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Indirect Impact of the COVID-19 Pandemic on Natural Gas Consumption by Commercial Consumers in a Selected City in Poland

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Abstract: In March 2020, a lockdown was imposed due to a global pandemic, which contributed to changes in the structure of the consumption of natural gas. Consumption in the industry and the power sector decreased while household consumption increased. There was also a noticeable decrease in natural gas consumption by commercial consumers. Based on collected data, such as temperature, wind strength, duration of weather events, and information about weather conditions on preceding days, models for forecasting gas consumption by commercial consumers (hotels, restaurants, and businesses) were designed, and the best model for determining the impact of the lockdown on gas consumption by the above-mentioned consumers was determined using the MAPE (mean absolute percentage error). The best model of artificial neural networks (ANN) gave a 2.17% MAPE error. The study found a significant decrease in gas consumption by commercial customers during the first lockdown period.

Keywords: forecasting gas consumption; neural networks; lockdown

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1. Introduction

Natural gas is an important raw material in the sustainable energy policy due to its growing importance in the global economy [1,2]. The global economy has observed a continuous growth of natural gas consumption since the 1960s, with a growth rate of 3.5% over the last five years. In 2019, 3.92 trillion m^3 of natural gas were consumed worldwide (Figure 1). Poland also shows an upward trend in the consumption of natural gas. The largest decrease was recorded in the period of political transition from 1987–1992 (Figure 2). Natural gas accounts for 36.2% of overall household energy consumption in the EU, ranking first. The share of natural gas consumption in Poland, however, is 18.4%, just behind coal consumption, which amounts to 32.3% [3]. Construction of new natural gas facilities is being considered. These would play a transitional role in the process of energy transformation towards the widest possible use of RES, which is referred to in the drafted EU energy policy and national energy development scenarios. The extent to which natural gas is used in the power industry will depend, among others, on the price of this fuel and on the prices of carbon dioxide emission allowances [4–6]. In the case of Europe, the risk of stagnation is observed. This is caused by a drop in consumption and restrictions regarding investments in gas-fuelled power plants and gas infrastructure development since infrastructure is not operating to its maximum capacity [7].

In light of the above information, natural gas consumption forecasts will have a major impact on public utilities and energy traders. Forecasting consumption will allow the determination of service charges for gas consumed in the future. Determining natural gas consumption in the near future enables planning decisions regarding the purchase of natural gas by national and local companies, its storage, scheduling network loads, and undertaking upgrading and investment tasks related to the day-to-day operation of the gas infrastructure by ensuring the security of the gas supply and its proper operation [8–15].

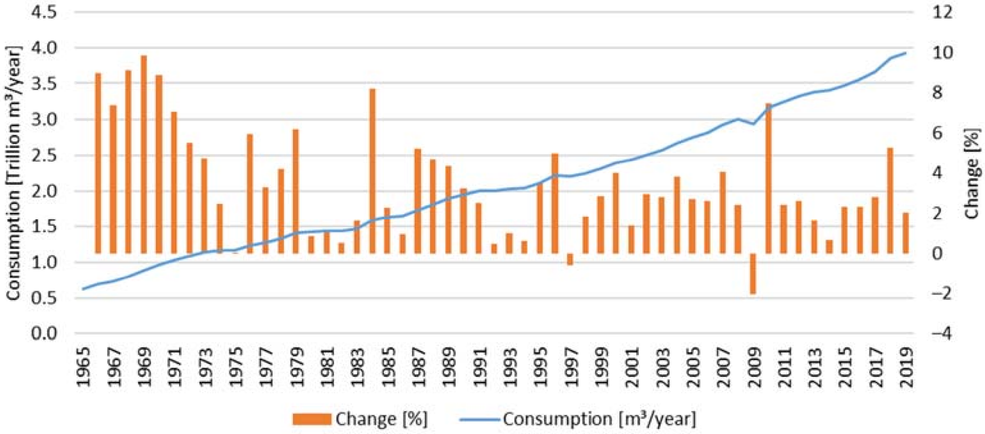

Figure 1. Changes in natural gas consumption worldwide [8].

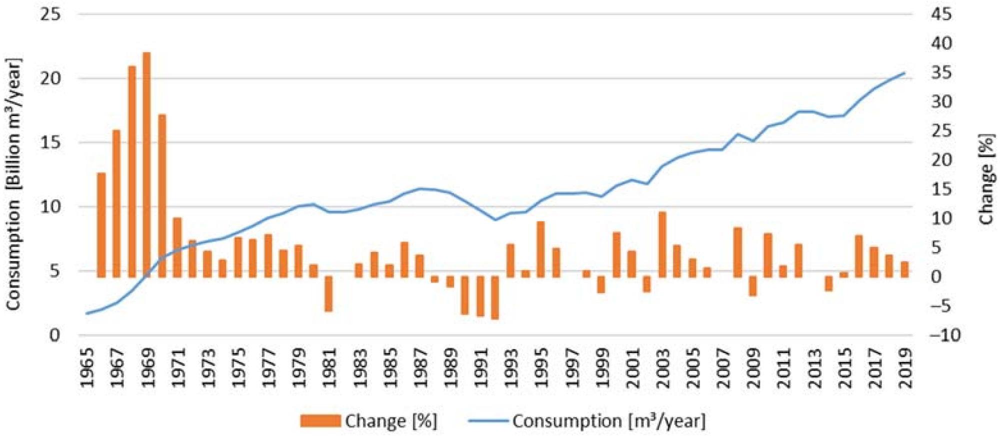

Figure 2. Changes in natural gas consumption in Poland [8].

2. The COVID-19 Pandemic

A global pandemic broke out in early 2020, resulting in a reduction of production and consumption of energy resources worldwide. The disease, caused by a highly contagious and new type of coronavirus, produces a number of complications that are dangerous to human life and health. The most serious of these include cardiac [16], otolaryngological [17], dermatological [18], thrombotic [19], neurological [20], and nephrological [21] complications. The disease has a high perioperative mortality rate [22], can cause liver damage [23] and is particularly dangerous for diabetics [24]. It can also produce serious complications in patients with pneumonia [25].

To limit the spread of the epidemic, governments in many countries have decided to introduce states of emergency, which imposed many restrictions on movement, public life, and the operation of industrial plants and services. The first country was France, which introduced a state of emergency on 17 March, followed by the United States and Poland on 20 March, Germany on 22 March, and the United Kingdom on 23 March. It is estimated that from January to June 2020, the global economy reduced natural gas consumption by about 4% [26–28]. The restrictions triggered a crisis in the availability of consumer goods, which resulted in the loss of jobs in many areas of the economy, but they also demonstrated the importance of energy independence [29].

National restrictions and restrictions of movement (lockdown) impacted many areas of life. In effect, the lockdown has had a positive impact on air quality [30,31]. This is relevant in that pollution levels affect the progression and spread of the disease [32–34]. There has been a reduction in linear (road) emissions associated with reduced traffic volumes. A change also occurred in travel preferences. People chose private transport rather than public transport more often [35].

The lockdown had an impact on reducing electricity consumption by economies in countries where it was introduced [36–39]. The UK reduced electricity consumption by 6%, Italy by 11%, France by 15%, and India by 26% [40]. The United States saw more than a 10% decrease in electricity consumption from 26 March to 6 June [41]. The magnitude of the reduction in electricity consumption in the US varied by area. For the NYISO (New York Independent System Operation), it amounted to 2% in the peak hour and as much as 12% for the MISO (Midcontinent Independent System Operator) [42]. Exceptions include Switzerland, Sweden, and Norway, where no strict restrictions were introduced. Countries whose power industry is based on coal (Poland and the Czech Republic) have increased their energy imports while Italy halved its import of energy from abroad [43]. Countries that use renewable energy sources (Germany) increased their share by about 8% as compared to the same period in 2019, amounting to 55% of total consumption. The largest share was produced by wind turbines (19%), solar panels (17%), and biomass (10%) [44]. It must be pointed out that the present energy crisis, the depletion of fossil fuels, and climate change increase the interest in renewable energy sources; the studies indicate that the changes are initiated by developed countries [45].

The decline in electricity consumption intensified with the prolonged crisis caused by production cuts [46]. In China, a relationship was observed between the daily number of cases and the future drop in electricity demand, which is extremely important in planning activities during a pandemic [47].

On the other hand, household consumption of electricity and water increased, resulting in higher utility charges [48–52]. During the pandemic, governments in many countries took measures to protect individual consumers, including disconnection bans or cancellation of bills to help those in a difficult financial situation [40].

Along with the pandemic, there was a change in consumer habits, resulting in a shift of peak hours in utility consumption [53,54]. The hours of maximum hot water draw of residents in Seoul (South Korea) can be cited as an example. The draw was lower from 04:00 a.m. to 10:00 a.m. compared to the time before the pandemic, but there was a definite increase in water consumption from 11:00 a.m. to 8:00 p.m. A dependency was also observed between the average number of actively infected persons in a given month and changes in hot water consumption [55].

Consumption of crude oil in the United States reached its lowest level in many years, with the price at around 30 USD per barrel. The low price was dictated not only by the global crisis caused by the pandemic but also due to the lack of agreement between the OPEC countries and the US [56–58]. The low price of oil, with no possibility of selling it, led to an increased demand for oil storage in chartered tankers. This situation resulted in a spike in tanker rental prices [59].

Natural gas consumption in households increased while consumption in the industry during this period decreased. The consequences of changes in the consumption of energy resources in Europe depended on the region, on the dependency of the economy on natural gas, and on the severity of the pandemic during the period in question. In the European Union, there was a 7% decrease from January to May relative to the previous year. This decrease amounted to 11% from March to May and 16% from April to May. The most notable change in natural gas consumption occurred in the power sector in Italy, where, from 10 March to 25 March, there was a decrease in gas consumption from 40 to 25 million m^3/day while in the industry, consumption dropped from 85 million (prior to 4 March 2020) to 35 million m^3/day (25 March). A sharp and sustained decline in LNG imports to Europe was also noted in mid-March. China, which experienced a decline in LNG imports in January, saw imports increase from February to June 2020 [60–63]. Forecasts indicate that if the shutdown of the economies continues, the decline in global natural gas consumption could amount to as much as 300 billion m^3 and 36 million tons of LNG. A long-term increase in natural gas consumption will depend primarily on launched relief programs and the systematic recovery of economies after the COVID-19 pandemic [64].

3. Literature Review

Literature is abundant with literature reviews [65–68]. One can select core areas where gas consumption forecasts are drafted.

3.1. National Level

Literature provides information on various forecasting models in particular countries. For Poland, a nationwide gas consumption analysis has been performed using the Hubbert's Model for a long-term forecast [69]. The Stochastic Gompertz Innovation Diffusion Process, as a stochastic growth model, has been used to determine the volume of gas consumed in Spain [70]. For Ireland, the national gas consumption forecast uses the Network Degree Day (NDDCA) model adapted to the climate [71]. For England, literature presents a relation whereby a daily air temperature drop by 1 centigrade causes an increase in electricity consumption by 1% and in gas consumption by 3% to 4% [72]. For two countries, the USA and Canada, gas consumption is forecasted using the Hubbert's Model [73]. For Turkey (currently Türkiye), gas consumption has been forecasted using econometric models, genetic models, artificial neural networks frequently used in the forecasting area, and time series [74–76]. China's gas consumption was analyzed using the PCMACP (Polynomial Curve and Moving Average Combination Projection) model [77] and Gray's model [78,79].

Artificial neural networks forecasted gas consumption in the economies of Belgium [80], USA [81], and Poland [82].

3.2. Cities Level

For Türkiye, genetic and autoregressive algorithms have been used [1]; the MARS (Multivariate Adaptive Regression Splines) and CMASR (Conic Multivariate Adaptive Regression Splines) methods were used for the city of Ankara [83] as well as artificial neural networks [84,85], SVR [84], and the Network Degree Day method [86]. For cities on the territory of China, the authors have used the following for gas consumption forecasting: the Structure-Calibrated Support Vector Regression model (SC-SVR) [14]; the least squares method [87]; the optimized genetic algorithm improved by ANN with backpropagation [88]; and a hybrid model based on a simulated annealing algorithm, cross-correlation coefficient, and auxiliary vectors [89]. Hybrid models achieve better results than traditional models; hence, they are more frequently chosen to forecast gas consumption in cities [90,91]. Gas consumption in Poland has been forecasted using ANN [92,93] while in the case of cities in Croatia, the FTW (Fermat-Torricelli-Weber) model was applied plus the function dependent on gas consumption and temperature [94]. Daily gas demand for a selected city in Greece was forecasted using a hybrid model, comprising the continuous wavelet transform (CWT), genetic algorithm, adaptive neuro-fuzzy inference system (ANFIS), and feed-forward neural network (FFNN) [83].

In Iran, for a case study involving the city of Karaj, artificial neural networks were applied (machine learning plus genetic programming) [95] while the city of Yosuju used a hybrid model [96]. A descriptive analysis was performed for a selected city in Italy [11] whereas for a city in Slovenia, gas consumption was forecasted using machine learning, linear regression, and a recurrent neural network [97].

4. Case Study

Forecasts were made for commercial consumers (such as hotels, restaurants, and bars) that were subject to restrictions imposed by the government in March 2020 due to the coronavirus pandemic. Natural gas consumption is correlated with ambient temperature: when temperature rises, there is a decrease in gas consumption; when it drops the demand for natural gas increases (Figure 3).

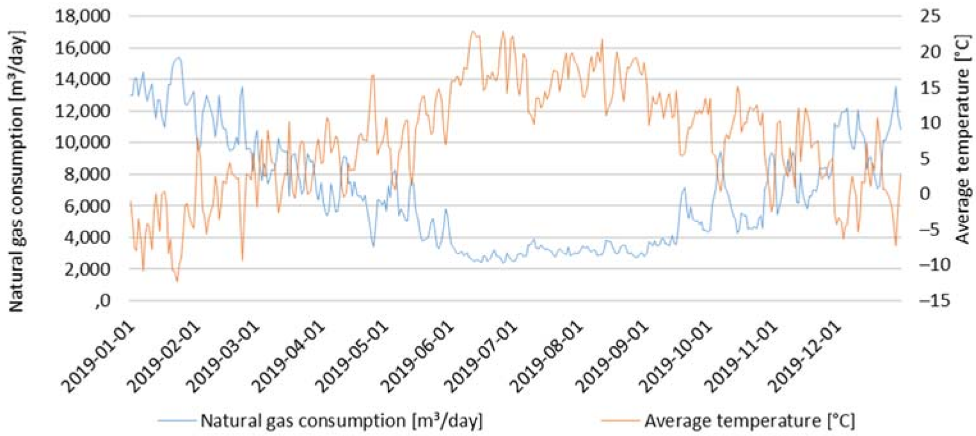

Figure 3. Natural gas consumption in 2019, depending on temperature [98].

Periods with the highest consumption are the winter months, such as January, February, and March as well as November and December. However, when considering gas consumption on a weekly basis, a slight drop can be observed on weekends (Figures 4 and 5).

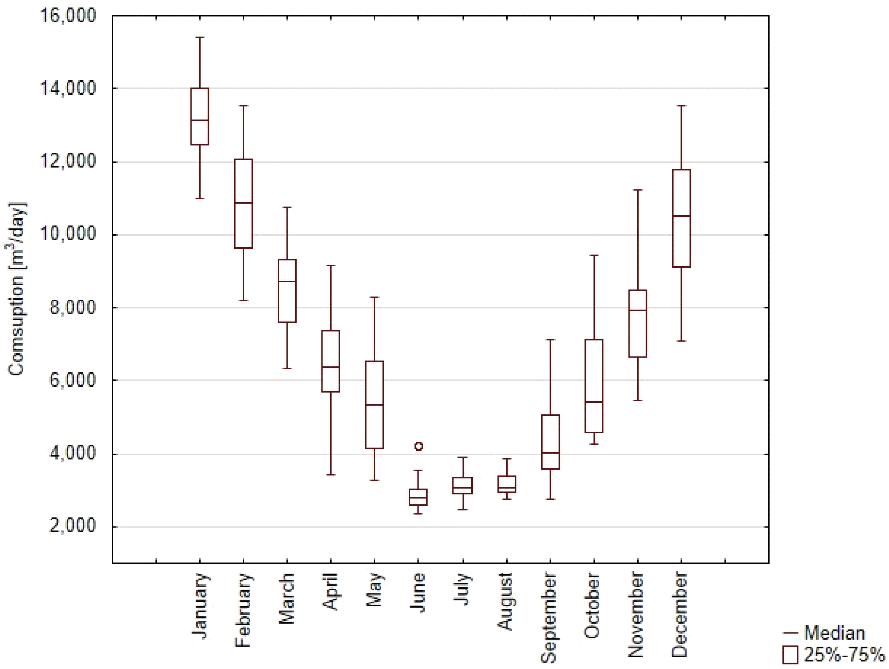

Figure 4. Average gas consumption in individual months (x-axis: natural gas consumption in m^3/day (24 h)).

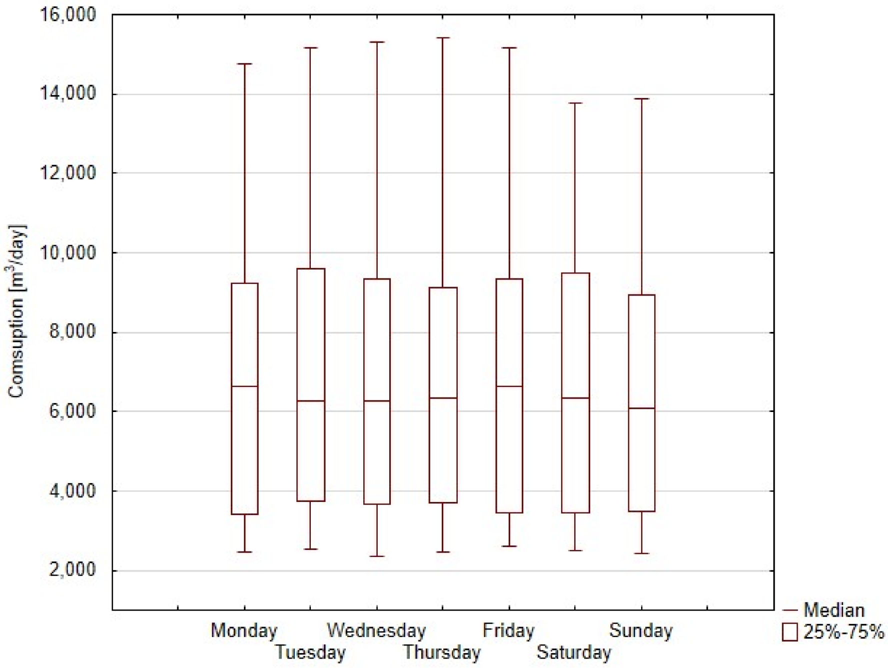

Figure 5. Average gas consumption on individual days of the week (*x*-axis: natural gas consumption in m^3/day (24 h)).

5. Neural Network

A neural network consists of an input layer, a hidden layer or layers, and an output layer. Each of these layers is made up of neurons, the basic building blocks of a neural network. An artificial neuron of the upstream layer is connected to all neurons of the downstream layer. There is no proper method for selecting the number of neurons in an ANN (artificial neural network). An excessive number of neurons can cause overfitting or the loss of the ability to generalize. Each neuron has a specific number of inputs whose significance is determined by weight values (wi). Artificial neurons can be compared to their biological models, and detailed descriptions can be found in the previously published literature [99,100]:

- u1: inputs on dendrites (incoming signals passing through inputs)
- w1: weights (correspond to synapses)
- Σ: summation function (corresponds to the nucleus)
- ϕ: activation function (corresponds to the axon hillock)
- y: output (corresponds to the axon)

An artificial neuron picks up signals and multiplies them by weights. The signals are then routed to a summation function, which is responsible for stimulating the neuron. Stimulated signals are directed to the nonlinear activation function where the signal is generated [101]. Currently, multilayer networks are most commonly used. The input layer does not accept the signal without changing it. Neurons are then activated in the first hidden layer, where most of the calculations are performed. The hidden layer processes the signal and creates a model closely related to the analyzed process. After analyzing the signals in the hidden layer, intermediate signals are generated to all neurons of the output layer. The output layer generates the output signal [102–104]. There are two neural network learning methods. In supervised learning, the teacher chooses weights through the model signals at input to produce the best representation of the signal at the output. In other words, the network selects weights based on the results to achieve the best representation. In unsupervised learning, the network receives an input signal and generates an output signal without providing output data. If input/output signals cannot be applied, the gain is used. The gain delivered to the system is interpreted as a negative or positive signal [103,105–109].

Due to their advantages, neural networks have found a wide application: in power engineering, for controlling boilers [110], in forecasting heat energy for house heating [111] and electricity consumption [112], or in forecasting gas consumption [66,80,86,113,114].

6. Calculations

When conducting neural network calculations to find the best model, the following activation functions were checked for the input layer: linear, logistic, tangentoid, and exponential. The same functions were used for the output layer neurons. The Broyden−Fletcher−Goldfarb−Shanno (BFGS) algorithm was used for the calculations. First, the effect of data quantity on the model quality was calculated. The models used learning data from three, six, nine, and twelve months. The larger the learning data set, the smaller the MAPE error (Figure 6).

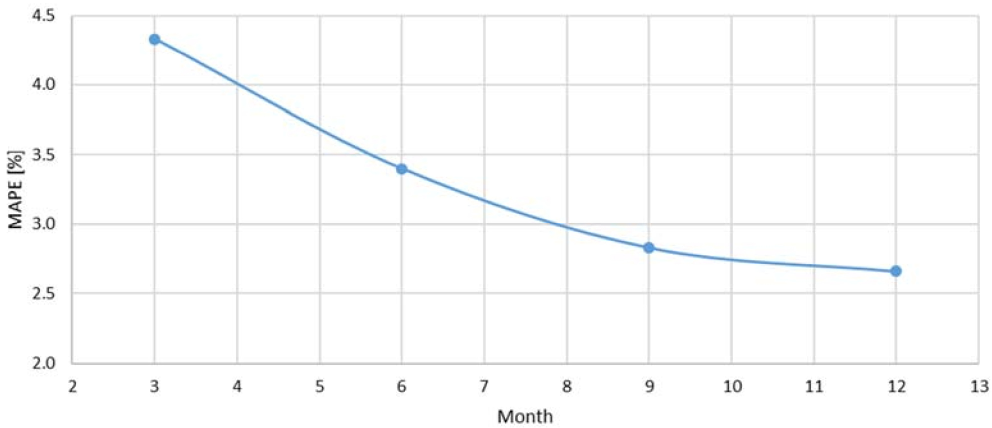

Figure 6. Impact of the learning set size on model quality.

Three types of temperatures were used separately to perform the calculations: 24-h average temperature, maximum and minimum temperature, or temperature at ground level. Additional data was also used for the calculations: wind speed, humidity, and additional meteorological data, including the duration of selected atmospheric phenomena (water vapour pressure, cloud cover, station level pressure, daily precipitation, day−night precipitation, amount of snowfall, water equivalent in snow, insolation, duration of rainfall, duration of the snowfall, duration of rain with snow, duration of fog, duration of dew, duration of frost, and duration of a thunderstorm).

Models were also created using historical data (from one and two days back). Backward data was used for all atmospheric data. The rule of using backward data is that in addition to information about temperature and wind speed that may have affected natural gas consumption on a given day of natural gas consumption, temperature and wind speed values that occurred in the past were used.

Based on this data, the new neural network learned to find the best model (Tables 1–3). Detailed information about the configuration of the individual networks is provided in the "Supporting Information" file (Table S1).

Table 1. Data ranges used to calculate the best model. Temperature: daily average, min/max, or at ground level.

Model No.	Independent Parameter					
	Atmospheric Data				Artificial Data	
	Temperature	Wind Speed	Humidity	Additional Data with Duration of Atmospheric Event	Days of the Week	Months
1	×					
2	×	×				
3	×	×				×
4	×	×			×	×
5	×	×			×	
6	×		×			
7	×	×	×			
8	×	×	×			×
9	×	×	×		×	×
10	×	×	×		×	
11	×		×	×		
12	×	×	×	×		
13	×	×	×	×		×
14	×	×	×	×	×	×
15	×	×	×	×	×	

Table 2. Data ranges used to calculate the best model. Temperature: daily average, min/max, or at ground level with data from 1 day back.

Model No.	Independent Parameter						
	Atmospheric Data					Artificial Data	
	Temperature	Wind Speed	Humidity	Additional Data with Duration of Atmospheric Event	Data from One Day Back	Days of the Week	Months
1	×				×		
2	×	×			×		
3	×	×			×		×
4	×	×			×	×	×
5	×	×			×	×	
6	×		×		×		
7	×	×	×		×		
8	×	×	×		×		×
9	×	×	×		×	×	×
10	×	×	×		×	×	
11	×		×	×	×		
12	×	×	×	×	×		
13	×	×	×	×	×		×
14	×	×	×	×	×	×	×
15	×	×	×	×	×	×	

Table 3. Data ranges used to calculate the best model. Temperature: daily average, min/max, or at ground level with data from 2 days back.

	Independent Parameter							
	Atmospheric Data						Artificial Data	
Model No.	Temperature	Wind Speed	Humidity	Additional Data with Duration of Atmospheric Event	Data from One Day Back	Data from Two Days Back	Days of the Week	Months
1	×				×	×		
2	×	×			×	×		
3	×	×			×	×		×
4	×	×			×	×	×	×
5	×	×			×	×	×	
6	×		×		×	×		
7	×	×	×		×	×		
8	×	×	×		×	×		×
9	×	×	×		×	×	×	×
10	×	×	×		×	×	×	
11	×		×	×	×	×		
12	×	×	×	×	×	×		
13	×	×	×	×	×	×		×
14	×	×	×	×	×	×	×	×
15	×	×	×	×	×	×	×	

7. Results

Results of the MAPE calculations for each estimated model will be presented in subsequent sections of this paper. For the 24-h average temperature, two models using data from the previous day and three models using data from the two previous days were improved (accounting for 20% of the models that used the 24-h average temperature). For the minimum and maximum temperature, one model improved after using data from one day back and two models improved after using data from two days back. The MAPE index value decreased when atmospheric event durations were added. Models that used the temperature at ground level for data from one day back improved in eight instances (accounting for more than 50% of all models), and nine models improved after using data from two days back (accounting for 60% of all models using data from previous days) (Figures 7–11).

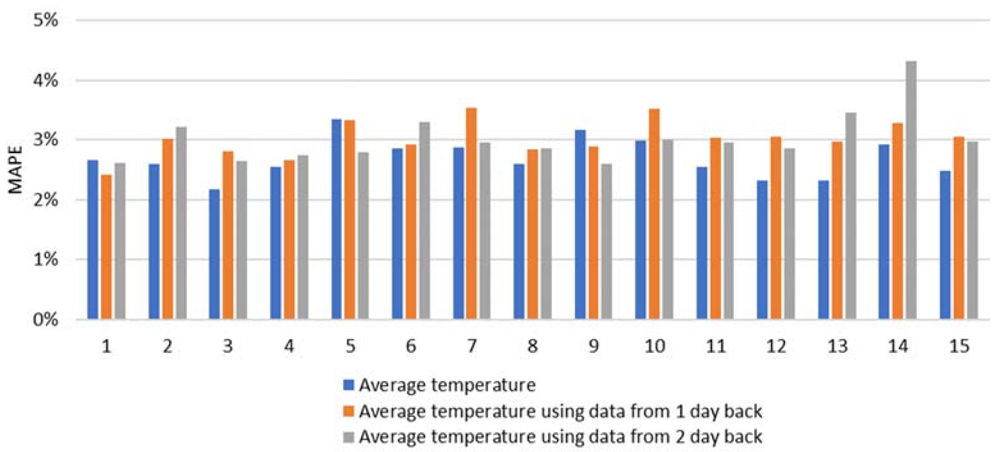

Figure 7. MAPE error results for the models using the 24-h average temperature.

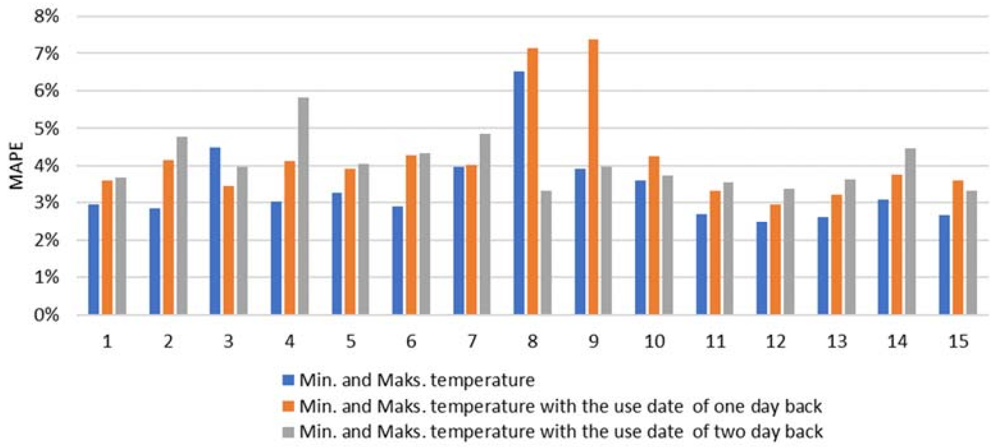

Figure 8. MAPE error results for the models using the min/max temperature.

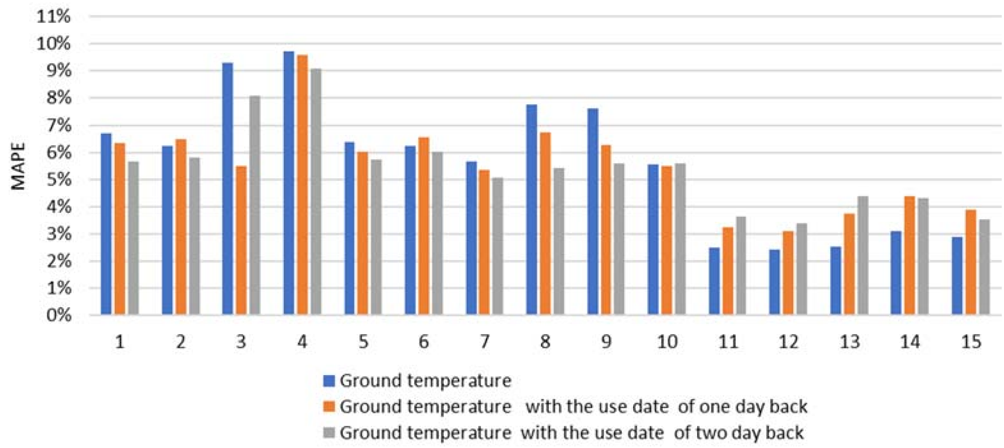

Figure 9. MAPE error results for the models using the temperature at ground level.

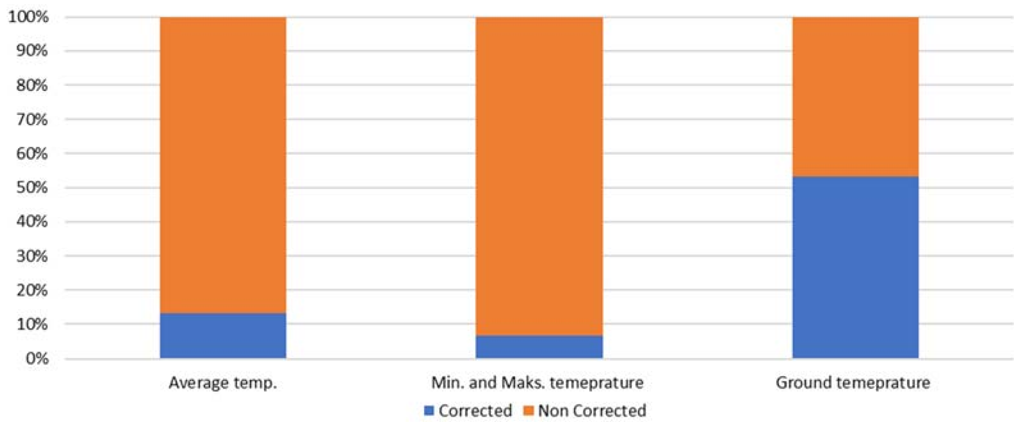

Figure 10. Ratio of models that have improved by adding information from the previous day.

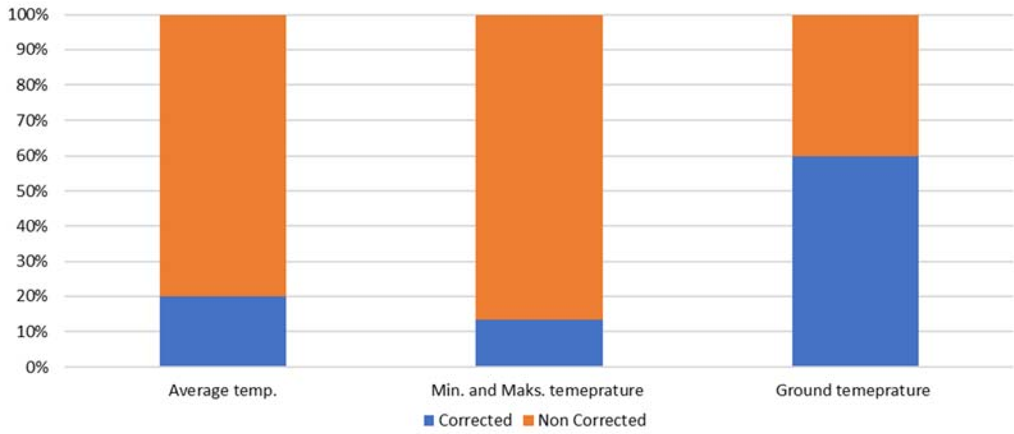

Figure 11. The ratio of models that have improved by adding information from two days back.

The best model turned out to be the one using the multi-l perceptron (MLP) 26-13-1 BFGS 12 average temperature. This means that there were 26 neurons in the input layer and 13 neurons in the hidden layers. The following quantities, among others, were used as independent parameters: temperature, wind speed, and months as "artificial data". The days of the week (Monday−Sunday) and months (January–December), as artificial data, are recorded as (0, 1). If consumption occurred on a specific day of the month (Monday, January), then Monday and January receive signal (1) as the input. Other days and months receive no signal (0). (Figure S1). The network was trained in the 12th learning cycle. It has the following activation functions: linear in the input layer and exponential in the output layer. Figure 12 shows the comparison of the predicted and actual natural gas consumption performed using the selected artificial neural network model for the month selected for the neural network validation process. There is a good fit between the two curves, resulting in a low MAPE error value (2.17%). In addition, Figure 13 shows the detailed fit of the forecast results. There is a good fit in the range of the "average" values; larger differences are seen only for the extremes of low and high natural gas consumption. This is due to a smaller quantity of learning data at extreme values of the variability interval in the available learning data. The forecast made by the model was compared to actual natural gas consumption in March 2020 (Figure 14).

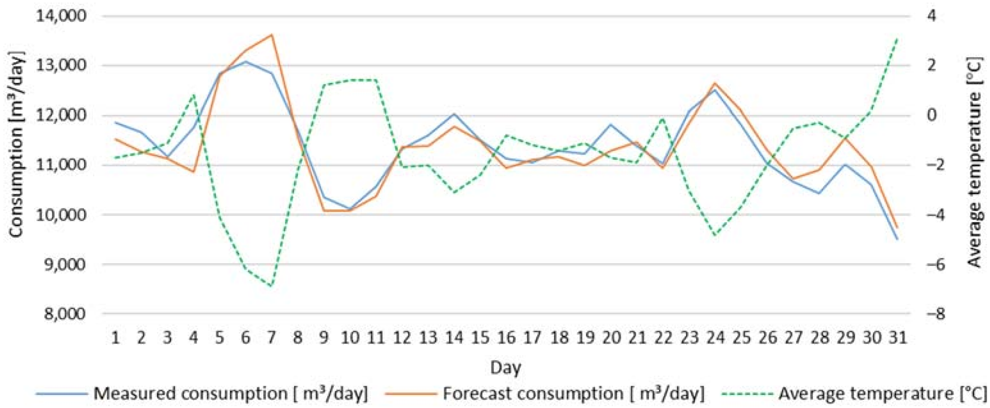

Figure 12. Comparison of natural gas consumption forecast to the actual measurement.

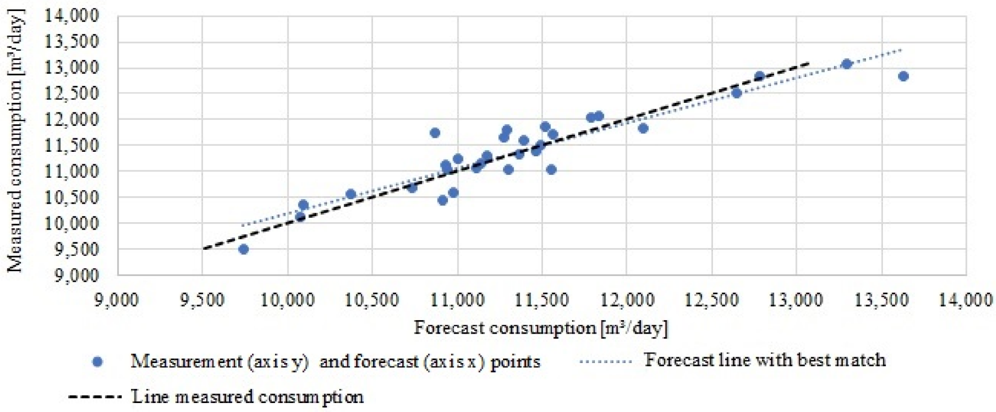

Figure 13. Forecast value and actual natural gas consumption fit on individual days.

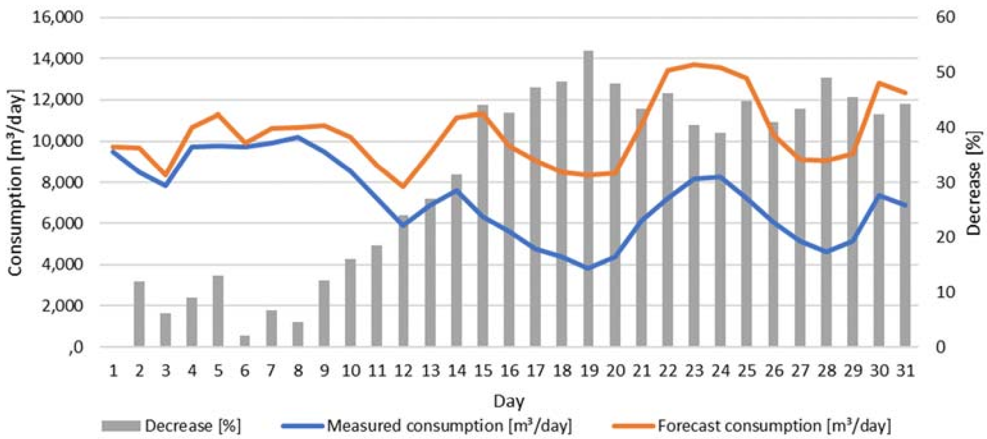

Figure 14. Forecast consumption vs. actual consumption in March 2020 after lockdown.

Figure 14 shows the comparison of the consumption forecast obtained using the selected artificial neural network with the smallest MAPE error to the actual consumption in March 2020. The consumption forecast was made for the available data without taking into account the impact of lockdown. It can be observed that the shape of both curves (forecasted and actual consumption) is highly consistent. The decrease in natural gas consumption caused by the COVID-19 pandemic was calculated from these parameters. The average decrease in natural gas consumption for the whole month was over 30%, increasing to nearly 45% when only the second half of the month was taken into account and reaching a maximum value of just over 54% on 19 March.

8. Conclusions

The COVID-19 pandemic that began in 2019 has had a strong impact on public health, the economy, and all aspects of society. There have been disruptions in supply and interruption of manufacturing and commercial activities. The pattern of electricity generation changed, with an increased share of renewable energy sources, while air quality improved. This infectious disease also had a major impact on the operations of the natural gas industry. There have been declines in natural gas consumption, reflecting the severity of the pandemic and introduction of restrictions. The most pronounced changes in natural gas consumption due to lockdown can be seen in commercial consumers. The impact of the pandemic on natural gas consumption of commercial consumers was analyzed, and evidence was presented that the lockdown resulted in a reduction of natural gas consumption for this group of consumers.

Based on the developed and validated artificial neural network model, a decrease was shown in the actual natural gas consumption as compared to predicted consumption in a normal operating situation. During the analysis for the month of March 2020, it can be seen that a more pronounced decrease in natural gas consumption started after 8 March, to reach a maximum on 19 March, at a level of 54%. After this period, the decrease in natural gas consumption oscillated between 40% and 45%.

Current observations show that the COVID-19 pandemic does not pose a high risk to natural gas distribution systems. However, the development of successive stages of the pandemic and the impact of reduced natural gas consumption on the financial standing of suppliers and consumers must be taken into account.

Further research should focus on the analysis of natural gas consumption in households and temporary changes that occurred in this group of consumers and whether consumption of the fuel has returned to levels from before the pandemic.

The current situation related to the COVID-19 pandemic should encourage the governments to undertake greater efforts oriented at energy transformation.

Renewable energy sources, principally including photovoltaics and wind farms, are experiencing dynamic growth. Energy transformation adopted by the European Parliament as well as a significant increase in fossil fuel prices have encouraged people to look for new alternative energy sources. The application of a new energy source can be perceived in an overly broad perspective as a supplementation or targeted replacement of fossil fuels used in industry and distribution to municipal clients. This is a result of the growing interest and demand for fuels originating from renewable sources, in relation to the implemented EU programs based on RES.

The use of biogas can serve as an example. Unfortunately, current legal regulations do not correspond to the needs for biomethane production: despite the fact that, theoretically, it has been possible for several years to input treated biogas in the gas networks, no biogas production plant has been connected to a distribution gas network.

Restrictive requirements as to the quality of the biogas input in the network cause technical problems and increase the production costs on the manufacturer's part.

To maximize the share of Polish businesses in the supply chain for construction and operation of biogas and biomethane plants and to stimulate the universally understood biogas and biomethane market in Poland, the "Memorandum for Biogas and Biomethane Development" was signed. This is a sector of major importance, and it is indispensable for performing the energy transformation process to achieve autonomy and self-reliance.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/en15041393/s1. Table S1. Information about all artificial neural networks models for average temperature. Table S2. Information about all artificial neural networks models for average temperature with 1 day ago. Table S3. Information about all artificial neural networks models for average temperature with 2 days ago. Table S4. Information about all artificial neural networks models for min/max temperature. Table S5. Information about all artificial neural networks models for min/max temperature with 1 day ago. Table S6. Information about all artificial neural networks models for min./max. temperature with 2 days ago. Table S7. Information about all artificial neural networks models at a ground-level temperature. Table S8. Information about all artificial neural networks models at a ground-level temperature with 1 day backdate. Table S9. Information about all artificial neural networks models at a ground-level temperature with 2 days ago. Figure S1. Topology of the best neural network MLP 26-13-1.

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