**ELECTRICITY PRICES PREDICTION**

**POWER SURGE:**

Illuminating the Future of Electricity Prices

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**Welcome to 'Power Surge:**

Illuminating the Future of Electricity Prices'. In this presentation, we will explore the exciting world of electricity prices and how they are shaping our future. Get ready to dive into the innovative solutions and trends that are revolutionizing the industry.

**Understanding Electricity Prices:**

Before we embark on this journey, let's understand the basics of electricity prices. We'll explore the factors that influence pricing, such as supply and demand, government policies, and renewable energy sources. Gain insights into how these elements impact your monthly bills and the future of energy consumption.

**Renewable Energy Revolution :**

The world is witnessing a revolution in renewable energy. Discover how solar, wind, and other sustainable sources are transforming the electricity landscape. We'll explore the benefits of these clean technologies, their impact on prices, and the potential for a greener and more affordable future.

**Smart Grid Solutions:**

The future of electricity prices lies in smart grids. Explore how advanced technologies, such as smart meters and demand response, are shaping the way we consume and pay for electricity. Learn how these innovations empower consumers, optimize energy usage, and pave the way for a more efficient and cost-effective grid.

**Energy Storage Breakthroughs :**

Energy storage is a game-changer in the electricity industry. Discover the latest breakthroughs in battery technology and other storage solutions. We'll explore how these advancements enable grid resilience, peak shaving, and renewable integration, ultimately leading to more stable prices and a reliable energy future.

**The Role of Data Analytics:**

Data analytics is revolutionizing the way we manage electricity prices. Discover how big data and machine learning algorithms are used to forecast demand, optimize pricing models, and identify cost-saving opportunities. Dive into the world of data-driven decision-making and understand how it shapes the future of electricity pricing.

**Policy and Regulation:**

Government policies and regulations play a crucial role in electricity prices. Explore the impact of policy decisions on pricing, the promotion of renewable energy, and the transition to a low-carbon future. Gain insights into the challenges and opportunities that arise from regulatory frameworks and their influence on the cost of electricity.

**Fundamental price drivers:**

The electricity price is determined by supply and demand. However, the supply price is highly variable on multiple factors and the demand is partly dependent on price. Here is a brief overview of the short to mid-term fundamental price drivers.

• Demand The demand is important for triggering the energy sources that supply electricity.

• Wind As a large proportion of the electricity is produced by wind power the wind speed is an important variable of the electricity price.

• Precipitation The amount of rain and snow stored in hydro reservoirs can be an important factor for electricity price.

• Temperature Temperature has a direct effect on the electricity demand and an indirect effect on electricity production. Demand is affected as electricity is used for heating. The temperature can affect the energy production as the wind generally is correlated with temperature. Hydropower is also affected by temperature, for example when snow or ice melts it can contribute to increased production.

• Commodity prices, for example, oil, and gas Commodity prices have a large effect on electricity prices where the total energy demand is highly dependent on these commodities. Commodity prices also affect other contraries with energy systems less dependent on these commodities as energy is transferred between zones.

• Transmission capacity The division of different price areas set by the transmission capacity between areas and country borders. Transmission capacity limits the flow of electricity and thus affects the price in a specific area. With unlimited transmission capabilities, the price in the two bidding areas would be the same.

**TCN:**

CNN is a class of neural networks. Compared to FNN CNN have convolution hidden layers, thus combining the outputs from several nodes into one node to create a denser structure. The layers of a typical FNN only have convolutional layers close to the output layers to match to the appropriate number of outputs. CNNs are efficient at processing high-dimensional data as the convolution layers recognize features from several layers [8].

TCN is a CNN with temporal components, similar to an RNN. A TCN network has two distinct features that separate them from a CNN. First, the input layers are always the same size as the output layers and secondly, CNN uses causal convolutions. Causal convolutions are strictly between the input sequence at time t to t-n and between the output at time t. There are no connections between input nodes at time t+n and outputs at time t. This feature of the neural networks prevents any information from the future to influence the output. TCN networks are typically not fully connected but use a dilated approach, where connections between nodes at specific intervals are connected. Dilated connections improve the performance of the network for long-term time series forecasting as it improves the ability to capture features from many time steps earlier. The convolution features combined with temporal components effectively combine the high performance of CNN with the memory functions of an RNN[9]. A typical structure of a TCN is presented. The main parameters in a TCN network are the filters, the kernel size and the dilation’s. Filters is the numbers of convolutions units in a network, similar to the number of hidden layers in other neural network structures. Kernel is the size of the input sequence that is used for decision making, generally a small number depending on the prediction task. Dilations is the depth of the TCN network and should be a multiple of two [17].

The receptive filed of a TCN network is defined as:

**R=1+2\*(K-1)\*N\*∑d**

Where R denotes the total receptive filed, K is the kernel size of in the network, N is the number of stacked layers and d is the dilutions in the network. [17] Generally the total size of the TCN network should be larger than the input length of the time series used.

**Predictive performance and optimal hedging:**

Overall the TCN model is found to give the lowest predicting errors for both SE1 and SE3 as seen in Figure 6 and 9. For SE1 the forecasting errors are consistently lower for the TCN model during all time periods, although the same clear trend is not observed for SE3 forecasting. For SE3 pricing area forecasting, the forecasting results do not favor the TCN model over the LSTM model. As shown with the correlation analysis SE3 prices are generally more dependent on outside factors such as commodity prices and hydro reservoirs. Long-term future contracts are also much stronger correlated with short-term future contractsin SE3 compared to SE1. Machine learning models are found to have higher forecasting accuracy for most of the test cases for spot price forecasting, similar to the results by [7]. In [9] it is concluded that TCN models can be more suitable than LSTM models for energy-related time series. Although [9] applied models for demand and power consumption data, the results on price forecasting are similar to the result on demand and consumption data where TCN outperforms LSTM models.

Evaluating the machine learning models’ performance on the optimal hedging approach it is found that the TCN model is preferable to the LSTM model. Interestingly the TCN model performed best on the SE1 data set and the LSTM model performed best on the SE1 data set. This indicates that different models can excel at different market dynamics. These results are consistent with the results for spot price forecasting in Table 6 and 9. Where the LSTM model relative performance is highest on the SE3 data set.

The computational time are an important aspect of the evaluation of different models, the suggested models have a complex architecture and require modern hardware to achieve useful training and running times. Observed computational times indicates that the TCN models takes longer time to train but are faster to run when trained compared to the LSTM model. Similar conclusions are drawn by [9], although the difference in training time is only 3.6 seconds or 15.8% compared to the 46.5 seconds or up to 42.5%. The TCN model is generally more complex with more trainable parameters tuned for the same data set compared to the LSTM model. The parallel connections allows it to processes longer sequences of input data compared to the linear approach of LSTM models. In real world applications the faster running time is a major benefit of the TCN model. The historical simulations of hedging portfolios resulted in time savings of about 40% for the TCN model compared to the LSTM model.

The historical simulations make several assumptions about the underlying data that might be possible to replicate in real-world scenarios. One of the major assumptions is that it is always possible to trade contracts at estimated historical closing prices. In real-world scenarios, the market liquidity might not be enough to support transactions and the indicated closing price might correlate poorly with the actual price. However real-world trading assumptions is an issue for both the standard portfolio and the portfolios with machine learning decision.

**Conclusion :**

**In conclusion, 'Power Surge:**

Illuminating the Future of Electricity Prices' has taken us on a creative journey through the dynamic world of electricity. We've explored the role of renewable energy, smart grid solutions, energy storage, data analytics, and policy in shaping the future of pricing. Embrace the opportunities and challenges ahead as we strive for a sustainable and affordable energy future.