Imperial College London

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Sustainable Electrical Systems: Coursework 2

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1 Wind output, System Sell Price (SSP) and System Buy Price (SBP) profiles

To get an overview and a high-level understanding of the data, the half-hourly profiles of wind output, SSP and SBP are plotted over the given period (15 days) and shown in Figure 1. It can be seen that the wind output is at its highest over the 15-day period on the first day, with an overall steady decline over the next 11 days. During the 12th day the turbine seems to spending most of its time in either below the cut-in speed or above the cut-off speed since its power output is close to zero (relative to other times during the 15 day period).

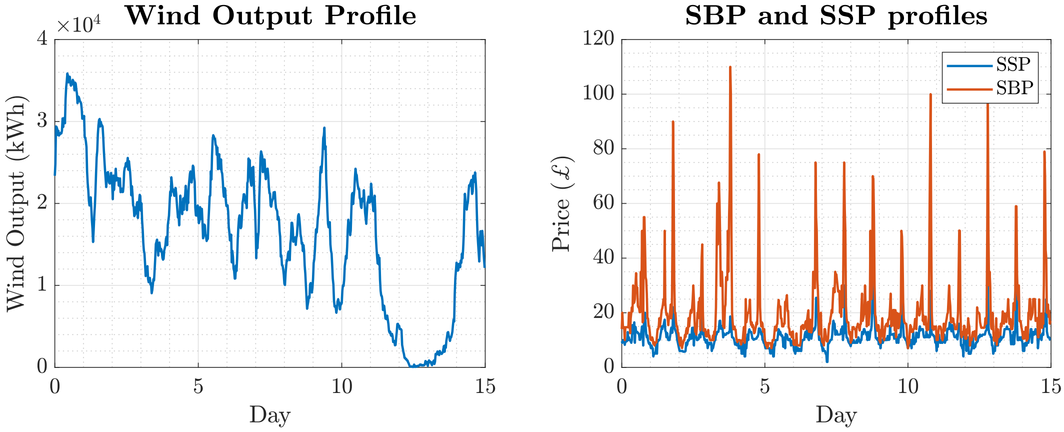

Figure 1: Wind output, SSP and SBP profiles over 15 days, taken at 30 minute intervals

2 Persistence Forecast Technique

The persistence forecast technique for output prediction is where the predicted output n steps ahead, is simply the most recent output. In the case of this problem setup, each time step is equivalent to 30 minutes, therefore a prediction for 1 hour gate closure is equal to the actual wind energy output 2 time steps prior, and 7 time steps for 3 hours-and-a-half gate closure. In the case of a 1-hour ahead prediction, for the first 2 time steps, there is no available data for prediction, thus 0 kWh is predicted to minimise the risk involved with high SBP. This is also done for 3.5 hours ahead prediction, but instead for the first 7 time steps, as necessary. The predicted wind outputs are plotted alongside the actual wind outputs as well as the resulting wind output prediction error for each of the gate closure scenarios, shown in Figure 2, noting that a positive error is when the prediction is below the actual energy output and a negative error is vice-versa.

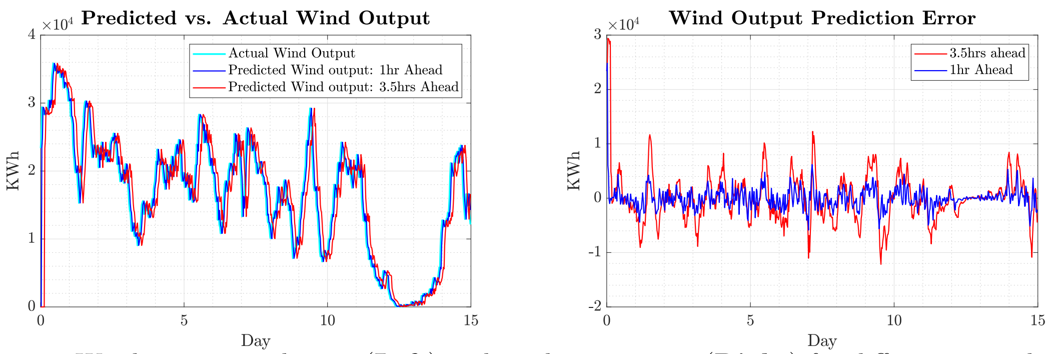

Figure 2: Wind output prediction (**Left**) and prediction errors (**Right**) for different gate closure times.

As expected, having a larger prediction horizon leads to greater prediction error (in terms of magnitude error), this is because there is of course dependency at each time-step on the previous time-step in terms of wind speed and thus output, therefore as the prediction horizon increases there is less-and-less correlation between the wind output at time step t and the wind output at time step $t - n$, where n

is the increasing prediction horizon. The greatest error occurs in regions where the rate of change of wind speed is high.

3 Balancing Mechanism

Now, using the same predicted wind outputs errors for the two different gate closures, the half-hourly imbalance can be calculated. As aforementioned, a positive error, e is an underprediction of wind output and thus the imbalance at that time point, t from participating in the Balancing Mechanism is equal to $e_t \cdot SSP_t$, since e_t is the error in prediction in kWh and SSP_t is the System Sell Price per kWh. Now for a negative error, there is an overprediction of wind output and thus the resulting imbalance is equal to $e_t \cdot SBP_t$ where $e_t < 0$, since the supplier must buy the remaining energy to match their quota. This calculation is performed at each time-step for the two scenarios, and the result is plotted in Figure 3.

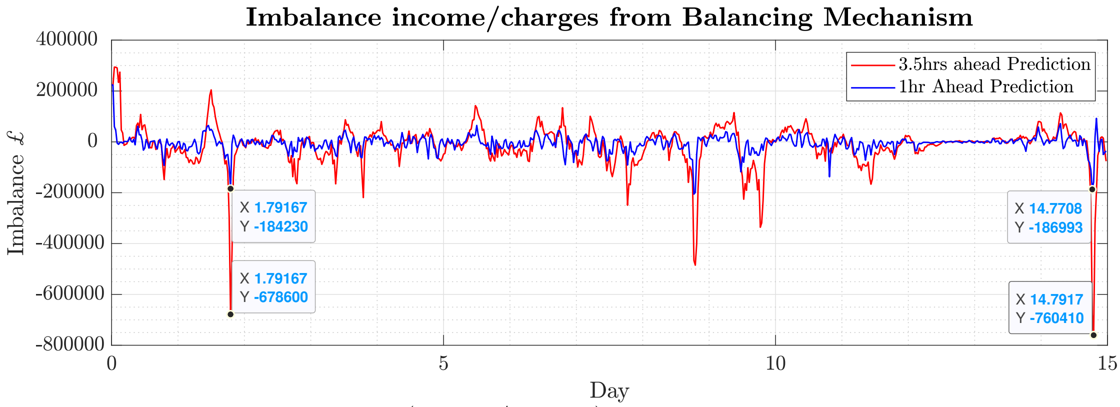

Figure 3: Half-hourly imbalance (income/charges) from participating in the Balancing Mechanism.

The results really highlight the potentially dire consequences associated with over-prediction. With the greater prediction horizon, the magnitude of prediction error is higher, meaning significant over-prediction is far more likely to occur, and if this happens to be when SBPs are high, then this leads to cases highlighted in Figure 3, where the difference in damages between the two prediction horizons is around £500,000 for just one 30-minute window.

4 Total Income and Penalties

Using the half-hourly imbalance from the previous question, the total income and penalties are calculated over the 15-day period and summarised in the table below to the nearest pound.

Prediction Horizon	**Total Income** (£)	**Total Penalties** (£)	**Total Profit** (£)
1 hour	533,720	922,281	-388,561
3.5 hours	1,310,611	2,340,866	-1,030,256

Table 1: Table showing total Incomes and Penalties for the Persistence Forecast technique for 1 hour and 3.5 hour gate closures over a 15-day period.

For a gate-closure of 3.5 hours the total losses is around 3 times more than for 1 hour gate closure. The overall net prediction error over the 15-day period for a 1-hour prediction horizon is +25.3MWh, and it is +103 MWh for a 3.5 hour prediction horizon, this means that both models are actually, in total, oversupplying energy, and yet both are making significant losses over the period. This highlights the incentivisation put on making sure suppliers are able to match their promised power outputs, with any big mistakes in under-delivering having significant financial implications, as seen with the overall profit of a 3.5 hour prediction horizon.

5 Alternative Trading Strategies

5.1 Weather Forecast with Wind turbine model

In this problem setup, the predicted wind output is clearly crucial to the imbalance and thus the trading strategy. A more accurate prediction of wind output clearly leads to less loss as a result of SBPs, as seen with the difference in performance between the 1 hour and 3.5 hour gate closures. A proposed improvement in prediction would be to use an established wind forecast data from sources such as the Met Office [2]. Using this weather forecast, and an accurate model of each turbine's power output according to wind speed, the resulting wind output can be predicted more accurately. The most simple of these models is to look at each turbine's power output curve, which can be determined either systematically (via models usually provided in turbine specifications) or empirically, by measuring and recording the wind output for different wind speeds, however, this power output curve is not a dynamic representation of the system and only considers the system response in 1 ms^{-1} increments, and not in a realistic scenario where wind speeds can change drastically and instantaneously. Instead, each component of the system can be mathematically modelled to produce an accurate end-to-end system representation of the power output according to a wind input, as described in [3]. Model parameters can be determined via Adaptive Filtering methods according to real-time data.

This improved wind output prediction can potentially be coupled with a process that aims to minimise overprediction during times where SBPs are high. Real-time signal modelling techniques such as ARIMA can be used to predict SBPs. Statistical modelling techniques can then be used to derive the probability distribution of the predicted wind output about the true value, and predicted wind outputs can be adjusted such that the prediction is less than the actual output with $X\%$ certainty which can be adjusted according to the SBP.

5.2 Deep Learning models

Time-series models such as LSTMs, Gated Recurrent Units, and Bidirectional units can be very powerful in time-series prediction tasks [4], which can be applied in the context of wind power output prediction. The greatest advantage of deep learning models is its versatility with dealing with different inputs, for example the input vector into an LSTM module at time t can consist of the output power at the previous time instance, y_{t-1}, the current wind speed, w_t, the turbine parameters such as the generator efficiency, tip-speed speed ratio at the time-instance, and fixed parameters such the hub height, and various blade parameters, and most importantly the SSP and SBP at a particular time instance. This model can then be trained on a cost function that maximises the profit, given that the sell price of generated energy that does not fall into the balancing mechanism is known. Denoting the predicted wind output as $f(\mathbf{x}_t)$, the actual energy output as y_t, the sell price of energy in the wholesale market (the energy that does not fall into the balancing mechanism, i.e. the promised amount of energy) as SP, the following cost function $J(\mathbf{x}_t)$ represents the resulting total money made (minus sign turns it into a minimisation problem).

$$-J(\mathbf{x}_t) = \begin{cases} SP \cdot f(\mathbf{x}_t) + SSP \cdot (y_t - f(\mathbf{x}_t)), & y_t > f(\mathbf{x}_t) \\ SP \cdot f(\mathbf{x}_t) - SBP \cdot (f(\mathbf{x}_t) - y_t), & y_t < f(\mathbf{x}_t) \end{cases} \tag{1}$$

If the network is trained on the cost function, then the model will learn its parameters such that the predicted wind output maximises the profit. The nature of this network architecture is shown in Figure 4.

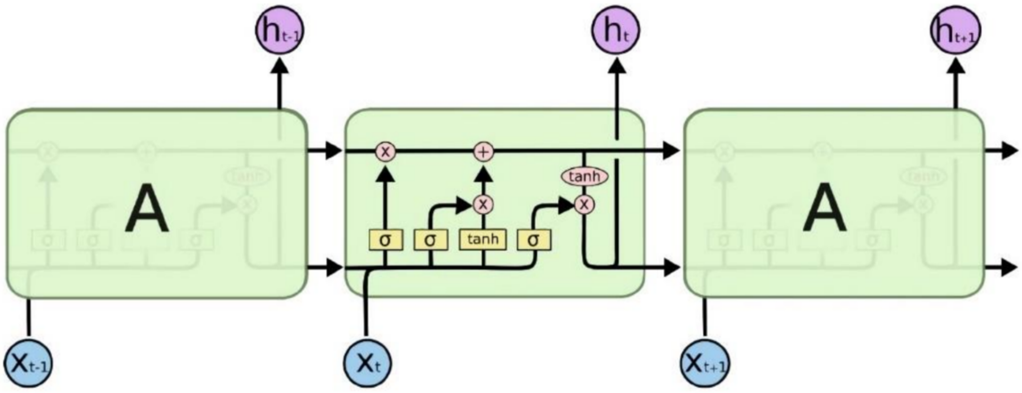

Figure 4: Demonstration of LSTM module being used for n-step ahead prediction

6 Summary

The balancing mechanism was introduced by the national grid to incentivise suppliers to achieve their contracted/predicted power outputs [1], to help keep the grid's supply and demand in balance. The SBP is always greater than the SSP, showing that the priority placed upon supply reaching demand is higher than demand matching the supply. Furthermore, the SBP spikes once and sometimes twice in a day, around the same time, these highlight critical points for the grid, this suggests that for the grid, and for the economy as a whole, the consequences associated with the undersupply of demand are far graver than other times when the SBP and SSP are close. The periodicity present in the SBP and SSP means that time-series modelling techniques such as ARIMA, or LSTMs could potentially be used for SBP and SSP prediction, allowing for suppliers to potentially adjust their predictions to account for the spiking SBPs (i.e. predicting such that oversupply more far more likely).

The persistence forecasting technique does not have any dependence on changing SBPs, meaning that the likely-hood of overpredicting wind output is the same during times when SBPs are high as when it is low. Because of this, although in both prediction horizon scenarios, the model in terms of kWh was under-predicting more than it was over-predicting, it led to huge overall losses over the 15-day period since large overpredictions often aligned with high SBPs with no restriction. Furthermore, a larger prediction horizon led to more volatile prediction errors, meaning that the risk of having a significant overprediction during high SBPs is even higher.

To account for the rising SBPs and the suboptimal prediction technique that is persistence forecasting, two alternative prediction strategies were suggested. One looked at using the weather forecast and mathematical models of the turbine to improve wind output prediction, predictions could then be adjusted such that the probability of a prediction being an overprediction is controlled by the user according to predicted SBPs (i.e. probability is chosen to be lower during times of high predicted SBPs). The other method suggested, was to use LSTMs with inputs of a variety of relevant data, such as the output power of the previous time instance, current wind speed, and turbine parameters (hub height, generator efficiency etc.). This model could then be trained on a cost function that is synonymous to the total profit, and in this way, the network can learn when and how much by to minimise risk such that profit is maximised. The only potential logistical downside to introducing these models is that some pre-existing data is needed to train these models.

References

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[4] José F. Torres, Dalil Hadjout, Abderrazak Sebaa, Francisco Martínez-Álvarez, and Alicia Troncoso. Deep learning for time series forecasting: A survey. *Big Data*, 9(1):3–21, 2021. PMID: 33275484. arXiv:https://doi.org/10.1089/big.2020.0159, doi:10.1089/big.2020.0159.