Article

A machine learning model for forecast procurement of secondary reserve capacity in power systems with significant vRES penetrations

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Abstract: The growing investment in variable renewable energy sources is changing how electricity markets operate. Players rely on forecasts to participate in markets closing between 1 and 37 hours ahead of real-time operation. Usually, transmission system operators (TSOs) use a symmetrical procurement of up and down secondary power reserves based on the expected demand. This work uses machine learning techniques that dynamically computes it using the day-ahead programmed and expected dispatches of variable renewables, demand, and other technologies. The study uses operational open data from the Spanish TSO from 2014 to 2023 for training. Benchmark and test data are from the period of 2019 to 2022. The proposed methodology improves the usage of the up and down secondary reserved power by almost 47% and 42%, respectively.

Keywords: reserve systems; energy markets; neural networks; forecast

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1. Introduction

The European Union's energy and climate goals for 2030 and 2050 emphasize the transition to a carbon-neutral energy system, driven by the large-scale integration of *variable Renewable Energy Systems* (vRES), such as wind and solar photovoltaic (PV) technologies [1]. While vRES are critical for achieving sustainability targets, such as SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action), their stochastic and intermittent nature poses significant challenges to power system operations, particularly in balancing energy supply and demand efficiently.[2][3]

The increasing penetration of vRES introduces greater uncertainty into energy markets, particularly in *Day-Ahead* (DA) forecasts, which are essential for the allocation of secondary reserves. These reserves, procured to address real-time imbalances between generation and consumption, often suffer from inefficient allocation methodologies. DA predictions frequently diverge from real-time conditions, leading to both over-allocation and under-allocation of reserves. This inefficiency not only results in higher operational costs but also compromises the optimal utilization of resources, thereby undermining the economic and energy efficiency of the system.

This paper focuses on enhancing the accuracy of DA forecasts for secondary reserve allocation, addressing the inefficiencies caused by vRES uncertainty. By leveraging machine learning techniques, this work develops predictive models that incorporate historical data on vRES generation, demand patterns, and system behavior. The objective is to dynamically adjust reserve allocations, ensuring that grid stability is maintained while minimizing excess reserve procurement.

The work present on this paper analyzes the benefits of using of machine learning techniques for an idependent, up and down, forecast of capacity procurement of secondary reserves. Publicly available operational data from the Spanish *Transmission System Operators* (TSO) was utilized, ensuring the replicability of the analysis. Typically, TSOs rely on bilateral agreements to acquire additional reserves, which can drive up costs. Analyzing the underutilization of secondary reserves and the frequent need for extraordinary capacity in Portugal and Spain highlights the inefficiencies in current methods for determining reserve requirements. [4]

The remainder of this paper is structured as follows. Section 2 provides an overview of wholesale energy markets and reserve systems, highlighting existing inefficiencies. Section 3 outlines the proposed methodology for dynamic reserve allocation using machine learning techniques. Section 4 presents case studies and evaluates the performance of the developed models. Finally, Section 5 summarizes the findings and discusses the implications for future energy systems.

2. Literature review

The increasing integration of vRES in power systems has created significant challenges for electricity markets and ancillary services. Traditionally, TSO rely on symmetric allocation of upward and downward reserves based on deterministic forecasts of demand. However, with vRES like wind and solar introducing substantial variability and unpredictability, these conventional methods have proven inefficient in addressing the real-time balancing needs of modern power grids.

Numerous studies highlight the limitations of static reserve procurement methods under high vRES penetration. The *European Network of Transmission System Operators for Electricity* (ENTSO-E) framework [5] outlines standardized methodologies for reserve sizing, such as *Frequency Containment Reserve* (FCR) and *automatic Frequency Restoration Reserve* (aFRR), but these often fail to adapt dynamically to changing system conditions. In Portugal, for example, the secondary reserve allocation formula used by the TSO employs a fixed ratio applied to expected demand, resulting in excessive allocation and energy waste . Similar inefficiencies are observed in the Spanish market, where reserve procurement lacks symmetry and adaptability to vRES production.

Dynamic procurement of secondary reserves has been proposed as a solution to address these inefficiencies [6], with an improvement in 13% and 8% for up and down secondary capacities. By incorporating real-time or near real-time forecasts of demand and renewable generation, dynamic methodologies aim to optimize reserve allocation, reducing both operational costs and resource wastage. Machine learning techniques have emerged as a powerful tool to support this transition. Studies such as [7] and [8] demonstrate the potential of predictive models to estimate reserve needs with greater accuracy, leading to significant reductions in over-procurement.

The literature also underscores the importance of enhancing forecast accuracy for vRES generation and consumption patterns. Traditional statistical models, including ARMA and ARIMA, have been widely used for time series forecasting. However, recent advancements in machine learning, such as *Long Short-Term Memory* (LSTM) networks and *Convolutional neural network* (CNN), have shown superior performance in capturing the nonlinear and temporal characteristics of renewable energy data [9]. These models can adapt to complex patterns and improve prediction accuracy, enabling more efficient management of reserves.

In summary, the literature identifies three key areas of focus: the inefficiency of static reserve allocation methods, the potential of machine learning to improve forecasting accuracy, and the need for market design adaptations to support dynamic reserve procurement. This paper builds upon these insights by applying machine learning techniques to optimize secondary reserve allocation in the Spanish electricity market, addressing both forecast uncertainty and market inefficiencies.

3. Electricity Markets and Ancillary Services

The operation of modern electricity systems relies heavily on well-structured markets to ensure the balance between generation and consumption. These markets encompass wholesale electricity markets, where energy is traded, and ancillary services markets, which guarantee the system's stability and reliability. The integration of vRES has added complexity to these operations, requiring more dynamic approaches to market design and reserve allocation.

3.1. Wholesale Electricity Markets

Wholesale electricity markets facilitate the trading of electricity between generators, suppliers, and other market participants. These markets are typically divided into three main categories: *day-ahead markets* (DAM), *intraday markets* (IDM), and real-time balancing markets. In the DAM, participants submit bids for energy delivery 12 to 37 hours before real-time operation. The market-clearing process determines the energy schedules and market prices based on supply and demand equilibrium [10]. While the DAM provides a foundation for energy trading, IDM allow participants to make adjustments closer to real-time, responding to unforeseen changes in demand or vRES generation.

Balancing markets, on the other hand, operate in near real-time to address deviations between scheduled and actual energy delivery. TSOs procure balancing services to ensure system equilibrium, activating reserves as needed. This process is particularly critical in systems with high vRES penetration, where forecasting errors can cause significant imbalances.[11] [12]

3.2. Ancillary Services and Reserve Requirements

Ancillary services are essential for maintaining grid stability and ensuring a reliable power supply. They include services such as frequency control, voltage regulation, and operating reserves. Among these, frequency control reserves play a crucial role in balancing supply and demand in real-time. These reserves are divided into three main categories:

- FCR: Activated automatically within seconds to stabilize frequency deviations.
- aFRR: Restore frequency to nominal levels and release FCR for subsequent use.
- *manual Frequency Restoration Reserve* (mFRR): Address longer-term imbalances through manual activation.

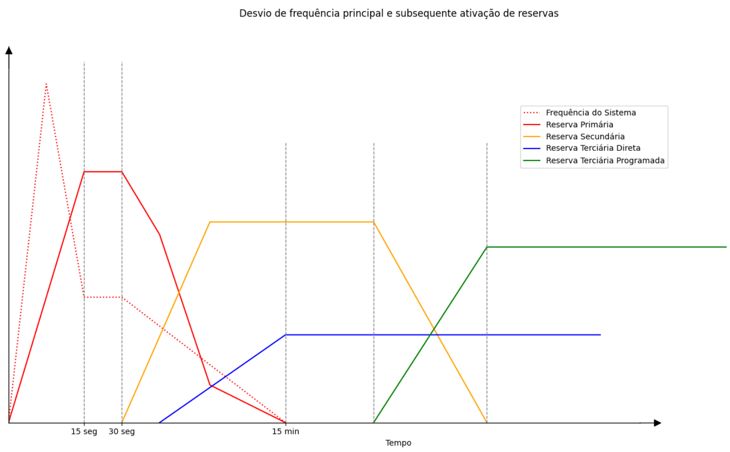

Figure 1. This is a figure. Schemes follow the same formatting. If there are multiple panels, they should be listed as: (**a**) Description of what is contained in the first panel. (**b**) Description of what is contained in the second panel. Figures should be placed in the main text near to the first time they are cited. A caption on a single line should be centered.

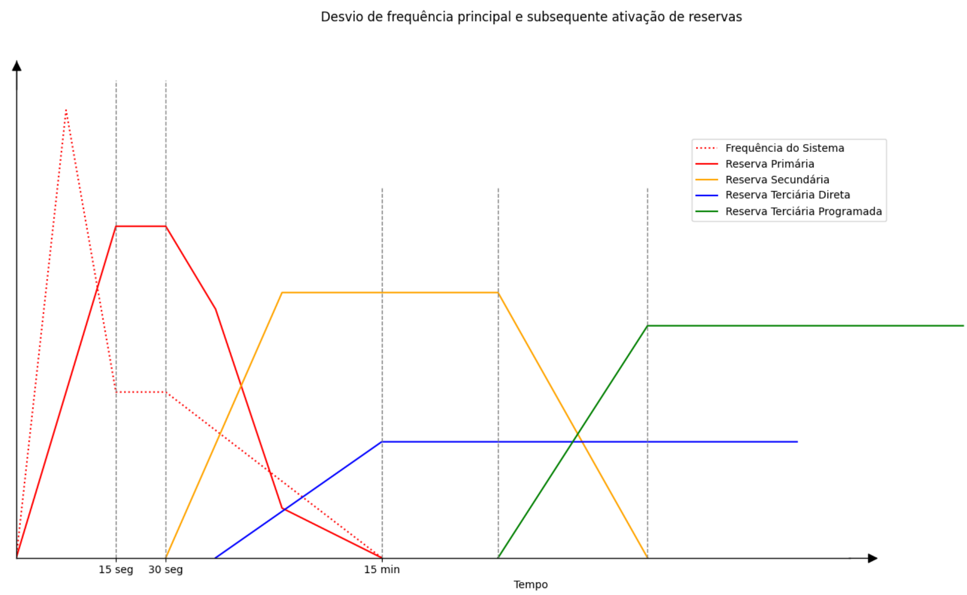

Figure 2. Esquema de activação do sistema de reservas. Adaptado de [5]

In Europe, the ENTSO-E provides guidelines for the procurement and activation of these reserves. Traditionally, TSOs acquire reserves symmetrically (equal upward and downward capacities), based on deterministic demand forecasts. However, this approach often leads to inefficiencies in systems with high vRES variability.

The Spanish and Portuguese markets provide examples of differing reserve procurement methods. In Portugal, the TSO employs a fixed ratio formula for secondary reserve sizing, which can result in excessive allocation. Conversely, the Spanish market lacks a standardized reserve procurement formula, relying instead on flexible, asymmetric procurement mechanisms [13]. These differences highlight the need for market design improvements to better accommodate the variability of vRES.

3.3. Dynamic Reserve Procurement and Market Adaptations

To address the challenges introduced by vRES, dynamic reserve procurement methods have been proposed. Unlike static methods, dynamic approaches consider real-time or near real-time forecasts of energy demand and renewable generation, allowing TSOs to adjust reserve allocations accordingly. This adaptability reduces over-procurement and minimizes costs, improving the efficiency of reserve markets.

The adoption of advanced forecasting tools, particularly machine learning techniques, is central to enabling dynamic reserve procurement. By leveraging historical and operational data, machine learning models can predict reserve needs with greater accuracy, addressing the uncertainties associated with vRES generation. Studies have shown that these models outperform traditional statistical methods, offering significant improvements in reserve management and cost reduction.

In conclusion, the evolving electricity markets and ancillary services frameworks must adapt to the challenges posed by high vRES penetration. Dynamic reserve procurement, supported by advanced forecasting techniques and market design improvements, offers a path toward more efficient and reliable power systems.

4. Dynamic procurement of secondary power

The dynamic procurement of secondary reserves represents a significant step forward in addressing the inefficiencies inherent in traditional static allocation methods. Unlike static reserve procurement, which relies on fixed ratios or historical averages, dynamic approaches incorporate real-time forecasts and system conditions to adjust reserve requirements. This adaptability is particularly critical for modern electricity systems with high penetration of vRES, where forecasting uncertainty and rapid changes in generation output challenge grid stability.

Dynamic reserve procurement involves estimating upward and downward reserve needs based on the expected deviations between day-ahead scheduled generation and real-time demand. By leveraging advanced forecasting tools, such as machine learning models, it becomes possible to predict these deviations with greater accuracy, optimizing the allocation of secondary reserves. Historical data on vRES production, system demand, and grid imbalances serve as inputs to these models, allowing the identification of patterns and trends that inform reserve procurement decisions.

Machine learning techniques, including LSTM networks and other time-series forecasting models, have demonstrated significant potential for improving reserve predictions [14][9]. These models can capture the nonlinear and temporal dependencies present in renewable energy data, outperforming traditional statistical methods such as ARIMA. By incorporating real-time weather forecasts, generation data, and demand profiles, dynamic approaches ensure that reserve procurement aligns more closely with actual system needs, reducing both over-procurement and under-procurement of reserves.

The dynamic approach also allows for asymmetrical procurement of upward and downward reserves, which is particularly relevant in systems with variable renewable generation. For instance, during periods of high solar generation, upward reserves may be less critical, whereas downward reserves become essential to accommodate excess production. Conversely, during low renewable output, upward reserves are prioritized to address potential generation shortfalls.

In summary, dynamic procurement of secondary reserves offers a more efficient and adaptive solution to balancing challenges in modern electricity systems. By leveraging machine learning techniques and real-time forecasts, this approach enhances reserve allocation, reduces operational costs, improving penetration of vRES.

4.1. Previsão de Necessidades de Reservas

A previsão das necessidades de reservas de frequência é uma componente essencial na gestão eficiente dos sistemas eléctricos, especialmente num cenário de crescente penetração das vRES.

O uso de técnicas de *machine learning* tem sido explorado como uma solução promissora para melhorar essas previsões. Estes modelos podem analisar grandes volumes de dados, identificar padrões complexos e ajustar previsões em tempo real, considerando factores como mudanças nas condições meteorológicas e padrões de consumo de energia. Ao incorporar a variabilidade das vRES nos modelos de previsão, é possível reduzir a incerteza e melhorar a alocação das reservas de frequência, resultando numa operação mais eficiente do sistema eléctrico.

Outro factor crítico na previsão das necessidades de reservas de frequência é a coordenação entre diferentes mercados e operadores de sistemas. A harmonização dos mercados europeus de balanço, incluindo a padronização das regras de oferta, leilão e remuneração, pode facilitar a integração das vRES e melhorar a eficiência geral do sistema. Com regras claras e uniformes, os produtores de energia renovável têm maior incentivo para participar activamente dos mercados de reservas, fornecendo capacidade adicional para apoiar a estabilidade da rede. Esta questão é particularmente relevante em mercados onde as vRES ainda enfrentam barreiras significativas para a participação, como regras complexas de licitação ou altos requisitos de capacidade mínima para participação.

Apesar dos avanços na previsão de necessidades de reservas, ainda existem desafios consideráveis. A precisão das previsões pode ser limitada pela qualidade dos dados disponíveis, bem como pela capacidade dos modelos de capturar todas as variáveis relevantes que afetam a operação da rede. Além disso, a crescente interconexão dos sistemas eléctricos e o aumento da troca de energia entre países exigem uma abordagem coordenada e colaborativa para a previsão de reservas, considerando tanto as condições locais como as condições regionais.

O desenvolvimento contínuo de técnicas avançadas de previsão e a integração de soluções baseadas em dados serão fundamentais para enfrentar esses desafios. À medida que mais dados históricos se tornam disponíveis e os modelos de previsão evoluem, espera-se que a gestão das reservas de frequência se torne cada vez mais eficiente, contribuindo para um sistema eléctrico mais resiliente e capaz de integrar altos níveis de Tal desenvolvimento, não apenas reduzirá os custos operacionais, mas também contribuirá para a segurança energética e para a transição para um sistema energético mais sustentável.

4.1.1. Previsão de Banda Secundária no Mercado Ibérico de Electricidade

A nível Europeu a ENTSO-E providencia várias metodologias para o dimensionamento das reservas de controlo descritas em [5]. A quantidade mínima recomendada de alocação necessária para a reserva de controlo secundária pode ser descrita da seguinte forma:

$$BR = \sqrt{a \times L_{max} + b^2} - b \tag{1}$$

onde:

- BR: Banda de Reserva de regulação secundária mínima necessária (MW).
- a e b: Coeficientes empiricos, a=10MW e b=150MW .
- L_{max}: Consumo máximo antecipado (MW).

Portugal

No mercado português para dimensionar a aFRR a Redes Energéticas Nacionais (REN) utiliza por base a equação 1 multiplicando um parâmetro horário, ρ:

$$BR = \rho \times \sqrt{a \times L_{max} + b^2} - b \tag{2}$$

onde:

- ρ: Paramêtro horário.

Na equação 2 BR equivale à banda a subir, sendo a banda a descer metade da banda a subir. De notar que em [12] BR é a banda de reserva, que equivale à soma da banda a subir e banda a descer, onde aí é sempre considerado que banda a subir são $\frac{2}{3}$ da Banda de Reserva total e a banda a descer é o restante $\frac{1}{3}$.

Este método de cálculo permite manter as reservas a corresponder às necessidades do sistema, mas têm uma uma alocação em excesso. Podemos verificar que no período 2013 a 2023, inclusive, as médias por hora têm cerca de 437% de alocação em excesso, o que corresponde, em média, a cerca de 221 MWh desperdiçados a cada hora.

Table 1. Média das Bandas Alocada e Usada (REN)

Banda de Reserva Alocada	Banda Reserva Activada	erro	erro %
271.57	50.53	221.04	437.43

Estando actualmente o TSO português a utilizar esta fórmula, e a obter estes resultados, este é um bom caso de estudo de optimização dos parâmetros da fórmula. Sendo que a e b são dados pela entidade europeia, propõe-se o estudo do parâmetro horário de modo a corresponder a banda de reserva calculada ao consumo real.

Espanha

No mercado espanhol não encontramos directivas de uso de uma fórmula como no caso português. Nem encontramos uma simetria directa entre as bandas a subir e a descer. Contudo, podemos verificar que a média horária dentro do mesmo período apresenta disparidades ainda maiores em quantidade média de energia alocada desperdiçada.

Table 2. Média das Bandas Alocada e Usada (REE)

	Banda de Reserva Alocada	Banda Reserva Activada	erro	erro %
Banda a Subir	662.94	158.10	504.84	319.32
Banda a Descer	549.27	168.20	381.07	226.55

Como temos uma boa quantidade de dados históricos e uma falta de definição e formulação exacta da necessidade, o caso espanhol é um bom caso de estudo para previsões usando *machine learning*.

4.1.2. Modelos *machine learning* para previsão

Grande parte da literatura sobre previsões em modelos de *machine learning* apresenta as mesmas arquiteturas, sendo depois aprimoradas consoante os dados e o problema.

No presente trabalho, apresentar-se-ão as arquitecturas mais usadas em previsões, como também algumas usadas noutros ramos, com a finalidade de tentar prever a compatibilidade neste problema.

Neste trabalho vamos usar arquiteturas de *Fully Connected Neural Network* (FCNN), CNN, LSTM e *Transformer*.

FCNN

A arquitetura mais simples FCNN, Redes Neuronais Totalmente Conectadas, é constituída por camadas em que cada neurónio está ligado a todos os neurónios da camada seguinte. Isto significa que cada caraterística de entrada tem um peso associado, e esses pesos são aprendidos durante o treino. A saída de cada neurónio é calculada através da aplicação de uma função de ativação à soma ponderada das suas entradas.

Cada neurónio gera uma operação, inicialmente aleatória, para tentar reproduzir uma função que traduza a entrada na saída ideal.

Esta arquitectura tem como base o Perceptão inicialmente proposto em [15]. Este apresentava um Perceptão que fazia uma decisão binária baseado nas somas pesadas de todas as entradas.

A ideia é a base utilizada actualmente, mas apresentava algumas limitações, e muita computação, o proposto por [16], eleva a ideia com a introdução da função de activação e o bias. Actualmente os neurónios mais usados têm por base o proposto em [17]:

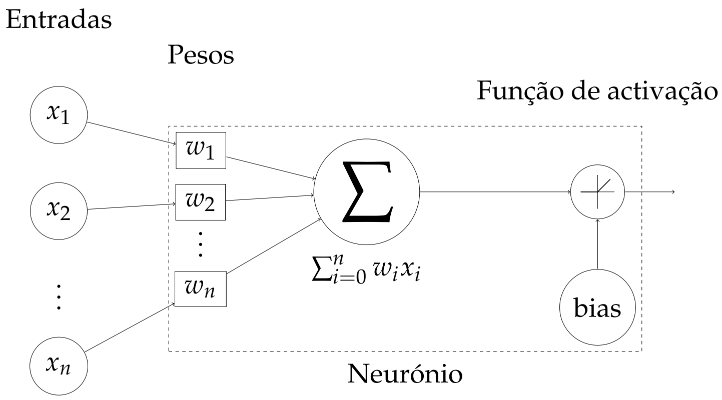

Figure 3. Ilustração de um neurónio. Adaptado de [17]

CNN

As Redes Neuronais Convolucionais (CNN) diferem das FCNN no sentido em que os filtros (neurónios) não são criados aleatoriamente, mas cada filtro trata de uma parte da camada de entrada. Nas convoluções é criada uma janela móvel que percorre a camada, criando um saída desse conjunto de pontos. Esta janela move-se sempre subsequentemente.

Esta operação é normalmente feita na dimensão (ou dimensões) em que queremos perceber padrões. Nos nossos dados a convolução será na dimensão temporal.

Se tivermos uma matriz com nove passos temporais (N,9,1), se o tamanho da janela de convolução for 3, teremos uma saída de tamanho 6 (N, 6, 1).

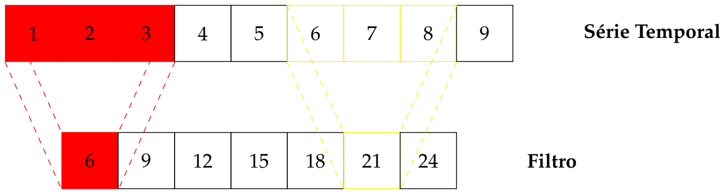

Figure 4. Ilustração da operação de Convolução

Anteriormente ignoramos o número de filtros. Mas as convoluções criam o número pedido de filtros para cada janela temporal. Aqui cada filtro vai funcionar como na camada FCNN, onde cada um começa com uma operação pseudo aleatória. Esta operação normalmente é feita na dimensão dos atributos.

Ou seja, a quantidade de filtros que esta camada irá produzir por convolução.

Se tivermos a mesma entrada que anteriormente mas com 4 atributos (N, 9, 4), e se definir o número de filtros para 2 teremos uma saída (N, 6, 2).

Ou seja, dois filtros por cada janela temporal.

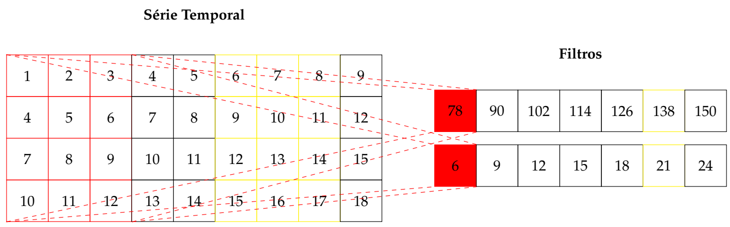

Figure 5. Ilustração da camada de Convolução

As convoluções podem realizar as operações em mais dimensões, é comum usar 2D para imagens, e 3D para vídeos. Neste trabalho apenas trabalhamos com convoluções 1D.

UNET

Num desenho especial de CNN, normalmente usando em modelação de imagens, e primeiro proposto em [18], a arquitectura UNET passa por criar uma rede de expansão dos filtros, usando convoluções, e de seguida uma rede de contracção dos mesmo, até aos tamanhos pretendidos.

Nas suas ligações, a arquitectura UNET junta informação de filtros passados (não de nível temporal mas de rede neuronal) para realçar informação já trabalhada, e assim identificar padrões de vários contextos diferentes.

É assim designada pois é uma rede (NET) que forma um U na sua expansão, contracção e ligações entre estes.

Em cada camada de *encoding* vão sendo usadas convoluções para criar novos filtros e diminuir a dimensionalidade, enquanto que na fase de *decoding* são usadas convoluções para aumentar a dimensionalidade e diminuir o número de filtros, adicionando a camada *decoder* de tamanho análogo.

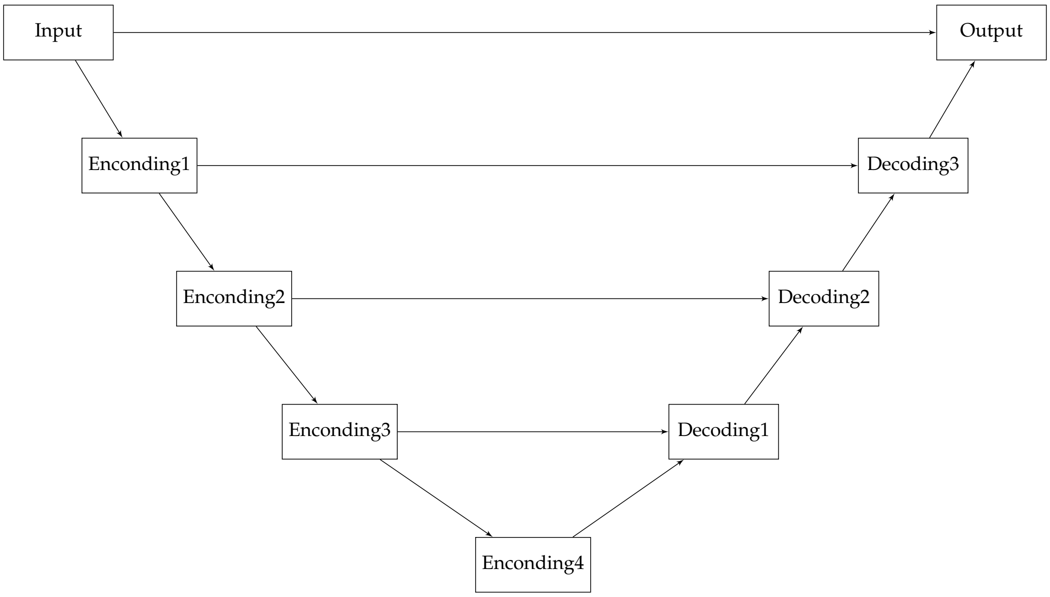

Figure 6. Ilustração uma rede UNET.

RNN

As Redes Neuronais Recorrentes (RNN) são projetadas para processar sequências de dados, onde a ordem dos elementos é fundamental. Estas funcionam transmitindo informações de um neurónio para outro numa cadeia, o que permite que cada neurónio seja influenciado pelo estado anterior da rede.

Esta operação é feita através de *loops* internos que permitem à rede "memorizar" informações das etapas anteriores. No entanto, as RNNs enfrentam dificuldades ao tentar lembrar informações de longo prazo, devido ao problema conhecido como desvanecimento do gradiente, onde os gradientes se tornam muito pequenos e impedem a actualização eficaz dos pesos da rede.

LSTM

As redes LSTM são um tipo especial de *Recurrent neural network* (RNN) projetado para superar os problemas de memória de longo prazo encontrados nas RNNs. Tal é conseguido através de uma estrutura de célula que mantém informações ao longo do tempo, permitindo que a rede memorize detalhes importantes mesmo após muitos passos no tempo.

As LSTMs usam mecanismos de portão para controlar o fluxo de informações, permitindo a desconsideração de informações irrelevantes e a manutenção das informações relevantes. Esta característica torna-as particularmente eficazes em tarefas que exigem o entendimento de dependências de longo prazo em dados sequenciais.

O uso de LSTM para previsões é uma área comum, mas aqui é seguido através das ideias partilhadas em [19], e reforçado pelo uso em previsões energéticas demonstradas em [14].

Transformer

Os *Transformers* são um tipo de arquitetura de modelo que utiliza mecanismos de atenção para pesar a importância de diferentes partes de um dado de entrada, primeiro apresentado em [20].

Ao invés de processar os dados sequencialmente, como sucede nas RNNs, os *Transformers* processam todos os elementos do dado de entrada simultaneamente,através de um mecanismo de atenção que calcula uma pontuação de atenção para cada par de elementos no dado de entrada, indicando quão relevante um elemento é para o outro. Estas pontuações de atenção são então usadas para ponderar a contribuição de cada elemento no resultado final.

Esta característica permite aos *Transformers* capturar dependências de longo alcance nos dados de forma eficiente, tornando-os extremamente eficazes para tarefas de processamento de linguagem natural, como tradução automática e sumarização de texto.

Este tipo de desenho é a base para os modelos generativos mais conhecidos como o *chatGPT* para linguagem ou o *Dall-E* para imagens.

5. Case-study

To evaluate the proposed methodology for dynamic procurement of secondary reserves, a case study was conducted using the Spanish electricity market as a benchmark. The Spanish power system is an ideal candidate for this analysis due to its significant integration of variable renewable energy sources (vRES), particularly wind and solar photovoltaic (PV) power. The case study aims to demonstrate the effectiveness of machine learning techniques in improving forecast accuracy and optimizing secondary reserve allocation.

5.1. Data Sources and Preprocessing

The case study utilizes publicly available operational and historical data from *Red Eléctrica de España* (REE), the Spanish TSO. The dataset includes the following key variables:

- **vRES Generation**: DA and real-time generation data for wind and solar power.
- **System Demand**: DA forecasts and real-time measurements of electricity consumption.
- **Reserve Activation**: Historical data on upward and downward reserve activation.
- **Market Prices**: DA and balancing market clearing prices.

The data spans multiple years to account for seasonal variability and long-term trends in vRES generation and demand. Data preprocessing steps included:

- Handling missing values using interpolation methods, with IterativeImputer [21][22].
- Aligning time-series data to ensure synchronization between forecasts, real-time values, and reserve activations.

For training the full dataset from 2014 to 2023, inclusive was used. As for validation it was chosen the years 2019-2022, in direct comparison with validation from [23]

Methodology Implementation

6. Conclusions

The results of the case study validate the effectiveness of machine learning techniques in improving the accuracy of reserve forecasts and optimizing reserve allocation. By dynamically adjusting upward and downward reserves based on real-time forecasts, the proposed methodology addresses the inefficiencies of static procurement methods. The observed cost savings and improved reserve utilization demonstrate the practical benefits of this approach for systems with high renewable penetration.

Additionally, the case study highlights the potential for asymmetrical reserve procurement to better reflect system needs, particularly during periods of extreme renewable generation variability. The integration of weather forecasts into the predictive models further enhances their reliability, ensuring that reserve procurement decisions are informed by real-time conditions.

In conclusion, the case study illustrates that dynamic reserve procurement, supported by machine learning techniques, can significantly improve the efficiency and cost-effectiveness of balancing services in modern electricity systems. These findings provide a strong foundation for further research and potential implementation in other power markets with similar challenges.

Abbreviations

The following abbreviations are used in this manuscript:

Glossary

aFRR	*automatic Frequency Restoration Reserve*. 2, 3, 5
CNN	*Convolutional neural network*. 2, 6–8
DA	*Day-Ahead*. 1, 9
DAM	*day-ahead markets*. 3
ENTSO-E	*European Network of Transmission System Operators for Electricity*. 2, 3, 5
FCNN	*Fully Connected Neural Network*. 6, 7
FCR	*Frequency Containment Reserve*. 2, 3
IDM	*intraday markets*. 3
LSTM	*Long Short-Term Memory*. 2, 4, 6, 8, 9
mFRR	*manual Frequency Restoration Reserve*. 3
PV	solar photovoltaic. 1
REE	*Red Eléctrica de España*. 9
REN	Redes Energéticas Nacionais. 5
RNN	*Recurrent neural network*. 8
TSO	*Transmission System Operators*. 1–3, 5, 9
vRES	*variable Renewable Energy Systems*. 1–4

Appendix A

Appendix A.1

The appendix is an optional section that can contain details and data supplemental to the main text—for example, explanations of experimental details that would disrupt the flow of the main text but nonetheless remain crucial to understanding and reproducing the research shown; figures of replicates for experiments of which representative data are shown in the main text can be added here if brief, or as Supplementary Data. Mathematical proofs of results not central to the paper can be added as an appendix.

Table A1. This is a table caption.

Title 1	Title 2	Title 3
Entry 1	Data	Data
Entry 2	Data	Data

Appendix B

All appendix sections must be cited in the main text. In the appendices, Figures, Tables, etc. should be labeled, starting with "A"—e.g., Figure A1, Figure A2, etc.

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