Deep Learning-Based Imbalance Market Price Range Predictions in the Day-Ahead Horizon

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***Abstract*— Variable Renewable Energy (VRE) sources are characterized by production uncertainty that is largely due to weather forecast errors. This leads to greater volumes in the real-time balancing markets that drive Imbalance Market (IM) price higher, creating economic opportunities for flexibility providers. However, lack of information on foreseen IM prices and regulation states at the time of day-ahead market closure, reduces the flexibility providers' opportunity of optimizing their portfolio. The objective of this paper is to investigate to which extent there is a correlation between the IM prices and weather parameters in the Dutch Imbalance Market. A Deep Learning (DL) model based on Feed-Forward Deep Neural Network (FFDNN) is developed with the aim to support VRE asset owners and flexibility providers to predict IM price ranges and regulation states in the day-ahead horizon. The parameters considered are temperature, solar radiation, wind speed, relative humidity, and cloud cover. A benchmark model using Support Vector Machine (SVM) is used to compare with the DL's model performance. Both models are trained and tested using data from the weather prediction model provided by Royal Netherlands Meteorological Institute (KNMI), and historical IM prices from the Dutch Transmission System Operator (TenneT), for the years 2018-2020.**

Keywords—Deep Neural Network, Imbalance Market, Machine Learning, Metrological Parameters, Support Vector Machine

I. INTRODUCTION

The urgency to meet decarbonization goals are reflected in energy policies that drive the increasing penetration of renewable energy (RE) production around the world. Despite relatively high investment costs, the associated environmental benefits and low operating costs have promoted RE development. Hence, the European wind and solar capacities are expected to increase by 8% and 13% respectively in 2021 [1]. In the Netherlands, which is the focus of this paper, the capacity of solar and wind installations in 2020 increased by 7.3 GW from 2019, leading to a significant energy generation increase from both resources by 40% [2]. This growth is mainly driven by the energy policies in place, such as the Dutch Renewable Energy Support Scheme (SDE+/++) [3]. This increase in energy production allowed Netherlands to be a net exporter in 2020 for the first time since 1981 [2], which is expected to impact electricity markets.

The unpredictability of solar irradiation and wind speeds lead to great uncertainties in variable renewable energy (VRE) production. These production errors result in deviations from the positions traded in day-ahead wholesale electricity markets, leading to higher volumes in the real-time balancing markets. Researchers showed that weather forecasts impact electricity prices [4], through influencing electricity demand [5], and by using electricity pricing models that forecasts day-ahead spot market prices [6], [7]. Since VRE generators forecast their production 12-36 hours before actual delivery to participate in the spot market, errors in production are expected due to errors in the weather forecast. These errors elevate the need for balancing power, where renewable generators are exposed to imbalance settlement charges [8].

Furthermore, the higher demand for balancing power drives the Imbalance Market (IM) prices higher, creating opportunities for flexibility sources, such as demand response, electric storage and electric vehicles. These flexibility sources can participate in the IM separately or coordinate their bids through energy arbitrage models to optimize their flexibility in sequential markets [9]–[12] such as day-ahead and intra-day markets. However, the main challenge they are facing is the lack of information regarding the next day's IM prices, which is required by the time of day-ahead market gate closure. There are a number of published models for price forecasting in the day-ahead horizon, with greater interest in the intraday market [13]–[17], compared to the imbalance market [18], [19], while both are still limited compared to the day-ahead price forecasting methods in the literature. This could be explained by the high volatility and prediction complexity of IM prices as suggested in [18]. Due to their high variance, current models can only partially capture their stochastic behaviour [19].

Machine Learning (ML) methods have been proposed in the literature as alternatives to statistical methods for electricity price forecasting, mainly for day-ahead markets. A summary of electricity price forecasting models is presented in [20], which is divided into several types with the most common being statistical models that include regression models, and computational intelligent (ML) models that include feed-forward deep neural networks (FFDNN), recurrent neural network (RNN), fuzzy neural networks and support vector machines (SVM). The majority of ML techniques, particularly deep learning (DL) architectures, require large data sets for model training which is not a prerequisite for SVM models [21]. The literature includes several applications of ML methods to electricity price forecasting. In [22], a fuzzy neural network model for the Spanish electricity market price prediction is proposed. In [23] the authors predict hourly electricity prices for January 2006 in the Australian market by training a multilayer neural network on 2005 data that consists of temperature, total demand, gas price and electricity price. The Belgium market data is used in a benchmark study in [24] that compare FFDNN and RNN to several statistical and ML models, where results showed that FFDNN and RNN models perform significantly better than most of the other methods, with FFDNN outperforming RNN.

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There are many exogenous factors that have a direct effect on IM price prediction. These factors include weather parameters, load forecasts, and unplanned power plant outages. In this paper, the focus is given to the weather parameters, particularly temperature, solar radiation, wind speed, cloud coverage, and humidity. These parameters have a direct effect on the output of VRE sources, and thus investigating the co-relation between these parameters and the IM prices is relevant.

DL approaches can be used to learn the non-linear relationships between inputs and outputs by constructing non-linear functions that approximate the real relationships between inputs and outputs within a sufficient network size [25]. To the best of the authors' knowledge, research on day-ahead horizon prediction for imbalance markets is still limited. The aforementioned work in the literature to predict day-ahead IM price [18], [19] does not retrieve valuable information for flexibility providers. The use of price ranges, rather than exact values, in the day-ahead horizon may be an alternative solution to overcome the volatility of the IM's prices. It reduces the complexity of the prediction problem by transforming it into a classification problem. A similar classification approach has been introduced in [26].

The contribution of this paper is twofold: firstly, to investigate to which extent there is a correlation between the IM and weather parameters in the Netherlands; secondly, to propose a DL model that supports (renewable) energy producers and flexibility providers to reach a coordinated bidding strategy for spot and imbalance markets by providing IM price range and regulation state predictions in the day-ahead horizon. The DL model uses FFDNN to capture the highly non-linear relationship between the IM and the five above-mentioned weather parameters: temperature, solar radiation, wind speed, relative humidity, and cloud cover. In order to assess the performance of the DL model, a SVM model is developed to serve as a benchmark to compare the DL's results. The models are trained and tested using Dutch weather predictions provided by the Royal Netherlands Meteorological Institute (KNMI) and IM prices from TenneT TSO for years 2018-2020.

The rest of the paper is organised as follows: Section II introduces the Dutch electricity markets, and the weather prediction model developed by KNMI. Section III presents the methodology adopted in this paper and describes the proposed DL model. In Section IV, results of the implementation are discussed, and conclusions are drawn in Section V.

II. Dutch Electricity Markets and Weather Forecast

This section provides an overview of the Dutch electricity markets and particularly the imbalance market. It also explains the weather forecast HARMONIE-AROME model developed by KNMI to forecast meteorological parameters with hourly resolution up to 48 hours ahead. The IM prices and regulation states along with KNMI's weather parameter forecasts are used as inputs to the proposed DL model discussed in section III.

A. *Electricity Market Organization in the Netherlands*

The Dutch electricity market includes long-term futures market, day-ahead (spot) market, intraday market, and real-time market for balancing purposes which is operated by Transmission System Operator (TSO), TenneT. Futures markets allow the demand and generation owners to hedge against price volatility by trading large energy volumes for months and years ahead. The rest of the demand and generation are matched in the day-ahead market as hourly products, which closes at 12:00 during the day before delivery (D-1), as shown in Fig.1. The intraday market continuously matches buy and sell offers after closure of the day-ahead market clearing, up to 5 minutes before delivery. This allows energy traders to make use of updated weather forecasts.

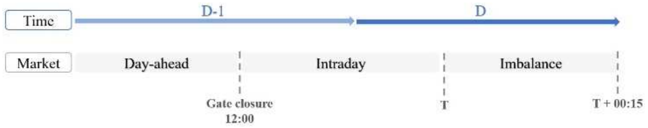

Fig. 1. Electricity markets

On the day of delivery (D), deviations from the day-ahead predictions may occur, where the actual energy delivery may be higher or lower than originally declared in the day-ahead market and possibly adjusted through the intraday market. Accordingly, real-time balancing markets and mechanisms are used by the TSO to activate upward or downward regulation and reserve power through Balance Service Providers (BSP). BSPs are the market party from which TenneT activates power for its balancing task [27].

In this work, the focus is given to the imbalance market, where 15-min products are traded in Imbalance Settlement Periods (ISP), also known as Programme Time Units (PTU). There are four regulation states that define the direction of activation: -1, 1, 0 and 2 [27]. A downward regulation state '-1' means that downward reserves are activated, which is caused by abundant generation or decreased demand. An upward regulation state '1' activates upward reserves when there is a shortage of generation or increase of demand. A zero-regulation state '0' indicated neither upward nor downward activation was required in that PTU, while regulation state '2' indicates there is activation of both upward and downward reserves.

Imbalances may occur due to several reasons, such as forecast errors in demand or generation, or unplanned generation or interconnector outages. The increased penetration of VRE sources with inherent prediction errors due to forecasts that are made 12-36 hours before the actual energy delivery cause deviations between the forecast at spot market closure and the real production. These sources are mainly solar PV and wind generators that predict their production according to weather forecasts published at gate closure time.

B. *Meteorological Parameter Forecast*

The weather forecasts are produced by the weather prediction model developed by the HIRLAM-ALADIN consortium and run at KNMI, HARMONIE-AROME, version CY40h1.1.1. The main components of the model are described in [28]. HARMONIE-AROME runs 8 times per day and produces forecasts up to 48 hours ahead, which become available around 2.5 hours after observation/analysis time. The true forecast horizon therefore is around 45 hours. HARMONIE-AROME is a non-hydrostatic model that runs on an area of 2000x2000 km^2 at a spatial resolution of 2.5x2.5 km^2. Lateral and upper boundaries are provided by hourly output data from the ECMWF model [29]. The model runs are cycled; a short-term forecast from the previous cycle is the first guess for the next analysis. The initial conditions are determined through a 3D-Var analysis. The different data-assimilation possibilities in limited area models are described in [30]. Every model run produces hourly output from hour 1 to hour 48. In a next version of HARMONIE-AROME 10–15-minute output will be produced to better suit the renewable energy market. In this study only the deterministic output was used, to mirror the most straightforward use of forecasts by market actor. Note that KNMI also produces ensemble forecasts with HARMONIE-AROME. These ensembles can give a more detailed, probabilistic insight into the predictability of the weather and hence the associated renewable power production.

HARMONIE-AROME is reasonably good in predicting parameters like wind and temperature; see e.g.: [31], where prediction errors for the 10-m wind speed have a typical standard deviation of 2-2.5 m/s for the stations in the European area, while 2-m temperature error is in the range of 1.5-2.5 K. However, a parameter like short wave downward (solar) radiation is a bigger challenge as clouds in weather models are very sensitive to the setup of the model, and cloud cover is very changeable in nature.

For the prediction of renewable energy production, forecasts for the global horizontal solar radiation and the wind speed at 100-, 200- and 300-meter heights are made available. (Note that the values at 100 m height are most suitable for wind power prediction.) Current forecast data can be retrieved from the KNMI open data portal [32].

III. Methodology

The objective of this paper is to forecast potential opportunities in the next day's imbalance market by predicting IM price ranges within a day-ahead prediction horizon. The proposed methodology consists of three consecutive phases as presented in Fig. 2. First, the input data for three years (2018-2020) is analyzed and processed. Then, it is divided into a training and validation set (2018-2019) and a testing set (2020). In the second phase of the methodology, ML models are developed and trained using the training set. The main model is a feed-forward deep neural network (FFDN); next to that a support vector machine (SVM) model serves as a benchmark to validate the results of the FFDN. In the final phase, both ML models' performances are tested using the test dataset and their prediction accuracies are compared.

A. Data Analysis

As shown in Fig. 2, there are two types of input data that are processed in the first stage: (i) IM prices and regulation states from TenneT [33], and (ii) weather parameters from KNMI. The data analysis and processing involve setting assumptions and adapting the raw data for the application.

1) Imbalance Market Data:
Firstly, since hourly products are traded in the spot market, hourly IM representations must be created first. Each four consecutive 15-minute PTUs are merged to represent an hourly value. The aim is to represent the available IM opportunities appropriately with upward regulation +1, downward regulation -1, or no regulation 0. The hourly representation is triggered either by the dominant state if found (that occurs most frequent within the four PTUs), or by the state with the greater price when no dominant state is identified.

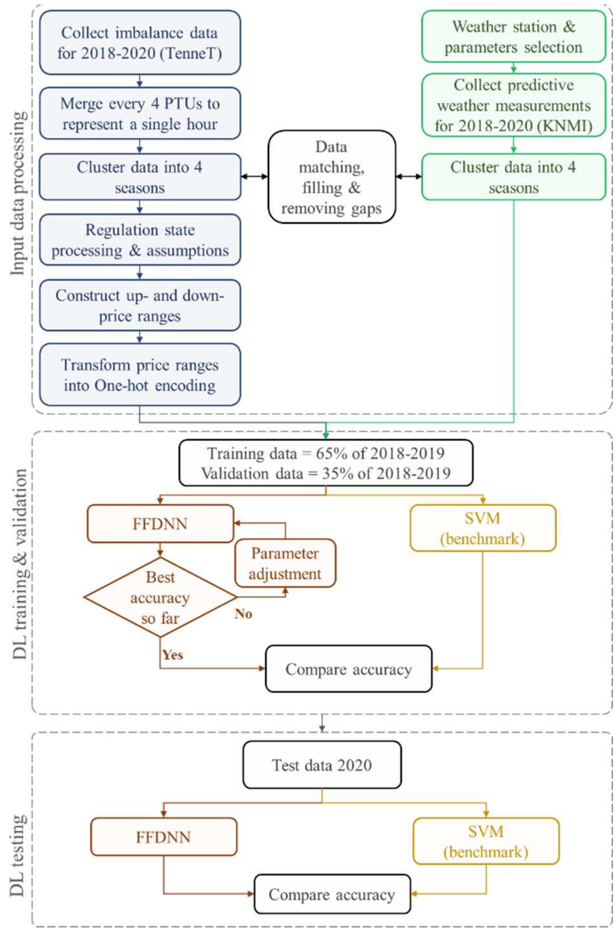

Fig. 2. Flowchart presenting methodology's steps

Fig. 3 shows the logic followed to merge the four PTUs into hourly values. It is inspired by the k-maps used to minimize Boolean expressions, but it is used here for mapping purposes. The horizontal and vertical labels represent the original regulation states of the four PTUs, i.e., PTU 1, 2, 3 and 4. The mapping represents the converted hourly regulation state. State +1 is assigned the highest up price, state -1 is assigned the lowest down price, and state zero is assigned zero price. The regulation state 2 is eliminated and converted into either +1 or -1 depending on whether the considered four PTUs are dominated by one of them. If no dominant state is identified, the conversion follows the regulation state of the PTU associated with the greatest price magnitude. This assumption is valid since flexibility providers are interested to know, during the day-ahead horizon, whether to expect the best opportunity to follow an upward or downward regulation, and accordingly plan their flexibility assets' profile.

Secondly, once the hourly PTUs are generated, they are then clustered into four seasons: Autumn (September, October and November), Winter (December, January and February), Spring (March, April and May), and Summer (June, July and August). The motivation behind seasonal clustering is to capture the seasonality effect of the data in the ML models. This assumption is valid as it enables the ML models to identify and learn the unique characteristics of every season and thus increases the accuracy of the models' predictions.

PTU 1,2 / PTU 3,4	0 0	0 1	0 -1	0 2	1 -1	1 2	-1 2
0 0	0	1	-1	2	2	1	-1
0 1	1	1	2	1	1	2	2
0 -1	1	2	-1	-1	-1	2	-1
0 2	2	1	-1	2	2	1	-1
1 -1	2	1	-1	2	2	1	-1
1 2	1	1	2	1	1	1	2
-1 2	-1	-1	-1	-1	-1	2	-1

Fig. 3. Logic of merging four PTUs.

Secondly, once the hourly PTUs are generated, they are then clustered into four seasons: Autumn (September, October and November), Winter (December, January and February), Spring (March, April and May), and Summer (June, July and August). The motivation behind seasonal clustering is to capture the seasonality effect of the data in the ML models. This assumption is valid as it enables the ML models to identify and learn the unique characteristics of every season and thus increases the accuracy of the models' predictions.

Since the IM prices are highly volatile and difficult to predict, a price range system for the upward- and downward regulation prices is proposed, which decreases the complexity of the problem. It also increases the accuracy performance of both models, DL and SVM, since the prediction of each time step is identified by a certain range, rather than the exact value. Hence, the models are designed for a multi-class classification problem. The ranges are constructed according to the distribution and dispersion of the prices of the whole data set, as illustrated in Fig. 4-6.

Fig. 4 and Fig. 5 compare the histogram plots for 2018-2019 and 2020 for the up- and down- prices per season respectively. The greatest frequency of upward prices falls in the range below 100€/MWh for 2018-2019 and is mostly concentrated in the 50-100€/MWh, whereas it falls in the range below 50€/MWh for 2020. As for the greatest frequency of downward prices, it falls in the range above -50€/MWh for all the 3 years (2018-2020). The box plot in Fig. 6 compares the distribution and dispersion of prices between 2018-2019 and 2020. For 2018-2019, the median for upward prices is between 50-56€/MWh and for downward prices it is around 0€/MWh. There is a larger interquartile range in 2020, particularly for up prices which also have a greater maximum (upper extreme). There are less outliers in the 2020 dataset with higher spreads for the down prices and lower spreads for the up prices. The changes of IM prices in 2020 are most probably related to the Covid-19 measures that also impacted the energy demand and the spot market prices [34].

According to the aforementioned insights drawn from the distribution of prices, four relevant price ranges are constructed. The first and second range, denoted μ_1 and μ_2, represent the upward regulation state with the price ranges $\mu_1 \leq 55$€/MWh and $\mu_2 > 55$€/MWh respectively. The price 55€/MWh is approximately the average day-ahead spot market price in the Netherlands, and thus is a reasonable threshold. For an energy arbitrage in sequential markets optimization, this is a reasonable proxy to indicate opportunities for flexibility providers. The third range represents the downward regulation state with negative price range, $\gamma \leq 0$. This assumption is valid since flexibility providers are expected to be less interested in downward prices that are above zero. Finally, the fourth range is the zero state with zero price, denoted ν, where $\nu = 0$.

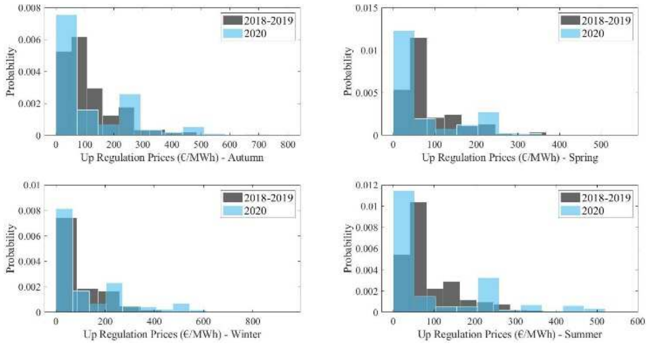

Fig. 4. 2018-2019 versus 2020 IM upward price histogram

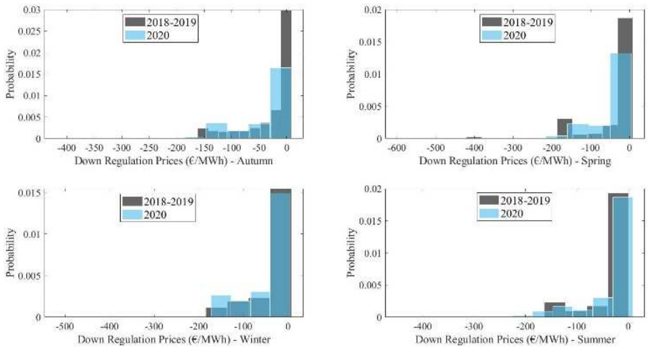

Fig. 5. 2018-2019 versus 2020 IM downward price histogram

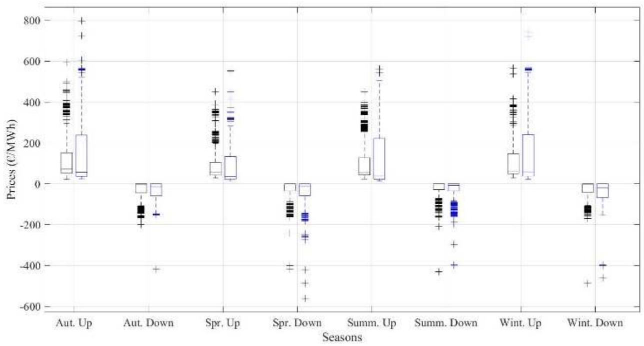

Fig. 6. 2018-2019 (black) vs 2020 (blue) IM Prices Boxplot

2) *Meteorological Data:*

The five meteorological parameters considered are: wind speed, solar radiation, cloud cover, temperature, and relative humidity. The values were extracted from two locations provided by KNMI's forecast model described in section II. Since IM are driven by uncertainty and intermittent behaviour of renewable generation (solar PV and wind), the selection of forecast locations is based on their installation capacity in the Netherlands. The greatest PV installed capacity is located in Noord-Brabant [35]. Hence, solar radiation and cloud cover measurements were collected from the location of Eindhoven's KNMI weather station. The rest of the parameters are extracted from the Lelystad weather station, which is within Flevoland. This province corresponds to the greatest wind power installation and is approximately central of Netherlands offshore and onshore locations as well [36]. The five parameters are then clustered into seasons and matched with the IM price ranges.

B. Deep Learning Model

Deep learning (DL) is one of the widely recognized machine learning methods for learning and extracting highlevel features from raw input data [37], [38]. DL models use various types of neural networks, which take input data, process it using hidden layers and assign adjustable weights during training. Finally, the DL model computes its predictions in the output layer. The structure of the DL model developed in this work is presented in Fig. 7. The model proposed follows a supervised Feed-Forward Deep Neural Network (FFDNN) architecture [39]. FFDNN flows information forward from an input layer, through multiple hidden layers, and towards an output layer. It should be noted that one of the comparable DL models to FFDNN is the Recurrent Neural Network (RNN). RNN is widely recognized for its performance in time-series applications. Even though the application in hand concerns the prediction of hourly IM prices, it is not considered a time-series problem. Hourly prices and regulation states in the IMs are not auto-correlated to previous or following hours. Even within an hour, one can witness all four regulation states taking place. Additionally, in certain price forecasting applications, FFDNN were reported to perform better than the RNN, see [24] and [40].

In the proposed FFDNN, the weather parameters are passed through a normalization layer along with the time stamps of every hour before entering the DL's input layer. Normalizing input data is common practice in DL applications that helps speed up the learning process and reduces the convergence time. The model is structured with 5 hidden layers composed of different number of neurons. In practice, there is no concrete way of analytically finding the best values for such hyperparameters for any given DL model [37], [39].

The common approach to determine such values is by systematic experimentation to discover what works best for the problem at hand. A similar approach is followed in the current application. The validation accuracy metric was used to identify the best hyperparameters, which are reported Fig. 7. The validation accuracy denoted A_v, calculates the model's accuracy to predict the true output using the validation training set, as given in (1).

$$A_{\upsilon} = \frac{Num.of\ \ correct\ predictions\ in\ validation\ set}{Num.of\ \ data\ points\ in\ validation\ set} \qquad (1)$$

The hidden layers use the rectified linear activation function (ReLu). ReLu is a piecewise linear function that is easier to train and often achieves better performance. Another key parameter that should be defined for any DL model is the optimizer. The optimizer is the algorithm used to update the model parameters, with the objective to reduce the model prediction losses. Here, the Adaptive Moment Estimation (Adam) is used, which is computationally efficient, requires less memory, well-suited for large data set problems, and it compares well to other stochastic optimization methods [41]. The Adam optimizer is used to optimize the categorical cross-entropy loss function, which is the most commonly used loss function for multi-class classification problems. Such loss function is suitable for the IM price forecasting since the output can only sit in one range. It calculates the difference between the model prediction, using a set of parameter values, and the actual value. The loss function, denoted Γ, is written in (2).

$$\Gamma = -\sum_{i=1}^{x} \alpha_i \log \tilde{\alpha}_i \quad (2)$$

Where α_i and $\tilde{\alpha}_i$ are i-th scaler value for the target and output value respectively, and   is the number of scale values in the model output. Finally, the output layer of the proposed DL model uses the Softmax activation function, which is the designated classifier function for multi-class classification problems. Before the DL model is trained, the IM training data set is one-hot encoded to make them appropriately readable to the categorical cross entropy loss function (2) [42].

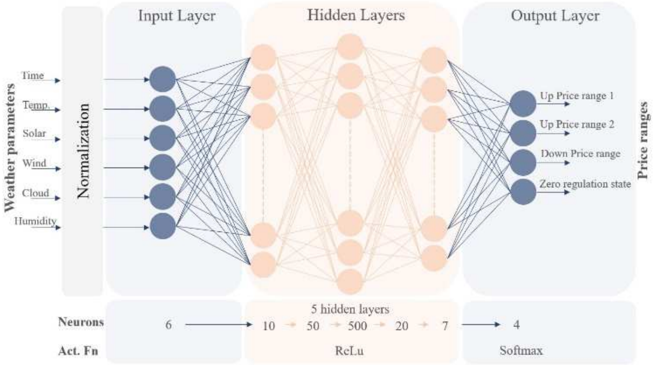

Fig. 7. DL Model Architecture for IM price classification

C. Benchmark: SVM Model

Support Vector Machine (SVM) is a supervised machine learning algorithm that is widely used for data classification [43], [44]. SVM is very often put in a comparison with deep learning in terms of accuracy and performance [45]–[47]. The basic concept of SVM is to efficiently fit a hyperplane that is able to categorize the output data [48]. SVM is widely used as a benchmark since its convex optimization method guarantees a global, and not a local, minimum.

IV. IMPLEMENTATION

Both ML models are implemented using Python language. The DL model uses the Deep Learning framework API Keras [49]. It uses a batch size of 50, with 1000 epochs to allow for a reasonable training time. To prevent unnecessary iterations, an early stopping technique is implemented, which stops training if the loss function seizes to improve. Another key hyperparameter is the learning rate for the optimizer. A good learning rate should maintain a good learning speed for the model and prevent overfitting. The value used for Adam optimizer is 1e-3, which yields the best results based on repeated trials. The SVM model uses the machine learning library scikit-learn and a Linear Support Vector Classifier (LSVC)   [50]. The LSVC is the most commonly used classifier in the scikit-learn library due to its scalability to large data sets. It uses the squared hinge loss function for optimal hyperplane fitting. The LSVC solves the dual optimization problem with tolerance 1e-4 and regularization parameter C = 1.

The datasets of 2018-2020 consist of matched one-hot encoded hourly IM prices, five hourly weather parameters (wind speed, solar radiation, relative humidity, cloud cover, and temperature), and their corresponding time stamps. Both the DL and SVM models are trained on 65% of the training data set of 2018-2019, with the remaining 35% being the validation set. Four seasonal models are developed to capture the different seasonal effects. Within each seasonal model, the number of data points is different due to gaps in the KNMI's prediction model. The input dataset for the training stage consists of 4,368 hours in Autumn, 3,648 in Spring, 4,392 in Summer, and 2,568 in Winter. The testing dataset of 2020 consists of the following data points: 2,184 each in Autumn, Spring and Summer, and 2,160 in Winter. Results for both the validation and testing for DL and SVM are presented and compared in Table I, along with a discussion on the different factors that impacted the accuracy of the prediction results.

A. Results

The training validation and testing accuracies for the proposed DL and SVM benchmark model are presented in Table I. Both models performed better during the training validation than during the 2020 testing, while the DL outperformed the SVM during all seasons. The training validation shows that prediction accuracy for Autumn is the best, followed by Winter, then Summer, whereas Spring is the most difficult season to predict the IM price ranges. This could be explained by Fig. 8 that illustrates how each input (meteorological parameter and time) influences the DL model's accuracy by eliminating it from the input dataset.

During winter, when it is the windiest time of the year, the wind speed has the greatest effect on the accuracy. By contrast, during spring, the cloud cover and solar radiation have great effects on the model's accuracy. Therefore, the inaccuracy is due to the difficulty of cloud prediction, which directly affects the solar radiation and the sunlight hours. During the spring of 2020, the number of sunshine hours were 805 hours, more than the 603 hours and 593 hours during the springs of 2018 and 2019, respectively. Hence, the solar-related weather predictions used for testing were better than those during the 2018-2019 training period.

TABLE I. VALIDATION & TESTING ACCURACIES

	Validation (2018-2019)		Testing (2020)	
	DL	SVM	DL	SVM
Autumn	41.01%	35.75%	28.16%	25.96%
Spring	31.87%	30.83%	29.49%	27.56%
Summer	34.27%	32.61%	26.24%	25.60%
Winter	37.49%	33.67%	25.79%	23.56%

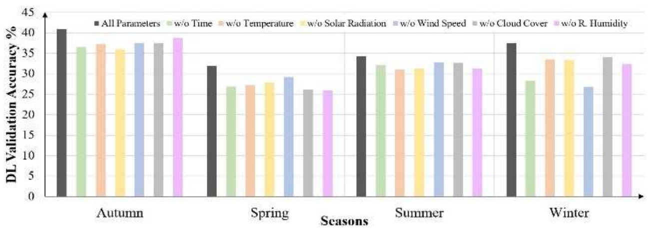

Fig. 8. Input parameter impact on DL model accuracy

Overall, Table I shows that during testing on 2020 data, the accuracy has decreased significantly with respect to the validation stage. The confusion matrix for the DL and SVM model results, illustrated in Fig. 9 and Fig. 10 respectively, show the price ranges that are mostly confused during the different seasons. The price ranges are up state Up1 ($\mu_1 \leq 55$), Up2 ($\mu_2 > 55$), down state ($\gamma \leq 0$), and zero state ($\gamma \leq 0$). The sum of the percentages for all elements in the confusion matrix equals to 100%, while the sum along each row gives the prevalence of a certain class in the data set. The main diagonal presents the percentage of correctly predicted price ranges. Summing up the values across the diagonal yields the accuracy percentages in Table I. Focusing on the Up2 and Down ranges, which are the most interesting to flexibility providers, it is clear that it is difficult to correctly predict them, and that the Down range is frequently confused with the Up2 range. IM prices fall within these ranges when weather forecast predictions vastly over- or under-estimate the correct values, which may explain why they are the most confused by one another. Moreover, it would have been more relevant to use forecast errors as inputs to the DL model, as it is the actual errors that drive the mismatch between the day-ahead and the real-time production. However, these errors are not known in advance.

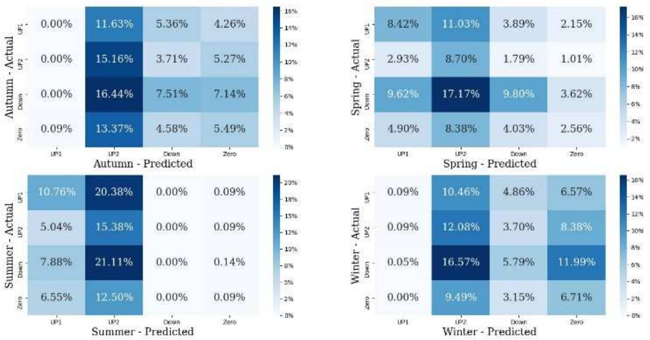

Fig. 9. Confusion Matrix for DL Model, 2020 Predictions (Testing)

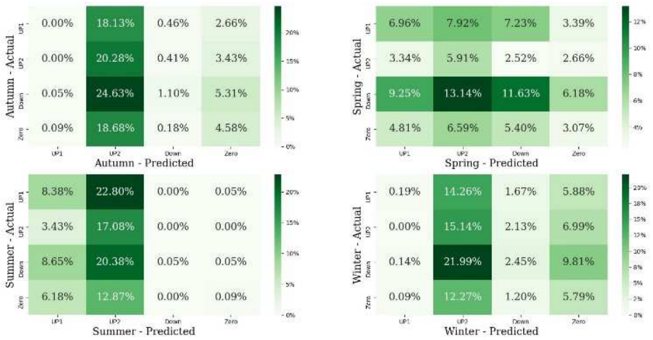

Fig. 10. Confusion Matrix for SVM Model, 2020 Predictions (Testing)

B. Discussion

As shown in the previous subsection, the DL model performed slightly better than the SVM benchmark model, despite the high volatility of the imbalance market. That being said, it is worth revisiting the assumptions, as well as the factors that can influence the performance of both ML models.

There are several endogenous factors that affect the models' performance. First, there is a clear trade-off between the models' accuracy and the price ranges considered. On one hand, more price ranges will narrow the range size, allowing more precise price estimation for flexibility providers. On the other hand, it will reduce the models' accuracy. Another design choice that has a direct impact on both models' performances is dividing the models into seasons. Since similar measurement of weather parameters can be observed in different seasons, training on a single model yielded lower accuracy. The single model led to a validation accuracy of 32.64% for DL and 30.02% for SVM. This design choice is suitable for the Netherlands, since the weather is generally cool, cloudy, and humid throughout the year.

From an exogenous perspective, the imbalance market data set for 2018-2019 has a noticeably wider variance when compared to that of 2020, as shown in Fig. 6. These differences are mainly triggered by the Covid-19 measures that impacted both the generation and demand. This has led to the testing accuracy in 2020 being lower than the training accuracy on the 2018-2019 data. The global electricity demand fell by around 2% in 2020, while the global renewable energy generation grew by almost 7% [34].

In addition, in the Netherlands, a significant increase in VRE installed capacity (7.3 GW) was witnessed during 2020 that led the Netherlands to become a net exporter of energy in 2020 for the first time since 1981 [2]. Also, since the Netherlands was a net importer during 2018-2019, it is difficult to indicate whether the Dutch weather is better correlated with the local IM volumes or the regional weather that includes that of neighbouring countries, since DA positions and the real-time realizations may not strongly correlate with Dutch weather if high volumes of DA capacity are imported from neighbouring countries. Hence, interconnections can result in a weak correlation between Dutch weather parameters and IM volumes.

A potential path to strengthen the proposed work is to include more exogenous factors in the input of the ML models. Such factors can include forecasted demand, installed capacities of different technologies, and the weather predictions of neighbouring countries weighted by the cross-border capacity. Another avenue for exploration would be to enhance the current FFDNN architecture or even try more complex ones.

Overall, the DL model proposed in this paper can serve as a decision support tool for flexibility providers to make strategic decisions. It provides a training accuracy of 31-41% depending on the season. With similar testing conditions, we expect higher accuracy than that of 2020. The accuracy is also expected to improve with larger training datasets. Hence, this DA prediction model of IM price ranges can serve as an input into energy arbitrage stochastic models for sequential market bidding. However, we note that the FFDNN requires about 2.5 times longer to train than the SVM.

V. Conclusion

The prediction of IM prices with a day-ahead horizon is a complex problem that is highly influenced by several factors such as weather parameters, total demand, installed capacity of VRE, cross-border capacity etc. The implementation of price ranges and seasonal segmentation in the proposed DL model showed a promising training validation accuracy that allows flexibility providers a chance of 31-41% correct prediction of next day's IM price ranges in the Netherlands. The testing validation was as low as 26-29%, due to unforeseen consequences of the 2020 pandemic. The accuracy could further be enhanced by incorporating the aforementioned factors in future work. The model may also be extended to incorporate the FCR market that trades 4-hour products. Furthermore, the model can also be extended to run on a rolling basis where it is updated closer to real-time using enhanced weather predictions. Furthermore, the model can be applied to different countries or larger geographical areas to better reflect the weather forecasts at the locations of participating players in the day-ahead and imbalance markets instead of focusing solely on two locations as in our case.

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