# The Impact of COVID-19 on Electricity Prices in Italy, the Czech Republic, and China

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**Abstract:** COVID-19 is likely to be the 2020s' deadliest pandemic according to the World Health Organization (WHO). There have been more than 3.7 million confirmed deaths after 15 months spread. Besides the loss of human lives, COVID-19 has other unfavorable impacts on society, education, and the economy. Due to successive lockdowns and the continuous quarantines, the demands on power resources have reduced. Therefore, there is a need to investigate the impacts of the COVID-19 pandemic on electricity prices (EP). In this paper, a set of six economic factors that are affected by COVID-19 and affect EP are considered. These factors were fed into a functional link artificial neural network (FLANN) to model the relationships between them and the EP. An empirical equation was formulated to help decision makers and strategic developers in the electricity markets come up with more appropriate plans. Italy, the Czech Republic, and China were used as case studies in this research.

**Keywords:** electricity prices; GDP; PMI; CPI; COVID-19; unemployment rate

## 1. Introduction and Related Work

The COVID-19 epidemic has had a notable and intense impact on various aspects of the lives and livelihoods of people around the world. Over 176 million infections and 3.8 million deaths, as of 16 June 2021 [1], have been confirmed worldwide. The majority of social and economic activities have been desolated due to the lockdowns. The consequences have been particularly severe for manufacturing and service sectors, such as tourism and transportation. Government regulations have been dedicated to decreasing the spread of COVID-19 through lockdowns, and stay-at-home plans have impacted energy price patterns [2]. Figure 1 shows the monthly electricity production in gigawatt-hours during the period 1 January 2020 to 1 January 2021 [3] in the Czech Republic. It is obvious from this figure that electricity production declined to the minimum in April 2020. Thereafter, it began to hike in September 2020, after staying in place for 4 months. The decline in the electricity production curve reflects the decrease in the EP due to the COVID-19 precautions. A data hub and cross-domain analysis integrating traditional electricity data with cross-domain sources such as public health and mobility data have been released to quantify

the impacts of these policies on electricity consumption [4]. A systematic review was presented in [5] to identify the impacts of stay-at-home living patterns on the electricity consumption of household buildings. The data were collected from different sources to assess the changes in overall electricity demand for various countries and US states. Diurnal EP and monthly nighttime light intensity were considered to monitor the economic activity in India [6]. The actual EP level is 90% lower than the regular one before COVID-19. A framework that can predict the behavior of dynamic electricity markets during the COVID-19 pandemic period was proposed in [7] to help to manage the electricity market by developing new strategies. The impacts of different containment measures taken by European countries in response to the COVID-19 epidemic on EP were compared in [8]. Two sets of countries were used for this comparison. The first set contained Spain, Italy, Belgium, and the UK as countries with severe restrictions. The other set contained the Netherlands and Sweden as countries with less restrictive rules. Three scenarios were analyzed in [9] to investigate the influence of forced lockdowns on the EP, and their impacts on the electricity transition. Multivariant time series were used along with bidirectional long short-term memory to predicate the effects of the COVID-19 response on the EP in the UK [10]. In [11], a comparative regressive and artificial neural network (ANN) model was developed to interpret the impacts of COVID-19 responses on the EP and petroleum demand in China. The impact of the COVID-19 response on the selling prices of electricity in Spain was highlighted considering the special level of uncertainty in global energy markets using time series algorithms [7]. In this study, a framework to model the dynamic electricity market during the global pandemic was developed to help technical role players to predict and develop strategies to get rid of the unfavorable impacts of epidemics.
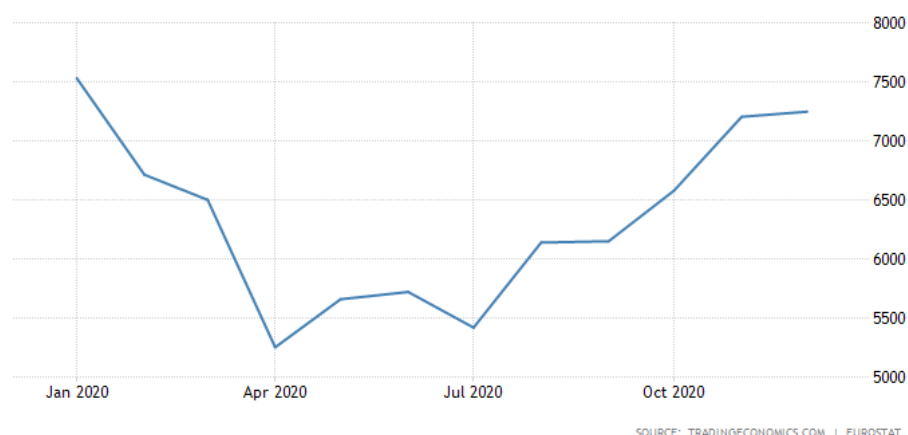


**Figure 1.** The monthly electricity production in Gigawatt-hours during the period 1 January 2020 until 1 January 2021 the in Czech Republic.

## 2. The Research Gap and Our Motivation

The direct relationship between economical factors and the EP during the COVID-19 pandemic is difficult to define, due to the data shortage and fluctuations. The available data are not plentiful enough to be fit into one of the well-known statistical methods. Moreover, they are not populous enough to train a standard ANN model, which gets more reliable when more data are used. Therefore, neither time series nor ANN-based models could efficiently predicate the EP values. These observations motivated us to investigate the performance of the FLANN model for EP prediction during COVID-19, because of its low complexity—it has only one neural layer. The FLANN model was employed in [12] for equalization of a nonlinear channel using an expansion function to provide the coveted nonlinearity. The FLANN model was also used in [13] for the identification of nonlinear systems. The trigonometric functions were employed in FLANN to estimate the short and long-term stock market prices in [14]. Orthogonal base functions are also used in FLANN, such as the Chebyshev polynomial [15].

### 3. Descriptions of the Economical Factors Used

The immediate relationship between the EP and the COVID-19 containment measures is challenging to define. Therefore, we determined this relationship by studying the impacts of COVID-19 spread on a set of four economical factors. These factors are listed in Table 1, and described in the following subsections.

**Table 1.** Economical factors used in the simulation study.

| Factor | Description |
|:---:|:---:|
| GDP | Gross Domestic Product |
| UR | Unemployment rate |
| CPI | Consumer Price Index |
| PMI | Purchasing Managers' Index |

#### 3.1. Gross Domestic Product (GDP)

COVID-19 did not affect people's lives and health only; it also caused global damage to the economy. Less consumption of goods and services was noticed compared to the pre-COVID-19 period. The policies that were imposed by governments to slow the spread of the virus worldwide caused lower demand for the majority of industries, such as the travel and tourism sectors. Stock markets have also suffered dramatic declines due to the coronavirus outbreak. All those dynamic changes led economies to lose large amounts of their GDPs. Figure 2 shows the percentage changes in quarterly GDP in the Czech Republic during the period 1 October 2019 to 1 April 2021 [16].
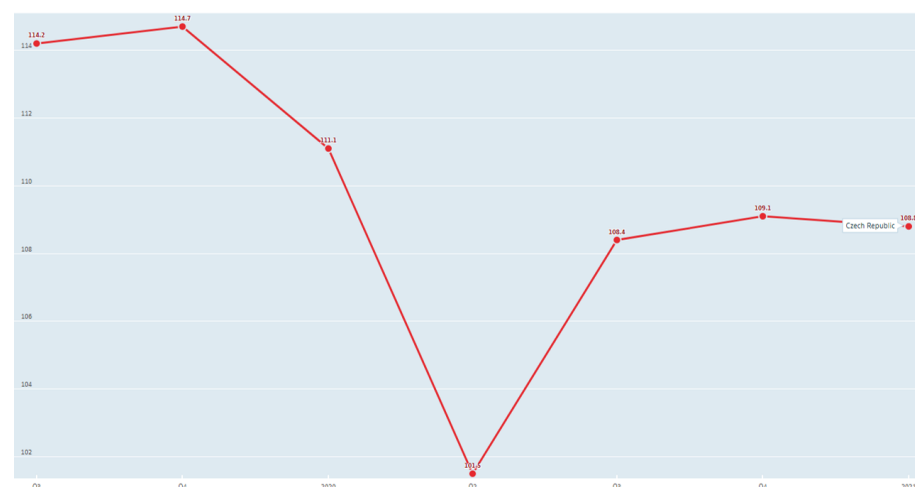


**Figure 2.** The percentage changes in quarterly GDP in the Czech Republic.

It was reported that GDP declined in Italy by 30% during the severe lockdowns, using a prediction approach on data collected from an Italian day-ahead power market [17]. The potential consequences of COVID-19 on GDP were simulated in [18] using a standard global equilibrium model.

#### 3.2. Unemployment Rate (UR)

The COVID-19 response has had a significant impact on the labor market. UR plays a vital role as a financial indicator for investors, and accordingly, they respond with dynamic strategies. Figure 3 shows the negative impacts of COVID-19 responses on the labor markets in Italy and the Czech Republic. This figure shows the UR for each country compared to the total currently active population, who are able to be employed, as a percentage. High UR values indicate few job opportunities, which might have been caused by less demand for some products or services during the lockdowns. Consequently, the EP

patterns changed to respond to these modifications during the COVID-19 period. Hybrid forecast approaches supported by linear and non-linear models were considered in [19] to precisely estimate the UR. The proposed model of UR can improve its estimates by reproducing the unemployment ratio distortion.
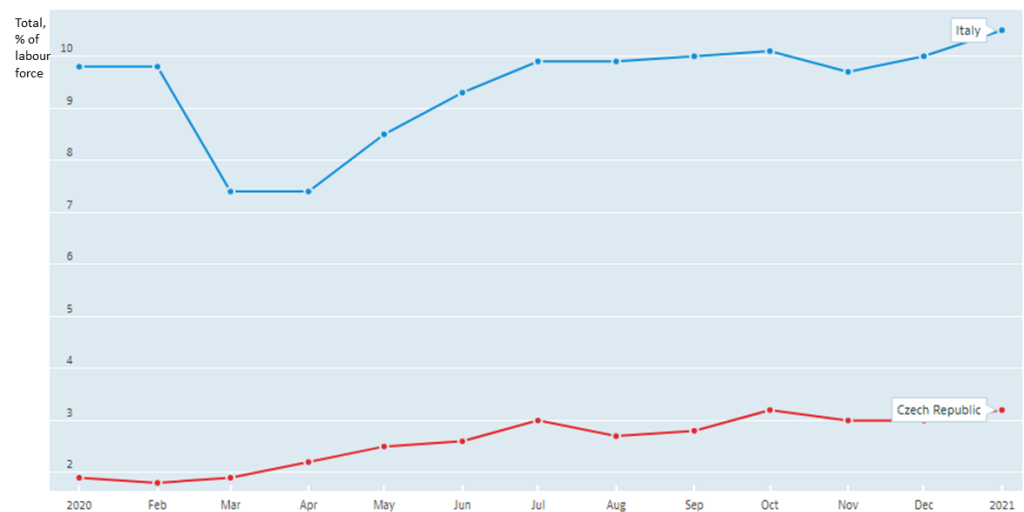


**Figure 3.** The negative impact of COVID-19 outbreaks on UR in Italy and the Czech Republic [20].

*3.3. Consumer Price Index (CPI)*

CPI is a measure that calculates the weighted mean of prices of a consumer basket. The basket regularly contains goods and services, such as transportation, food, and medical care. CPI is computed by taking price changes for each item in the basket and averaging them. It has been proven that the cost of living is associated with the changes in the CPI. Therefore, the CPI is one of the most important indicators used for identifying periods of inflation and deflation. The EP levels were −5% and −4.7% in the Czech Republic and Italy, respectively, during the COVID-19 period, compared to pre-COVID-19. In contrast, food demand increased 0.6% and 0.7% in the Czech Republic and Italy, respectively, as shown in Table 2.

**Table 2.** Changes in energy and food demand during the COVID-19 outbreaks in Italy and the Czech Republic.

| Perspectives | Czech Republic | Italy |
| --- | --- | --- |
| EP | −5% | −4.7% |
| Food demands | 0.6% | 0.7% |

*3.4. Purchasing Managers' Index (PMI)*

PMI is an index of the principal trends of macroeconomics in the manufacturing and service sectors. It consists of a diffusion index that reviews whether the market state, as observed by purchasing managers, is growing, staying the same, or shrinking. The importance of the PMI is providing information about current and expected business conditions to decision makers and investors. Figure 4 shows the changes in PMI in China . These data were collected from a questionnaire given to 430 organizations. The manufacturing PMI is computed using five weighted indices as follows: fresh orders (30%), production (25%), employment (20%), suppliers' delivery times (15%), and value of the purchased items (10%), with the delivery times index being inverted so that it is more intuitive. A value greater than 50 represents growth of the manufacturing sector compared to the past month; aa value that is less than 50 represents a decrease in development; 50 intimates no difference.
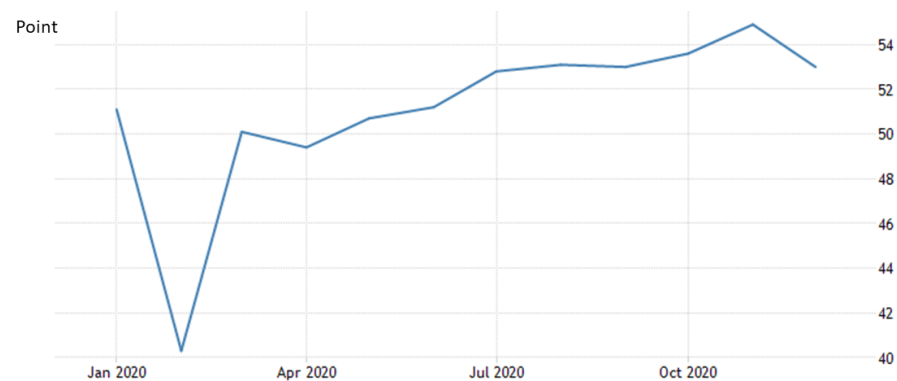
**Figure 4.** Changes in PMI in China during the COVID-19 pandemic [21].

## 4. The Proposed Approach for EP Estimation

We aimed to investigate the impacts of the COVID-19 pandemic on macroeconomics by analyzing macroeconomic factors. Therefore, a set of six economical determinants was been used as input to the FLANN model, and the EP was the output of the FLANN model, as shown in Figure 5. The values of the six economical variables and the EP were collected during the same period: from 1 January 2020 to 1 January 2021. Those measurements are defined in Table 3, along with their links to online, live data sources. Normally, the more data, the more accurate the model can be. However, the proposed FLANN model can provide precise outputs with fewer data points than the other artificial neural networks need because of the functional expansion that it applies to the input set. The input values were first normalized before they are feed into the FLANN model using Equation (1):

$$v_{norm} = \frac{v - v_{min}}{x_{max} - x_{min}} \tag{1}$$

where $v_{norm}$ is the normalized value of $v$; $v_{min}$ and $v_{max}$ are the minimum and maximum values for a certain factor, respectively.
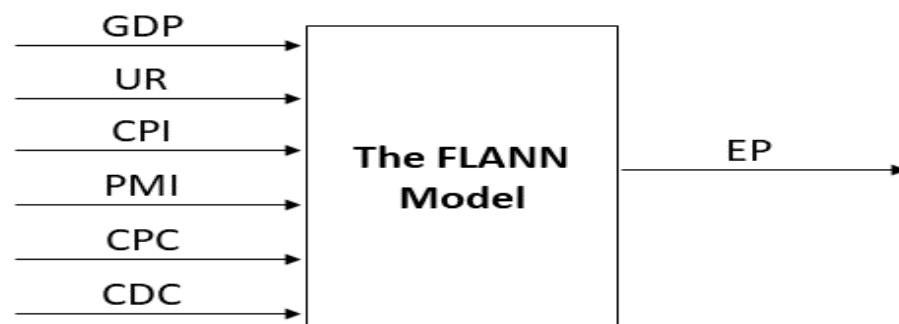


**Figure 5.** The proposed FLANN model.

**Table 3.** Data sources for the economical factors used in simulation study.

| Factor | Link to Data Source |
|---|---|
| GDP | The Organization for Economic Co-operation and Development, GDP, https://data.oecd.org/gdp/quarterly-gdp.htm, accessed on 16 June 2021 |
| UR | The Organization for Economic Co-operation and Development, Unemployment rate, https://data.oecd.org/unemp/unemployment-rate.htm, accessed on 16 June 2021 |
| CPI | The Organization for Economic Co-operation and Development, Inflation (CPI), https://data.oecd.org/price/inflation-cpi.htm, accessed on 16 June 2021 |
| PMI | The Organization for Economic Co-operation and Development, PMI, https://www.investing.com/economic-calendar/czech-markit-markit-pmi-812, accessed on 16 June 2021 |
| CPC | Global No.1 Data Platform, Statista.com, Number of COVID-19 confirmed cases, https://www.statista.com/statistics/1104327/czechia-coronavirus-COVID-19-new-cases, accessed on 16 June 2021 |
| CDC | Data science environment, kaggle.com, Number of COVID-19 death cases, https://www.kaggle.com/sudalairajkumar/novel-corona-virus-2019-dataset?select=COVID_19_data.csv, accessed on 16 June 2021 |
| EP | International Energy Agency, Iea.com, Electricity Statistics, https://www.iea.org/data-and-statistics/data-product/monthly-electricity-statistics, accessed on 16 June 2021 |

### 4.1. The FLANN Model for EP Estimation

Here, a FLANN-based estimation approach is proposed to figure out the relationship between the aforementioned factors and the EP. Figure 6 shows the structure of the FLANN

model. In this study, four expansion functions were applied to find the most reliable function and recommend it for practical use. The input to the FLANN model is the *i*th set, $x_i$, which contains the six values of the economical factors. The output of the FLANN is the corresponding predicated $y_i$, which represents the EP value, where $1 \leq i \leq I$, and $I$ is the number of input sets. The expansion functions used in developing the models are listed. The model was trained using 70% of the data collected from the online resources monthly. The remaining 30% of data points were used to validate the resultant model.

1. The trigonometric expansion:

$$\boldsymbol{\Phi}_t(x_i) = \{x_i, \cos \pi x_i, \sin \pi x_i, ..., \cos N\pi x_i, \sin N\pi x_i\} \tag{2}$$

where $N$ = number of trigonometric terms; $M = 2N + 1$ is the total number of terms after expansion.

2. The polynomial expansion:

$$\boldsymbol{\Phi}_p(x_i) = \left\{x_i, x_i^2, ..., x_i^N\right\} \tag{3}$$

where $|x_i| \leq 1$, $N$ is the degree of the polynomial, and $M = N + 1$ is the total number of terms after expansion.

3. The exponential expansion:

$$\boldsymbol{\Phi}_e(x_i) = \left\{x_i, e^{x_i}, e^{2x_i}, ..., e^{Nx_i}\right\} \tag{4}$$

where $|x_i| \leq 1$, $N$ is the number of exponential terms, and $M = N + 1$ is the total number of terms after expansion.

4. The Chebyshev expansion:

$$T_{N+1}(x_i) = 2x_i \, T_N(x_i) - T_{N-1}(x_i) \tag{5}$$

where $T_0(x_i) = 0$, $T_1(x_i) = x_i$. If $N = 5$, then the expanded number of terms is $M = N = 5$. Those terms are as given in (6):

$$\boldsymbol{\Phi}_c(x_i) = \left\{x_i, \ 2x_i^2 - 1, \ 4x_i^3 - 3x_i, \ 8x_i^4 - 8x_i^2 + 1, \ 16x_i^5 - 20x_i^3 + 5x_i\right\} \tag{6}$$

where $|x_i| \leq 1$.

The FLANN model firstly expands the input $x_i$ to $M$ terms. Thereafter, each expanded value, $\phi_m(i)$ is multiplied by a weight $\omega_m(k)$. The value of $k$ represents the index of the current iteration during the FLANN learning phase. The $\omega_m(k)$ values are then modified by the standard least mean square (LMS) algorithm at the end of each repetition. The Sigmoid function is used as an activation function, as given in (7):

$$\hat{y}(i, k) = \frac{1}{1 + e^{-s(i,k)}} \tag{7}$$

The $s(i, k)$ value is calculated as in (8):

$$s(i, k) = \sum_{m=1}^{M} \phi_m(i) \, \omega_m(k) \tag{8}$$

The estimated error, $e(i, k)$, is computed as:

$$e(i, k) = y_i - \hat{y}(i, k) \tag{9}$$

The value of $y_i$ is the actual output corresponding $i$th input $x_i$, and $\hat{y}(i,k)$ is the estimated output at the $k$th iteration. The LMS updates the $M$ weights for each $i$th input. The weights are modified as in (10):

$$\omega_m(k+1) = \omega_m(k) + \Delta\omega_m(k) \tag{10}$$

The update of any $m$th weight in each run, $\Delta\omega_m(k)$, is computed as:

$$\Delta\omega_m(k) = \sum_{i=1}^{I} \sum_{m=1}^{M} \frac{2\mu\,\omega_m(i)\,\delta(i,k)}{M \times I} \tag{11}$$

where $I$ is the sample set size used for the training. $M$ is the number of expanded terms. $\mu$ is the learning rate parameter, which should have a value between 0 and 1. The term $\delta(i,k)$ is computed as:

$$\delta(i,k) = \frac{1 - \hat{y}^2(i,k)}{2}\,e(i,k) \tag{12}$$
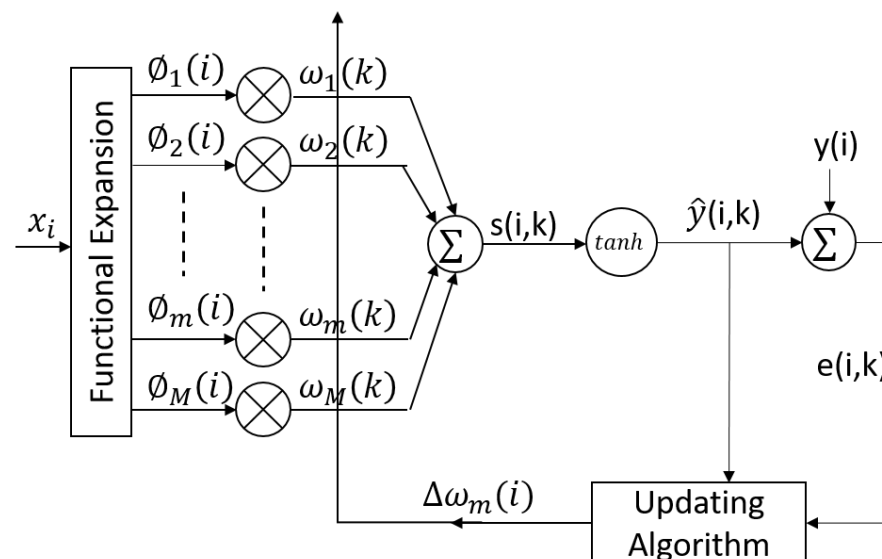


**Figure 6.** The block diagram of the FLANN model.

*4.2. Simulation Study*

The model was trained for 1000 epochs. The mean square error (MSE) for each expansion function after convergence was measured and listed in Table 4. The learning curves for each expansion function are shown in Figure 7 as well. After finishing the training phase, the ultimate weights of all models were saved, which provide the empirical relationship between the input parameters and the EP predicated during implementation time. The empirical equation for estimating the EP obtained from the Chebyshev-based FLANN model is:

$$EP(i) = sig\left(\sum_{k=1}^{6}(\omega_k(0)\,v_{i,k} + \sum_{n=1}^{4}\omega_k(n)\,[2v_{i,k}\,T_{n-1}(v_{i,k}) - T_{n-2}(v_{i,k})])\right), \; T(0) = 1 \tag{13}$$

where $sig$ represents the sigmoid function. $v_{i,k}$ is the $i_{th}$ value of the economical factor $k$. The weights after training of the FLANN model are shown in Table 5. These weights could directly be used in the formula given in (13). By substituting these weights and the value of $v_{i,k}$, the $EP_i$ is predicated very fast.

**Table 4.** a comparison of FLANN model convergence with four different base functions.

| Expansion Function | MSE after Convergence |
|---|---|
| Polynomial | 0.06 |
| Trigonometric | 0.05 |
| Exponential | 0.04 |
| Chebyshev | 0.01 |

**Table 5.** Estimated weights $\omega_k(n)$ of the Chebyshev-based FLANN models to be used in the empirical formula.

| k | n = 0 | n = 1 | n = 2 | n = 3 | n = 4 |
|---|---|---|---|---|---|
| 1 | 0.091 | 0.021 | −0.144 | 0.761 | −0.066 |
| 2 | 0.043 | −0.078 | 0.38 | 0.072 | 0.057 |
| 3 | −0.026 | 0.497 | 0.637 | −0.239 | −0.086 |
| 4 | 0.417 | −0.089 | 0.691 | 0.277 | 0.737 |
| 5 | −0.084 | −0.103 | −0.404 | −0.54 | 0.044 |
| 6 | 0.436 | −0.094 | −0.053 | −0.369 | 0.564 |
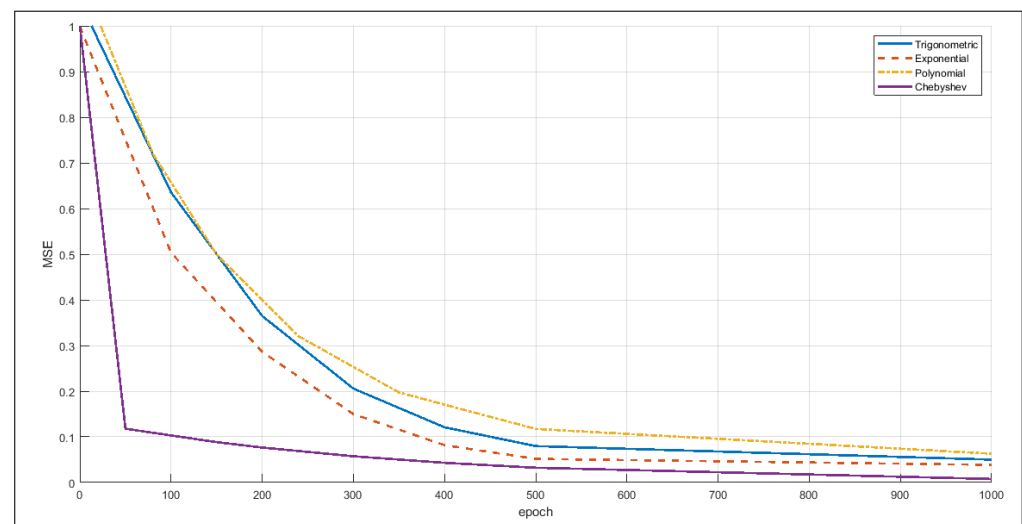


**Figure 7.** A comparison of convergence properties during model training.

## 5. Experimental Results

A comprehensive investigation was done to validate the robustness of the proposed model against the changes in the input set. Therefore, three different study cases were considered—Italy, China, and the Czech Republic—to verify the simulation results. These three scenarios were taken into account because Italy experienced a bad situation during the COVID-19 period. China was the first place where COVID-19 started to spread rapidly; thus, the Chinese indicators from that time are very important. The Czech Republic's conditions were moderate and under control in the period considered. Figures 8–10 show both estimated and actual EP for one year from 1 January 2020 until 1 January 2021 in the Czech Republic, Italy, and China. The expected curves and actual curves are approximately identical, which reflects the strength of the proposed FLANN model. The actual EP for each country were collected and considered one set of target outputs. The FLANN model's output was compared to the actual EP value by value, and the MSE between actual EP and model output for each country was computed and listed in Table 6. Time series-based techniques are less effective when the volume of historical data is low, and that is the situation here. The changes in EP came about due to external factors; any technique that does not take those factors into account will fail. The results obtained in the FLANN model considered multiple factors that directly and indirectly affect the EP values. To avoid overfitting problems while training the

model, expansion functions were used to provide enough and related data. Furthermore, the structure on FLANN includes a single layer of neurons which itself reduces the overfitting level. The results retrieved from the experimental studies are promising and encourage the use of the proposed model to estimate power prices using little data.

**Table 6.** The MSE values between actual EP and estimated EP for the Czech Republic, Italy, and China.

| Country | MSE Value |
| --- | --- |
| Czech Republic | 0.0609 |
| Italy | 0.0718 |
| China | 0.0402 |
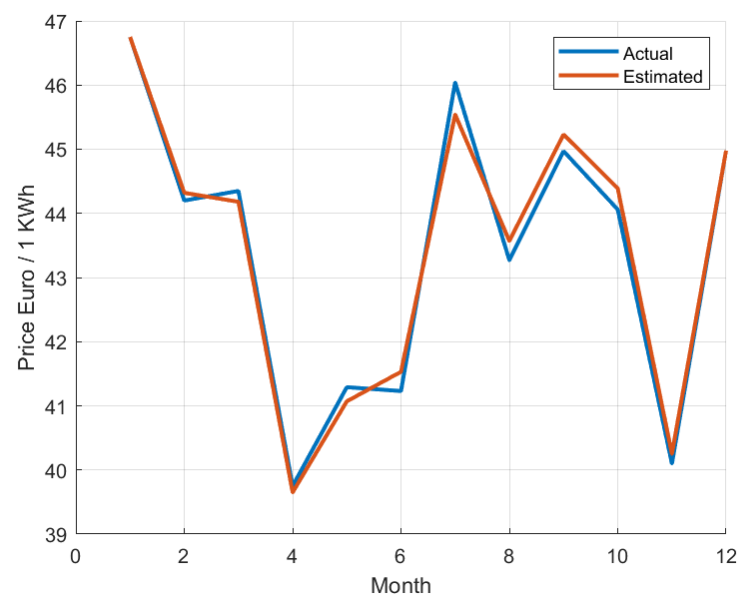


**Figure 8.** A comparison of estimated EP and the actual EP values in the Czech Republic.
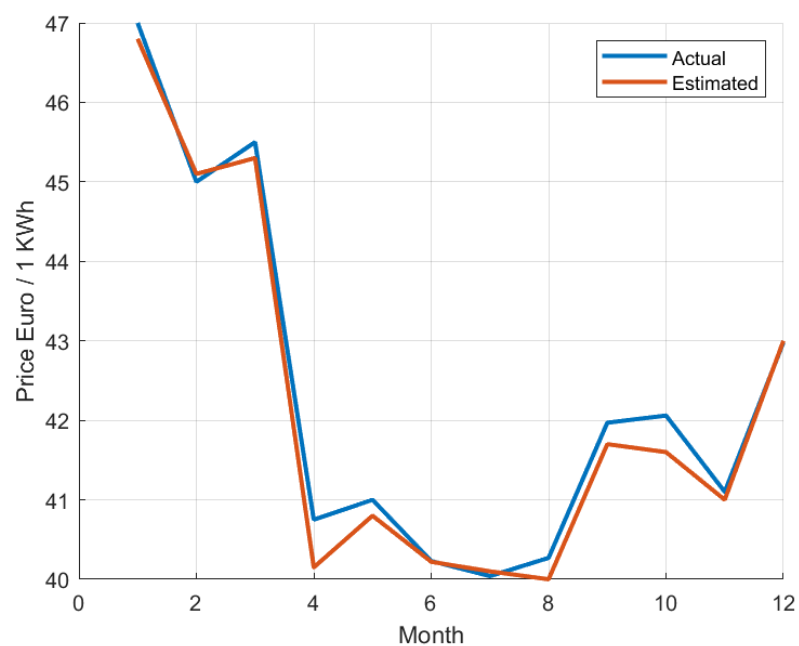


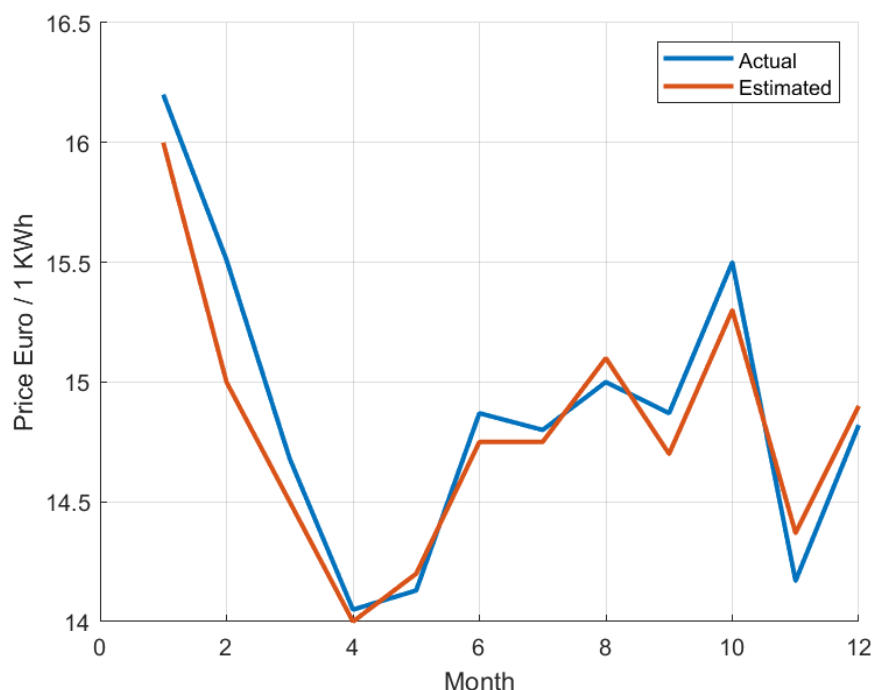**Figure 9.** A comparison of estimated EP and the actual EP values in Italy.

**Figure 10.** A comparison of estimated EP and the actual EP values in China.

## 6. Conclusions

In this paper, the impact of the COVID-19 pandemic on EP was investigated using a set of economical factors. The EP values were predicated using a low complexity and fast FLANN model. EP estimation is vital for strategic planning. The FLANN model was selected for this study because of the functional expansions in the first layer of FLANN, and it provides the required nonlinearity for accurate estimation. The Chebyshev-based FLANN model outperformed the other three FLANN structures we tested. The availability of more statistics would significantly improve the accuracy of the proposed model. Therefore, collecting more data belonging to different countries would help to train our model, and consequently, make a more reliable FLANN model.

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