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Curvas de Demanda para Reserva Operativa para la Integración de Energía Renovable Variable en el Sistema Eléctrico Chileno

Operating Reserve Demand Curves for the Integration of Variable Renewable Energies in the Chilean Power System

Sergio Díaz-Pizarro[1], Esteban Gil[2] and Jorge Berríos[3]

[1]Departamento de Ingeniería Eléctrica, Universidad Técnica Federico Santa María, Chile. correo electrónico: sergiodiaz81@gmail.com
[2] Departamento de Ingeniería Eléctrica, Universidad Técnica Federico Santa María, Chile. Orcid: 0000-0001-9414-1063. correo electrónico: esteban.gil@usm.cl
[3] Departamento de Ingeniería Eléctrica, Universidad Técnica Federico Santa María, Chile. correo electrónico: jorge.berrios.14@sansano.usm.cl

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Resumen

La masiva incorporación de fuentes renovables variables afectará la definición óptima de reservas de operación en los sistemas eléctricos. Además, para asegurar inversiones eficientes en nueva capacidad de generación, las señales de precios deben reflejar adecuadamente las condiciones de escasez en distintos momentos, capturando la temporalidad de la confiabilidad y seguridad eléctrica. Las Curvas de Demanda de Reservas Operativas (ORDC) son un mecanismo dinámico que evalúa las condiciones de estrechez de suministro en el sistema, considerando distintas fuentes de incertidumbre que afectan el equilibrio entre generación y demanda, y determina un precio eficiente a la escasez. Este artículo propone la implementación de un mecanismo basado en ORDC adaptado a las necesidades del mercado eléctrico chileno. Los resultados de simulación muestran que el mecanismo efectivamente proveería mejores señales de precios durante eventos de escasez, potencialmente generando mejores incentivos para la inversión que apoyen la transición energética del país.

Palabras clave: Reservas Operativas, Suficiencia, Servicios Complementarios, Generación Eólica y Solar

Abstract

The increasing integration of variable renewable sources will have a significant impact on the optimal determination of operating reserves in electric systems. Moreover, to ensure efficient investments in new generation capacity, price

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signals must accurately reflect scarcity conditions at different times, taking into account the time-sensitive nature of electrical reliability and safety. Operating Reserve Demand Curves (ORDC) serve as a dynamic mechanism that assesses supply tightness conditions in the system, considering various sources of uncertainty that affect the balance between generation and demand, and establishes an effective scarcity price. This article proposes the implementation of an ORDC-based mechanism tailored to the specific requirements of the Chilean electricity market. Simulation results demonstrate that this mechanism would effectively deliver improved price signals during scarcity events, potentially stimulating investments that support the country's energy transition.

Keywords: Operating Reserves, Capacity, Ancillary Services, Wind and Solar generation

1. Introduction

As renewable energy becomes more integrated into the market, the income generated from energy sales in the spot market is expected to decrease. This is because technologies like wind and solar have lower variable costs compared to fossil fuels. Therefore, it is necessary to replace or reduce large generators that are primarily fueled by fossil fuels with renewable energy sources that exhibit unpredictable behavior. This will help ensure quality standards in both 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 estimate the operating reserve demand curve, probabilistic processes will be used to represent the energy that the consumer pays for the 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.

This paper 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.

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 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], 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.

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.

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.

4. Operative 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.

5. 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. Figure 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.

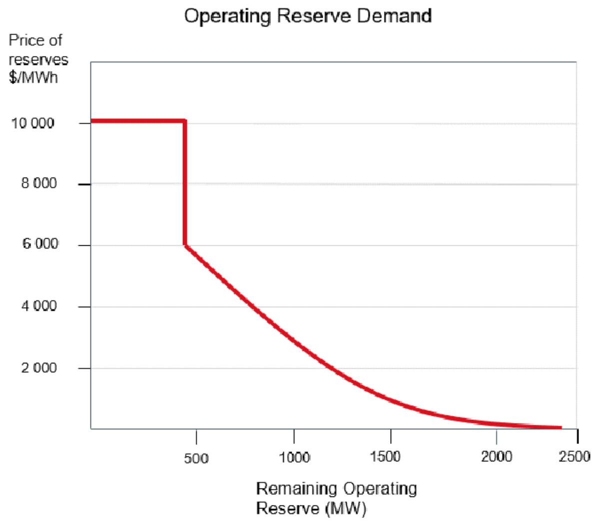

Fig. 1 Demand curve associated with operating reserves applied in ERCOT [1].

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 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.

6. 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 paper). 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.

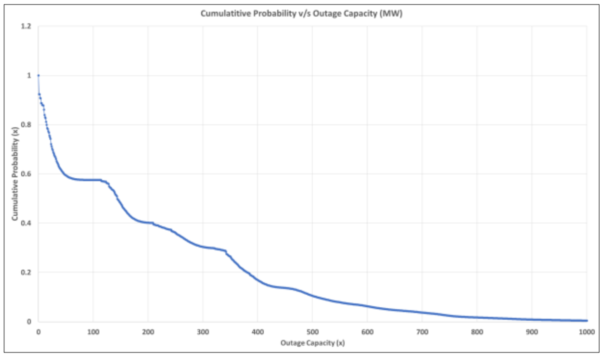

Fig. 2 Cumulative Probability v/s Outage Capacity for the System described in Appendix (Figure prepared by the authors).

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. 7 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 paper.

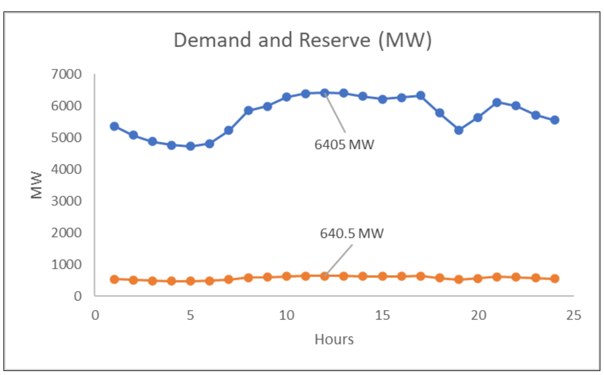

Fig. 3 Demand and Reserve Curves used for the system modelled (Figure prepared by the authors).

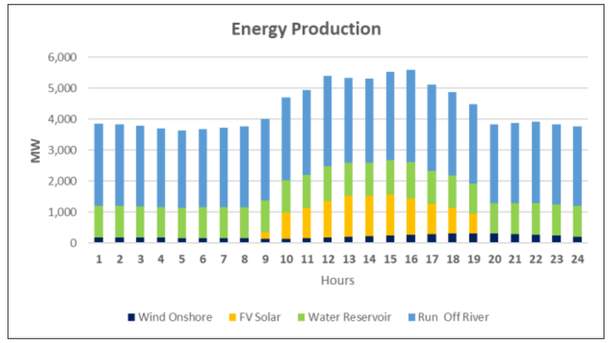

Fig. 4 Vector energy production for renewable technologies (Figure prepared by the authors).

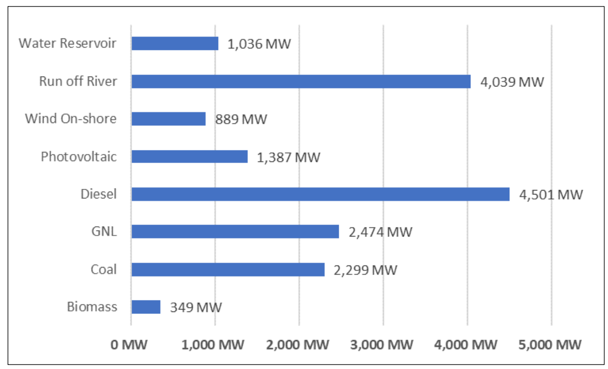

Fig. 5 Technology installed capacity of the modelled system (Figure prepared by the authors).

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:

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

$VOLL = Value\ of\ Lost\ Load = 314\ USD/MWh$
$MC = System\ Marginal\ Cost\ at\ hour\ h$
$LOLP_h\ (R)\ at\ different\ levels\ of\ Reserve$

The figures presented above 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.

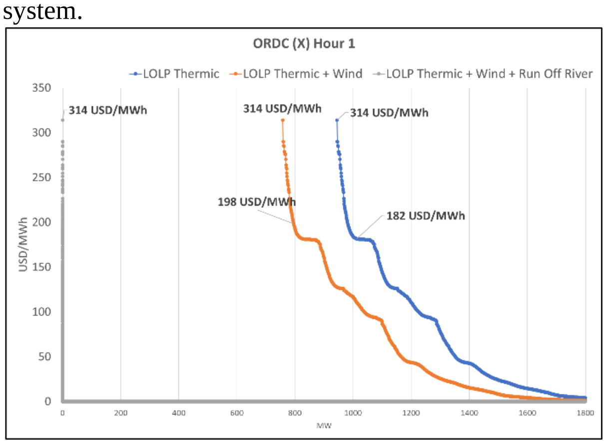

Fig. 6. Evolution of the ORDC for **hour 1** in terms of the inclusion of renewable generation (Figure prepared by the authors).

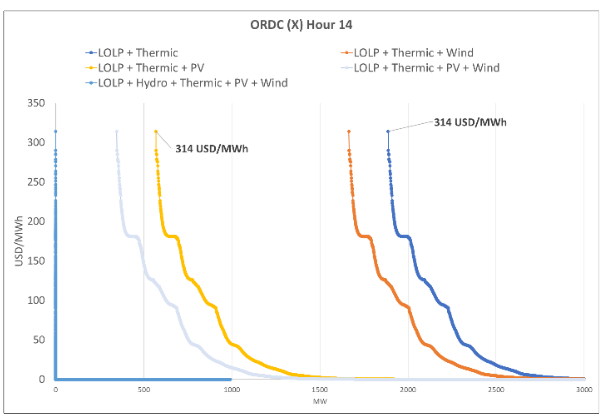

Fig. 7 Evolution of the ORDC for **hour 14** in terms of the inclusion of renewable generation (Figure prepared by the authors).

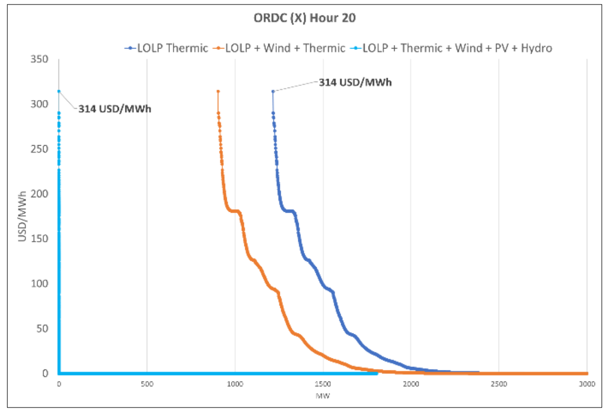

Fig. 8. Evolution of the ORDC (x) for **hour 20** in terms of the inclusion of renewable generation (Figure prepared by the authors).

7. 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, the following objective function to be optimized is programmed in Julia Language to obtain the respective ORDCs for real operation of the system.

The equation to use to implement the unit commitment is:

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

$$s.t.$$

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

$$\forall h$$

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

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

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

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

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

$$Pg_{g,h} \leq coefDisp_{g,h} * Pint_{g} \tag{9}$$
$$\forall\, h, g \; solar\ and\ wind\ plants$$

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

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

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

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

$VC = Variable\ Cost\ \left[\frac{USD}{MWh}\right]$
$Pg_{g,h} = Unit\ g\ Producction\ [\mathrm{MW}] at\ hour\ h$
$ST\ C_g = Starting\ Cost\ unit\ g$
$SP\ C_g = Stoping\ Cost\ unit\ g$
$v_{g,h} = Unit\ g\ starts\ at\ hour\ h$
$z_{g,h} = Unit\ g\ stops\ at\ hour\ h$
$\beta = transmission\ losses\ \%$
$PHP = Producction\ Run\ of\ Rivers\ units\ [\mathrm{MW}]$
$PHE = Producction\ Water\ Storage\ units\ [\mathrm{MW}]$
$D_h = Demand\ at\ hour\ h\ [\mathrm{MW}]$
$R_h = Reserve\ at\ hour\ h\ [\mathrm{MW}]$
$\rho = Water\ density\ \left[\frac{Kg}{m^3}\right]$
$g = specific\ gravity\ \left[\frac{m}{s^2}\right]$
$\eta = efficiency\ \%$
$Q = flow\ \left[\frac{m^3}{s}\right]$
$H = height\ [\mathrm{m}]$

$S_h = Water\ stored\ at\ hour\ h$
$u_{g,h} = 1\ when\ unit\ g\ is\ on\ and\ 0\ when\ unit\ g\ is\ off$
$Pinst_g = Installed\ Capacity\ unit\ g$
$P_{\min g} = Minimum\ Capacity\ in\ unit\ g$
$coefDisp_{g,h}$
$= Producction\ Pattern\ of\ wind\ and\ solar\ plants$

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).

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 Operating Reserve Demand Curves (ORDCs) based on available resources and demand.

		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

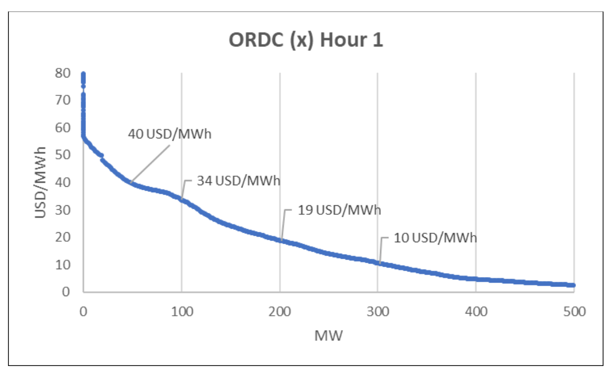

Fig. 9. ORDC (x) for hour 1 when 1400 MW are disconnected and a net demand of 2046 MW (Figure prepared by the authors).

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.

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).

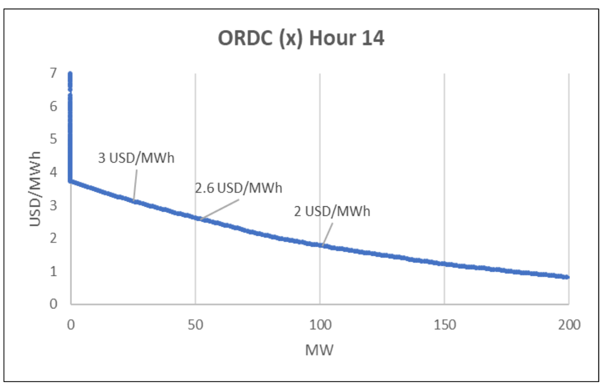

Fig. 10. ORDC (x) for hour 14 when 1400 MW are disconnected, and a net demand of 1610 MW is required (Figure prepared by the authors).

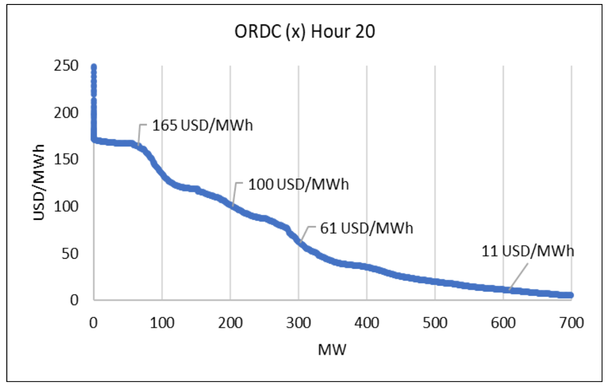

Fig. 11. ORDC (x) for hour 20 when 1400 MW are disconnected, and a net demand of 2356 MW is required (Figure prepared by the authors).

8. 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 paper, 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.

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