Demand Response Aggregator Participation Strategies in the French Electric Day-Ahead Market

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***Abstract*—This paper focuses on providing tools for the Demand Response Aggregator (DRA) and establishing an optimised strategy to maximise expected revenues. The authors concentrate on the French market, where the role of the Aggregator has been operational for several years, providing Demand Response and enabling demand flexibility. A thorough analysis is conducted of the mechanism through which DRAs participate in the Day-Ahead Market (DAM) to trade *energy* in the form of flexibility. This mechanism operates under defined rules, allowing DRAs to employ certain strategies and optimise their operations. Under this premise, the French context is analysed, and a DAM price predictor is defined to estimate prices before the DAM closure time. This, combined with existing mechanisms, enables the DRA to anticipate and implement its bidding strategy. As a result, the potential earnings that the DRA could achieve are quantified and analised, which can subsequently incentivise and mobilise end consumers to offer flexibility to the system. The DAM price predictor provides robust results and is a tool that a DRA can utilise.**

***Index Terms*—Demand Response Aggregator, Flexibility, Electricity Markets, Probabilistic Forecasting, Quantile Regresion**

I. Introduction

Currently, due to the need to balance electric generation and demand in real time at all hours, numerous options have been researched to meet this requirement, such as balancing services [1] and real-time technical constraints imposed by the system operator (SO) to ensure grid stability [2]. One of the options to balance the generation and the demand involves the role of the independent aggregator, who, under the concept of flexibility and active demand response, participates in the electricity markets [3].

France is the European country that pioneered the implementation of the small energy assets' aggregator role. Nowadays, these providers are already operating and have defined rules [4]. Among these rules is the Block Exchange Notification of Demand Response (NEBEF, by its French acronym) mechanism, which allows Demand Response Aggregator (DRA) to participate in the Day-Ahead market (DAM) to sell energy (flexibility) and compensate the retailers for the variations caused in their forecasted demand. The NEBEF mechanism was set in 2014 [5].

In this paper, the NEBEF compensation mechanism is explored, and a price prediction model for the DAM is implemented using public data provided by the French system operator (RTE) and the European Network of Transmission System Operator for Electricity (ENTSOE) transparency platform. This prediction model aims to help the aggregator determine the optimal times to participate in the DAM and sell flexibility from end consumers, considering the NEBEF mechanism. This article focuses on DRAs that include remotely read consumers, as the NEBEF mechanism operates differently for this type of consumer compared to profiled consumers [5]. This paper aims to identify an optimal participation strategy in the French day-ahead market through the use of the NEBEF mechanism.

II. Demand Response in the French Electric Day-Ahead Market

In mainland France, any consumption site can participate in the energy markets following the rules of the NEBEF mechanism by providing Demand Response (DR) in exchange for remuneration on energy markets, either through over-the-counter transactions or via day-ahead and intraday power exchanges, on fair and equal terms with generation, without requiring the approval of suppliers.

There are two routes to participation:

- Become a DRA directly, provided the site has a minimum load reduction capacity of 100 kW.
- Engage a third-party DRA and participate indirectly. In this scenario, the consumption site receives payment in accordance with the terms of the contract established with the DRA.

The main actor in the NEBEF mechanism is the DRA, who manages the consumption of its customers and sells the resulting load reduction—treated as if it were actual energy—on the energy markets. The DRA acts as a third-party intermediary between the final consumers and the retailer. In practice, the DRA offers demand response blocks on the energy markets and declares its response schedules to the SO. The NEBEF mechanism facilitates the exchange of these "energy blocks" between the DRA and the electricity supplier of the consumption sites involved. The mechanism is designed to respect the reserve procurement process, meaning that the operator is not necessarily contracted with the same balance responsible party as the consumers they manage. Consequently, their actions

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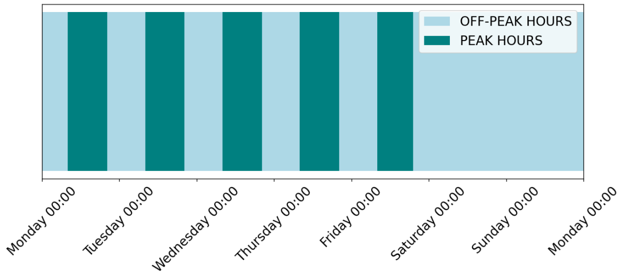

Figure 1. Weekly distribution of Off-Peak hours and Peak hours for remotely-read consumers [6] [7]

may impact the imbalance of the balance responsible party of the consumers. Pursuant the French Energy Code, DRA pay a fixed compensation defined by the NEBEF to electricity suppliers that are directly affected by DR activation. Finally, the SO is responsible for verifying the actual load reduction achieved by the DRA.

The NEBEF compensation price is set in advance by RTE. This price is also dependent on the hour and day on which the provision of flexibility is taking place. This relationship with day and hour is determined by whether the system considers it an "Off-Peak period for Remotely-Read (OPRR) consumers or a "Peak" period for Remotely-Read (PRR) consumers. Fig 1 illustrates the temporal axis showing the designated periods throughout a week. The system operator (RTE) designates weekdays from 08:00 to 19:59 as PRR and weekends and national holidays as OPRR [6] [7]. Table I illustrates the historical NEBEF compensation payment for the different moments of the year, values shown are in €/MWh.

There are several methods of performance control for the real load curtailed by the DRA during a DR event. The most used method consists in comparing the following two curves:

- The reference curve: is the minimum between the mean electric loads just before (past reference) and just after (post reference) the DR event, over a period of time equal to that of the demand response event.
- The demand response curve: is the mean electric load during the DR event.

This estimation method is called the corrected double reference method and is used by RTE in order to quantify the real power reduction achieved by the consumer. DR events cannot exceed a maximum of two hours per block and the duration between two DR events must not be less than the maximum duration of the two bids. Fig. 2 illustrates the calculation of the load curtailed.

TABLE I
NEBEF Compensation payment in €/MWh for Remotely-Read consumers

Year	WINTER		SUMMER	
	OPRR	PRR	OPRR	PRR
2025	62.00	98.91	50.40	51.60
2024	80.47	170.99	64.08	78.09
2023	160.00	376.00	117.00	151.00
06/2022 - 12/2022	54.79	104.09	45.67	74.41
01/2022 - 05/2022	91.12	142.16	71.49	98.50
2021	43.69	53.81	38.68	43.90

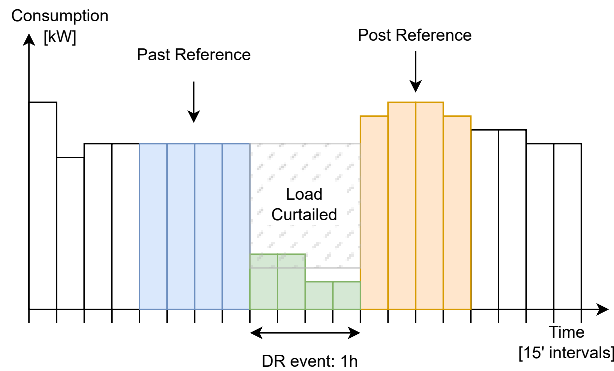

Figure 2. Ilustration of the calculation of the load curtailed

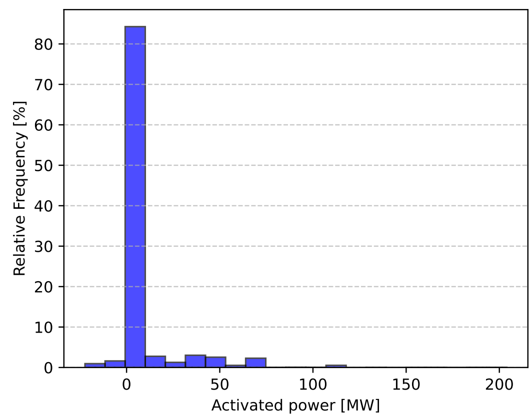

Figure 3. Relative Frequency Distribution [%] of power called through the NEBEF mechanism during 2024 [10]

Under the structure of this mechanism, some optimisations have been developed by small end-consumers in order to participate in DR events [8] [9].

During 2024, 24.55% of the time the NEBEF mechanism was used to trade some flexibility by the DRAs. Fig. 3 shows the relative frequency of the traded power quantity. Positive values indicate upward direction for the electric system (consumption decrease), while negative values indicate downward direction for the system (consumption increase). The maximum power traded at a certain moment was 204 MW. If the analysis is filtered by days, it is found that the NEBEF mechanism was called at least during one time interval in 296 days of the entire year. This indicates that in 296 days, a certain flexibility was traded using this mechanism. This is normal, as certain hours are typically more likely to be called upon to provide flexibility (those where the DAM price exceeds the compensation price). The moment of day when the most flexibility is traded on the greatest number of occasions using the NEBEF mechanism is between 23:00 and 00:00. Flexibility was traded on 200 days during that moment of the day [10].

III. Methodology

To define the participation strategy, the DRA must first be able to determine beforehand whether there will be interesting

TABLE II
DAM PRICE MODEL EXOGENOUS VARIABLE

i	Variable	Unit	Source	Publication Time
1	Consumption forecast for day D+1	MWh	RTE	07:00
2	Interconnection exchanges schedule for day D+1	MW	RTE	10:00
3	Total Nuclear generation availability for day D+1	MW	RTE	06:00
4	French DAM price for hour h on day D	€/MWh	ENTSOE	13:30 (D-1)
5	Swiss DAM price for hour h on day D+1	€/MWh	ENTSOE	11:10

prices in the DAM to which flexibility can be offered. This translates to knowing whether the DAM will exceed the NEBEF compensation price and by how much. With this, the DRA makes the decision of whether to provide flexibility at a certain moment of the day and decide the incentives to offer to the end-consumers to incentivise their mobilisation. For a specific hour, the difference between the DAM price and the NEBEF compensation price must be split between the end-consumer (incentive for mobilisation) and profit for the DRA. With this objective in mind, a price forecast model is designed.

A. DAM Forecasting models

The accurate prediction of day-ahead electricity prices (EPF) is critical in liberalised markets for enabling effective bidding strategies and optimising operational costs. Recent advancements have focused on leveraging computational intelligence and statistical models to address the complex nature of electricity price dynamics.

The aim of this price forecast can be multiple. Prices can be predicted to offer electric generation and enter the market, they can be predicted to schedule consumption for the next day, particularly if as a consumer they have a market-indexed tariff, they can be predicted for flexibility purposes, etc. In this case, the focus is on attempting to predict for this latter objective, always taking into account the NEBEF mechanism. In other words, the objective is not to accurately predict the DAM price with the highest possible precision for all hours, but rather to predict with the greatest certainty during which hours the price will exceed a certain level (the compensation price of the NEBEF mechanism).

In this context, multiple approaches are explored in European markets. Authors in [11] explore the Bayesian deep learning method for probabilistic forecasting addressing heteroscedasticity through dedicated neural network structures. This approach is applied for the Italian and Belgium markets. Comparatively, authors in [12] explored traditional and advanced machine learning techniques such as ARIMA, multiple linear regression, and XGBoost in the Turkish electricity market. This study underscores the importance of incorporating exogenous variables like cross-border electricity prices for enhancing forecast accuracy. Authors in [13] discuss Quantile Regression (QR) models, applied to the markets of Portugal and Spain, with very good results. They highlight the importance of not relying solely on ML and adding explanatory and understandable variables, a sort of hybrid model that the QR model allows. The authors in [14] were the first to use QR models to estimate DAM prices along with prediction intervals.

Focusing on papers related to French markets, the authors in [15] stress the importance of considering whether it is an OPRR or PRR period for their predictions, and also note that for central European markets, it is interesting to use the Swiss market price, as it becomes available before the others. The authors in [16] also examine some of the exogenous variables that best help predict the DAM market price in France.

The literature highlights a growing trend toward complex hybrid and probabilistic approaches in EPF, often prioritizing computational power over interpretability. However, the DAM market remains predictable and explainable for now. This paper intentionally sets aside overly complex AI models whose results lack transparency, focusing instead on interpretable models that provide clear insights into market dynamics.

QR models are considered an interesting tool for predicting DAM prices, as they are able to calculate the expected value for previously assigned quantiles. These quantiles are calculated using a significance level and adjusting the cost function (in this case, minimize the MAE) to the quantile to be calculated. Furthermore, by leveraging linear regression models, which are quite explanatory, it allows for tracing and quantifying the likelihood of occurrence of certain price ranges. These models are the ones chosen to be used by the authors in this article.

B. French DAM price forecast

Fig. 4 shows an example of 10 days data, where the NEBEF compensation prices and the DAM clearing price are shown.

The model developed for this purpose uses the input data (exogenous variables) presented in Table II. The value of the

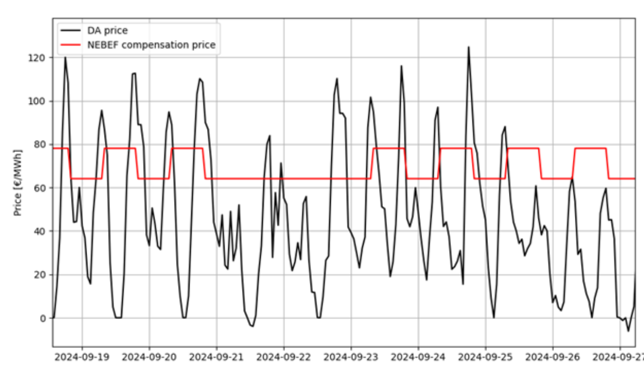

Figure 4. NEBEF compensation price vs French DAM price

exogenous variable $i = 5$ can be obtained because the Swiss DAM is cleared around 11:00 (UTC+1) and published around 11:10, 50 minutes before the French DAM closes.

These exogenous variables are those that, having conducted a correlation analysis with the hourly DAM price, exhibit the highest correlation with the target variable being predicted. This correlation analysis and intermediate results fall outside the scope of this article. The exogenous variables used in the model reflect key characteristics of the electric system. However, temporal exogenous variables, such as local holidays and seasonal patterns, are also incorporated.

For this analysis, data from 01/01/2023 to 01/01/2025 are used. Data up to 01/10/2024 are used to train the model, and the months of 10, 11, and 12 of 2024 are used as test data, simulating "out-of-sample" predictions from that date on, even if it is a backtest simulation.

Based on the models reviewed, it is decided to build a QR model for the prediction task. QR models provide a robust framework for analysing the conditional distribution of a response variable by estimating its quantiles as functions of one or more predictor variables. Unlike ordinary least squares regression, which focuses solely on modelling the conditional mean, quantile regression captures the variability in the response variable across its distribution. The method minimises an asymmetrically weighted sum of absolute residuals, allowing for the estimation of conditional quantiles at specified levels.

In this instance, they are interested in ascertaining the degree of probability or confidence interval by which they are above or below the NEBEF price, thereby rendering this model ideal. Consequently, they aim not only to minimise the error of the median but also that of the various percentiles, with a focus on the 2.5% and 97.5% percentiles.

IV. Results

Fig. 5 graphically illustrates the output of the DAM price forecasting model. The model provides three price values for each predicted hour: a median value or 50th percentile, and then a higher value at the 97.5th percentile and a lower value

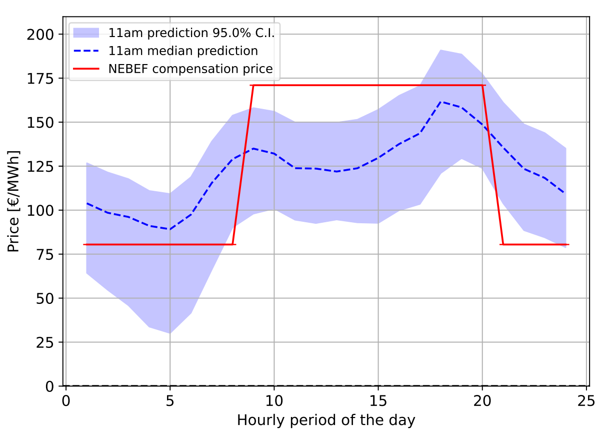

Figure 5. NEBEF compensation price vs French DAM price at 21-11-2024

at the 2.5th percentile. The blue band therefore represents the prediction with a 95% confidence interval.

The most interesting value is that of the 97.5th percentile, as it will enable us to determine whether the aggregator can go to the DAM to sell flexibility and when it cannot. The 50th percentile and 2.5th percentile values are also of interest, as they will define the margin that the DRA can discuss with its customers to request flexibility. The relationship between price and the various market elements is established by Equation (1):

$$\text{DAM} - \text{NEBEF} = \text{DRA revenue} + \text{flex. incentive} \quad (1)$$

Despite being a relatively straightforward and simple equation, this article delves deeper into the left-hand side, where the objective is to maximise that part. As NEBEF compensation payment is known in advance, energy should be traded during the hours when the DRA is certain that DAM - NEBEF term is mazimised. The right-hand side of Equation (1) and how to incentivise the end-user are left out of the scope, although incentives on the end-user's flexibility could potentially be part of the optimisation process. Equation (2) represents the mathematical problem being addressed.

$$i^* = \arg \max_{i \in \{1,\ldots,24\}} (\text{DAM}[i] - \text{NEBEF}[i]) \quad (2)$$

Focusing in Fig. 5, the results for 21 November 2024 are shown, in addition with the representation of the NEBEF compensation price. Visually, it is apparent at which times of the day the DRA has a probability of doing business through submitting bids. Furthermore, in these cases, the 97.5th percentile limit is above the compensation price that the DRA must pay to the retailer.

The predictor's performance yields a Mean Absolute Error (MAE) of 14.03 €/MWh, a Root Mean Square Error (RMSE) of 20.51 €/MWh, and a Daily Mean Absolute Percentage Error (DMAPE) of 22.67%. These values are obtained by comparing the median of the predictor's output against the actual value observed in the DAM. Fig. 6 illustrates the price forecast for a week, alongside the price ultimately cleared by the Day-Ahead Market (DAM). Each forecast is made at 11:15 on each day for the following day.

However, this is not the only aspect that is being evaluated. The aim is for the predictor to be useful for the DRA in trading flexibility. In this regard, it is found that 99.8% of the time, when the predictor indicates that the 97.5th percentile of the prediction will be above the NEBEF, it indeed is.

On weekdays, the most interesting hours for this purpose are the ones immediately preceding the start of the PRR period (06:00-06:59 and 07:00-07:59) and those immediately following the end of the PRR period, at the end of the day (20:00-20:59 and 21:00-21:59). Fig. 7 illustrates the relative frequency distribution of the hourly periods at which Equation (2) has been met for the dates under analysis.weekends and local holidays, the periods 18:00–18:59 and 19:00–19:59 have also been identified as particularly relevant for trading flexibility, as these correspond to OPRR periods.

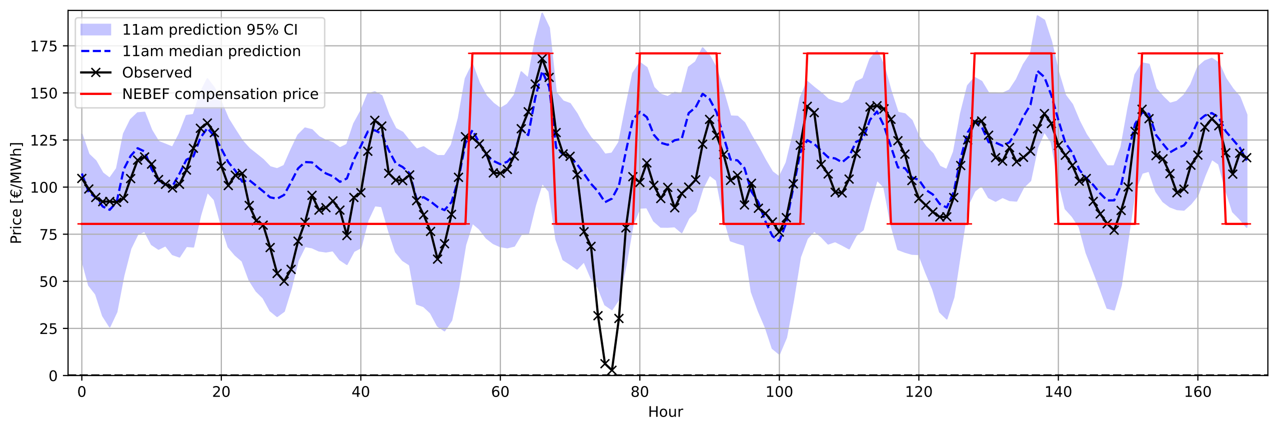

Figure 6. NEBEF compensation price vs French DAM price at 21-11-2024

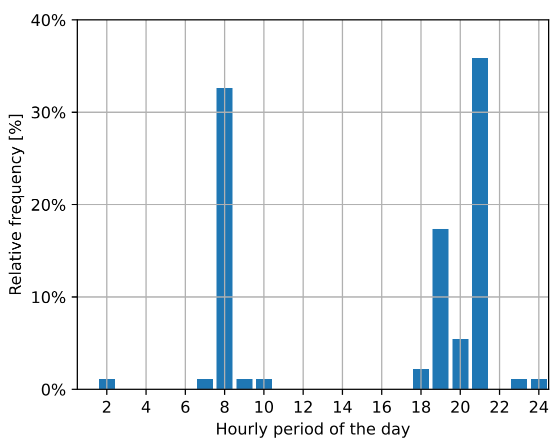

Figure 7. Relative Frequency distribution of the hours with the highest expected revenue

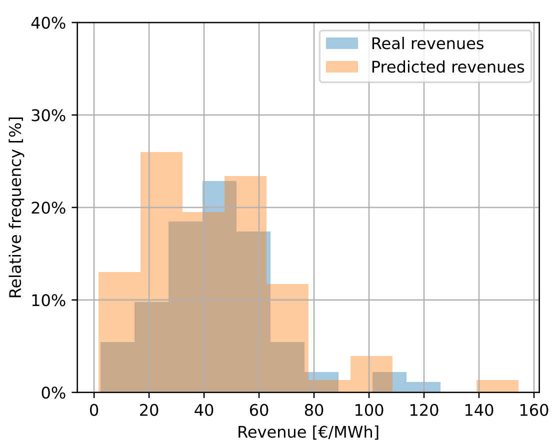

Figure 8. Relative Frequency distribution of the daily highest expected revenue

However, in most days, there are two distinct moments during the day when it is interesting to engage in this trading, one early in the day and another late in the day. Furthermore, this is subject to the limitation that DRA must wait for a period of time longer than the maximum duration of the two expected bids, as explained in Section II.

In periods where the price is expected to exceed the NEBEF price, the mean expected return is 44.70 €/MWh (0.0447 €/kWh), which is to be shared by the DRA between its own revenue and the incentive offered to the end-user to deliver the desired flexibility. Fig. 8 illustrates, for the analysed three month period, the relative frequency distribution of the hour with the highest expected revenue. Two distributions are shown: one representing the actual maximum 1-hour revenue observed each day, and the other the maximum 1-hour revenue predicted by the algorithm. The similarity between both distributions indicates that the algorithm successfully identifies the most profitable time slots. In this context, if the DRA follows the algorithm's recommendation and schedules energy trades during the predicted peak revenue hour, it consistently obtains high revenues. Moreover, since the predicted distribution is entirely located in the positive revenue domain, this implies that the DRA would never incur financial losses when applying this strategy.

V. Conclusions

The analysis presented highlights the critical role that DRA play in enhancing demand-side flexibility within the French electricity market. By leveraging the NEBEF mechanism, these entities facilitate the efficient integration of demand response into the market. This can be integrated in flexible demand resources and flexibility initiatives.

This approach presents preliminary results of using a QR model for predicting the DAM price, focusing on identifying when the DRA have an opportunity to trade flexibility in France and the potential gain that could be obtained. The approach provides interesting results and lays the groundwork for optimising this process. The interaction between the DRA and the end user could incorporate various ideas, such as exchanging this energy in a local flexibility market.

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