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

João Passagem Santos[1]* and Hugo Algarvio[2]*

[1] Affiliation 1; e-mail@e-mail.com
[2] LNEG—National Laboratory of Energy and Geology, Est. Paço Lumiar 22, 1649-038 Lisbon, Portugal
* Correspondence: fc55144@alunos.ciencias.ulisboa.pt (J.P.S), hugo.algarvio@lneg.pt (H.A.)

Abstract: The growing investment in variable renewable energy sources is changing how electricity markets operate. In Europe, players rely on forecasts to participate in day-ahead markets closing between 1 and 37 hours ahead of real-time operation. Usually, transmission system operators 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. Frase sobre tecnicas usadas com a keyword neural networks . The study uses operational open data from the Spanish operator 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: energy markets; forecast; machine learning; neural networks; reserve systems; secondary capacity; variable renewables

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 [1–3]. While vRES are critical for achieving sustainability targets, such as Sustainable Development Goals (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 [4,5].

The increasing penetration of vRES introduces greater uncertainty into energy markets, particularly in Day-Ahead (DA) forecasts, which are essential for the allocation of the automatic Frequency Restoration Reserve (aFRR), also known as secondary reserves [6,7]. 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 [8,9].

This paper focuses on enhancing the accuracy of DA forecasts for secondary reserve allocation, addressing the inefficiencies caused by vRES uncertainty [10,11]. By leveraging machine learning techniques, this work develops predictive models that incorporate historical data on vRES generation, demand patterns, and system behavior [12,13] . The objective is to dynamically adjust reserve allocations, ensuring that grid stability is maintained while minimizing excess reserve procurement [8,14].

The work presented on this paper analyzes the benefits of using of machine learning techniques for an independent, up and down, capacity procurement of secondary reserves.

Citation: Passagem Santos, J.; Algarvio, H. A machine learning model for procurement of secondary reserve capacity in power systems with significant vRES penetrations. *Journal Not Specified* **2024**, *1*, 0. https://doi.org/

Received:
Revised:
Accepted:
Published:

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 reserves in Portugal and Spain highlights the inefficiencies in current methods for determining reserve requirements [8,9,14,15].

The remainder of this paper is structured as follows. Section 2 presents a literature review on dynamic reserves and machine learning. Section 3 provides an overview of wholesale energy markets and reserve systems, highlighting existing inefficiencies. Section 4 outlines the proposed methodology for dynamic reserve allocation using machine learning techniques. Section 5 presents a case study and evaluates the performance of the developed models. Finally, Section 6 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 [**?**] outlines standardized methodologies for reserve sizing, which are Frequency Containment Reserve (FCR), aFRR and manual Frequency Restoration Reserve (mFRR), 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.

The majority of the literature focuses on using historical data to compute the procurement of secondary reserves [10,16,17] Operational methodologies are needed to be used by TSOs.

Dynamic procurement of secondary reserves has been proposed as a solution to address these inefficiencies, with an improvement in 13% and 8% for up and down secondary capacities by 2022 [14]. 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. Furthermore, five different mechanisms for procuring secondary power in Spain were analyzed for the Spanish power system by 2030, with renewable penetrations higher than 70% [8]. The dynamic procurement methodology proposed in this study enables cost reductions for Spanish secondary power by 27% when using block bids and 34% when using flexible bids. These results highlight the increasing importance of dynamic reserve procurements with the rising uncertainty of higher penetrations of vRES. Machine learning techniques have emerged as a powerful tool to support this transition. Studies such as [12] and [13] demonstrate the potential of predictive models to estimate reserve needs with greater accuracy, leading to significant reductions in over-procurement. De Vos et *al.* proposed a machine learning approach to estimate imbalance uncertainty, with the goal of adjusting the size of Belgium's operating reserves from an annual to a daily basis, resulting in a 5% reduction [12]. Kruse, Schäfer, and Witthaut introduced an ex-post machine learning method to determine the appropriate size for secondary reserves. They identified key variables that most accurately estimate errors, which are essential for detecting when secondary control is activated. Additionally, to enhance the efficiency of cross-border capacity allocation in balancing service exchanges, legislation recommended coupling balancing mechanisms, as demonstrated in the Nordpool market [9,18].

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 [**?**]. 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 [11]. 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 [19].

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 [19]:

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

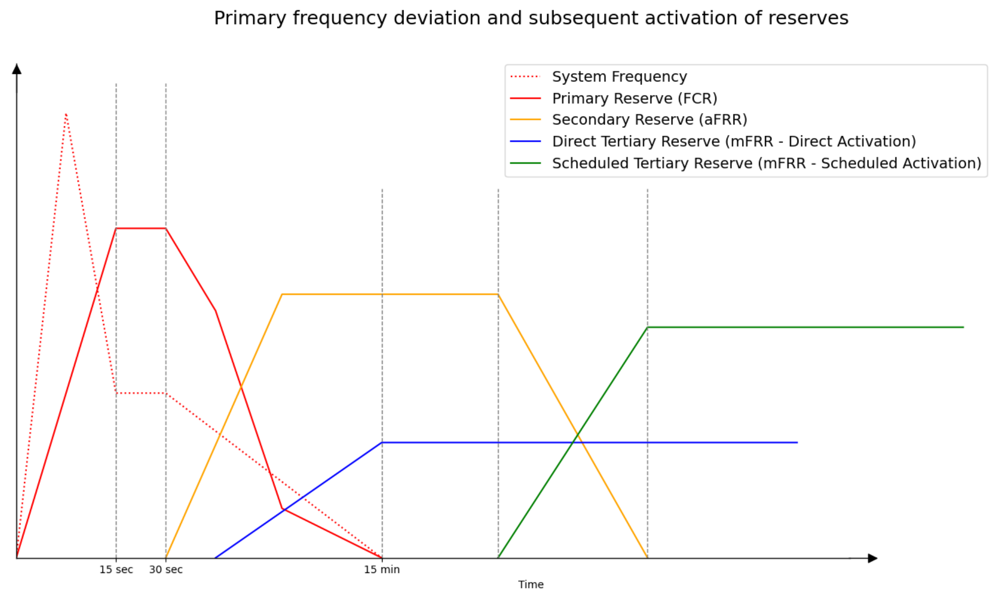

Figure 1. Ancillary Services response scheme. Adapted from [?]

3.3. Iberian Reserve Markets

Iberian Market of Electricity (MIBEL) is the iberian example of energy market integration across countries. Acting as a bond between portuguese and spanish electricity markets, *Operador do Mercado Ibérico de Energia Português, Sociedade Gestora do Mercado Regulamentado, S.A.* (OMIP) and *Operador del Mercado Ibérico de Energía - Pólo Espanhol, S.A* (OMIE). This joint market consists of bilateral, derivatives, and spot markets.

Even though there is a joint market, each country's TSO, Red Eléctrica de España (REE) for Spain and *Redes Energéticas Nacionais* (REN) for Portugal, manages it's own ancillary services independently.

3.3.1. Static Reserve Procurement

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. For secundary reserve ENTSO-E proposes:

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

where:

- R: Secondary Control Reserve.
- a and b: empiric coefficients, a=10MW and b=150MW .
- L_{max}: maximum anticipated consumer load.

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. Creating a symmetrical distribution for upward and downward bands, respectively $\frac{2}{3}$ and $\frac{1}{3}$ of the reserve band.

The given formula is based on ENTSO-E equation (1), adding an hourly ratio ρ:

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

The hourly ratio ρ varies between 20% (1.2) and 60% (1.6), upscaling the the ENTSO-E suggestion for up regulation.

Conversely, the Spanish market lacks a standardized reserve procurement formula, relying instead on a more flexible procurement mechanism [16]. Where the upward and downward bands distribution is not directly symmetric. These differences highlight the need for market design improvements to better accommodate the variability of vRES.

4. Dynamic procurement of secondary power

This study proposes a dynamic procurement based on machine learning techniques, trained with historical hourly data with custom made model architectures

4.1. Methodology Implementation

The methodology applied was a "brute force" choosing of better model, which can lead to better fine tuning results than a more complex architecture as shown in [20].

With multiple model related variables in study:

Table 1. Training and architecture variables.

Variables	Options
Architecture	CNN LSTM RNN UNET Transformer
Advance Loss function	Mirror Weights N/A
Loss function	MAE MSE MSLE
Activation	linear ReLU GELU
Weights	Temporal Distance to mean No Weights

For that we will study different architectures already proven to work in energy forecast [?], or in forecast in general [?], such as Fully Connected Neural Network (FCNN), LSTM, CNN. Testing also architectures proven to work in other fields, such as UNET [?] from image segmentation, or Transformers [?], the current machine learning state of art architecture. Although for Transformer, processing limitation won't allow for a deep study of potential the given problem.

As for the loss function used, we shall test it with the three most common regression loss function: MAE, MSE, MSLE, which are means of the given error, in absolute terms, the square os the errors, and the logarithmic square, respectively. The last two functions give more importance to larger errors.

But since the problem we are trying to solve is not only of finding the smallest error, but to make sure the there is less negative and positive error than the benchmark we create a custom loss function to encapsulate the final loss calculation, the Mirror Weights.

This function acts as a weight distributor for the negative and positive errors, in such a way that the a ratio defines which size gives more meaning to the final loss calculation. This was created since the error in missing energy is on a 10^5 dimension, and on surplus 10^6.

In a default loss function trying to lower the absolute error, this difference means most work would be to lower surplus errors even at the expenses of raising the missing error. The created function allows for more behaviors, and some of them were studied, but the one with better results was defaulting surplus results weight 1, and making the weights of missing values its own error, multiplied by a ratio. Insights on given different ratio outcomes can be seen below:

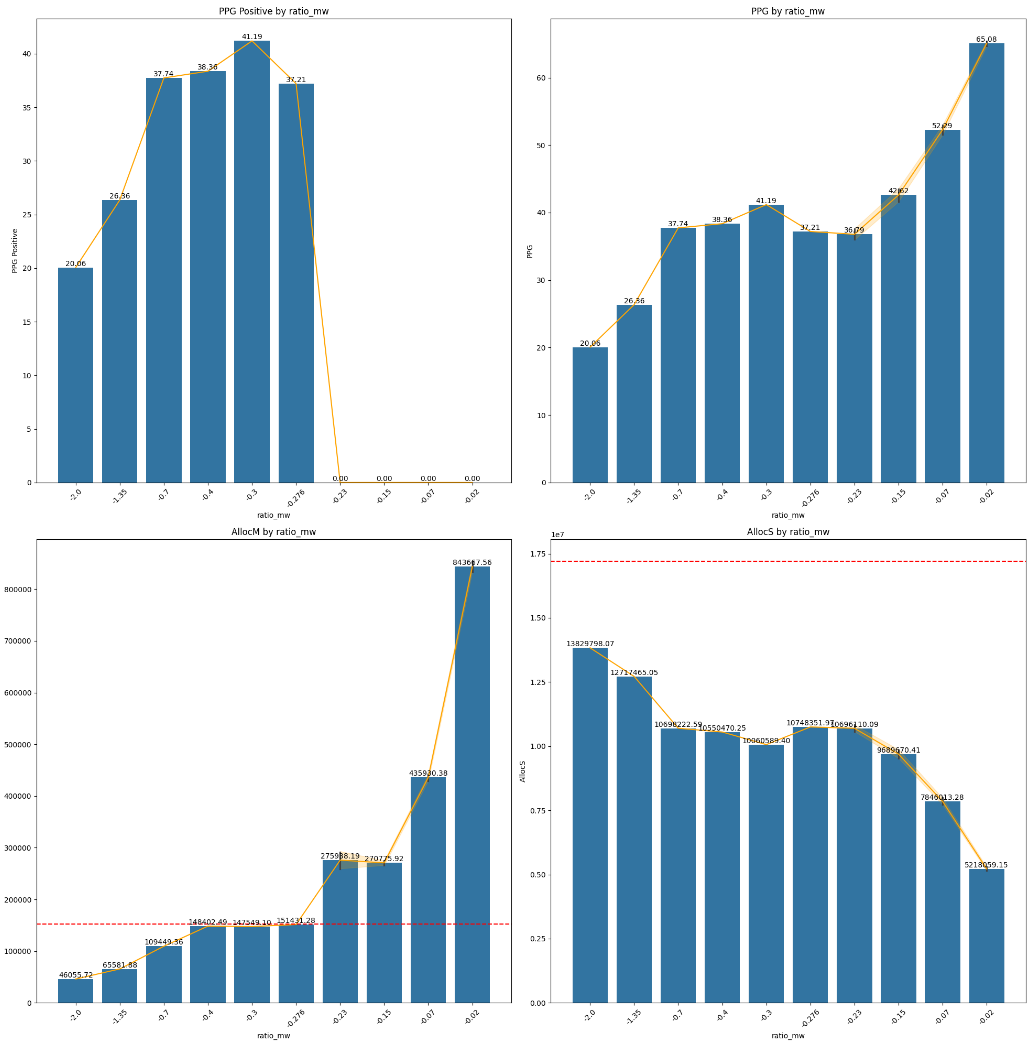

Figure 2. Mirror Weights ratio influence on metrics

Were the red doted line shows the benchmark values, and our goal is to have both below the benchmark line.

As for activation research suggested it could provide significant impact on the outcome [20**?**]. The test were done using the most common activations for regression problems, where we separated activations inside the model structure (on each deep layer), and the final layer. These are: linear leaves inputs unchanged, Rectified Linear Unit (ReLU) outputs the input if positive and zero otherwise, while Gaussian Error Linear Unit (GELU) smooth this behavior by applying a Gaussian-based probabilistic transformation.

And the last model variable in test were the weights, these given directly to the model training, not in a custom loss function. These weights are multiplied with the Mirror Weights.

Temporal weights give weight one to the oldest sample and add one per time sample, making older data less relevant, in an attempt to be more aware of latest trends. The distance to mean purpose is to give more weight values further away from the mean, this would serve as a way to alleviate mean related generalization and catch spike inducing patterns.

Where each of the model variables in study is a layer of training, giving the best model within that scope we would go to the next variable with the given best option so far. Going back and forward as to not loose best possible choices.

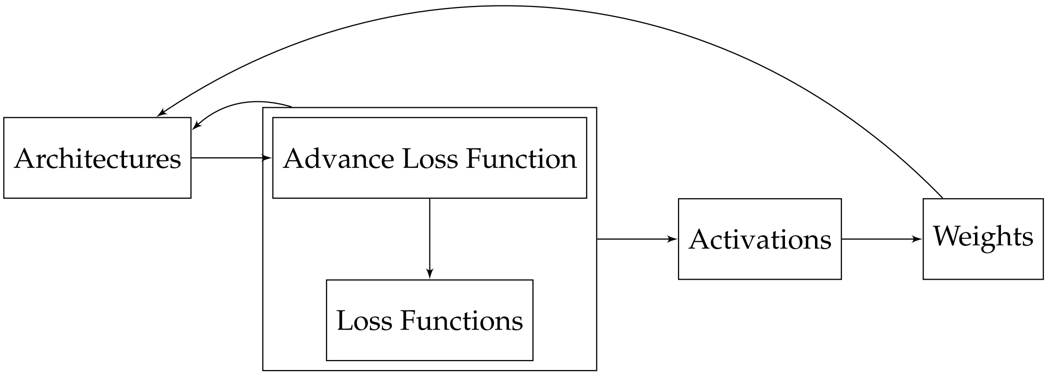

Figure 3. Model choice method scheme.

For the purpose of controlling and processing this experiment three python packages were created.

- Alquimodelia: A keras based model builder package, to create the necessary models with each different arch and variable.
- Alquitable: A keras based workshop package, to create custom callbacks, loss functions, data generators.
- MuadDib: A machine learning framework that uses Alquimodelia to test and choose best models on given conditions automatically.

The experiments were done using keras>=3 with a torch backend on a CPU laptop. Explicar o que é keras?

4.2. Metrics

With distinct weights, the metrics, are used to choose best model on each iteration, and they can be divided into two groups:

1. Model metric, where we just use the usual regression metrics adding a metric for how much did the model missed in allocating for the validation period.
2. Comparative metrics, where we assert percentage gains over the current allocation method.

4.2.1. Model Metrics

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - p_i)^2} \tag{3}$$

where t is the observed value, p is the forecast and n is the number of samples.

$$SAE = \sum_{i=1}^{n}|t_i - p_i| \tag{4}$$

SAE can be divide into the following metrics, where we obtain the error, within the time period, of allocated energy not enough for the needs, and too much energy allocated, separately.

The missing allocation (AllocM) is computed as follows:

$$AllocM = \begin{cases} 0 & ,\text{if } p \geq t \\ t - p & ,\text{if } p < t \end{cases} \tag{5}$$

The surplus allocation (AllocS) is computed as follows:

$$AllocS = \begin{cases} 0 & ,\text{if } p \leq t \\ p - t & ,\text{if } p > t \end{cases} \tag{6}$$

These metrics are needed to get a better error than the benchmark, but also to have less wasted AllocM, and less occurrences of AllocS.

4.2.2. Model/benchmark comparative metrics

Performance Percentage Gain (PPG) is the percentage of how much better is the model over the benchmark, it is computed as follows:

$$PPG = \frac{SAE_{benchmark} - SAE_{modelo}}{SAE_{benchmark}} \times 100 \tag{7}$$

The following metrics are the same but for only missing allocation and surplus allocation.
Performance Percentage Gain Missing (PPGM) computes the performance of the missing allocation as follows:

$$PPGM = \frac{AllocM_{benchmark} - AllocM_{modelo}}{AllocM_{benchmark}} \times 100 \tag{8}$$

PPGM computes the performance of the surplus allocation as follows:

$$PPGS = \frac{AllocS_{benchmark} - AllocS_{modelo}}{AllocS_{benchmark}} \times 100 \tag{9}$$

The PPGPositive metric is showing how much better is the model over the benchmark, but only if PPGM and PPGM are positive.

$$PPGPositive = \begin{cases} PPG & ,\text{if } PPGM \ \& \ PPGS \geq 0 \\ 0 & ,\text{if } PPGM \parallel PPGS < 0 \end{cases} \tag{10}$$

5. Case-study

To evaluate the aplicability of machine learning techniques for secondary reserve allocation the study was conducted using the Spanish electricity market historical data.

5.1. Data Sources and Preprocessing

The case study utilizes publicly available operational and historical data from the Spanish TSO, REE. Available at *Sistema de Información del Operador del Sistema* (ESIOS). The dataset includes the following key variables:

Table 2. ESIOS data used on the study.

ESIOS Code	ESIOS Name	Variable	Units
632	Secondary Reserve Allocation AUpward	Up Allocated	MW
633	Secondary Reserve Allocation ADownward	Down Allocated	MW
680	Upward Used Secondary Reserve Energy	Up Used	MWh
681	Downward Used Secondary Reserve Energy	Down Used	MWh
1777	Wind D+1 Daily Forecast	DA Wind	MWh
1779	Photovoltaic D+1 Daily Forecast	DA PV	MWh
1775	Demand D+1 Daily Forecast	DA Demand	MWh
10258	Total Base Daily Operating Schedule PBF Generation	DA Schedule Generation	MWh
14	Base Daily Operating Schedule PBF Solar PV	DA Schedule PV Generation	MWh
10073	Base Daily Operating Schedule PBF Wind	DA Schedule Wind Generation	MWh
10186	Base Daily Operating Shedule PBF Total Balance Interconnections	DA Scheduled Tie Lines	MWh

The data spans multiple years to account for seasonal variability and long-term trends in vRES generation and demand. Data preprocessing only handled missing values using interpolation methods, with IterativeImputer [?][?].: 262 263 264

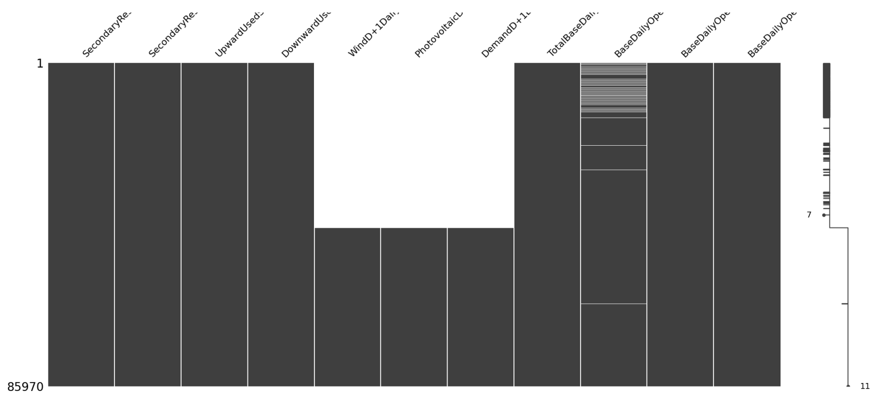

Figure 4. Missing Data

To choose the temporal space of the models temporal auto-correlations were checked: 265

Table 3. Temporal self correlation.

horas	1	2	24	23	25	168	144	192	48
Up	0.44	0.24	0.22	0.19	0.19	0.17	0.16	0.16	0.16
Down	0.43	0.22	0.25	0.20	0.19	0.21	0.19	0.20	0.19

We wanted to forecast DA values, so we will be forecasting 24 hours ahead. As for the input for that forecast the temporal correlactions present 168 hours as the next correlation after the one day period, which represents a week. We add also variable to account for each time range: day, day of year, month, day of week.

And so our models will receive data in (Batch Size, 168, 18) shape for input, and (Batch Size, 24, 1) shape for output.

5.1.1. Training Data

For training the full dataset from 2014 to 2023, inclusive was used. follows a description of said data:

Table 4. Training data summary.

	mean	**std**	**min**	**max**
Down Used	168.20	199.67	0.00	1721.40
Up Allocated	662.94	150.62	399.00	958.00
Down Allocated	549.27	126.67	312.00	956.00
Up Used	158.10	191.62	0.00	1654.80
DA Wind	5824.12	3413.15	71.33	20879.30
DA PV	1666.31	2719.60	0.00	14925.30
DA Demand	27944.24	4479.39	14170.00	41773.00
DA Schedule Generation	27249.43	4603.58	13470.50	42707.60
DA Schedule PV Generation	1714.09	2815.35	0.00	16358.90
DA Schedule Wind Generation	6525.51	3582.36	308.60	21619.60
DA Scheduled Tie Lines	290.58	2157.11	-7817.00	6858.50

With each variable correlation to used secondary reserve energy:

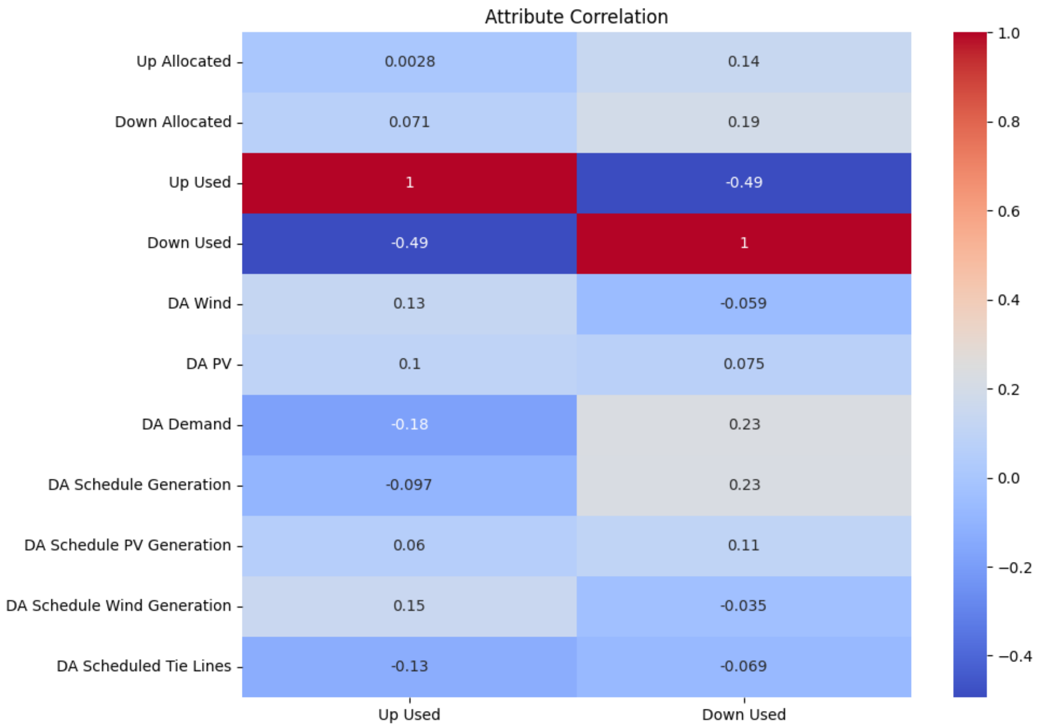

Figure 5. Attribute correlation

5.1.2. Validation Data 276

As for validation it was chosen the years 2019-2022, in direct comparison with validation from [14]. 277 278

Using the non comparitive metrics we have the following results: 279

Table 5. Metric Results for validation data.

	RMSE	SAE	AllocF	AllocD
Up Allocation (MW)	536.55	17357826.75	152679.00	17205147.75
Down Allocation (MW)	408.99	12981575.55	479191.60	12502383.95

And the correlation between allocated energy in the current method to the used energy can be seen in the following image: 280 281

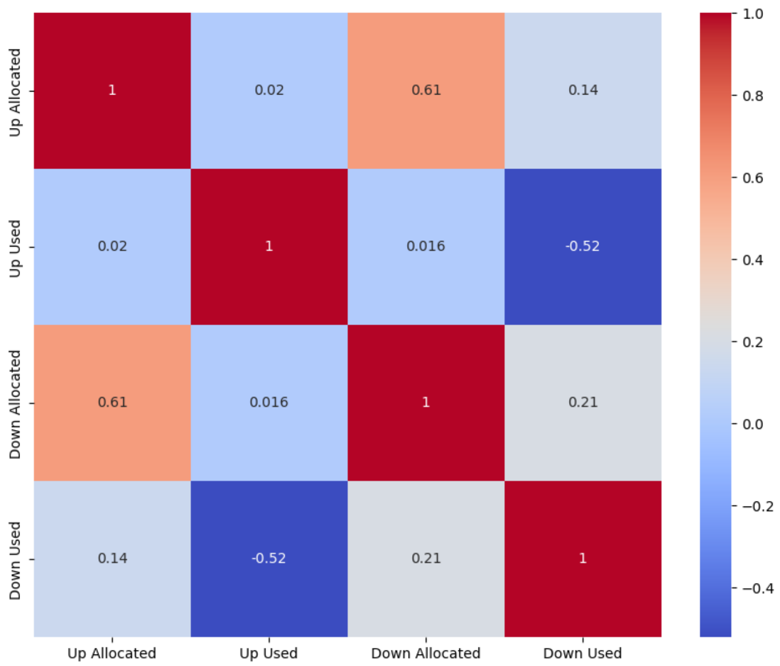

Figure 6. Attribute correlation benchmark

5.2. Results

The best results for each architeture can be seen below, were Vanilla means it's only one layer deep, and Stacked means two layers deep:

Table 6. Metric results for up and down forecast.

	Arquitetura	RMSE	SAE $\times 10^6$	AllocM $\times 10^5$	AllocS $\times 10^6$
Up Allocation	UNET	304.34	9.19	1.47	9.05
	VanillaCNN	363.35	11.49	1.48	11.34
	VanillaFCNN	430.56	13.71	1.52	13.56
	StackedCNN	285.37	9.05	5.51	8.50
	Transformer	267.64	8.28	6.37	7.65
Down Allocation	UNET	262.71	7.52	4.71	7.05
	VanillaCNN	290.88	8.71	4.79	8.23
	VanillaFCNN	345.38	10.50	4.77	10.03
	Transformer	351.15	10.69	4.59	10.23
	StackedCNN	270.28	8.16	9.92	7,17

Table 7. Comparative metric results for up and down forecast.

	Architecture	PPG %	PPG M %	PPG S %	PPG Positive %
Up Allocation	UNET	47.00	3.60	47.39	47.00
	VanillaCNN	33.83	2.76	34.11	33.83
	VanillaFCNN	21.01	0.69	21.19	21.01
	StackedCNN	47.86	-261.16	50.60	0.00
	Transformer	52.27	-317.32	55.55	0.00
Down Allocation	UNET	42.07	1.65	43.62	42.07
	VanillaCNN	32.89	0.01	34.15	32.89
	VanillaFCNN	19.09	0.40	19.81	19.09
	Transformer	17.63	4.18	18.15	17.63
	StackedCNN	37.12	-106.92	42.64	0.00

Within the validation time, best model results can be summarized by: 285

Table 8. Model Results and (allocated) values wthin 2019-2022.

	mean	std	min	max
Down Allocation (MW)	(542.59) 387.28	(126.09) 189.23	(363.00) 0.00	(946.00) 1711.80
Up Allocation (MW)	(623.68) 391.31	(152.39) 157.08	(419.00) 0.00	(958.00) 1797.19
Hourly Capacity (MW)	(1166.27) 778.59	(250.19) 213.68	(816.00) 174.85	(1891.00) 2281.04
Extraordinary Down Energy (MWh)	(169.93) 82.20	(153.95) 60.80	(0.10) 0.01	(1226.40) 333.51
Extraordinary Up Energy (MWh)	(139.31) 56.46	(136.45) 41.46	(0.40) 0.03	(922.80) 212.13

The proposed model presente an overall improvement of ~47% in upward allocation 286
amd ~42% in downward allocation, comparing to current allocation methods. 287
Where the hourly means differences between benchmark and validation results are: 288

Table 9. Mean Δ% between model and benchmark

	Δ%
Down Allocation (MW)	-28.62
Up Allocation (MW)	-37.26
Hourly Capacity (MW)	-33.24
Extraordinary Down Energy (MWh)	-51.62
Extraordinary Up Energy (MWh)	-59.47

Average hourly improvements are of ~37% and ~29% respectively, which also is an 289
improvement on state of the art [14] with 13% and 8%. The current study can free in 290
average ~33% of hourly resources, lowering the need to activate the third reserve in ~52% 291
and ~59%. 292

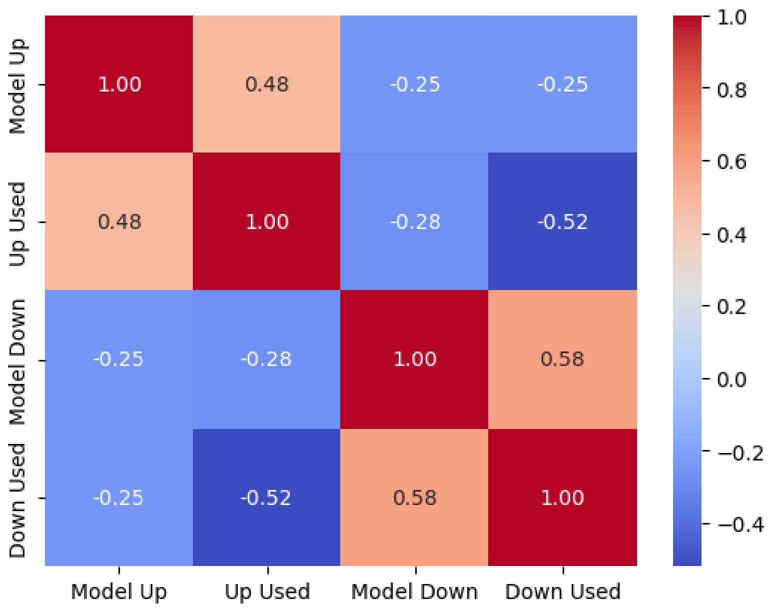

Figure 7. Attribute correlation

We can also check that the correlation between used and alocated is bigger than in the 293
current method, achieving 48% in upward energy and 58% in downward. 294

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:

aFRR	automatic Frequency Restoration Reserve
CNN	Convolutional neural network
DA	Day-Ahead
DAM	day-ahead markets
ENTSO-E	European Network of Transmission System Operators for Electricity
ESIOS	*Sistema de Información del Operador del Sistema*
FCR	Frequency Containment Reserve
IDM	intraday markets
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
mFRR	manual Frequency Restoration Reserve
MIBEL	*Iberian Market of Electricity*
MSE	Mean Squared Error
MSLE	Mean Squared Logarithmic Error
OMIE	*Operador del Mercado Ibérico de Energía - Pólo Espanhol, S.A*
OMIP	*Operador do Mercado Ibérico de Energia Português*
PV	solar photovoltaic
REE	*Red Eléctrica de España*
REN	*Redes Energéticas Nacionais*
SDG	Sustainable Development Goals
TSO	Transmission System Operators
vRES	variable Renewable Energy Systems

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