POWER PURCHASE STRATEGY OF RETAIL CUSTOMERS UTILIZING ADVANCED CLASSIFICATION METHODS

L. Jonáková,[*] *I. Nagy*[†]

Abstract: This study reflects a unique task with significant business potential, on the edge of the wholesale and retail power market, i.e., optimization of power derivatives purchase strategy of retail customers. Even though the definition of the task as well as initial assumptions may be highly complex, essentially, the purpose of this study can be narrowed down to the estimation of buying signals. The price signals are estimated with the use of machine learning techniques, i.e., one-, two- and three-layer perceptron with supervised learning as well as long short-term memory network, which allow modelling of highly complex functional relationships, and with the use of relative strength index, i.e., momentum technical indicator, which on the contrary allows higher flexibility in terms of parameters adjustment as well as easier results interpretation. Thereafter, performance of these methods is compared and evaluated against the established benchmark.

Key words: *power, trading signal, classification, technical analysis, fundamental analysis, neural networks*

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1. Introduction

At the beginning of the nineties, the European energy sector went through a period of deregulation, within which the government monopolies were eliminated. In contrast with the prior arrangement, in which the power producers also assumed the role of suppliers, liberalization enabled the entry of other subjects on the market. The sector became attractive to smaller power producers as well as to traders, who filled in the blank space in the supplier chain. The increase in competition has been accompanied not only by the utilization of new technologies and the decrease in price, but also by the development of the power derivatives market [10].

The power market can be divided into wholesale and retail markets. The wholesale market is intended exclusively for the power producers and traders, not for the end-consumers. Therefore, the trading is exempt from any taxation as well as from

[*]Lenka Jonáková – Corresponding author; Czech Technical University in Prague, Department of Applied Mathematics, Na Florenci 25, 110 00, Prague 1, E-mail: jonaklen@fd.cvut.cz

[†]Ivan Nagy; Czech Technical University in Prague, Department of Applied Mathematics, Na Florenci 25, 110 00, Prague 1

any state-regulated fees. On the contrary, the main purpose of retail market is the power supply to the end-consumers, and the state-regulation is applied here. Despite the considerable differences, retail prices can be derived from the wholesale prices to a great extent [10].

This study reflects a unique task with significant business potential, on the edge of the wholesale and retail market, i.e., optimization of power derivatives purchase strategy of retail customers. Due to the increased demand for complexity of services from retail consumers, suppliers started to incorporate a specific requirement for gradual purchase into the power delivery bilateral agreements. This mechanism enables end-consumers to buy the demanded volume in many tranches for price which is derived directly from the wholesale price, and in this way to diversify price risk. Some of the consumers take a step further and use this opportunity to speculate on the wholesale price development. So-called gradual purchase, in different forms, is becoming increasingly popular in the Central Europe. Consequently, this methodology was also adopted by some of the regulated exchange platforms in the region, such as Power Exchange Central Europe, a.s., (PXE) [26] and Czech Moravian Commodity Exchange Kladno (CMCEK) [6]. Popularity of the method can be documented on figures from PXE; approximately one quarter of all power consumers have chosen the gradual purchase approach during the last three years. It corresponds to 88 % of total traded volume on the PXE power retail market, which indicates considerable desirability of this procedure among clients with large consumption [26].

In the Western Europe the tendency seems to be heading more intensively toward digitalization initiatives, e.g., real-time management of smart grids, where supply and consumption is priced against the spot market. Even though gradual purchase does not offer the same level of pricing efficiency, it is a publicly recognized and very easily implemented solution to risk diversification without any additional costs for hardware or software equipment. Therefore, the business potential of this approach is believed to be significant and worth further research.

2. Definition of the Task

For the purposes of the study, we will consider the following representative scenario: Retail customer demands a contract for a yearly electricity supply. Based on the delivery profile, the customer is offered a margin by supplier defined in relative or absolute terms, i.e., the final price equals the margin multiplied or added to the wholesale price, respectively. Prior to contract confirmation, the customer can choose which wholesale contract will be used as a reference for the price fixing. The customer has the possibility to purchase the demanded power volume in n tranches and can fix the price k-times in one day, i.e., he is able to fix the price for the k/n portion of the whole delivery in one day. The final price equals the average of all fixing prices. In case the end-customer does not fix the price in the predefined number of steps, the fixing proceeds automatically at the furthest possible date(s).

Even though the definition of the task as well as initial assumptions may seem highly complex, essentially, after the contract confirmation, the customer role is limited to providing supplier with purchase instructions and to speculate in this way on the wholesale market. Therefore, the purpose of this study can be simplified and narrowed down to the estimation of buying signals. An analysis will be exploited for the Czech power yearly baseload futures, with delivery in the front year, which are used by end customers as reference contracts most frequently.

It is important to emphasize that contrary to speculative power traders, who can flexibly increase or decrease their risk exposure by managing their open position, retail customers do not have such a possibility, and thus, improvement in the efficiency of estimating trading signals in this business area has a significant potential from the risk management as well as economic perspective.

Considering the input data are believed to include non-stationarity, non-linearity, and noise, price signals will be estimated with the use of a one-, two- and three-layer perceptron with supervised learning. Assuming potential autocorrelation dependencies within the time-series, long short-term memory neural network will be further exploited. Even though these machine learning methods usually offer an exceptional performance in terms of prediction accuracy, the training process is slow and the interpretation of causal relationships within the models is very challenging. The threat of overfitting as well as of non-sufficient model robustness is thus more tangible. Therefore, a technical analysis, specifically Relative Strength Index, which is well established indicator among traders, easy to calculate, and allows higher flexibility in terms of parameter adjustment as well as easier results interpretation, will also be used for the data classification. Thereafter, the performance of these methods will be compared and evaluated against established benchmark.

2.1 Case Study

Given a gradual purchase of a power supply, which is fixed against the wholesale reference yearly baseload contract with delivery in 2019 within one year before its delivery, let's assume the following three price fixing scenarios:

1. Optimal four-step price fixing (orange colour in Fig. 1)
2. Evenly distributed four-step price fixing (yellow colour in Fig. 1)
3. Continuous price fixing (i.e., fixing against everyday settlement price, green colour in Fig. 1)

The optimal way to fix the price would be to proceed all four fixing steps on 12.02.2018 for the yearly minimum price 33.75 EUR/MWh. Given the 253 data samples and assuming uniform random selection of the buying signals, the probability of randomly choosing the optimal result is in the order of tenths of a percent.

Considering the distribution of trading days, evenly distributed four-step fixing on 02.01.2018 (settlement price: 38.09 EUR/MWh), 02.05.2018 (settlement price: 39.62 EUR/MWh), 03.09.2018 (settlement price: 51.06 EUR/MWh) and on 14.12.2018 (settlement price: 57.82 EUR/MWh) would lead to the final price 46.65 EUR/MWh. This procedure presents a partial effect of price risk diversification.

Continuous price fixing can be represented as a simple cumulative moving average, i.e., average of all settlement prices available from the very beginning of

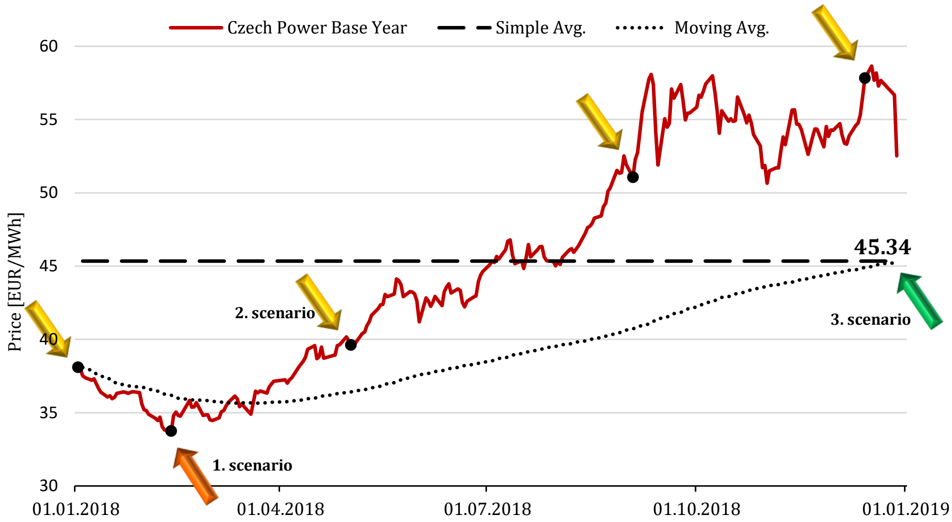

Fig. 1 *Price development of Czech power with baseload delivery in 2019 (case study of price fixing scenarios).*

the respective year. The fixing against everyday settlement price provides the second-best result, i.e., 45.34 EUR/MWh. This approach represents a very popular method of price fixing, which ensures on average profit-loss result. Officials of cities, municipalities and other important subjects responsible for power purchase are often exposed to significant public pressure and do not want to take the responsibility for any estimation of buying signals. Therefore, risk diversification strategies and algorithms that can be easily automated, like this one, seem to be highly demanded.

2.2 Benchmark

The continuous price fixing presented in the previous chapter (see the third scenario) will be considered a benchmark for the purposes of further analysis and results evaluation.

3. Data

The data matrix consists of daily settlement prices from 02.01.2007 to 30.09.2020, and comprises 3565 samples. The dataset is further divided into training and validation datasets in proportion 2:1, specifically data samples till 31.12.2015 will be used for training and the rest for validation. Within our research, the following fundamental as well as technical indicators will be examined.

3.1 Fundamental Data

- Price of the Czech Base Power Front Year (EUR/MWh)
  Power supply of 1 MW for a period of one year (delivery 24/7), with a place of delivery in the Czech Republic.
- Price of the TRPC Coal API2 Front Year (EUR/Tonne)
  European API2 thermal coal yearly futures.
- Price of the ICE Brent Front Month (EUR/Bbl)
  Monthly financial futures based on the ICE daily settlement price for Brent futures.
- Price of the TTF Gas Front Year (EUR/MWh)
  Yearly gas futures with physical delivery in a virtual trading point the Title Transfer Facility.
- Price of the IEU ECX EUA Front Year (EUR/Tonne)
  Entitlement to emit one tonne of carbon dioxide equivalent gas.
- S&P Index (EUR)
  Stock market index of 500 of the largest publicly traded companies in the United States [19].

The specific contracts and trading platforms were selected with respect to the liquidity of trading to ensure as efficient pricing procedures as possible. The fundamental data are further discussed in Chapter 4.

3.2 Technical Data

- relative strength index (RSI)
- 14-day moving average
- 14-day volatility

3.3 Output Specification

Price of the Czech base power is being classified into ten categories by dividing the interval of all the settlement prices within the respective year into 10 equally large sections (1-st category representing very strong buy signal, 2-nd strong buy signal, ..., 10-th being very strong sell signal), and is used in this form as the model output for the purposes of model training.

Today's model output, i.e., estimated trading signal, encompasses information about short-term trend on the market, and is derived from today's values of input variables. Contrary to a prediction of future absolute price values, prediction of the current trading signal increases model robustness, while preserving an added value for a market participant in a form of trend indication, which allows to enter profitable trading position.

As presented in the right bottom corner of Fig. 2, distribution of trading signals across the whole dataset is slightly skewed. This might demonstrate a more aggressive approach toward power selling, perhaps taken by power utilities due to the hedging strategies.

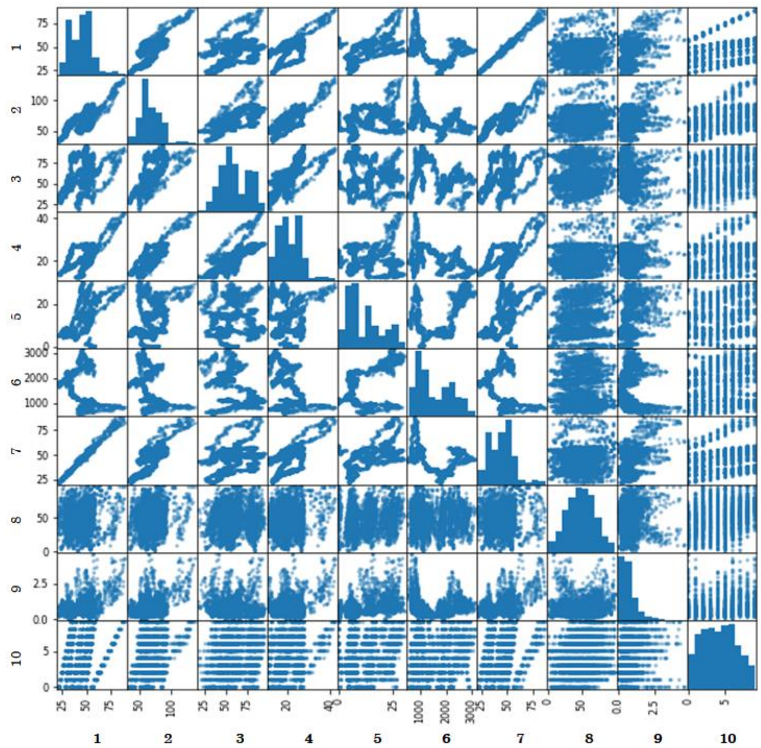

Fig. 2 *Scatter plot of the input data representing functional relationships among variables (1 – price of Czech power, 2 – price of coal, 3 – price of brent, 4 – price of gas, 5 – price of EUA, 6 - S&P, 7 – moving average, 8 – RSI, 9 – volatility, 10 – trading signal).*

4. Data Analysis

As anticipated, prices of the long-term contracts reflect the long-term market situation. They are mainly influenced by macro-economic events, infrastructure growth, which can be very difficult to quantify, and furthermore by the prices of power resources, which are present in the process of power production. Thus, it is important to identify the energy mix of power production in the relevant area.

According to the national energy mix of the Czech Republic, brown coal covers more than 40 percent of the overall energy production [3]. Therefore, the price of coal is one of the most important factors in the process of power prices modelling. As presented in Fig. 3, during the last eight years the correlation between power and coal prices has been significant. Another variable closely related to the price of coal and considerably influencing power pricing is the price of emission allowances.

The low price of emission allowances reduces the benefits of using green technologies and favours less expensive production from coal power plants [8]. Therefore, the power prices rise with the increase in price of emission allowances, and vice versa. Renewable energy resources cover almost 12 % of the overall energy production [3].

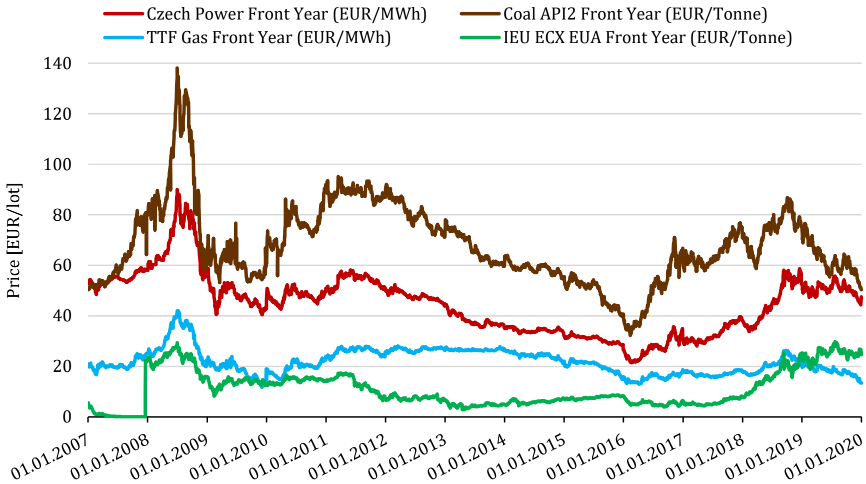

Fig. 3 *Development of commodity prices.*

The third place is occupied by natural gas, whose share on the production is about 6 % [3]. As can be observed in Fig. 3, the correlation between power and gas prices is very strong, however, the volatility significantly differs. The volatility of gas prices is much lower because, contrary to power, gas is a storable commodity and thus the trading risks are reduced. Nuclear energy, which makes up more than one third of the production, should also be considered [3]. Even though the operating costs of nuclear power plants are very low, coal power plants have a perceivable competitive advantage in the areas where the access to cheap resources is possible. This situation occurs not only in the Czech Republic, where coal mining fully covers the domestic consumption, but also in the USA, South Africa, Australia, India and China [17]. Last but not least, an important resource influencing power pricing is oil. Due to its crucial influence on the global economy, the price of oil is one of the most important indicators of the world's industrial development. While oil covers only a negligible percentage of the overall power production of the Czech Republic [3], yet about five years ago apparent dependency between prices of these two commodities was observed. However, during the last couple of years the correlation has been disrupted as a cause of political interventions in this sector.

The effect of the global economy on Czech power prices is demonstrated in Fig. 4. As can be observed, between years 2007 and 2009 prices reacted to the global financial crisis with a sharp and significant increase. In 2011, prices responded to other market uncertainty caused by the Fukushima nuclear disaster. After that we witnessed five years of price decrease, primarily caused by the decrease in the price of fossil fuels and by the significant support of renewable energy resources, whose prices were artificially suppressed due to the subsidies provided. However, at the beginning of 2016 the long-term trend changed, and prices started to increase due to the outage of nuclear power plants in France. The increasing trend continued and was further supported by Brexit vote result, which caused market uncertainty and the abrupt growth in price. The effect of the global economy can be partially captured not only by changes in price of oil, but also by changes in price of stock market indices, such as S&P, MSCI or Dow Jones.

Fig. 4 *Development of price of Czech base front year power contract.*

5. State-of-the-art

There are two main approaches used by professionals for the purposes of estimation of trading signals, i.e., technical analysis, which assumes recurrently appearing trends and patterns over time, and fundamental analysis aspiring to determine intrinsic value of an asset.

Due to its very easy application as well as efficiency, technical analysis has gained importance over time and is now the most equally spread kind of analysis [11]. However, efficiency of various indicators significantly differs among different types of assets. Effectiveness of moving average (MA) based indicators as well as many others is demonstrated for example in [1, 2, 31]. Ability to yield positive returns was also proved in case of other frequently used indicators, such as relative strength index (RSI) or stochastic oscillator (SO) [18]. Furthermore, in some cases RSI, SO as well as parabolic strategies even exceeded performance of the MA-based indicators [16]. It is important to highlight, that profitability of technical indicators may be affected by volatility, e.g., as demonstrated in [22], some technical trading rules are most profitable during period with the highest volatility and vice versa. Nevertheless, utilization of technical indicators is still not fully standardized, and thus in most cases expertise of the user is crucial.

Research in the field of energy industry seems to be primarily focused on the analysis of spot market [30], rather than forward market, because of its impact on physical portfolio dispatch and short-term optimisation decisions. Initially, widely used statistical methods such as autoregressive models and Markov models, as well as some artificial intelligence techniques such as support vector machine, random forest and decision trees, were in many cases outperformed by various types of artificial neural networks [4, 15, 23–25, 29]. However, considering the benefits of specific network structures, the literature is not very united. In the context of spot market forecasting, the outstanding performance of machine learning models, especially the deep neural networks, over statistical methods were thoroughly presented in [24,25,28]. As discussed in [24,29] and [15], also GRU (gated recurrent unit), long short-term memory neutral network and some of the hybrid neural networks show promising results in this area of research. On the other hand, according to [23], the best performance was achieved with convolutional neural network. To summarize, generalization capability of machine learning techniques provides in many cases an advantage against the conventional statistical methods. However, network structure needs to be tailored to the specifics of the task, e.g., deep neural networks can provide an outstanding performance only in case of a sufficient number of data samples [24]. In the context of this study, i.e., considering the availability of an extensive input dataset and possible autocorrelation dependencies of the time-series, the use of deep neural networks as well as recurrent networks seems reasonable.

Neural networks applications are also very popular in the financial sector as financial services organizations are the second largest sponsors of research in this area [20]. Two main approaches can be taken in order to improve model accuracy, i.e., improvement of the model structure, and improvement of the input data quality and selection. Even though it seems rather logical that these two approaches have to go hand in hand to obtain reliable results, most of the reported analyses focus on improving of the model structure while utilizing only historical samples of the output itself. This imbalance was pointed out and demonstrated for example in [14]. Nevertheless, even while using the PCA (principal component analysis) module, which is a popular feature extraction algorithm, the accuracy of the model was not improved, most probably because of utilization of shallow ANNs. At the same time, a convolutional neural network exploiting popular filtering routine used in computer vision showed much worse results compared to other CNN (convolutional neural network) structures as well as compared to shallow ANN [14]. This analysis demonstrates a strong demand for task-dependent model structures as well as an adaptive approach determining input variables.

Generally speaking, publications referring to the estimation of trading signals in the financial sector point at a similar direction as the review of articles focusing exclusively on the power spot market. Certain structures of deep feed-forward neural network classifiers [7], convolutional neural networks [14] and recurrent neural networks, including long short-term memory [27], proved to be powerful tools in this field worth further study. When accompanied with an extensive and suitable input data set, these methods are believed to improve the performance of other conventionally used methods.

Unfortunately, analysis of the forward power market, which is the main subject of this study, seems to be in the professional literature rather neglected. Available sources do not sufficiently describe the fundamental pricing and analysis. Instead, many papers follow the risk premium model presented by Fama and French [9], where futures prices are derived as the sum of the expected spot price and risk premium. Unfortunately, comparison of the power futures market with the power spot market is in certain aspects highly problematic. Contrary to the power futures, power spot prices usually show strong autocorrelation dependencies, and as was documented above, their modelling is therefore usually highly efficient.

6. Methods

6.1 Relative Strength Index

This momentum indicator compares the magnitude of recent gains and losses to evaluate overbought or oversold conditions in the market. By its definition, the index lies within 0 and 100, where a value below 30 represents oversold market, and value above 70 indicates overbought situation [5].

$$\mathrm{RSI} = 100 - \frac{100}{1 + \mathrm{RS}}, \tag{1}$$

$$\mathrm{RS} = \frac{\sum \text{Up changes for the period under consideration}}{\sum |\text{Down changes for the period under consideration}|}. \tag{2}$$

RSI is computed over a rolling time period. 14-day time window, which is suggested and widely used in most technical analysis software, was also used for the purposes of this study.

6.2 Classification with Feed-forward Neural Network

Let's assume a feed-forward neural network, where $x = (x_1, \ldots, x_i)$ denotes a high-dimensional input and y a low-dimensional categorical output. Prediction $\hat{y}(x)$ is defined as

$$z_0 = x, z_1 = \sigma_1 \left(z_0 W_1 + b_1\right), \ldots, z_L = \sigma_L \left(z_{L-1} W_L + b_L\right), \tag{3}$$

$$\hat{y}(x) = \sigma_{L+1}(z_L W_{L+1} + b_{L+1}), \tag{4}$$

where $W_l \in R^{d_l \times d_{l-1}}$ is the weight matrix, $b_l \in R$ is the bias term, d_l is the number of neurons in layer l and σ_l is the activation function. Layers 1 to L are called hidden layers, i.e., L represents the depth of the routine [25].

For the purposes of this study, one-, two- and three-layer feed-forward neural network will be examined, i.e., with zero, one and two hidden layers, respectively. It should be noted that the classification with the one-layer neural network is an equivalent to a simple logistic regression. Hyperbolic tangent is used as an activation function in the hidden layers. Given the output is categorized into 10 classes, softmax function is used as an activation function in the output layer. Thus, topology of the examined networks can be expressed as $(d_1, 10)$, $(d_1 d_2, 10)$ and $(d_1 d_2 d_3, 10)$, where $d_1 = d_2 = d_3 = \text{number of input variables}$.

Calculation was proceeded in Python programming environment with the use of Keras API. The Adam algorithm, which combines benefits of adaptive gradient algorithm as well as root mean square propagation [21], is used as an optimizer. Learning is processed in 150 epochs, while learning rate is set to 0.001.

Sparse categorical crossentropy, allowing multi-class classification without data transformation to one-hot encoding, is used as the loss function (see Eq. 5).

$$L = -\frac{1}{N}\sum_{c=1}^{C}\sum_{i=1}^{N} y_i^c \log \hat{y}_i^c, \tag{5}$$

where i represents a specific observation, N is the number of training data samples, c represents the category, y_i^c is the true label and $\hat{y}_i^c$ is the predicted probability of the i-th observation belonging to the c-th category [12].

6.3 Classification with Long Short-Term Memory Network

Recurrent neural network (RNN) differs from the feed-forward structure by the use of a hidden layer with an autoregressive component; let's denote it h_{t-1}. A particular type of RNN called long short-term memory (LSTM) allows a network to learn which of the previous states can be forgotten [13].

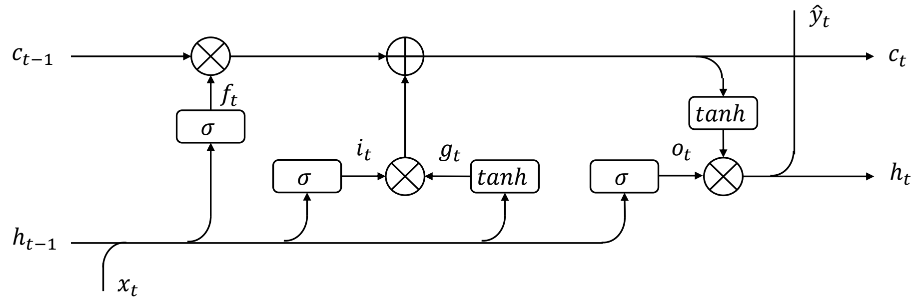

Fig. 5 *Hidden layer of a long short-term memory model.*

The hidden state is generated by another hidden cell state c_t, which allows the model to remember long-term dependencies. Output is generated as

$$h_t = o_t * \tanh(c_t) \tag{6}$$

$$c_t = f_t * c_{t-1} + i_t * k_t \tag{7}$$

$$k_t = \tanh(W_c\,[h_{t-1}, x_t] + b_c), \tag{8}$$

where $*$ denotes the pointwise multiplication, while $f_t * c_{t-1}$ represents the long-range dependence.

State equations can be expressed as

$$\begin{pmatrix} f_t \\ i_t \\ o_t \end{pmatrix} = \sigma(W_c\,[h_{t-1}, x_t] + b_c), \tag{9}$$

where f_t, i_t and o_t are input, forget and output states [25].

For the purposes of this study, network with one hidden LSTM layer consisting of d neurons is used, where d is a number of input variables. 14-day window was exploited to predict the target class. Also in this case, the Adam optimizer with learning rate 0.001 is utilized, learning is processed in 150 epochs, and sparse categorical crossentropy is being used as the loss function.

6.4 Simulation of Price Fixing

Prices which were estimated to belong to the 1-st category, representing a very strong buy signal, will be utilized for the purposes of simulated price fixing procedure. In case the examined model does not distinguish any prices as the strong buying opportunity for the respective year, price fixing will be proceeded 15 days before the end of contract expiry, as it is a common practice.

7. Results

7.1 Evaluation Metrics

While solving a classification task, the commonly used evaluation metric is a percentage of correctly classified data, i.e., accuracy. However, in case of a multinominal classification problem, which can be perceived as a generalization of logistic regression, it is highly beneficial to calculate other types of evaluation metrics, which are commonly used in the context of estimating continuous output, such as mean absolute error (MAE), mean square error (MSE) or root mean square error (RMSE). Furthermore, confusion matrices will be presented, allowing deeper understanding of the model generalization abilities.

For the purposes of this study, model estimates need to be evaluated not only from the quantitative but also from the qualitative perspective. Even when low prediction accuracy is achieved, the model might still offer significant improvement in the price fixing. However, in this case RMSE should be lower than 4, considering the number of output classes. Thus, in the following chapter accuracy as well as RMSE are examined.

7.2 Fundamental Approach

Based on conducted empirical research, the most relevant fundamental variables were estimated to be the price of Czech power, coal, brent, gas and emission allowances, i.e., the vector of input variables can be defined $x = (x_{\text{power}}, x_{\text{coal}}, x_{\text{brent}}, x_{\text{gas}}, x_{\text{EUAs}})$; S&P index was excluded from the input dataset because its utilization did not improve model performance. At first sight, model accuracy as well as loss function and RMSE improve with the increasing complexity of the model structure (see Tab. I). However, closer examination shows that the generalization abilities of the fundamental approach is insufficient. Except the LSTM, models do not successfully distinguish strong buying signal in all the respective years, and thus alternative procedure, i.e., price fixing at the last instance before contract expiry, must be executed. Confusion matrixes in Figs. 6, 8 and 10 also present unsatisfactory performance of the feed-forward neural networks, which capture only limited spectrum of possible outputs. Only LSTM offers more robust prediction efficiency, as shape of the confusion matrix more closely resembles diagonal (see Fig. 12);

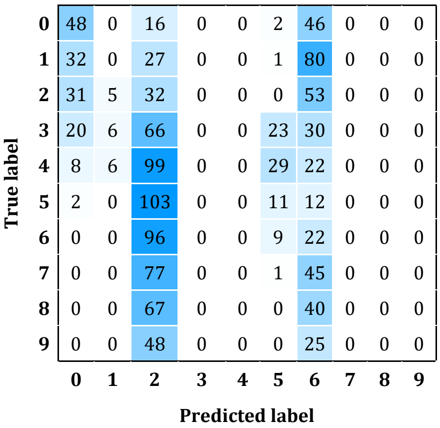

Fig. 6 *Fundamental approach – classification with the logistic regression (i.e., one-layer feed forward neural network).*

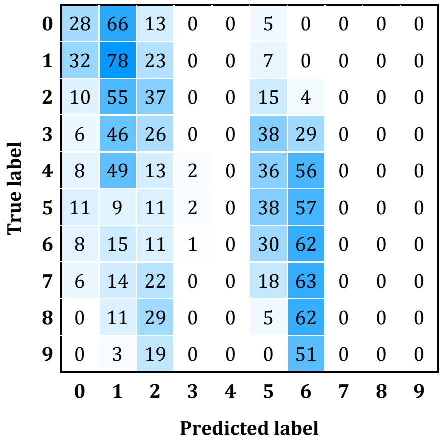

Fig. 7 *Technical approach – classification with the logistic regression (i.e., one-layer feed forward neural network).*

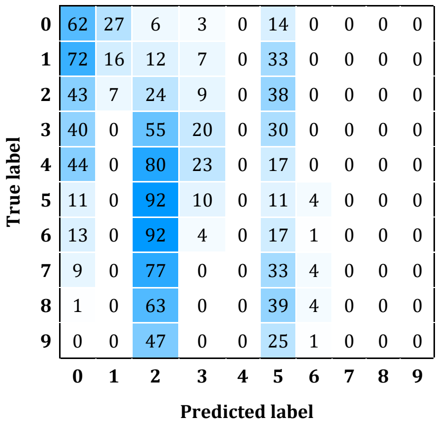

Fig. 8 *Fundamental approach – classification with the two-layer feed forward neural network.*

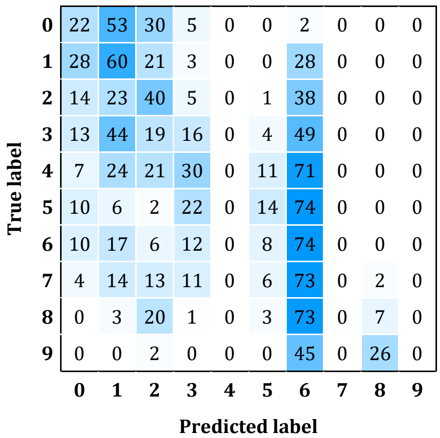

Fig. 9 *Technical approach – classification with the two-layer feed forward neural network.*

also distinct improvement of the price compared to the usual fixing procedure was achieved (see Tab. II).

7.3 Technical Approach

For the purposes of technical analysis, the price of the Czech power, relative strength index (RSI), 14-day moving average and 14-day volatility were used as the input variables, i.e., the vector of input variables is defined $x = (x_{\text{power}}, x_{\text{RSI}}, x_{\text{MA}}, x_{\text{volatility}})$. Unexpectedly, the research has shown that the technical approach offers

Method	Accuracy (%)		Loss		RMSE
	Training	Testing	Training	Testing	Testing
Logistic Regression (i.e, one-layer NN)	25.03	9.11	2.05	3.03	3.57
Two-layer Neural Network	30.58	10.81	1.91	2.95	3.39
Three-layer Neural Network	37.29	13.23	1.66	3.21	3.42
LSTM	28.89	13.06	1.85	2.64	3.44

Tab. I *Evaluation of prediction efficiency of the models.*

Year	Usual Fixing Procedure	Logistic Regression (i.e., 1-layer NN)		Two-layer Neural Network		Three-layer rNeural Network		LSTM	
		Abs.	Δ %	Abs.	Δ %	Abs.	Δ %	Abs.	Δ %
2016	27.06	23.68	−12.50	25.97	−4.00	33.17	22.60	25.04	−7.50
2017	32.87	39.47*	20.10*	29.77	−9.40	32.28	−1.80	35.23	7.20
2018	45.29	55.30*	22.10*	55.30*	22.10*	35.39	−21.90	38.40	−15.20
2019	50.46	46.08*	−8.70*	46.08*	−8.7*	46.08*	−8.70*	48.60	−3.70
2020 (till 09/2020)	43.95	40.84	−7.10	45.77*	4.10*	45.77*	4.10*	43.77	−0.40
Avg.	39.93	41.07	2.80	40.58	0.80	38.54	−1.10	38.21	−3.90

*No strong buying signal was distinguished by the model; therefore, price fixing was executed at the last possible instance, i.e., 15 days before the contract expiry.

Tab. II *Simulation of price fixing and its comparison with the usual fixing procedure.*

much better generalization abilities than the fundamental one. Even though accuracy, loss function as well as RMSE of the one-, two- and thee-layer neural networks are very similar, confusion matrixes of the more complex structures demonstrate better ability to estimate trading signal, especially in the categories 7 to 9, which represent selling signals (see Figs. 7, 9 and 11). Although LSTM offers the best result in terms of price fixing (Tab. IV), it does not offer the best generalization abilities, as presented in Fig. 13.

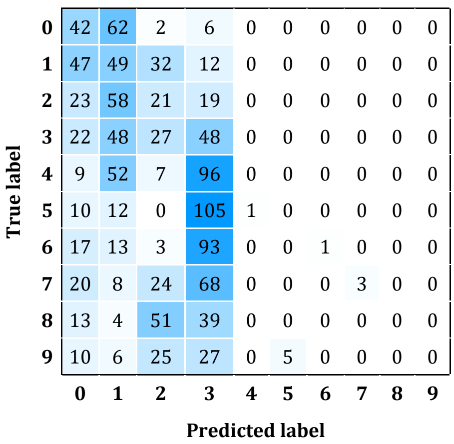

Fig. 10 *Fundamental approach – classification with the three-layer feed forward neural network.*

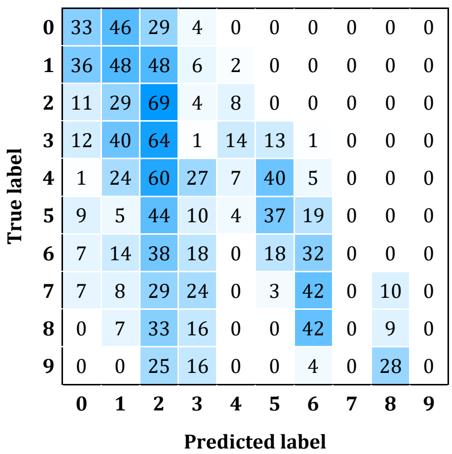

Fig. 11 *Technical approach – classification with the three-layer feed forward neural network.*

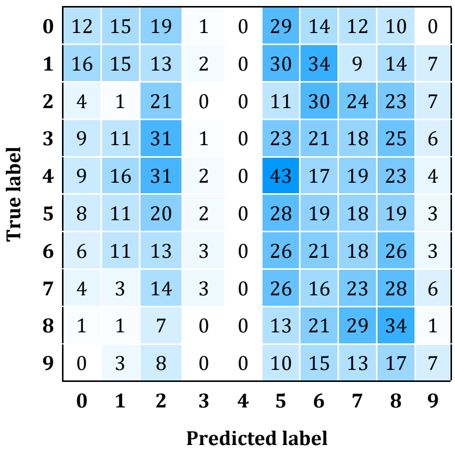

Fig. 12 *Fundamental approach – classification with the LSTM.*

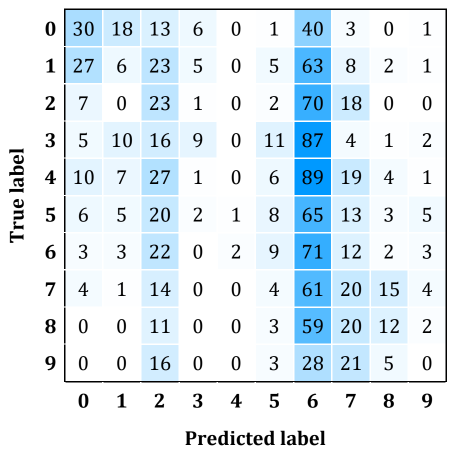

Fig. 13 *Technical approach – classification with the LSTM.*

Method	Accuracy (%)		Loss		RMSE
	Training	Testing	Training	Testing	Testing
Logistic Regression (i.e., 1-layer NN)	19.87	19.19	2.11	2.18	2.64
Two-layer neural network	24.3	18.79	2.04	2.18	2.51
Three-layer Neural network	25.63	19.03	1.92	2.27	2.74
LSTM	22.19	14.44	1.97	2.51	3.04

Tab. III *Evaluation of prediction efficiency of the models.*

Year	Usual Fixing Procedure	Relative Strength Index		Logistic Regression (i.e., 1-layer NN)		Two-layer neural network		Three-layer Neural network		LSTM	
		Abs.	Δ %	Abs.	Δ %	Abs.	Δ %	Abs.	Δ %	Abs.	Δ %
2016	27.06	26.19	−3.2	26.09	−3.6	25.11	−7.2	26.24	−3.0	24.74	−8.6
2017	32.87	28.96	−11.9	29.42	−10.5	28.49	−13.3	29.40	−10.6	28.59	−13.0
2018	45.29	36.55	−19.3	36.01	−20.5	38.05	−16.0	35.91	−20.7	36.24	−20.0
2019	50.46	48.68	−3.5	49.03	−2.8	48.24	−4.4	45.77	−9.3	47.78	−5.3
2020 (till 09/2020)	43.95	42.10	−4.2	41.42	−5.8	42.19	−4.0	41.27	−6.1	41.87	−4.7
Avg.	39.93	36.50	−8.4	36.39	−8.6	36.42	−9.0	35.72	−9.9	35.84	−10.3

Tab. IV *Simulation of price fixing and its comparison with the usual fixing procedure.*

8. Discussion & Conclusion

The main goal of this study was an estimation of trading signals in the context of Czech power futures market, and subsequent optimization of the purchase strategy of retail customers. Continuous price fixing, which is a very popular and commonly used method ensuring average profit-loss result, was used as a benchmark to evaluate benefits of the exploited methods.

Trading signals were estimated with the use of two different approaches, the fundamental analysis and technical analysis. Even though the fundamental value of power can be easily derived from the prices of energy resources, such as coal and gas, the research has shown that the technical analysis offers much better generalization abilities in terms of estimating trading signals.

Contrary to the fundamental approach, each of the examined methods within the technical analysis achieved steadily better results through all the examined years compared to the usual fixing procedure and ensured average savings of more than 8 %. Moreover, all the proposed neural networks achieved better results compared to the relative strength index, a well-established technical indicator used among traders. Among all, the best generalization abilities were achieved while using the three-layer feed forward neural network; in this case average savings made almost 10 % compared to the continuous fixing procedure. Thus, this method was determined to be the most appropriate for the purposes of estimation of buying signals.

Considering an average auctioned volume in the order of tens of thousands of MWhs, the potential average savings while utilizing the proposed solution reach value in range of tens to hundreds of thousands of EUR per one auction in comparison to the benchmark.

Even though the discussed solutions already exceeded the defined benchmark, there are some perceived areas for potential improvement. Despite the unique abilities of neural networks to solve many types of non-linear and non-stationary problems, in most cases it is very difficult to interpret results. Thus, utilization of a Bayesian approach is proposed as a part of further research. It is also proposed to explore other types of neural networks, such as convolutional networks or fuzzy neural networks. Additionally, it might be beneficial to explore other types of activation functions, such as rectified linear unit (ReLu), which can also improve the overall performance of learning.

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