, Esteban Gil, Jorge Berríos, "*Operating Reserve Demand Curves for the Integration of Variable Renewable Energies into the Chilean Power System*", XI Simposio Internacional sobre la Calidad de la Energía (SICEL 2023), La Paz, Colombia, Noviembre 1-3, 2023.

Appendix B

Minimum Capacity [MW]	Maximum Capacity [MW]	Name	Resource
0	10	Arauco 01	Biomasa
0	10	Arauco 02	Biomasa
0	4	Arauco 03	Biomasa
0	3	Celco 01	Biomasa
0	2	Celco 02	Biomasa
0	3	Celco 03	Biomasa
0	1	Licantén 01	Biomasa
0	21	Valdivia 02	Biomasa
0	6	Valdivia 03	Biomasa
0	23	Valdivia 04	Biomasa
0	6	Viñales 01	Biomasa
0	10	Viñales 02	Biomasa
0	6	Viñales 03	Biomasa
0	17.02	Santa Fe 01	Biomasa
0	16.83	Santa Fe 02	Biomasa
0	16.14	Santa Fe 03	Biomasa
0	10.76	Santa Fe 04	Biomasa
0	10	Laja CMPC 02	Biomasa
0	10.9	Pacífico CMPC 02	Biomasa
0	10.5	Pacífico CMPC 03	Biomasa
0	13	Lautaro 01	Biomasa
0	9	Lautaro 02	Biomasa
0	4	Lautaro 03	Biomasa
0	22	Lautaro 2 *	Biomasa
0	14.31	Energía Pacífico	Biomasa
0	1.8	Los Colorados 01	Biomasa
0	17.42	Los Colorados 02	Biomasa
0	9.7	Masisa	Biomasa
0	13.4	Escuadrón	Biomasa
0	9	cholguan 00	Biomasa
0	4	cholguan 01	Biomasa
0	19	Nueva Aldea 01	Biomasa
0	15.7	Santa Marta	Biomasa
50	113.4	Ventanas 01	Carbón
50	208.6	Ventanas 02	Carbón

50	321	Santa María	Carbón
50	249	Nueva Ventanas	Carbón
50	242	Campiche	Carbón
50	122.2	Bocamina 01	Carbón
50	342	Bocamina 02	Carbón
50	142.9	Guacolda 01	Carbón
50	142.9	Guacolda 02	Carbón
50	137.1	Guacolda 03	Carbón
50	139	Guacolda 04	Carbón
0	139	Guacolda V	Carbón
0	21.39	Nehuenco 01 FA GNL	GNL
100	340.05	Nehuenco 01 GNL	GNL
100	384.2	Nehuenco 02 GNL	GNL
50	128	Quintero 01 CA GNL	GNL
50	129	Quintero 02 CA GNL	GNL
100	392	San Isidro 02 GNL	GNL
0	20	San Isidro FA GNL	GNL
100	350	San Isidro GNL	GNL
100	312	Nueva Renca GNL	GNL
100	312	Nueva Renca GNL Conv	GNL
0	30	Nueva Renca Int GNL	GNL
0	50	Papeles Cordillera S.A	GNL
0	5	CMPC Tissue	GNL
0	132	Los Guindos	Petróleo Diésel
0	66.5	Doña Carmen	Petróleo Diésel
0	52.7	Laguna Verde	Petróleo Diésel
0	18	Laguna Verde TG	Petróleo Diésel
0	132	Los Vientos	Petróleo Diésel
0	139	Santa Lidia	Petróleo Diésel
0	24.3	Horcones TG Diésel	Petróleo Diésel
0	51.6	Antilhue TG 01	Petróleo Diésel
0	50.9	Antilhue TG 02	Petróleo Diésel
0	125.3	Candelaria CA 01 Diésel	Petróleo Diésel
0	128.56	Candelaria CA 02 Diésel	Petróleo Diésel
0	104.19	Los Pinos	Petróleo Diésel
0	310	Nehuenco 01 Diésel	Petróleo Diésel

0	391	Nehuenco 02 Diésel	Petróleo Diésel
0	92	Nehuenco 9B 01 Diésel	Petróleo Diésel
0	16	Nehuenco 9B 02 Diésel	Petróleo Diésel
0	52.4	Yungay 01 Diésel	Petróleo Diésel
0	52.09	Yungay 02 Diésel	Petróleo Diésel
0	53.48	Yungay 03 Diésel	Petróleo Diésel
0	41.16	Yungay 04 Diésel	Petróleo Diésel
0	13.9	Cenizas	Petróleo Diésel
0	9	Chiloé	Petróleo Diésel
0	9	Constitución Elektragen	Petróleo Diésel
0	6	Maule	Petróleo Diésel
0	33.25	Emelda 01	Petróleo Diésel
0	36	Emelda 02	Petróleo Diésel
0	23	Diego de Almagro TG	Petróleo Diésel
0	350	San Isidro 02 CC Diésel	Petróleo Diésel
0	305	San Isidro Diésel	Petróleo Diésel
0	110	Taltal 01 Diésel	Petróleo Diésel
0	110	Taltal 02 Diésel	Petróleo Diésel
0	81	El Peñón	Petróleo Diésel
0	28.5	San Lorenzo 01	Petróleo Diésel
0	26	San Lorenzo 02	Petróleo Diésel
0	7.7	San Lorenzo 03	Petróleo Diésel
0	59	Teno	Petróleo Diésel
0	81	Trapén	Petróleo Diésel
0	18.8	Esperanza 01	Petróleo Diésel
0	1.8	Esperanza 02	Petróleo Diésel
0	1.6	Esperanza 03	Petróleo Diésel
0	13.07	Newen	Petróleo Diésel
0	36	Degañ	Petróleo Diésel
0	81.2	Termopacífico	Petróleo Diésel
0	153.04	Cardones	Petróleo Diésel
0	22	Colihues	Petróleo Diésel
0	22.2	Olivos 01	Petróleo Diésel
0	93	Olivos 02	Petróleo Diésel
0	13	Calle-Calle	Petróleo Diésel
0	15	Chuyaca	Petróleo Diésel

0	46.7	Coronel TG Diésel	Petróleo Diésel
0	8	Quellon 02	Petróleo Diésel
0	312	Nueva Renca Diésel	Petróleo Diésel
0	30	Nueva Renca FA GLP	Petróleo Diésel
0	92	Renca	Petróleo Diésel
0	23.8	El Salvador TG	Petróleo Diésel
0	2.27	Con Con	Petróleo Diésel
0	2.13	Las Vegas	Petróleo Diésel
0	0.4	Linares	Petróleo Diésel
0	3	Placilla	Petróleo Diésel
0	3	Quintay	Petróleo Diésel
0	0.4	San Gregorio	Petróleo Diésel
0	3	Totoral	Petróleo Diésel
0	58	Colmito	Petróleo Diésel
0	100	Espinos 01	Petróleo Diésel
0	24	Espinos 02	Petróleo Diésel
0	36	Diego de Almagro FV	Solar
0	50	San Andrés FV	Solar
0	93	Llano de Llampos FV	Solar
0	2	Pama FV	Solar
0	2	Lomas Coloradas FV	Solar
0	68	Salvador FV *	Solar
0	55	Lalackama FV *	Solar
0	35	Chañares *	Solar
0	69	Javiera*	Solar
0	3	El Pilar Los Amarillos	Solar
0	16.3	Lalackama Etapa II	Solar
0	108	Conejo Etapa I	Solar
0	36	Luz del Norte Etapa I	Solar
0	38	Luz del Norte Etapa II	Solar
0	23	Chaka Etapa I	Solar
0	27	Chaka Etapa II	Solar
0	109.9	Quilapilún	Solar
0	90.6	Pampa Solar Norte	Solar
0	50	Guanaco Solar	Solar
0	36	Luz del Norte Etapa III	Solar
0	97	Carrera Pinto	Solar
0	31	Luz del Norte Etapa IV	Solar

0	67.4	Valleland	Solar
0	144	PFV Olmué	Solar
0	100	Pelícano	Solar
0	100	El Arrayán	Eólica
0	20	Eólica Punta Colorada	Eólica
0	18.2	Eólica Canela 01	Eólica
0	60	Eólica Canela 02	Eólica
0	48	Monte Redondo	Eólica
0	46	Eólica Totoral	Eólica
0	110	Los Cururos	Eólica
0	90	Talinay Oriente	Eólica
0	61	Talinay Poniente*	Eólica
0	11	Ucuquer II Eólico	Eólica
0	33	Negrete Cuel	Eólica
0	36	San Pedro Eólico	Eólica
0	45	Punta Palmeras	Eólica
0	99	Tal Tal Eólico	Eólica
0	88	Renaico	Eólico
0	24	Los Buenos Aires	Eólico
0	1036	Embalse Laja	Hidro con regulación
0	2019.5	Hidro de pasada A	Hidro sin regulación
0	2019.5	Hidro de pasada B	Hidro sin regulación

Appendix C

Central	Fuel	Maximum Capacity	iFor
Arauco 01	Biomasa	10	0.029548
Arauco 02	Biomasa	10	0.026919
Arauco 03	Biomasa	4	0.026919
Celco 01	Biomasa	3	0.01325
Celco 02	Biomasa	2	0.01325
Celco 03	Biomasa	3	0.01325
Licantén 01	Biomasa	1	0.01233
Valdivia 02	Biomasa	21	0.024306
Valdivia 03	Biomasa	6	0.024306
Valdivia 04	Biomasa	23	0.024306
Viñales 01	Biomasa	6	0.012809
Viñales 02	Biomasa	10	0.012809
Viñales 03	Biomasa	6	0.012809
Santa Fe 01	Biomasa	17.02	0.029548
Santa Fe 02	Biomasa	16.83	0.029548
Santa Fe 03	Biomasa	16.14	0.029548
Santa Fe 04	Biomasa	10.76	0.029548
Laja CMPC 02	Biomasa	10	0.039746
Pacífico CMPC 02	Biomasa	10.9	0.025948
Pacífico CMPC 03	Biomasa	10.5	0.020388
Lautaro 01	Biomasa	13	0.100247
Lautaro 02	Biomasa	9	0.16393
Lautaro 03	Biomasa	4	0.16393
Lautaro 2 *	Biomasa	22	0.16393
Energía Pacífico	Biomasa	14.31	0.095839
Los Colorados 01	Biomasa	1.8	0.146296
Los Colorados 02	Biomasa	17.42	0.005308
Masisa	Biomasa	9.7	0.127942
Escuadrón	Biomasa	13.4	0.085956
cholguan 00	Biomasa	9	0.020307
cholguan 01	Biomasa	4	0.020307
Nueva Aldea 01	Biomasa	19	0.039798
Santa Marta	Biomasa	15.7	0.002099
Ventanas 01	Carbón	113.4	0.050879
Ventanas 02	Carbón	208.6	0.073648
Santa María	Carbón	321	0.029293

Nueva Ventanas	Carbón	249	0.039251
Campiche	Carbón	242	0.047254
Bocamina 01	Carbón	122.2	0.05241
Bocamina 02	Carbón	342	0.091618
Guacolda 01	Carbón	142.9	0.031688
Guacolda 02	Carbón	142.9	0.050523
Guacolda 03	Carbón	137.1	0.019434
Guacolda 04	Carbón	139	0.027403
Guacolda V	Carbón	139	0.022851
Nehuenco 01 FA GNL	GNL	21.39	0.029959
Nehuenco 01 GNL	GNL	340.05	0.047001
Nehuenco 02 GNL	GNL	384.2	0.047001
Quintero 01 CA GNL	GNL	128	0.098979
Quintero 02 CA GNL	GNL	129	0.034772
San Isidro 02 GNL	GNL	392	0.03403
San Isidro FA GNL	GNL	20	0.01283
San Isidro GNL	GNL	350	0.03403
Nueva Renca GNL	GNL	312	0.051924
Nueva Renca GNL Conv	GNL	312	0.051924
Nueva Renca Int GNL	GNL	30	0.051924
Papeles Cordillera S.A	GNL	50	0.052239
CMPC Tissue	GNL	5	0.05009
Los Guindos	Petróleo Diésel	132	0.072217
Doña Carmen	Petróleo Diésel	66.5	0.944947
Laguna Verde	Petróleo Diésel	52.7	0.944947
Laguna Verde TG	Petróleo Diésel	18	0.969503
Los Vientos	Petróleo Diésel	132	0.001709
Santa Lidia	Petróleo Diésel	139	0.00001
Horcones TG Diésel	Petróleo Diésel	24.3	0.646025
Antilhue TG 01	Petróleo Diésel	51.6	0.108444
Antilhue TG 02	Petróleo Diésel	50.9	0.017559
Candelaria CA 01 Diésel	Petróleo Diésel	125.3	0.021173
Candelaria CA 02 Diésel	Petróleo Diésel	128.56	0.017216
Los Pinos	Petróleo Diésel	104.19	0.035762
Nehuenco 01 Diésel	Petróleo Diésel	310	0.029959
Nehuenco 02 Diésel	Petróleo Diésel	391	0.029959
Nehuenco 9B 01 Diésel	Petróleo Diésel	92	0.140725
Nehuenco 9B 02 Diésel	Petróleo Diésel	16	0.140725
Yungay 01 Diésel	Petróleo Diésel	52.4	0.00001

Yungay 02 Diésel	Petróleo Diésel	52.09	0.00001
Yungay 03 Diésel	Petróleo Diésel	53.48	0.00001
Yungay 04 Diésel	Petróleo Diésel	41.16	0.00001
Cenizas	Petróleo Diésel	13.9	0.253718
Chiloé	Petróleo Diésel	9	0.005241
Constitución Elektragen	Petróleo Diésel	9	0.005241
Maule	Petróleo Diésel	6	0.15303
Emelda 01	Petróleo Diésel	33.25	0.022445
Emelda 02	Petróleo Diésel	36	0.00001
Diego de Almagro TG	Petróleo Diésel	23	0.132423
San Isidro 02 CC Diésel	Petróleo Diésel	350	0.03403
San Isidro Diésel	Petróleo Diésel	305	0.01283
Taltal 01 Diésel	Petróleo Diésel	110	0.112856
Taltal 02 Diésel	Petróleo Diésel	110	0.307469
El Peñón	Petróleo Diésel	81	0.00001
San Lorenzo 01	Petróleo Diésel	28.5	0.00001
San Lorenzo 02	Petróleo Diésel	26	0.00001
San Lorenzo 03	Petróleo Diésel	7.7	0.00001
Teno	Petróleo Diésel	59	0.082155
Trapén	Petróleo Diésel	81	0.001005
Esperanza 01	Petróleo Diésel	18.8	0.082925
Esperanza 02	Petróleo Diésel	1.8	0.00001
Esperanza 03	Petróleo Diésel	1.6	0.026101
Newen	Petróleo Diésel	13.07	0.030628
Degañ	Petróleo Diésel	36	0.005728
Termopacífico	Petróleo Diésel	81.2	0.00001
Cardones	Petróleo Diésel	153.04	0.00001
Colihues	Petróleo Diésel	22	0.278169
Olivos 01	Petróleo Diésel	22.2	0.278169
Olivos 02	Petróleo Diésel	93	0.278169
Calle-Calle	Petróleo Diésel	13	0.214494
Chuyaca	Petróleo Diésel	15	0.198363
Coronel TG Diésel	Petróleo Diésel	46.7	0.155396
Quellon 02	Petróleo Diésel	8	0.651253
Nueva Renca Diésel	Petróleo Diésel	312	0.051924
Nueva Renca FA GLP	Petróleo Diésel	30	0.480784
Renca	Petróleo Diésel	92	0.480784
El Salvador TG	Petróleo Diésel	23.8	0.055415
Con Con	Petróleo Diésel	2.27	0.00001

Las Vegas	Petróleo Diésel	2.13	0.00001
Linares	Petróleo Diésel	0.4	0.798335
Placilla	Petróleo Diésel	3	0.00001
Quintay	Petróleo Diésel	3	0.00001
San Gregorio	Petróleo Diésel	0.4	0.00001
Totoral	Petróleo Diésel	3	0.390465
Colmito	Petróleo Diésel	58	0.052716
Espinos 01	Petróleo Diésel	100	0.00033
Espinos 02	Petróleo Diésel	24	0.00033

Appendix D: Code used for Cumulative Probability in Visual (Excel)

```
SysCap = Sheets("PlantData").Cells(53, 2)

For Row1 = 10 To SysCap + 11
 For Col1 = 4 To 8
 Cells(Row1, Col1) = 0
 Next Col1
Next Row1

Application.ScreenUpdating = False
Dim n, C, U As Double
Step = Sheets("COPT").Cells(5, 3) ' PAso discretos de la tabla
TotCap = 0

Dim Msg, Style, Title, Response
Msg = "You have chosen " & Step & " step increment." & Chr(13) & "Your
calculation is going to take a while." & Chr(13) & "Do you want to continue?" '
Define message.

Style = vbYesNo + vbQuestion + vbDefaultButton2 ' Define buttons.
Title = "Capacity Outage Probability Calculation" ' Define title.
Response = MsgBox(Msg, Style, Title)

If Response = vbYes Then ' User chose Yes.

Groups = 49

For i = 2 To Groups + 10
 n = Sheets("PlantData").Cells(i, 4) ' Assign number of generating units
 C = Sheets("PlantData").Cells(i, 5) ' Assign generating unit capacity
 U = Sheets("PlantData").Cells(i, 6) ' Assign forced outage rate
 Sheets("COPT").Select

 For j = 1 To n
 TotCap = TotCap + C
 Pn = 1
 X = 0

 Do While Pn > 0
 Cells(10 + X, 1) = X ' To index the states
```

```
 Cells(10 + X, 2) = TotCap - X ' To display the available capacity
 Cells(10 + X, 3) = X ' To display the outage capacity
 If Cells(10 + X, 3) = 0 Then
 Cells(10 + X, 4) = 1
 Else
 Cells(10 + X, 4) = Cells(10 + X, 8)
 End If
 Cells(10 + X, 5) = X - C
 If Cells(10 + X, 5) <= 0 Then
 Cells(10 + X, 6) = 1
 Else
 Cells(10 + X, 6) = Application.WorksheetFunction.VLookup(Cells(10 + X, 5),
Range("C10:D5000"), 2)
 End If
 Cells(10 + X, 8) = Cells(10 + X, 4) * (1 - U) + Cells(10 + X, 6) * U
 Pn = Sheets("COPT").Cells(10 + X, 8)
 If X = 0 Then
 Else
 Cells(10 + X - 1, 7) = Cells(10 + X - 1, 8) - Cells(10 + X, 8)
 End If
 X = X + Step
 Loop
 Next j
Next i
 Sheets("COPT").Range("A1").Select
 MsgBox ("Well done! " & X - 1 & " capacity outage states are calculated.")
Else ' User chose No.
 MsgBox ("You have terminated the calculation.")
End If
```

Appendix E: Unit Commitment Code in Julia Language

```
# Locación de carpetas y archivos en computadora
D:\Personal\Tesis\Codigo Julia\Modelo PUC
cd="D:/Personal/Tesis/Codigo Julia/Modelo PUC_A/";# Estipular current
directory
Demand_path_to_file=cd*"inputs\\Demanda.csv"; #Path archivo .csv con
datos de demanda
Gx_path_to_file=cd*"inputs\\Gx.csv"; #Path archivo .csv con datos de
demanda
results_path_to_file=cd*"results\\generacion.csv";
commitment_path_to_file=cd*"results\\commitment.csv";
lp__path_to_file=cd*"results\\modelJuMP.lp";
lp1__path_to_file=cd*"results\\model.mps";

using CSV,DataFrames, JuMP, HiGHS

Demanda=DataFrame(CSV.File(Demand_path_to_file));
Gx =DataFrame(CSV.File(Gx_path_to_file));
BETA = 0.2; #perdidas
#t=Gx[!,:t]; #ramping down limit
#s=Gx[!,:s]; #ramp up limit
#a=Gx[!,:a]; #Fixed cost
b=Gx[!,:b]; #start-up cost
c=Gx[!,:c]; #shut down cost
d=Gx[!,:d]; #variable cost
PMin=Gx[!,:pmin];
PMax=Gx[!,:pmax];
Nombre_central=Gx[!,:Central];

L=Demanda[!,:d];
reserva=Demanda[!,:r];
T=size(Demanda,1);
#T=1
nGen=size(Gx,1);

caudal=zeros(nGen,24);
produccion=zeros(nGen,24);
```

```
for j in 1:nGen
    for i in 1:24
        produccion[j,i]=Gx[j,12+i];
    end
end

for j in 1:nGen
    for i in 1:24
        caudal[j,i]=Gx[j,37+i];
    end
end




P_ini=[0;0;100]; #potencia inicial
U_ini=[0;0;1]; #condición inicial
Z_ini=[0;0;0]; #condición inicial

problema1 = Model(HiGHS.Optimizer);
set_time_limit_sec(problema1, 3.0)
#problema1 = Model(with_optimizer(Ipopt.Optimizer))
#problema1 = Model(with_optimizer(ECOS.Optimizer))
#problema1 = Model(with_optimizer(Clp.Optimizer))

#Definición de variables
@variable(problema1, p[1:nGen, 1:T] >= 0) #energia producida
@variable(problema1, u[1:nGen, 1:T], Bin) #estado de la unidad i en el
periodo t
@variable(problema1, y[1:nGen, 1:T], Bin) #se encendio la unidad
@variable(problema1, z[1:nGen, 1:T], Bin) #se apago la unidad

#nGen=1;

#@objective(problema1, Min,
sum(a[j]*u[j,t]+d[j]*p[j,t]+y[j,t]*b[j]+z[j,t]*c[j] for j=1:nGen for t
=1:T))
@objective(problema1, Min, sum(d[j]*p[j,t]+d[j]*caudal[j,t] for
j=1:nGen for t =1:T))


#Restricciones
```

```
#@constraint(problema1, consPowerBalance[t=1:T],  sum(p[j,t] for j =
1:nGen) == L[t])
@constraint(problema1, consPowerSecurity[t=1:T],  sum(PMax[j]*u[j,t]
for j = 1:nGen) >= L[t]+reserva[t])
@constraint(problema1, consPowerBalance[t=1:T],  (1-
BETA)*(sum(p[j,t]+caudal[j,t] for j = 1:nGen)) == L[t])


@constraint(problema1, consPMax[j=1:nGen, t=1:T],  p[j,t] <=
PMax[j]*u[j,t]*produccion[j,t])
@constraint(problema1, consPMin[j=1:nGen, t=1:T],  p[j,t] >=
PMin[j]*u[j,t])

#@constraint(problema1, logic_0[j=1:nGen, 1],  y[j,1]-z[j,1] == u[j,1]
- U_ini[j])
@constraint(problema1, logic_0[j=1:nGen, 1],  y[j,1]-z[j,1] == u[j,1])
@constraint(problema1, logic[j=1:nGen, t=2:T],  y[j,t]-z[j,t] == u[j,t]
- u[j,t-1])
@constraint(problema1, logic2[j=1:nGen, t=1:T],  y[j,t]+z[j,t] <= 1)

#restriccion ligada a produccion por caudal
for i in 1:nGen
    if Nombre_central[i]=="Embalse Laja"
        @constraint(problema1, embalse_laja[t=1:T], p[i,t]==0)
    end
end

for i in 1:nGen
    if Nombre_central[i]=="Hidro de pasada A"
        @constraint(problema1, embalse_pasada_A[t=1:T], p[i,t]==0)
    end
end

for i in 1:nGen
    if Nombre_central[i]=="Hidro de pasada B"
        @constraint(problema1, embalse_pasada_B[t=1:T], p[i,t]==0)
    end
end


#rampas
```

```
#@constraint(problema1, rampa_up_0[j=1:nGen, 1],    p[j,1]-P_ini[j] <= s[j]*U_ini[j] + s[j]*y[j,1])
#@constraint(problema1, rampa_up[j=1:nGen, t=2:T],  p[j,t]-p[j,t-1] <= s[j]*u[j,t-1] + s[j]*y[j,t])

#@constraint(problema1, rampa_up_0[j=1:nGen, 1],    p[j,1]-P_ini[j] <= s[j])
#@constraint(problema1, rampa_up[j=1:nGen, t=2:T],  p[j,t]-p[j,t-1] <= s[j])

#@constraint(problema1, rampa_down_0[j=1:nGen, 1],    P_ini[j]-p[j,1] <= t[j]*u[j,1]+ t[j]*z[j,1])
#@constraint(problema1, rampa_down[j=1:nGen, k=2:T],  p[j,k-1]-p[j,k] <= t[j]*u[j,k] + t[j]*z[j,k])

#@constraint(problema1, rampa_down_0[j=1:nGen, 1],    P_ini[j]-p[j,1] <= t[j])
#@constraint(problema1, rampa_down[j=1:nGen, k=2:T],  p[j,k-1]-p[j,k] <= t[j])

# print optimization model
#print(problema1)

JuMP.write_to_file(problema1, lp__path_to_file);

JuMP.write_to_file(problema1, lp1__path_to_file);

# save the status
optimize!(problema1)
primal_status(problema1)

# output results
println("Valor Objetivo: ", objective_value(problema1))
#println("Hour 1 Dispatch = ", JuMP.value.(p[:,1]))
#println("Hour 2 Dispatch = ", JuMP.value.(p[:,2]))
#println("Hour 3 Dispatch = ", JuMP.value.(p[:,3]))
#println("Hour 4 Dispatch = ", JuMP.value.(p[:,4]))
#println(" Generadores = ", JuMP.value.(p))

#println("X = ", JuMP.value.(u[:,1]))
#println("X = ", JuMP.value.(u[:,2]))
#println("X = ", JuMP.value.(u[:,3]))
```

```
#println("X = ", JuMP.value.(u))
#println("y = ", JuMP.value.(y[:,1]))
#println("y = ", JuMP.value.(y[:,2]))
#println("y = ", JuMP.value.(y[:,3]))
#println("y = ", JuMP.value.(y))
#println("z = ", JuMP.value.(z[:,1]))
#println("z = ", JuMP.value.(z[:,2]))
#println("z = ", JuMP.value.(z[:,3]))
#println("z = ", JuMP.value.(z))


generacion = DataFrame(JuMP.value.(p), :auto);
CSV.write(results_path_to_file, generacion, delim =";");

commitment = DataFrame(JuMP.value.(u), :auto);
CSV.write(commitment_path_to_file, commitment, delim =";");


# output of the results
#dfProduct = DataFrame(vcat(hcat("Scenario", "Generator",
reshape(1:N,1,N)), hcat(sort!(repeat(1:SC,G)), repeat(1:G,SC),
reshape(pProduct_opt,SC*G,N))))
#dfIG      = DataFrame(vcat(hcat("Scenario",
 reshape(1:N,1,N)), hcat(             1:SC,
reshape(pIG_opt     ,SC,  N))))
#dfUC      = DataFrame(vcat(hcat(            "Generator",
reshape(1:N,1,N)), hcat(                             1:G,
reshape(pCommitt_opt,   G,N))))
#dfSRMC    = DataFrame(vcat(hcat("Scenario",
 reshape(1:N,1,N)), hcat(             1:SC,
reshape(pSRMC_opt   ,SC,  N))))
#CSV.write("Output.csv", dfProduct, delim = ";")
#CSV.write("IG.csv",     dfIG,      delim = ";")
#CSV.write("UC.csv",     dfUC,      delim = ";")
#CSV.write("SRMC.csv",   dfSRMC,    delim = ";")
```

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