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Research paper

Influence of smart meters on the accuracy of methods for forecasting natural gas consumption

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ABSTRACT

In 2019, natural gas accounted for 25.4% of gross inland consumption in the European Union (EU), making it one of the most important energy sources in the EU. The importance of natural gas, together with the ongoing liberalization of the gas market, has made the natural gas sector significantly commercially sensitive. To reduce the risk of financial losses, balance group managers often need to have an accurate forecast of natural gas consumption. An accurate forecast will ensure small deviations between actual gas consumption and reserved gas volumes and transmission system capacity resulting in less balancing energy required, which is sold at a higher price in the final balancing process.

This paper researches the optimal number of smart meters and best fitted consumption data distribution in order to achieve satisfactory results in terms of the accuracy by using simple forecasting methods. Beside mentioned, this paper provides accuracy overview of various already available forecasting methods, as well as the selection of input parameters for forecasting short term natural gas consumption. Using the calculated linear temperature dependence together with the lognormal distribution, the consumption of natural gas was simulated for 12 different cases. The simulation showed that, if more than 10 000 smart meters were installed, deviation between average estimated natural gas consumption and the real data would be less than ±2.96 %. In case of 100 000 smart meters installed, deviation would be less than ±1.20 %, but the "large" partly temperature independent consumers must be disregarded.

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1. Introduction

Nowadays, the economic development and energy consumption in the EU are directly related to each other to some extent (Acaravci and Ozturk, 2010; Pirlogea and Cicea, 2012; Balitskiy et al., 2016). According to Eurostat (2021), in 2019, natural gas accounted for 25.4% of gross inland consumption in the EU, making it one of the most important energy sources in the EU. Its importance, as well as the ongoing liberalization of the natural gas market, have made natural gas sector more commercially important (Provornaya et al., 2020), especially in regions with declining domestic natural gas production.

In markets with balance groups like in the EU, a balance group is an interest grouping of participants in the gas market, i.e., a group with one or more energy entities organized on a commercial basis. It is the responsibility of the balance group manager to balance the balance group within transport system, i.e., to adjust the quantities of gas delivered to and from the transport system, so that the transport system operator performs as few balancing operations as possible. In addition to the trade of natural gas itself, energy entities also trade with the capacities of the transport system. The differences between the actual gas consumption and reserved gas quantities and transmission system capacities greatly affects the quantity of the balancing energy needed, which is sold at a higher price at final balancing process. Balance group managers must receive information timely and frequently enough about the level of deviation from forecasted consumption in order to better optimize their business by reacting on time. An accurate forecast of natural gas consumption can greatly reduce this need for balancing and thus ensure not only financial improvement of business but also better optimization of the gas transport and distribution system.

1.1. Forecasting in energy sector

With the development and improvement of the energy sector, forecasting methods have become an integral part of it. Forecasting is used to improve the optimization, operations, planning, management, and efficiency of the entire system. Literature review has shown that forecasting in energy sector is used for a variety of purposes, such as forecasting wind speed, photovoltaic

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power output, general energy consumption, electricity consumption, heat demand, natural gas consumption, price forecasting, etc..

Since Renewable Energy Sources (RES) show strong instability, discontinuity, and randomness, increased energy production from this sources resulted in need for better energy storage capacities (Wang et al., 2019). Given that the increase in storage capacity increases the cost of energy production, forecasting methods have been identified as one of the ways to optimize and reduce energy production costs in RES systems. Cadenas and Rivera (2007) forecasted wind speed in the South Coast of the state of Oaxaca in Mexico with Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN). Results showed that both models can predict the monthly power production of wind power stations within satisfying boundaries. Authors Liu et al. have published several papers on the topic of wind speed and wind energy forecasting in order to show the importance and future development of this topic (Liu et al., 2019a, 2020a). In their research, they applied several different new models for wind speed forecasting, and all models showed satisfying or superior results when compared to other models and methods (Liu et al., 2018, 2019b, 2020b). In addition to the above mentioned, a literature review showed a multitude of other papers in which wind speeds were forecasted in different ways. Most new models were based on today's increasingly popular neural networks (with algorithms and/or filters for processing input parameters) (Chen et al., 2018; Memarzadeh and Keynia, 2020; Deng et al., 2020), but other machine learning methods such as linear and nonlinear autoregressive models (Lydia et al., 2016), random forest algorithm, LASSO regression, gradient boosting decision tree algorithm (Demolli et al., 2019) and multi-resolution multi-learner ensemble (Chen and Liu, 2020) were also used. Madvar et al. (2019) even analyzed the text in published patents in order to forecast the trends in the development of wind turbine technologies. Sobri et al. (2018) made an extensive review on recent developments in solar energy forecasting where they concluded that Artificial Intelligence (AI) approaches are widely used due to capability of solving the complex structure of data and that AI methods outperform traditional ones. Wang et al. (2020a) also proved previous statement by combining deep learning and time correlation in order to achieve Mean Absolute Error (MAE) of only 2.35% in forecasting photovoltaic (PV) power generation.

Apart from forecasting energy production from RES, forecasting energy consumption has also been recognized as a very effective tool for making important decisions in planning energy development strategies (Zeng et al., 2017) or optimizing small scale energy consumption (Tran et al., 2020). When it comes to type of methods used for energy planning, Debnath and Mourshed (2018) concluded that the most commonly used methods are based on ANN followed by, support vector machine (SVM), autoregressive integrated moving average (ARIMA) and other machine learning methods. Most of the literature reviewed has also shown that new models are mostly a hybrid of several different machine learning methods/algorithms and ANN is almost always used in at least one part of the model. Some of the observed models were developed for short-term forecasting of energy consumption in households (Alobaidi et al., 2018) and residential/business buildings (Tran et al., 2020; Jallal et al., 2020) for the purpose of autonomous optimization of energy consumption. Other models were used for long-term forecasting of energy consumption in developing countries such as China (Xiao et al., 2018; Ye et al., 2019), but also in developed countries like the USA (Prado et al., 2020) for the purpose of better long-term energy supply and strategy planning.

Although the goal of the global energy sector is to achieve a carbon-neutral economy, one of the main obstacles to this is the financial viability of climate-neutral projects. Considering the importance and economic factor of price prediction, various forecasting models have been used in last few year in order to forecast EU's and China's market carbon price (Sun and Zhang, 2018) and hourly (Yang et al., 2017), day ahead (Anbazhagan and Kumarappan, 2014), monthly (Qiao and Yang, 2020) or annual (Jeong et al., 2014) electricity price. Beside pricing, forecasting was also used in order to analyze the investment value for PV power generation with carbon market linkage (Tian et al., 2017). In addition to the purposes already mentioned in this chapter, models for forecasting electricity (Lahouar and Hadj Slama, 2015) and heat demand (Spoladore et al., 2016; Izadyar et al., 2015) can also be found in the literature.

A review of the literature has shown that forecasting models in the observed energy sectors are constantly evolving or improving and that neural networks have certainly been recognized as the most popular machine learning method used.

1.2. Objective of the paper

Given the well-known characteristics of the gas energy sector and the gas markets, this paper examines the installation of smart meters and determination of consumption data distribution as an alternative to using complex machine learning forecasting methods. The objective of this paper is to analyze the optimal number of smart meters required to achieve satisfactory accuracy in forecasting natural gas consumption by using simple forecasting methods. In order to better develop the model for forecasting natural gas consumption with the use of smart meters (daily gas consumption data), the forecasting methods developed so far as well as the input parameters used in them were analyzed in the next chapter.

1.3. Natural gas consumption forecasting methods

Many authors have so far applied different methods with different input parameters to forecast natural gas consumption more accurately. Forecasts were made for different areas of application (district, city, region, national, worldwide) and for different time periods (hourly, daily, annual). This chapter analyzes the various methods for forecasting natural gas consumption developed or used in the last several years. The results of the developed methods were observed, that is, the accuracy of the forecast of natural gas consumption for the beforementioned different time periods.

Zhang and Yang (2015) used the Bayesian Model Averaging to forecast annual natural gas consumption in China. They analyzed the data collected for the period from 1965 to 2012 and used theoretical and applied analysis to determine the quality of their model. Their model achieved best MAPE (0.026) when compared to Grey prediction model, Linear regression model and Artificial neural networks (MAPE ranging from 0.045 to 0.057. This model was then used for forecasting annual natural gas consumption in China from 2015 to 2020 in three different scenarios (low, reference and high).

Akpinar et al. (2016) used daily gas consumption data from 2011 to 2014 to forecast consumption for the next year in Sakarya Province, Turkey. Two ANN models were used to predict consumption, the first with a back propagation algorithm (BP) and the second with an Artificial Bee Colony (ABC) algorithm. ANN with ABC algorithm showed better results in all cases, with the best MAPE of 17%, while the best MAPE for BP algorithm was 26%. Very similar models were also used in future research done by Akpinar et al. (2017) where ANN with ABC and three hidden layers achieved MAPE of 14.9%.

Bai and Li (2016) used Structure-Calibrated Support Vector Regression (SC-SVR) approach with the Extended Kalman Filter to forecast daily natural gas consumption in the city of Anqing, China. This model was also compared to standard Least Squares Support Vector Regression (LSSVR) model and Back Propagation Neural Network (BPNN) to prove the superiority of the chosen method. Authors concluded that SC-SVR has proven its superiority over two other methods, with MAPE of 2.36% compared to 3.61% from BPNN and 4.77% from LSSVR.

Zeng and Li (2016) used Self-adapting Intelligent Grey Model (SIGM) to simulate China's natural gas demand from 2002 to 2010 and to forecast natural gas demand from 2011 to 2014. Chosen model was compared to classical Grey Model (GM), Discrete Grey Model (DGM) and Event Difference Grey Model (EDGM) to point out the inherent drawback of fixed structure and poor adaptability of these two models. SIGM has proven slightly better than the other methods in simulation period (only 0.14% better MAPE than GM), but also showed good results in forecasting period with MAPE of 5.02% compared to second best GM MAPE of 6.19%.

Wang et al. (2018) proposed hybrid forecasting model by combining The Particle Swarm Optimization algorithm and Wavelet Neural Network (PSO-WNN). Proposed model and two more forecasting models (ANN, WNN) were first trained using China's annual natural gas consumption from 1995 to 2012 and then were used for forecasting annual natural gas consumption from 2013 to 2016. PSO-WNN model achieved best results with MAPE of 2.31% followed by WNN (4.12%) and ANN (6.03%).

Merkel et al. (2018) presented Large Deep Neural Network (LDNN) approach compared with LR and two shallow ANN for forecasting short term gas consumption in 62 different consumption areas in the U.S. First 10 years of data was used for training neural networks and then the networks were tested for period of one year. Overall, LDNN showed best forecasting results in comparison with other methods, but if the areas are viewed separately LDNN did not produce the best results in all areas.

Hribar et al. (2019) implemented and compared Linear Regression (LR), Kernel Machine (KM), Recurrent Neural Network model (RNN) and empirical models (Two-reservoir model, Two-reservoir model with linear memory and Two-reservoir model with nonlinear memory) based on data analysis for forecasting gas demand with hourly resolution up to 60 h into the future. All models were used for forecasting natural gas consumption in the city of Ljubljana. It was concluded that models were more accurate if they included the influence of past temperature and that nonlinear models become more accurate using forecasted temperature for training. When considering the accuracy of used methods, the RNN showed best results along with the LR whose advantage over the RNN is much shorter training time. All the models in this paper showed largest error on occasional events like holidays, where, due to the smallest increase in error, LR method was proven to be the best one.

Lu et al. (2019) used Cross Factor-Simulated Annealing-Fruit Fly Optimization Algorithm-Support Vector Machine (CF-SA-FFOA-SVM) algorithm to forecast natural gas consumption in Kunming city, China. This study was based on consumption data from January 1, 2012 to November 30, 2013 (total of 700 datasets) and this data was used to forecast natural gas consumption for three different forecasting period (10, 20, 30 days). Results obtained by using mentioned algorithm were compared with results obtained with four different methods (PSO-SVM, BPNN, GM (1,1) and Arima) and authors of this paper concluded that CF-SA-FFOA-SVM algorithm achieved best MAPE for all three forecasting periods.

Ravnik and Hriberšek (2019) developed a method for forecasting preliminary allocation and natural gas consumption based on standard natural gas consumption profiles. Within this method they developed eight types of consumption profiles for 17 gas consumer groups using sigmoid model function. Consumption profiles were tested on measurements of gas consumption of 260 end consumers from different consumer groups across Slovenia during 4 year period. Best results were achieved by using models where temperature independent part is known along with the separation of workdays and weekends. Accuracy of these methods increases with the increase of the dataset due to model's capability of better learning from larger dataset, i.e. authors concluded that at least 14 600 consumers are needed in order to achieve ±1% accuracy in forecasting daily total consumption.

Su et al. (2019a) developed a method based on the integrated Wavelet Transform, Bi-Long Short-Term Memory (LSTM) model, LSTM model and Genetic Algorithm to forecast hourly gas demand. This method had an accuracy of 99% on the Mackey Glass series while the forecasting errors while using winter set of real-world data was from 5.84 to 6.78% for 10 h forecast. This method was also compared with a Non-linear Autoregressive model (NAR) and three-layer LSTM model where it showed its superiority over other two models.

Wei et al. (2019) developed novel hybrid model by combining Improved Singular Spectrum Analysis with Long Short-Term Memory (ISSA-LSTM) to forecast daily natural gas consumption in four big cities (London, Melbourne, Hong Kong and Karditsa) located in three different climate zones. Performance comparison was made with other advanced forecasting methods (MLR, BPNN, SVR, LSTM, SSA-LSTM) and the newly developed hybrid model proved its superiority over all other methods. This ISSA-LSTM method had Mean Absolute Range Normalized Error (MARNE) around 5% for all cities except for Hong Kong (14%) where the natural gas consumption is more complex considering that Hong Kong is located in tropical zone.

Erdem and Kesen (2020) used five different machine learning methods to forecast monthly natural gas consumption in Turkey. Monthly data on natural gas consumption from 2010 to 2015 were used for training and consumption was forecasted for the period from 2016 to 2018. They compared the results obtained with ANN, Regression, Multiple Seasonality Time Series, Random Forest Tree and Time Series. However, the amount of data required is applicable for country-level analysis, and not for specific behavior of gas consumption in one urban region.

Lu et al. (2020) proposed Kernel-based Nonlinear Extension of the Arps decline model (KNEA) with implemented Grey Wolf Optimization (GWO) algorithm to forecast annual natural gas consumption for seven kinds of datasets taken from the EIA. These datasets represent seven different kinds of natural gas users and they were collected annually from 1997 to 2018 (total 22 years). KNEA-GWO model had the best MAPE (from 1.36% to 4.42%) when compared to five other forecast models (KNEA, PSO-SVM, RBFNN, GM (1,1) and Random forest).

Stathakis and Stambologlou (2020) compared seven different models for forecasting annual natural gas consumption for one region in Greece. The models were trained on consumption data of the previous 20 years and the results of the analysis showed that ARIMA achieved 16.1% better forecasting accuracy than the remaining models.

Tan et al. (2020) constructed combined forecasting model of electricity, heat, cooling and gas based on Multi Task Learning theory combined with Least Squares Support Vector Machine (MTL-LSSVM) for forecasting energy consumption of the Suzhou industrial park. Forecasting results of this model showed up to 19% better accuracy than the results from two other single task learning models (ELM and LSSVM).

Wu et al. (2020) proposed new Grey Bernoulli model for forecasting annual natural gas consumption of United States, Germany, the United Kingdom, China and Japan. Authors used annual consumption data from 2005 to 2017 in order to forecast future natural gas consumption from 2018 to 2022. Testing of this model has produced data with remarkable MAPE's in most of the cases and authors concluded that proposed model has better forecasting accuracy than other ordinary Grey models.

Zhou et al. (2020) proposed a novel Discrete Grey Model considering Nonlinearity and Fluctuation (DGMNF (1,1)) for the purpose of forecasting annual natural gas consumption from 2018 to 2025 in Jiangsu Province, China. Model was trained with historical data on natural gas consumption from 2005 to 2017 for the mentioned province and the results were compared to 7 different forecasting methods. MAPE for proposed model was less than 2% while the second best result was achieved by using Non-linear grey Bernoulli model with MAPE that was around 5%.

Liu et al. (2021) developed a Discrete Fractional Grey Model with a time power term (DFGM (1,1, t^{α})) in order to forecast annual natural gas consumption in China for time period from 2019 to 2025. This model was trained and tested on consumption data from 2001 to 2018 and it showed best MAPE when compared four other forecasting methods. Authors concluded that annual natural gas consumption in China will remain on a steady upward trend and proposed several measures to promote natural gas consumptions.

Svoboda et al. (2021) created dataset with 52 584 data points (six full years) which are assembled from three main components (natural gas consumption, weather variables and natural gas price). Purpose of this dataset is to enable availability of "hard to get" consumption data to other scientists in order to help them in development of future short-term forecasting methods. Authors also prosed certain guidelines for development of forecasting models/methods and gave several conclusions concerning forecasting of natural gas consumption.

Wu et al. (2021) have developed a grey model with a latent information function for the purpose of determining possible outliers. The model was developed using the annual production and consumption of natural gas in the USA and China for the purpose of forecasting the same for the period from 2013 to 2015. The results showed that the introduction of the latent information function enabled the recognition of certain outliers and thus improved the accuracy of this model.

Yukseltan et al. (2021) consider that it is important for most of the parties involved in gas market to accurately forecast daily, monthly and annual natural gas consumption of some city or region. Authors proposed a model consisting of a modulated expansion in Fourier series with supplementation of deviations from comfortable temperatures which act as a regressor. They used daily consumption data for period from 2002 to 2017 for Istanbul West, Istanbul East, Ankara, Eskisehir and Bursa in order to forecast daily, monthly and annual natural gas consumption for a period of one year in future. MAPE of forecasted data was relatively good (mostly under 10%) and authors concluded that the advantage of the proposed model is capability of fairly accurate long term forecasts, even with minimal input information.

Zheng et al. (2021) have developed a new model based on the Conformable Fractional NonHomogeneous Grey Bernoulli Model (CFNHGBM (1,1, k)) for the purpose of forecasting natural gas production and consumption in North America. They used annual production and consumption data from 2008 to 2018 to forecast the same for the period from 2019 to 2021. The results showed that the newly developed model achieves better performance compared to the four other competitive grey models.

Predicting annual natural gas consumption is most commonly used in developing countries (e.g. China) to design energy development strategies, organize markets, plan future project development, etc. Ten observed methods for predicting annual natural gas consumption use quite different machine learning models, but it is evident that in all methods the better results are obtained by using more complex machine learning models.

In addition to the above, other methods observed are used for the more interesting short-term (hourly, daily) forecasting of natural gas consumption. These types of methods have the best perspective to be used by distribution system operators, transmission system operators, natural gas suppliers and natural gas traders. Eight out of thirteen observed methods for forecasting natural gas consumption use neural networks modified with certain algorithms and/or mathematical/statistical methods ("complex neural networks") to achieve better accuracy than the shallow neural networks or other machine learning methods. As in the forecast of annual natural gas consumption, here it is not possible to conclude with certainty which of the above methods is the best for short-term forecasting, but it is obvious that more complex methods give better results. The same can be concluded for the methods which were not based on the use of neural. Between all the above mentioned methods, one that conceptually stands out, is the one developed by Ravnik and Hriberšek (2019). Unlike the others, this method used simple mathematical functions combined with a large set of natural gas consumption data from each consumer group and temperature data to predict natural gas consumption. With this method, the accuracy of the forecast is improved with the implementation of so-called smart meters, meters that read hourly gas consumption (high-resolution data) which will be described in more detail in later chapter. Unlike the method that will be proposed later in the paper, this method uses a significantly higher resolution of consumption and temperature data as well as the division of end users into different groups and calendar information.

1.4. Input parameters for natural gas consumption forecasting methods

By observing the input parameters (Table 1) for methods mentioned earlier, it is easy to conclude that the consumption of natural gas is crucial, and in some methods, the only input parameter. Natural gas consumption is the only input parameter used in eleven observed methods, seven of which forecast annual natural gas consumption. For three methods, it is quite unusual to be able to achieve good results when forecasting short-term natural gas consumption without any other input parameter, especially temperature. For one method, the reason for the good accuracy is the active use of historical consumption data and the type of consumer (81% commercial users) while the other two methods use sliding window technique. Furthermore, in all other methods for short-term natural gas forecasting, the two most important input parameters, natural gas consumption and temperature are always used. In addition to temperature, other weather indicators are also often used, such as humidity, wind speed, atmospheric pressure, etc. Beside mentioned, although less frequent, some methods also use calendar information (weekdays, holidays, weekends) and various economic indicators. From the observed, natural gas consumption and temperature are certainly recommended as input parameters for short-term natural gas consumption forecast.

1.5. The contribution of this work

After literature review, it is identified that there are no analysis of needed number of gas smart meters that will give enough data for forecasting natural gas consumption by existing methods. The scientific contribution of this research is statistical approach for determination of required number of installed gas smart meters to achieve satisfactory forecast of natural gas consumption.

Table 1
Input parameters used in observed forecasting methods.

Authors	Input parameters
Zhang and Yang (2015)	GDP, urban population, industrial structure, energy efficiency, energy consumption structure, exports of goods and services
Akpinar et al. (2016)	Daily natural gas consumption (from 2011 to 2014)
Bai and Li (2016)	Natural gas consumption (366 daily records — first 300 used for training)
Zeng and Li (2016)	Natural gas consumption (only 9 datasets)
Akpinar et al. (2017)	Daily natural gas consumption (from 2011 to 2014), seven-day natural gas consumption before forecasting day
Wang et al. (2018)	Natural gas consumption, per capita GDP, total amount of gas production, household consumption level, population with access to gas, urbanization ratio (1995–2016)
Merkel et al. (2018)	Natural gas consumption, heating degree day, dew point, cooling degree day, day of the week, day of the year (10 years training, one year testing)
Hribar et al. (2019)	Natural gas consumption (8 winter seasons-city's total hourly consumption), outdoor temperature, time of the day, i.e., time (mod) 1 day, time of the week, i.e., time (mod) 1 week, presence of public holiday, presence of school holiday, day between public holiday and weekend
Lu et al. (2019)	Natural gas consumption, daily temperature data
Su et al. (2019a)	Natural gas consumption, date and time, weather, climate, gas price
Ravnik and Hriberšek (2019)	Natural gas consumption (260 consumers — 32856 hourly measurements per consumer), average temperature
Wei et al. (2019)	Natural gas consumption (3 years of training data, 5 months of testing data), daily low temperature, daily average temperature, daily high temperature, daily low dew point, daily average dew point, daily high dew point, daily low humidity, daily average humidity, daily high humidity, daily low visibility, daily average visibility, daily high visibility, daily low air pressure, daily average air pressure, daily high air pressure, daily low wind speed, daily average wind speed, daily high wind speed, daily precipitation, day, month, year, daily natural gas price
Tan et al. (2020)	Weather factor (temperature index, humidity index, wind speed, atmospheric pressure), calendar information (working day, holiday), economic factors (per capita GDP, electricity price, electricity flow), technical conditions (electric load history date, heat load history date, cooling load history date, gas load history date)
Erdem and Kesen (2020)	Monthly natural gas consumption (from 2010 to 2018)
Lu et al. (2020)	Natural gas consumption (annual data from 1997 to 2018 for 7 different users)
Stathakis and Stambologlou (2020)	Annual natural gas consumption, GDP, GDP/capita, energy (kWh) consumption/household, electricity (kWh) consumption/household
Wu et al. (2020)	Annual natural gas consumption (from 2005 to 2017)
Zhou et al. (2020)	Annual natural gas consumption (from 2005 to 2017)
Liu et al. (2021)	Annual natural gas consumption (from 2001 to 2018)
Svoboda et al. (2021)	Natural gas consumption, weather variables, natural gas price
Wu et al. (2021)	Annual natural gas production and consumption (from 2007 to 2012)
Yukseltan et al. (2021)	Daily natural gas consumption (from 2002 to 2017), daily temperature
Zheng et al. (2021)	Annual natural gas production and consumption (from 2008 to 2018)

The method is based on determining the statistical distribution of gas consumption deviations recorded at smart meters from average consumption curve, which is used to upscale the forecast to total number of consumers in the observed region. The method includes only gas consumption and respective atmospheric temperature values, and eliminates the need for detailed data about consumers, such as household properties, building types, different consumers (private, industrial, business facilities, etc.). The objective of the research was to determine needed number of gas smart meters, not to improve or establish a new forecast method.

2. Implementation of smart meters and their use in forecasting natural gas consumption

The installation of smart meters and the realization of smart grids is a new step towards optimizing energy consumption (Bagdadee et al., 2020; Maruf et al., 2020). EU member states with well-developed gas and electricity markets such as Great Britain, Netherlands, France, Italy, Austria, Sweden, etc. have started or are considering large scale projects to install smart meters for electricity and/or gas in large number of households (Castelnuovo and Fumagalli, 2013; DECC and Ofgem, 2011; Van Aubel and Poll, 2019). This is due to the many benefits that come with their installation, such as reduced household energy consumption (Sovacool et al., 2017), emission reduction, reduced operating and consumption costs (Sheikhi et al., 2015), better optimization of the energy system (Leiva et al., 2016), smoother consumption fluctuation and improved supply reliability (Su et al., 2019b). Most of the energy savings and emission reduction are the result of customers easier consumption tracking which results in changing their habit with the main goal of cost reduction, therefore changing consumption patterns (Mogles et al., 2017; Buchanan et al., 2016). Apart from energy savings, smart metering data was also successfully used in building energy characterization (Melillo et al., 2020), development of daily electricity consumption profiles (Gouveia et al., 2017) and determination of gas consumption per individual appliance in residential buildings (Tewolde et al., 2013). The main disadvantage of installing smart meters is that installation is a fairly expensive and time-consuming process. One example is the UK, where the total cost is estimated to be over £11 billion and the whole process will take more than 5 years (Sovacool et al., 2017).

2.1. Data resolution

Currently, there are many consumers in the European Union who use meters without remote reading, which means that the resolution of energy consumption data is fairly low (Stegner et al., 2019), i.e. energy consumption readings are made on a monthly basis or even less frequently. With the installation of smart meters, the resolution of energy consumption data is increasing exponentially, and it is possible to obtain consumption data almost in real time (Pesantez et al., 2020). Such a large amount of data greatly contributes to the optimization and easier adaptation of the energy system to the needs of consumers (Tornai et al., 2016) and constantly fluctuating energy market. This high-resolution data can also greatly help in the design and development of district heating systems, given that most existing district heating are oversized due to lack of thorough understanding of energy demand (Wang et al., 2020b).

2.2. Installation of smart meters

In this case, gas smart meters were installed across three closely located smaller cities and their rural surroundings at 3337 different end users (households, schools, kindergartens, business facilities, etc.) in the eastern part of Croatia. The structure of end consumers, i.e. the percentage of households, public buildings, business facilities, etc. is a business secret or the unknown to the distribution system operator and is not publicly available, but it is known that most smart meters are installed in temperature-dependent consumers. The uncertainty of the structure of final consumers is overridden by statistical distribution determination of consumption deviations from average consumption, which is described in more detail below. These smart meters are programmed to collect consumption data every 6 h and send the sum of the same every 24 h at 6 am. The reason why data is sent as a sum is to save battery power when sending data. If the data were sent every six hours the built-in battery life would be four times shorter. Likewise, if a larger amount of data were sent once a day in terms of sending daily consumption subdivided into periods of six hours, the battery life would also be significantly shorter.

3. Developing an accurate model for natural gas consumption forecasting

The use of smart meters allows the collection of a very large amount of input data which is the most important factor for the successful development of an accurate method. Fig. 1 shows the authors step by step suggestion for developing an accurate method for forecasting natural gas consumption. In addition to consumption data, the authors propose the use of high-resolution data on temperature. Some additional parameters can also be used, but their use can be characterized as less important. Since it is suggested to use high-resolution data, this data should be filtered to eliminate possible outliers that can reduce the accuracy of the method. Once obtained, the database is used as input for an already existing or newly developed forecasting model. New model, of course, needs to be tuned and the forecasting results need to be validated successfully so that proposed model could be used to forecast unknown data. In case that the obtained forecasted results are not satisfactory in terms of accuracy, the authors suggest the formation of a better-quality database or improvement of the forecasting model.

3.1. Data collection, processing, filtering and determination of data distribution

Following the proposed flowchart, data was obtained from gas smart meters installed at 3337 metering points in the eastern part of Croatia (3 cities and their rural surroundings). The collected data is a reading of the gas meter, i.e. the meter sends data on a daily basis on the total consumption of natural gas from the moment when the meter was installed. The daily consumption was then easily calculated by subtracting the total consumption recorded on the observed day from the total consumption recorded on the previous day. Collected data was first filtered due to improper logging (smart meter failure, network problems and/or users with zero consumption) because the accumulation of

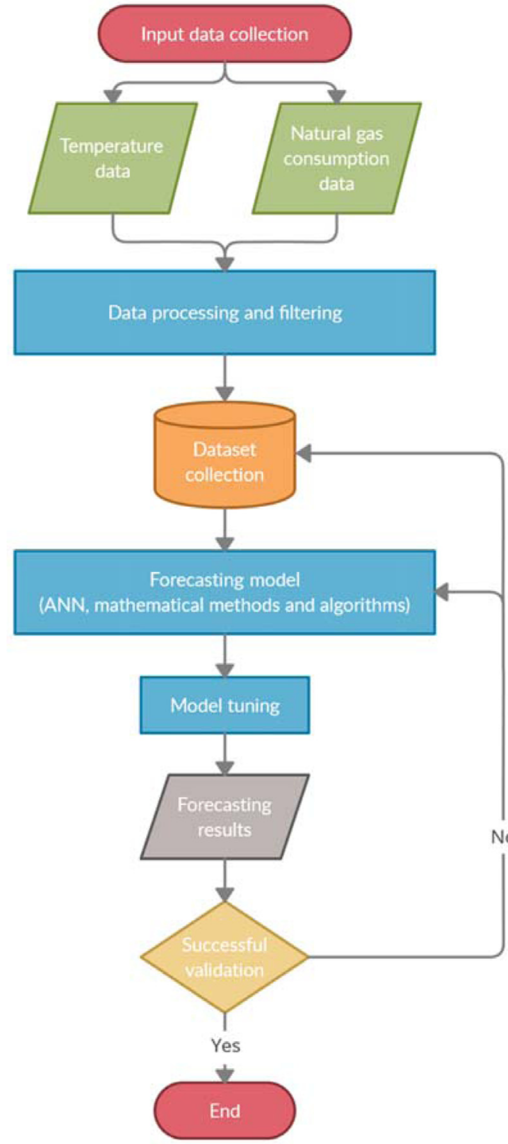

Fig. 1. Proposed flowchart for developing accurate method for natural gas consumption forecasting.

errors can produce a significant total deviation in forecast. After filtering, dataset from 2486 smart meters was used in further analysis. This dataset consisted of daily natural gas consumption measured in m^3 during several months in last heating season for significantly different temperatures.

The assumption is that average daily natural gas consumption obtained via observed 2486 smart meters can be used to upscale the consumption to regional level and to correlate the consumption with daily measured (or predicted) temperature. Temperature data was collected from publicly available meteorological database where the mean daily temperatures are available for the observed locations. Consumption was linearly correlated with temperature (r value $= -0.9634$, p value $= 0.00048$, and standard error stderr $= 0.03484$) according to the formula below:

$$V_g = -0.28 \cdot t + 8.2026$$

Where V_g = daily gas consumption (m^3) and t = daily average temperature (°C).

Next step was determining deviations (relative errors, %) of real-world measured data from average (real) consumption. These

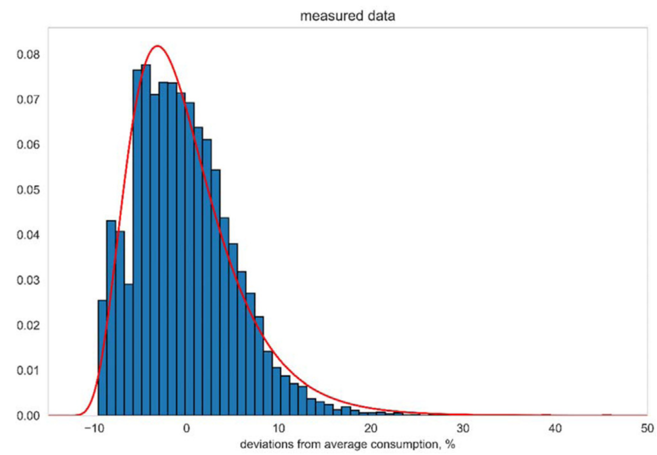

Fig. 2. Best fit (lognormal) distribution (shape = 0.4, loc = −14.4014, scale = 13.2018).

deviations were tested for several statistical distributions (by coding the function for distribution testing in Python programming language, using scipy.stats library, Jones et al., 2001). Goodness of fit of observed distributions was evaluated by Kolmogorov–Smirnov (K–S) test, i.e., the test statistic (D, supremum between cumulative density functions of two samples) and p-values (the probability that the D statistic value will be larger than observed). Finally, the distributions with best fit were evaluated visually by plotting (Fig. 2) to finally select the lognormal distribution as representative, based on the deviations at different temperatures i.e., days.

4. Results

Distribution parameters defined in the last chapter along with real-world historical temperature data were used for random sampling i.e., simulation of real-world consumption data in time period from 1st of October to 1st of April (heating season). Random sampling was done by using Python programming language for cases of 100, 1000, 10 000 and 100 000 installed smart meters. The mean value was calculated for all simulated values and the deviation of the mean value for the simulated data from the mean value obtained by the previously mentioned correlation ($V_g = -0.28 \cdot t + 8.2026$) was calculated. For each of these cases, the impact of removing "large" consumers from distribution, i.e., limiting the maximum daily gas consumption, was also observed. These limits were set at a maximum daily consumption of 50, 250 and 500 m^3 per day. Figs. 3–5 show the average deviations as a function of temperature for all the above cases (12 cases).

The simulation shows that, if more than 10 000 smart meters were installed, deviation between average estimated natural gas consumption and the simulated real-world data would be less than ±2.96% in case of maximum daily consumption of 50 m^3. In case of 100 000 smart meters installed, this deviation would be less than ±1.20%. If average daily temperature forecast is accurate, total gas consumption in observed regions could be estimated with ±1.20% accuracy (see Table 2). Presented methodology can be used for different regions, however distribution parameters should be evaluated separately for each case, because they depend on characteristics of natural gas users.

It is also evident that "large" consumers can cause an unfavorable increase in deviation due to the fact that at higher temperatures they have a significantly greater impact on the observed consumption of a region. This impact is mainly due to the fact that a large part of natural gas consumption by "large" consumers is temperature independent.

Table 2
Overview of maximum deviations from simulated real-world consumption for all cases.

Samples	Maximum daily consumption (m^3)	Maximum deviation (%)
100	50	−27.51
1000	50	−8.33
10 000	50	2.96
100 000	50	1.20
100	250	27.55
1000	250	9.86
10 000	250	2.84
100 000	250	−1.26
100	500	−30.86
1000	500	−10.28
10 000	500	−4.39
100 000	500	−3.03

5. Conclusion

A review of the available methods concludes that in most cases more complex methods have proven to be more accurate, although one method has proven to be fairly accurate despite using a simple mathematical function. The reason for this is the availability of a large set of data on natural gas consumption which proves that the availability of high-resolution data is extremely important for achieving accurate natural gas consumption forecast. High-resolution data availability can be achieved by installing smart meters for the majority of users. Based on conducted research, natural gas consumption and temperature were suggested as parameters that should be used for modeling a new method for forecasting natural gas consumption.

Following the proposed flow diagram, the actual consumption data was analyzed and the linear temperature dependence of natural gas consumption for the observed region was calculated. Using the obtained temperature dependence together with the lognormal distribution, the consumption of natural gas was simulated for 12 different cases. The analysis of the results showed that the best results are achieved with the largest number of installed smart meters (100 000), but quite satisfactory results can also be achieved with 10 000 installed smart meters. "Large" partly temperature independent consumers should be disregarded because they can cause an unfavorable increase in forecasting deviation. The results of this research show that the availability of high-resolution data on natural gas consumption obtained by gas smart meters significantly influence the accuracy of natural gas forecasting methods. Also, this paper proves that during the partial installation of smart meters in a particular region or city, it is necessary to strategically identify locations for the installation of smart meters. Quality distribution of smart meters to a wide range of consumers with different profiles will provide a representative sample that can be used to upscale natural gas consumption in the observed area.

Nomenclature

ABC — Artificial bee colony
ANN — Artificial Neural Network
ARIMA — Autoregressive Integrated Moving Average
CF-SA-FFOA-SVM — Cross Factor-Simulated Annealing-Fruit Fly Optimization Algorithm-Support Vector Machine
BP — Back Propagation
BPNN — Back Propagation Neural Network
CFNHGBM (1,1, k) — Conformable Fractional NonHomogeneous Grey Bernoulli Model
DGM — Discrete Grey Model
DFGM (1,1, t^{α}) — Discrete Fractional Grey Model with a time power term

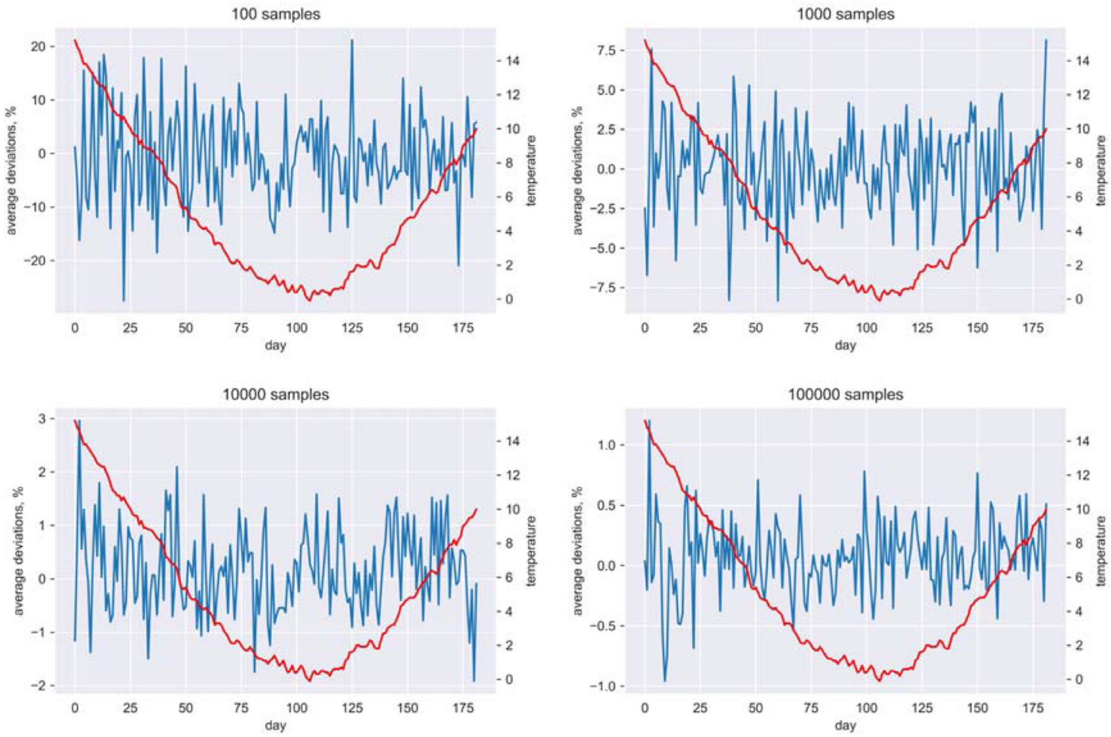

Fig. 3. Deviations from simulated real-world consumption of natural gas during heating period (maximum daily consumption = 50 m^3).

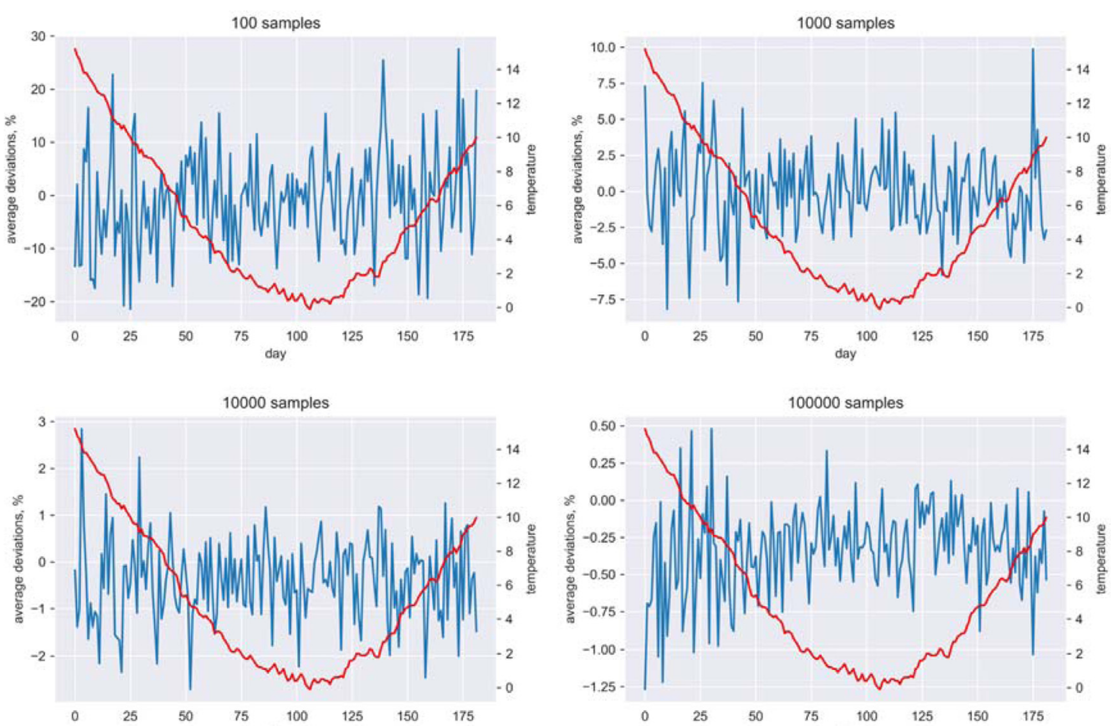

Fig. 4. Deviations from simulated real-world consumption of natural gas during heating period (maximum daily consumption = 250 m^3).

DGMNF (1,1) — Discrete Grey Model considering Nonlinearity and Fluctuation
EDGM — Event Difference Grey Model
ELM — Extreme Learning Machine
GM — Grey Model
ISSA-LSTM — Improved Singular Spectrum Analysis with Long Short-Term Memory
KM — Kernel Machine
KNEA — Kernel-based Nonlinear Extension of the Arps decline model
KNEA-GWO — Kernel-based Nonlinear Extension of the Arps decline model with implemented Grey Wolf Optimization
LASSO regression — Least Absolute Shrinkage and Selection Operator

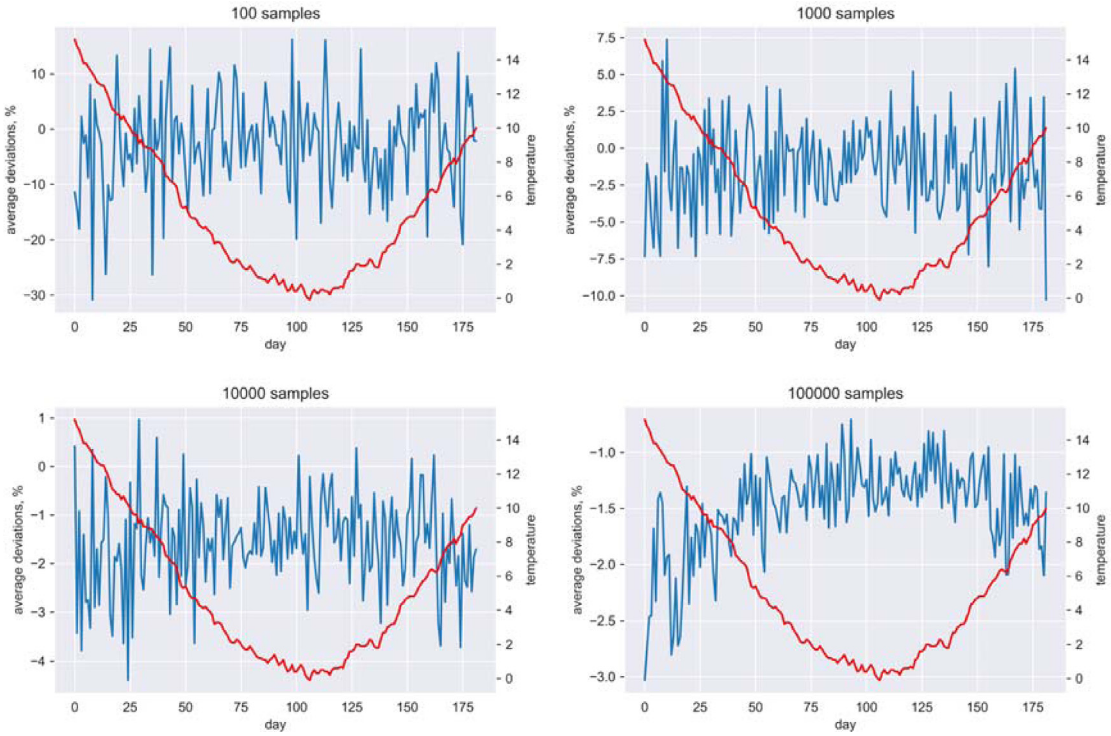

Fig. 5. Deviations from simulated real-world consumption of natural gas during heating period (maximum daily consumption = 500 m^3).

LDNN — Large Deep Neural Network
LR — Linear Regression
LSSVM — Least Squares Support Vector Machine
LSSVR — Least Squares Support Vector Regression
LSTM — Long Short-Term Memory
MAE — Mean Absolute Error
MAPE — Mean Absolute Percentage Error
MLR — Multiple Linear Regression
MTL-LSSVM — Multi Task Learning theory combined with Least Squares Support Vector Machine
NAR — Non-linear Autoregressive
PSO-SVM — SVM optimized by Particle Swarm Optimization algorithm
PSO-WNN — The Particle Swarm Optimization algorithm and Wavelet Neural Network
RBFNN — Radial basis function neural network
RNN — Recurrent Neural Network
SC-SVR — Structure-Calibrated Support Vector Regression
SIGM — Self-adapting Intelligent Grey Model
SSA-LSTM — Singular Spectrum Analysis with Long Short-Term Memory
SVM — Support Vector Machine
SVR — Support Vector Regression
WNN — Wavelet Neural Network

CRediT authorship contribution statement

Ivan Smajla: Conceptualization, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Daria Karasalihović Sedlar:** Conceptualization, Investigation, Writing - original draft, Supervision. **Domagoj Vulin:** Conceptualization, Formal analysis, Simulation, Writing - original draft, Visualization. **Lucija Jukić:** Conceptualization, Investigation, Writing - original draft, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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