# Energy Price Forecasting in Sweden's Day Ahead Market

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***Abstract*—As one of the more prominent fields in the forecasting of data, electric price prediction has become a necessary tool for companies to use in order to obtain an advantage over their competitors. As a project developed under Energy Director, this paper documents the implementation done in order to predict prices in Sweden's energy Zone 3, the country's most inhabited area.**

**Energy Director provides all the electricity-price historical data, which, along with weather data obtained from the Swedish Meteorological and Hydrological Institute, and petrol prices serves as the dataset for this paper. Three different models are implemented in order to obtain results varying in complexity and execution time: Linear regression, Long Short Term Memory, and Lasso Estimated Auto-Regression.**

**Due to hardware and time constraint, the results vary when compared to those of previous works, the LEAR model performs the best of all three, followed by LSTM, and finally, as expected, the baseline linear regression model. Walk forward nested cross-validation is performed in all of the models, with a testing time ranging from November 2019 to July 2022, which shows an increasing trend in data that makes highly-deviated values hard to predict.**

**Electricity price forecasting is a field with a huge industry backing it up, and as such is always pushing the limits of hardware and software implementations. This paper serves as a basic review of what can be done in order to predict electricity prices, and how different models working with different technologies bring fruition to results that can be used by important companies in the sector, such as Energy Director.**

***Index Terms*—Energy Price Forecasting, Deep Learning, Long Short Term Memory, Linear Regression, Least Absolute Shrinkage and Selection Operator, Lasso Estimated Auto-Regression**

## I. Introduction

The electrical grid is a complex system requiring a balance between production and consumption not allowing production to fall below consumption nor allow for production to be to far above consumption, the price of energy changing drastically from one hour to the next. The contributing factors in supply can be global conditions, congestion, hydro reservoirs, weather, outages, natural gas prices and many more. The demand can change based on the temperature, hour of the day, and the day of the week. Energy being produced in renewable sources such as wind, solar, hydro, geo-thermal and hydrogen provide for cheaper forms of energy which are consumed before the use of more costly fossil fuels such as coal which are used to balance with consumption. Energy producers can sell in various frequency markets such as day ahead, intraday, and frequency containment.

Forecasting energy prices is a complicated matter since the energy price relies on several different factors. Some of the dictating factors may be, the supply and demand, production prices, especially relevant for fossil fuel produced energy, policies such as taxes, currency exchange rates, and weather conditions. The mentioned factors are discussed by [2] and they are common variables to observe whilst forecasting energy prices in Europe.

The Nordic countries depend on the same variables when pricing energy with only a few differences. Since these countries produce a lot of energy from renewable sources, such as wind power and hydroelectric power, the energy production is heavily influenced by weather conditions. If the weather conditions are sub-optimal, less energy will be produced which will decrease the supply and by that the energy prices will rise. Nordic countries also have colder winters in general than many other European countries, which increases the demand during winters for heating purposes. Another case for Sweden in particular is that the tax rates for fossil fuels are very high, so if the supply can't meet the demand, requiring the use of fossil fuels, the prices may also rise.

### A. Motivation

Energy Director is a Swedish company that stores and produces energy by utilizing batteries and hydro-power using historical weather and real time data in order to optimize the utilization of power plants. It can be challenging for their company to sell this energy in the market as the prices of energy can fluctuate to a great extent daily and hourly. In order to ensure that their company utilizes it resources properly getting the best price kr/MWh through the use of machine learning in the prediction of energy prices in the day ahead market is an important economic factor. The main prediction task given by Energy Director was to predict the electricity price of Sweden's most populated energy zone SE3 and to make this prediction one day ahead.

## II. Background and Related work

According to Lago et al. [4][5] there are 3 primary methods showing the best results that are used when forecasting in the day-ahead markets. The first are classified as statistical methods that is Linear Regression(LR) that take a combination of explanatory features as inputs to predict the price of the market for that day. In addition ensemble methods that use a combination of forecasts from the same model that make individual predictions with varying windows of the data, spanning from a few months to a few years. The second being other Machine Learning(ML) and Deep Learning(DL) models that included Support Vector Regression(SVR), Multi-Layer Perceptron(MLP), Recurrent Neural Networks(RNN), Long Short Term Memory(LSTM) a type of RNN and Convolutional Neural Networks(CNN). The third being the use of hybrid models that use the combination of several techniques, which include decomposition methods such as empirical mode decomposition, and Wavelet Transform(WT). Heuristic optimization algorithms to estimate the model or hyper-parameters including particle swarm optimization, differential evolution, and other genetic algorithms. Clustering algorithms such as k-means, fuzzy clustering, and enhanced game theoretic clustering. Most of the innovations that have been seen in models is the inclusion of feature selection methods such as Least Absolute Shrinkage and Selection Operator(LASSO), elastic net, and Recursive Feature Elimination(RFE).

As explained in Li et al.[6] one of the problems facing researches is the curse of dimensionality within in the Nordic market, one of the solutions to this issue is the use of feature selection techniques. Within their research they include a data set of 62 features of both Nordic and non-Nordic countries of price, consumption, production, and flow of electricity. Various hybrid architectures incorporating different feature selection techniques were used in order to improve the performance of LSTM which included, Pearson's Correlation(PC), Particle Swarm Optimization - Extreme Learning Machine(PSO-ELM), Genetic Algorithm-Extreme Learning Machine(GA-ELM), RFE-SVR, and LASSO. In addition to the feature selection methods encoder and decoder methods were also used as well as CNN and convolution in conjunction and separately for comparison. The findings showed that overall LSTM is considered to be accurate in the predictions of energy prices, the features selection method has an effect on which features are considered more important and ultimately selected. The best performing models were those that were auto-encoded with LSTM and the best feature selection was done on the RFE-SVR technique.

Chang et al.[1] proposed a new model for energy price forecasting, the hybrid model utilizing a discrete WT time frequency analysis method that would decompose the energy price series into a better performing series that is smoother showing more stability. The whole hybrid model was made with the WT in combination with a Adam optimized LSTM. First Adam LSTM model was compared against other LSTM models that utilized different optimizers such as stochastic gradient decent, and RMSprop. The results for the best optimizer showing that Adam had the best fitness with LSTM. Then the hybrid model was compared against a Differential Evolution(DE) optimized LSTM model, and a normal Adam optimized LSTM. The results showing that the WT hybrid LSTM model performed the best. The hybrid model was then compared against a general regression neural network, back propogation neural network, and a normal LSTM model the results being the WT-Adam-LSTM model performing the best.

Lago et al.[5] applied an energy price forecasting experiment on several markets which included NordPool in the Nordics, Pennsylvania New Jersey and Maryland in the United States, Belgium, France, and Germany. The models used within the experiment included LASSO Estimated Auto-Regression(LEAR) where the optimization of the gamma was calculated using Least Angle Regression(LARS) for the daily basis and Akaike information criterion (AIC) for the in sample. The next model was an MLP model which utilized tree-structured Parzen estimator and Bayesian optimization for hyper-parameter tuning and feature selection, in addition each of the models had ensemble counterparts. The LEAR models were also compared on 4 different calibration windows, while the MLP models were compared on different hyper-parameters. The results showing that the ensemble MLP DNN models outperformed the LEAR models on a majority of the data sets as well as the performance metrics. In another study Lago et al.[4] made a comparison of numerous models which found that of the proposed DL models the Deep Neural Network(DNN), LSTM and Gated Recurrent Unit(GRU) performed statistically better as compared to the other models

### A. Baseline: Linear Regression

As explained by Jędrzejewski et al. in [3], electricity price forecasting is a branch of forecasting that can be traced back to the 1990s, and as such, plenty of different implementation techniques have been developed and improved over the years. One of the first attempts at predicting electricity prices was done using linear regression techniques, which are based on the assumption of linear relationships between the predicted variable and the input features. Representing the former as a weighted sum of the latter. Earlier regression models included past prices in their input, along with exogenous or external variables, and seasonal components. Seasonality was often represented as a set of binary encoded variables taking a 1 for the given day and 0 for the rest of them. This form of electricity price forecasting implementation was quickly substituted by single-output shallow neural networks, but up to this day acts as a reliable and efficient way to predict day-ahead prices in numerous fields.

### B. Long Short Term Memory

An LSTM model described by Van Houdt et al.[8] is a type of RNN which was designed in order to solve the vanishing and exploding gradient problem that can occur when learning long term dependencies. RNN's are capable of updating the current state based on the current and past states input data due to the cyclic connection structure, although when the gap between relevant input data gets large the relevant information is incapable of forming the proper connection as stated by Yu et al.[9]. The layers in the RNN are made of recurrent cells, these cells can either be tanh or sigma cells, these cells use the input, the weight of the input, recurrent information and the weight of that information, and the bias. The cells states are affected by the current input and the past states with feedback connections, long term dependencies occur due to error signals vanishing or blowing up from flowing backwards in time. LSTM's were developed in order to solve the exploding or vanishing gradient problem by introducing gates into the cell, in the initial design it consisted of an input and output gate. Shown in Fig. 1 is the original LSTM architecture which is divided into the input where the recurrent information and the input are used in conjunction with their respective weights along with the bias to update the cell state. The output gate uses the cell state along with the recurrent information as well as the input to determine the new state along with the new recurrent information.

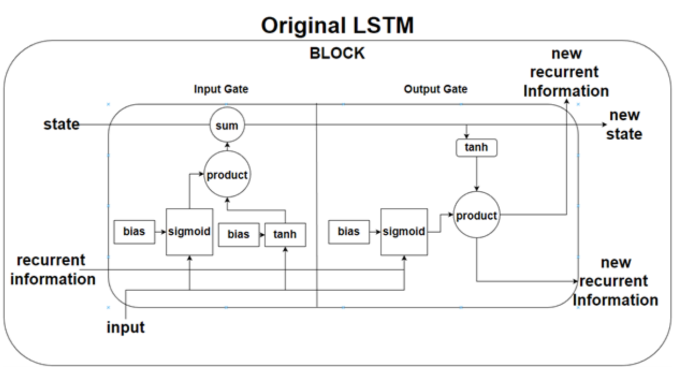


Fig. 1. Original LSTM Yu et al. [9]

According to Van Houdt et al.[8] the addition of the forget gate was later added so that the state within the network could be reset this is depicted in Fig. 2. With the addition of this forget gate the algorithm determines what is discarded or retained within the cell state with the sigmoid function setting the value as 1 for keep and 0 for discarding the information.

As stated in Van Houdt et al.[8] can be applied to a number of problem domains from but in particular it can said to be well suited in the application of time series predictions that require temporal memory. It is also found that predictions can be improved by using different architectures or a combination of architectures as well as tuning of the hyper-parameters. One

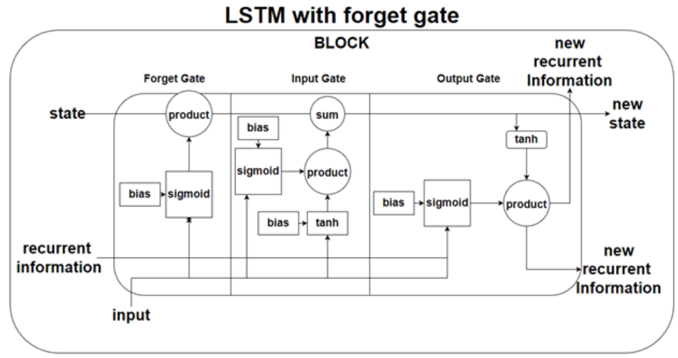


Fig. 2. LSTM with forget gate Yu et al. [9]

of the disadvantages to using LSTM or any DNN for that matter has to do with the large amount of features used to train the model as the the performance can degrade due to overfitting as stated in Li et al.[6].

### C. LASSO Estimated Auto-Regression

Auto-regressive models are models used for time series. The predictions are regressed on one or several previous values from the time series, ergo *auto-regression*. Lasso is an embedded feature selection method, by combining the Lasso method and the auto-regressive model, we get the LEAR.

The LEAR model used in this paper is the same model suggested by Lago et al. [5] which is an open-access model for energy forecasting. The characteristics of this particular model are that it follows the architecture of a full ARX model that uses exogenous variables for a parameter-rich auto-regressive specification, and it uses L1-regularization as feature selection. To improve the performance of the LEAR model over the full ARX model, some changes were made by Lago et al. [5]. To stabilize the transformation to the data, a transformation called the area hyperbolic sine variance was added. To calculate the transformation the *asinh* function is used on a logarithmic value. The value in question is the price data that was standardized by subtracting the median and dividing by the mean absolute deviation. The model predicts the hourly day-ahead prices by first recalibrating each prediction in a window of three years, then it looks at the day before, the second day before, three days before, and one week before to make its prediction. The LEAR model also has support for hyperparameter optimization which can further improve the results of the model with the cost of computational power.

## III. Method

### A. Data Analysis

With this project, data from various sources were collected, all containing information about Sweden. These data sources included information about water reservoirs, weather stations, energy prices, and oil prices. Because the data were collected from a variety of sources it was recorded in varying time intervals and frequencies. A clear majority of data was weather

TABLE I
FEATURES

| Feature | Start | End | Description |
|---|---|---|---|
| SE3 | | | Current energy price for Zone 3. |
| Date | | | Year, Month and Day |
| One Hot Encoded Weekday | Monday | Sunday | One hot encoded with a 1 or 0 if the day is that weekday. |
| SE3 | (-1) | (-24) | Last 24 hours of energy price in Zone 3. |
| Air Temp SE1 | (-10) | (-14) | Temperature reading from northern of Sweden. |
| Air Temp SE2 | (-9) | (-15) | Temperature reading from upper middle of Sweden. |
| Air Temp SE3 | (-7) | (-16) | Temperature reading from bottom middle of Sweden. |
| Air Temp SE4 | (-10) | (-16) | Temperature reading from southern of Sweden. |
| Diesel Price | | | Gasoline price of the current day. |

data from SMHI (Swedish Meteorological and Hydrological Institute) this data consisted of data from hundreds of stations recording temperature, wind speed, and precipitation.

Sweden contains four energy zones (SE1, SE2, SE3, SE4) the main goal of the models that are being tested is to predict the energy price of zone SE3.

*1) Preprocessing:* The data preprocessing was done in three main steps. Firstly the weather station data was separated into each energy zone where the station was located. Secondly, the now zone-by-zone weather data was grouped by date and time to show the average information at a given time in a given zone. Lastly, some data tables were not displayed on an hourly basis, this was processed to display hourly data, this means that data that were previously in the day-by-day format now were displayed as 24 separate instances all containing the same data point. No data manipulation in terms of interpolating was used to transform the data, it was chosen to do no interpolating because of the risk of affecting the data into not representing the real world.

After all data tables were joined by date and time the end table consisted of 47 208 rows of data and 23 columns, this data spanned from 2017-03-03 to 2022-07-19. The features now displayed as hourly were lagged to include the previous 24 hours of data points; this in term expanded the table of data from the original 23 features to 346 features. Furthermore, a one-hot encoding was included to represent weekdays this means seven more columns each with a binary value representing the current weekday of the data row were added to the table bringing the total to 353 features.

*2) Feature selection:* To reduce the number of features used, a simple linear correlation was made to identify relevant features. Each feature with an absolute correlation higher than 0.1 were chosen, this resulted in 58 features, to these the one-hot encode and year, month day were added, totalling in 69 features.

*3) Data Splits:* The data sets were tested with a walk forward 10-Fold Nested Cross-Validation similar to that of what was described in Li et al.[6], found in Fig. 3 the initial data set is split in half and at each iteration the train set increases with the inclusion of the previous test set.

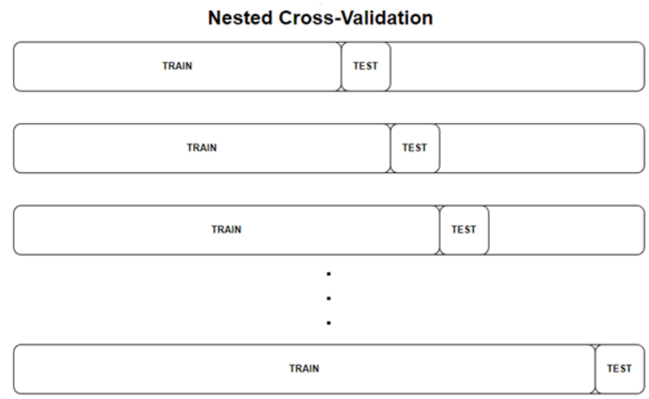


Fig. 3. Walk Forward Nested Cross-Validation

*4) Seasonality and trend:* According to Lago et al in [5] among many other professionals, the study of the trend and seasonality in a time-series model serves as a way of better understanding the data and as such, allows for modifications to improve its accuracy. As can be seen in Fig. 4, over the course of the last years there has been an increase in price, and as such, it has to be considered in the implementation in order to accurately predict the day-ahead prices. When it comes to seasonality, a correlation chart can be plotted in order to see how prices correlate over time, as seen in Fig. 5, where the weekly seasonality of prices can be truly appreciated.

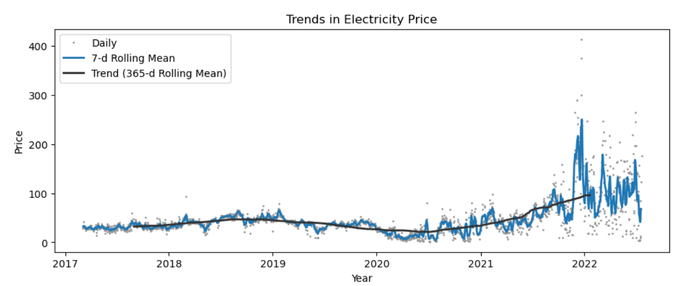


Fig. 4. Trends in electricity price

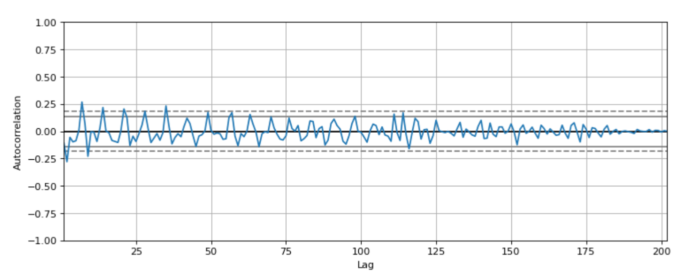


Fig. 5. Daily lag and price correlation

*5) Performance metrics:* The selection of performance metrics were chosen based on industry standard in similar electricity price forecasting [5] [7] [6] [1], the metrics are Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

$$MAE = \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{2}$$

## IV. Experimental Design

### A. Baseline: Linear Regression

The baseline model constitutes the simplest implementation of the project. However, in order to make the most out of it, it includes data modifications that other models do not, one of them being trend removal. In order to get rid of the trend, a first-order differencing is performed for all the data. This operation calculates the feature difference between two given rows, obtaining an overall representation of how the data changes over time. As for the seasonality, following the guidelines provided in [3], the day of the week is represented in binary encoding, representing the given day as 1, while the rest of the days of the week are 0. Finally, as a way to periodically implement the model, we perform walk forward nested cross-validation, training, and testing the model over time until reaching the final result.

### B. Long Short Term Memory

The LSTM implementation consisted of an LSTM-LSTM Encoder-Decodoer model that Wei and Becker [6] used as one of their LSTM models to test. In this model the raw input timeseries is transformed trough a LSTM Encode layer and sent to an intermediate repeat vector. This Encoded vector is then processed and decoded by another LSTM layer that outputs the final prediction. This encode/decode layout is according to Wei and Becker [6] capable of finding complex dynamic information in a time series. Our model consisted of 3 layers. The first Encode layer had 100 neurons a drop out of 0.3 and used L1 regularization on the weight matrix. The second layer is a repeat vector with the size 1. Third and final layer is another LSTM layer with 100 neurons. To train the model an Adam optimizer with a learning rate of 0.0002 were used.

### C. LEAR

The LEAR model used for energy forecasting in this project was cloned from the authors of Lago et al. [5] publicly open GitHub. Nothing in the model itself needed to be modified to make our forecasting work, instead the data processed for this project needed to be further tweaked. The input features needed to be named as Exogenous *n*, where n is the number of the exogenous variable (1,2,...,n). Also for the sake of convenience, the predictions for every run are saved as files with the date of the prediction and each hour of that day with every corresponding price. Another thing that was implemented in the LEAR model specifically for this project was k-fold cross-validation. Every run with the validations results got its own save file with predictions and a separate plot to visualize any differences between each run. Although this has no impact on the LEAR model itself, it needed to be done for the sake of this project.

One thing that the LEAR model had to offer that was not utilized in this project was hyper-parameter optimization. Although doing this would probably further improve the predictions of the LEAR model, it was neglected due to the computational cost factoring in the time constraints of this project.

## V. Results

### A. Baseline

From the baseline linear model we obtain two different results: one of them predicts the difference in prices from the actual day to 24 hours into the future, while the other predicts the actual price 24 hours into the future. Fig. 6 shows the comparison between the predicted difference and the actual 24-hour difference in prices. Table II shows the cross-validation performance of the model over a testing period of time of three years.

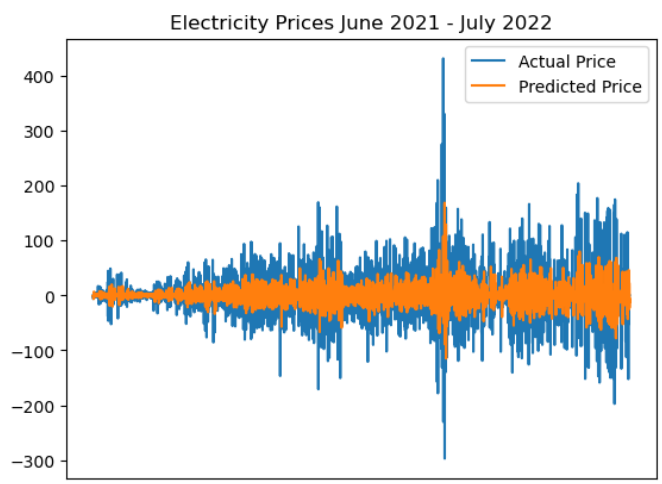


Fig. 6. Day-ahead difference prediction

### B. LEAR

As clearly visualized in table III There seems to be a trend for the LEAR model to perform better in the earlier portion of the test set.

The LEAR model, according to its results, seem to be a relatively accurate model when the energy market has stable prices and not so many fluctuations. These fluctuations can be displayed by Fig. 10. Here it is shown that the actual prices for each date vary drastically and do so nearly every day from this segment of the test data. This is probably the cause of the energy market from late 2021s throughout the 2022s being more volatile in this time period.

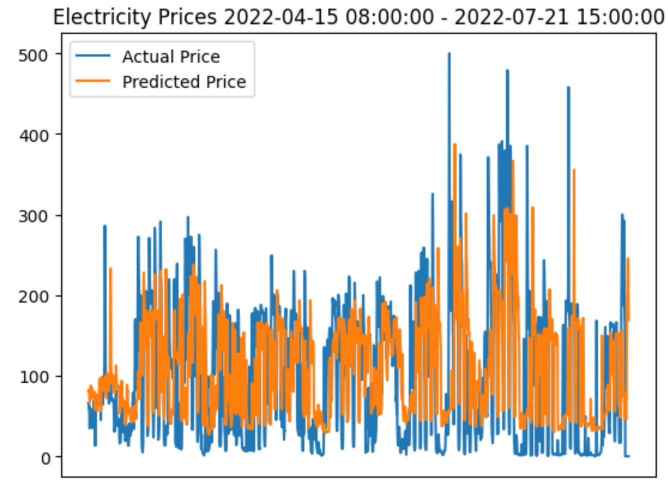


Fig. 7. Worst Baseline time period predictions

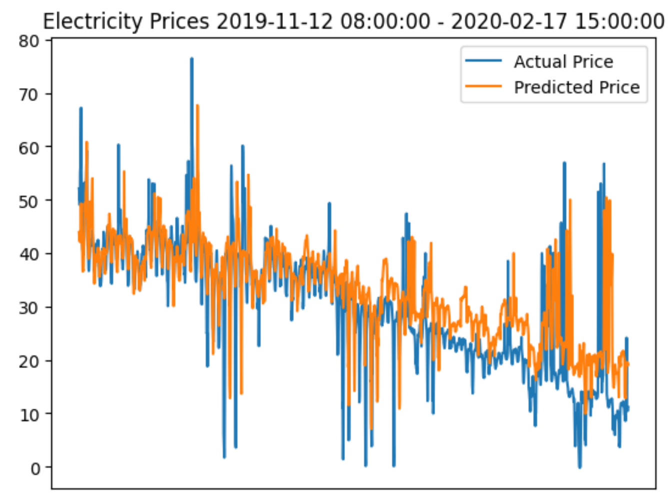


Fig. 8. Best Baseline time period predictions

On the other hand, when the market is stable and prices do not have nearly as many fluctuations as displayed in Fig. 11 the accuracy is much more impressive.

Finally to show how visualize how the LEAR model predicts it's hourly prices in Fig. 12 we can observe that the model follows the pattern quite well during the day although it was not able to predict that the prices were going to be as high as they actually were

### C. LSTM

As the Table IV shows, the data is easy predicted until the end of 2021 and forward. A similar trend can be seen in Fig. II and Table III. The performance of LSTM is stable until 2021-09-28 and forward, here the data gets hard to predict and LSTM is failing to predict the variance in the data this can be seen in when comparing the variance of actual prices lines from Fig. 13 and Fig. 14. From Fig. 15 it can be seen that

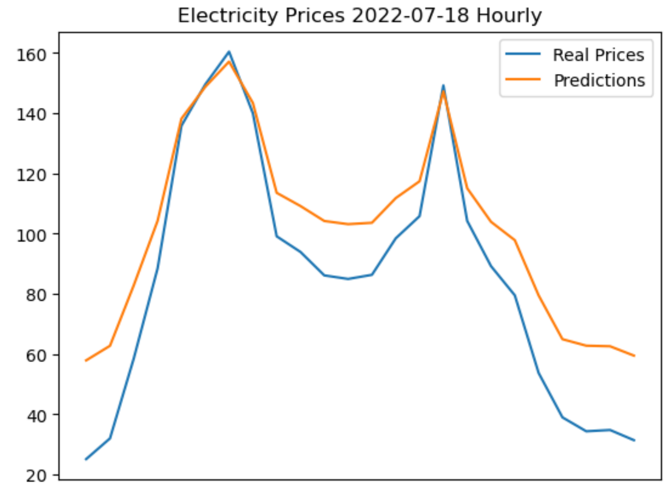


Fig. 9. Magnifying the Baseline predictions on one specific day

TABLE II
BASELINE MODEL RESULTS

| Dates | RMSE | MAE |
|---|---|---|
| 2019/11/12 - 2020/02/17 | 7.292 | 5.172 |
| 2020/02/18 - 2020/05/25 | 8.780 | 6.037 |
| 2020/05/26 - 2020/08/31 | 14.381 | 8.396 |
| 2020/09/01 - 2020/12/07 | 19.154 | 11.189 |
| 2020/12/08 - 2021/03/15 | 18.403 | 10.511 |
| 2021/13/16 - 2021/06/21 | 13.446 | 9.723 |
| 2021/06/22 - 2021/09/27 | 19.560 | 13.626 |
| 2021/09/28 - 2022/01/03 | 64.264 | 43.559 |
| 2022/01/04 - 2022/04/11 | 67.332 | 51.329 |
| 2022/04/12 - 2022/07/19 | 76.866 | 58.299 |
| Average | 30.948 | 21.784 |

TABLE III
LEAR RESULTS

| Dates | RMSE | MAE |
|---|---|---|
| 2019/11/12 - 2020/02/17 | 3.728 | 2.343 |
| 2020/02/18 - 2020/05/25 | 9.036 | 6.728 |
| 2020/05/26 - 2020/08/31 | 11.987 | 7.527 |
| 2020/09/01 - 2020/12/07 | 11.735 | 7.484 |
| 2020/12/08 - 2021/03/15 | 16.678 | 10.101 |
| 2021/13/16 - 2021/06/21 | 10.394 | 7.336 |
| 2021/06/22 - 2021/09/27 | 10.930 | 7.208 |
| 2021/09/28 - 2022/01/03 | 39.982 | 28.657 |
| 2022/01/04 - 2022/04/11 | 56.443 | 42.717 |
| 2022/04/12 - 2022/07/19 | 54.388 | 39.982 |
| Average | 22.530 | 16.006 |

LSTM follows a normal days energy price well even during the period where the price had the most fluctuations.

### D. Analysis

From the results of all models it is clear that the data for 2021 and forward has been extremely fluctuating and a difficult task to predict. All models had an increase in MAE and RMSE for the three last periods.

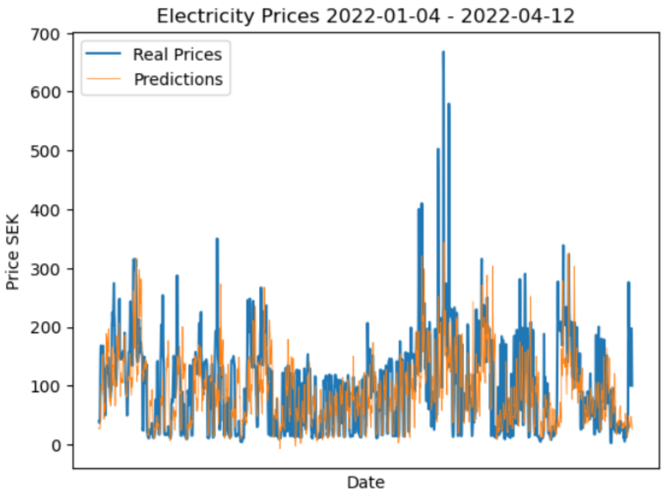


Fig. 10. Worst LEAR time period predictions

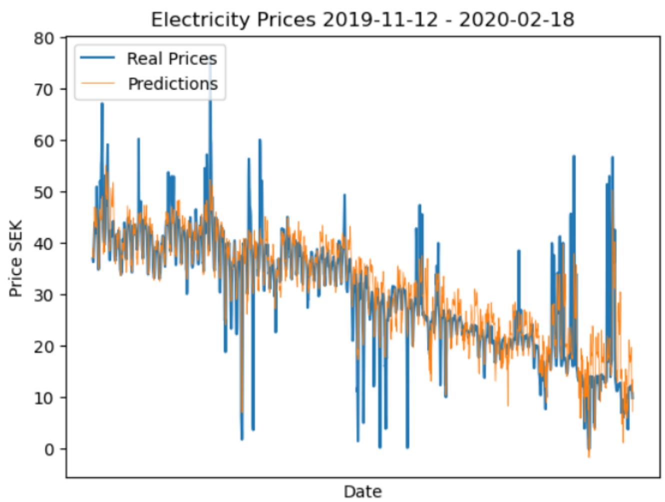


Fig. 11. Best LEAR time period predictions

An interesting pattern can be seen for all Fig. 9, Fig. 12 and Fig. 15 showing the different models snapshots of one day. Here it can be seen that the baseline overestimates the lows but predicts the daily highs almost perfectly, the LSTM model follows the low and mid day low better but are underestimating the highest peaks. Lastly the LEAR is following the overall pattern but underestimates the entire day which could be why it performs the best, it tries to follow the overall pattern instead of capturing the variance.

# VI. Discussion

The performance is some what indicative to what was expected although the performance of the LSTM model were subpar, this is most likely to insufficient understanding of deep neural network layouts and LSTM. The linear regression model performed over expectations compered to literature found, the given tone was that linear regression was always going to be worse than LSTM and LEAR, but building the LSTM model proved to be difficult and at many times in the project the LSTM was the clear worst performing model. Over

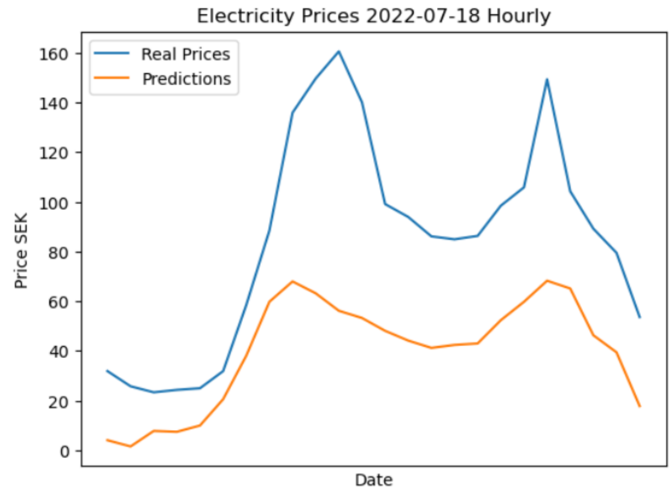


Fig. 12. Magnifying the LEAR predictions on one specific day

TABLE IV
LSTM Results

| Dates | RMSE | MAE |
|---|---|---|
| 2019/11/12 - 2020/02/17 | 5.58 | 3.6 |
| 2020/02/18 - 2020/05/25 | 9.02 | 6.79 |
| 2020/05/26 - 2020/08/31 | 12.96 | 8.65 |
| 2020/09/01 - 2020/12/07 | 17.95 | 11.06 |
| 2020/12/08 - 2021/03/15 | 17.27 | 9.89 |
| 2021/13/16 - 2021/06/21 | 13.67 | 9.69 |
| 2021/06/22 - 2021/09/27 | 20.53 | 13.92 |
| 2021/09/28 - 2022/01/03 | 68.92 | 44.13 |
| 2022/01/04 - 2022/04/11 | 63.59 | 48.73 |
| 2022/04/12 - 2022/07/19 | 72.92 | 53.00 |
| Average | 30.241 | 20.946 |

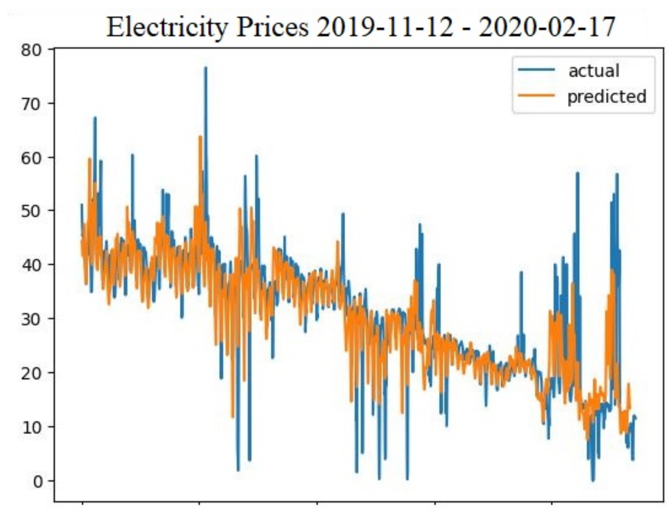


Fig. 13. Best LSTM time period predictions

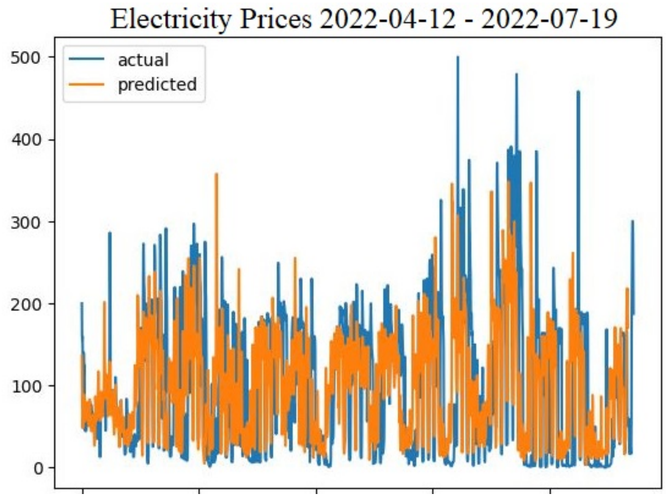


Fig. 14. Worst LSTM time period predictions

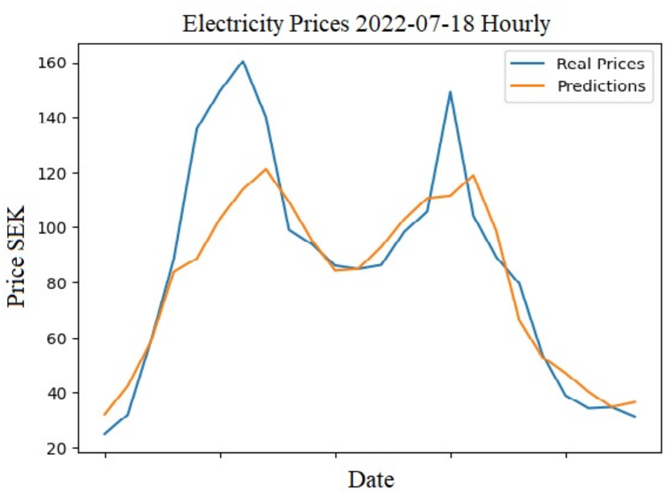


Fig. 15. Magnifying the LSTM predictions on one specific day

time the modeling and tuning of LSTM showed progress and was a continuous process.

As can be seen in Fig. 9, Fig. 12 and Fig. 15 the different models makes a different type of error and they might perform better as a group prediction. Meaning that possibly the best model would be to make predictions from the Baseline and LSTM and use these in the LEAR model. Combining the LSTM Fig. 15 and the baseline Fig. 9 so that the correct highs from baseline could be combined with LSTM's ability to follow the lows would during this snapshot yield the perfect prediction.

To further improve the performance of all models an more robust feature selection processes should have been implemented. With this feature selection processes additional features could have been included to examine their impact on the energy price. Additionally hyper-parameter tuning using an optimization algorithm could further improve the LSTM model and the windows for the training set could be reduced to handle model drift as the values become more an more volatile from the start of the data to present.

## VII. Conclusion

To conclude the purpose of this project, to find the best-fitting model to forecast energy prices in the SE3 zone in Sweden, it has been found that the LEAR model was the best performing with the dataset worked with. Although the LSTM model was initially thought to outperform both the baseline model and the LEAR model, the time constraints of this project did not allow for the LSTM to come to fruition in time. What has been observed for all the models used for this project was that the more volatile the energy market is, the less accurate the models will perform. This can be observed in Table II, Table III, and Table IV. The clear trend here is that all the models start of with ample results in the first segments of the test data and then tend to worsen over time.

What can be done for future work for this project is to further develop the LSTM model to make it live up to its true potential and utilize the supported hyper-parameter optimization of the LEAR model to elevate the results even more. Other types of auto-regression models could be tested to challenge the LEAR model or forecast using different types of neural networks would also be helpful in the field of energy forecasting. New features for the dataset could be introduced to find new factors that drive the energy pricing market, such as the inflation index or energy prices from different European countries.

As it is right now, the LEAR Model is the suggested model to use for energy forecasting according to the results and analysis done in this paper.

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