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Review Article

Natural gas consumption forecasting: A discussion on forecasting history and future challenges

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A R T I C L E I N F O

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A B S T R A C T

Natural gas consumption forecasting technology has been researched for 70 years. This paper reviews the history of natural gas consumption forecasting, and discusses the changes in forecasting horizons, influencing factors, and forecasting performance. According to the characteristics of forecasting models used in different periods, the history of natural gas consumption forecasting can be categorized into initial stage, conventional stage, AI stage, and all-round stage. The stage characteristics, typical models, advantages and disadvantages at different stages have been summarized. The review results show that, affected by the development of computer science and AI technology, short-term forecasting is the fastest-growing forecasting horizon, followed by long-term and medium-term. Additionally, long-term forecasting is mainly affected by production, population, and economic variables. Medium-term forecasting is mainly affected by economic and temperature variables. Influencing factors of short-term forecasting mainly depend on temperature variables, weather condition and date type. Furthermore, the statistical analysis of data characteristics, model characteristics and forecasting results presents that time series models are the best models for long-term forecasting. It has the lowest average mean absolute percentage error (1.90%) in long-term forecasting. To the medium-term and short-term forecasting, AI-based models present the best performance. Among them, artificial neural network models (2.21%) are preferred for medium-term forecasting, and support vector regression models (4.98%) are more suitable for short-term forecasting. Besides, this paper proposes a framework for model selection, and provides specific suggestions for future research directions.

1. Introduction

Since natural gas became the main energy source for sustainable development, the demand for natural gas has grown exponentially around the world. Fig. 1 shows the development of natural gas in various regions of the world from 1990 to 2019 (Enerdata, 2020). It can be seen that natural gas consumption has been on the rise since 1990, and the consumption in past five years are 3555, 3631, 3725, 3917, and 4018bcm, respectively. The large-scale consumption of natural gas not only reflects the success of environmental protection policies and the rapid growth of economic, but also contributes to the ineffective management of gas supply. An effective gas supply management mainly depends on accurate natural gas consumption forecasting technology, which can help countries and enterprises to formulate reasonable gas supply plans, manage supply contracts, improve operational efficiency, provide basic data for production and infrastructure construction planning, while saving energy and reducing costs. It relates to the safety, reliability and economic benefits of national and enterprise gas supply systems. For example, 98% of Turkey's natural gas consumption is purchased through foreign natural gas company. If there is no accurate consumption forecast, the loss will reach billions of dollars. Therefore, natural gas consumption forecasting is essential for the sustainable development of any country.

Many researches on natural gas consumption forecasting technology have been carried out to date, and hundreds of advanced forecasting models have been developed for improving the accuracy, including traditional statistical models, AI-based models and combined models. Two researchers have already reviewed these existing forecasting techniques. Soldo (2012) reviewed almost all papers in the field of

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Abbreviations

AFF	Adaptive Feed-Forward
AFL	Adaptive Functional Link
AFLC	Adaptive Functional Link Combiner
AI	Artificial Intelligence
ANFIS	Adaptive Network-based Fuzzy Inference System
ANN	Artificial Neural Network
AR	Autoregressive model
ARE	Absolute Relative Error
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BAN	Best Asymptotically Normal
BPNN	Back Propagation Neural Network
CBR	Case Based Reasoning
CC	Correlation Coefficient
CCMGA	Cat Chaotic Mapping Genetic Algorithm
CDD	Cooling Degree Day
CF	Cross Factor
CPI	Consumer Price Index
DEA	Data Envelopment Analysis
DL	Deep Learning
DM	Data Mining
DmGNn	Data mining Genetic-neural Network
DNN	Deep Neural Network
ELFIS	Emotional Learning based Fuzzy Inference System
ELNN	Elman Neural Network
FDEA	Fuzzy Data Envelopment Analysis
FFNN	Feedforward Neural Network
FFOA	Fruit Fly Optimization Algorithm
FGC	Fuzzy-Genetic Combiner
FM-MLP	Forecasting Monitoring-Multi Layered Perceptron
FNN	Fuzzy Neural Network
FSA	Factor Selection Algorithm
GA	Genetic Algorithm
GAuLF	Gas Automated Load Forecaster
GDP	Gross Domestic Product
GIP	Gross Industrial Product
GM	Grey Model
GRNN	Generalized Regression Neural Network
HDD	Heating Degree Day
ISSA	Improved Singular Spectrum Analysis
IWOA	Improved Whale Optimization Algorithm
LDC	Local Distribution Company
LGA	Life Genetic Algorithm
LM	Levenberg-Marquardt
LogR	Logistic Regression
LR	Linear Regression
LS	Least Squares
LSTM	Long Short-Term Memory
MA	Moving-Average
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MARNE	Mean Absolute Range Normalized Errors
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression
MNAPE	Mean Normalized Absolute Percentage Error
MR	Multiple Regression
MSE	Mean Square Error
NLR	Non-Linear Regression
NMGM	Nonlinear Metabolic Grey Model
NMSE	Normalized Mean Square Error
PCCA	Principal Component Correlation Analysis
PCMACP	Polynomial Curve and Moving Average Combination Projection
PSO	Particle Swarm Optimization
R^2	Squared correlation coefficient
RBFNN	Radial Basis Function Neural Network
RBM	Restricted Boltzmann Machines
RE	Relative Error
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RVM	Relevance Vector Machine
SA	Simulated Annealing
SARIMAX	Seasonal Autoregressive Integrated Moving Average with additional variables
SC-SVR	Structure-Calibrated Support Vector Regression
SD	Standard Deviation
SE	Standard Error
S.E.P.	Strategy Evaluation Program
SFA	Stochastic Frontier Analysis
SIGM	Self-adapting Intelligent Grey Model
SMOSVM	Sequential Minimal Optimization Support Vector Machine
SOFM-MLP	Self-Organizing Feature Map Multi-Layer Perceptron
SVM	Support Vector Machine
SVR	Support Vector Regression
SVD	Singular Value Decomposition
TS	Time Series
WMAPE	Weighted MAPE
WNN	Wavelet Neural Network
WT	Wavelet Transform

natural gas consumption and production forecasting from 1949 to 2010, discussed in terms of applied area, forecasting horizon, input data and models. Tamba et al. (2018) extended Soldo's work to 2015, they provided analysis and synthesis of published papers on models and applied area, input data, data source, data size, forecasting horizon, results and model performance. However, Soldo and Tamba only listed and classified the papers in these fields. There is still no related research that can describe the history of natural gas consumption forecasting, and summarize the characteristics in different stages clearly. Additionally, there are a lack of review studies that discuss the development history from a more multivariate perspective, including forecasting horizon, influencing factors, and forecasting performance.

To narrow these knowledge gaps, this paper systematically reviews the history of natural gas consumption forecasting, summarizes the characteristics, typical models, advantages and disadvantages at different stages, discusses the changes in forecasting horizons, influencing factors, and forecasting performance, and proposes the prospects and suggestions for future research directions. The rest of this work is organized as follows: In section 2, the research methodology of this work is described. Section 3 reviews the history of natural gas consumption forecasting based on the development of forecasting models, discusses the changes in forecasting history. Section 4 of this paper presents the future research directions and suggestions for natural gas consumption forecasting. Major conclusions are presented in Section 5.

2. Methodology

The research method of this work can be summarized as follows:

- Searching the related papers

Search engines: Google scholar, a powerful paper search tool, that are critical to academic researchers.

Search keywords: The search keywords used in this paper include: gas load forecasting, gas load prediction, gas consumption forecasting, gas consumption prediction, gas demand forecasting, and gas demand prediction.

Search period: From the appearance of the first natural gas consumption forecasting model to present (1950–2019).

In this step, 98 papers were collected.

- Screening the collected papers

There are two criteria for screening papers. Firstly, it must be a paper related to the forecasting of natural gas consumption, and does not include other energy sources except natural gas, nor does it consider the forecasting of natural gas price, production, etc. Secondly, the paper must include at least one forecasting method.

In this step, 72 papers were selected from the 98 papers searched.

- Reviewing the papers

Review the forecasting model, applied area, country, forecasting horizon, data size, influencing factor, and performance of all the collected papers.

In this step, all the results of 72 published papers were listed in Appendix.

- Introducing the history and future of natural gas consumption forecasting technology

In section 3, the history of natural gas consumption forecasting technology was divided into four stages based on the development of forecasting models, summarized the characteristics, typical models, advantages and disadvantages at each stage. In addition, how the forecasting horizon, influencing factor, and forecasting performance (3 indicators with significant changes) have changed throughout the development of natural gas consumption forecasting technology were discussed.

Section 4 presented the future research directions for natural gas consumption forecasting, and provided specific suggestions for model and parameter selection.

In this step, the characteristics, typical models, advantages and disadvantages for each historical stage were listed in corresponding table.

3. History of natural gas consumption forecasting

Research on natural gas consumption forecasting started in the 1950s. According to the characteristics of forecasting models used in different periods, the development history can be divided into four stages: Initial stage (1950–1970), Conventional stage (1970–1992), Artificial Intelligent (AI) stage (1992–2006) and All-round stage (2006-present). Fig. 2 presents the most important events in the development history of natural gas consumption forecasting.

3.1. Initial stage

The Initial stage of natural gas consumption forecasting was 1950–1970. Limited by the backward computing conditions, scientists in this period established simple structural statistical models that mainly based on factors, such as natural gas prices, national income, production, trading volume, etc., to forecast long-term natural gas consumption (Durrer et al., 1969; Elliott and Linden, 1968). Statistical models could predict future trends via establishing relationships between one or more independent and dependent variables (Catalina et al., 2013). Not only can obtain reliable forecasting results, but it can be used to find the relationship between gas consumption and influencing factors (Tsekouras et al., 2007). Early statistics models including Hubbert curve model, Exponentially Weighted model, Least Squares model, Logistic Regression model, Gompertz curve model, etc.

Verhulst (1950) considered natural gas consumption as a function of user's primary income and gas price, established a forecasting model based on analyzing the demand of 46 natural gas plants in France. During the same period, Hubbert proposed a logarithmic growth curve called "Hubbert curve" (Hubbert, 1949, 1956), which can describe the changes in oil production by analyzing the life cycle of fossil energy production in the United States. The curve model successfully forecasted the peak of U.S. oil production from 1967 to 1973 for nearly 10 years in advance, making "Hubbert curve" extremely famous, and many researchers have applied it to the forecasting of natural gas consumption (AI-Fattah and Startzman, 2000; Siemek et al., 2003; Wang et al., 2016).

Berrisford (1965) believed that successful natural gas demand forecasting depended heavily on finding the best weighted model for current and previous temperatures. Therefore, an exponentially weighted forecasting model that didn't need to consider seasonal patterns was proposed. The new model greatly improved the fitting capability of data, and the accuracy could be maintained even under prolonged abnormal weather conditions. Ward (1965) used least squares, semi-logarithmic and double-logarithmic statistical models to forecast energy consumption in the next 7 years, and pointed out that accurate yearly load forecasting requires a professional perspective, such as petroleum and economics, to consider all internal and external factors that are likely to affect energy consumption to getting better predictions.

Balestra and Nerlove (1966) developed a forecasting model named BAN model, based on ordinary least squares method, to forecast the demand for natural gas in the residential and commercial sector. The proposed model provides a significant beginning for long-term forecasting of natural gas consumption (Berndt et al., 1980). Johnson (1968) proposed that except for inherent factors, such as national income,

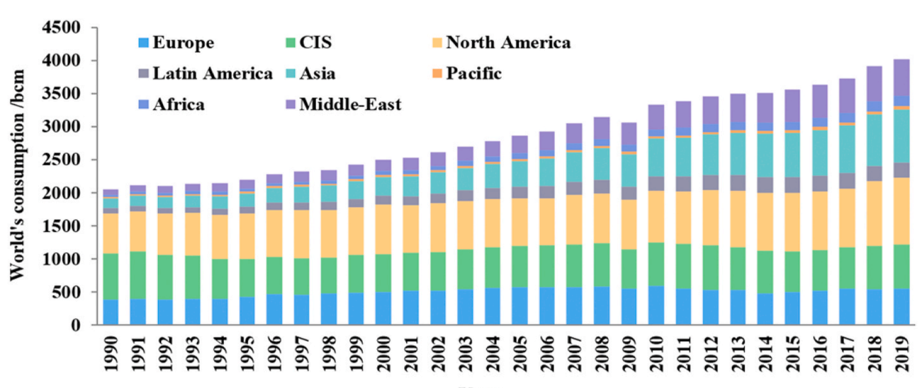

Fig. 1. Consumption statistics of natural gas in different regions (Enerdata, 2020).

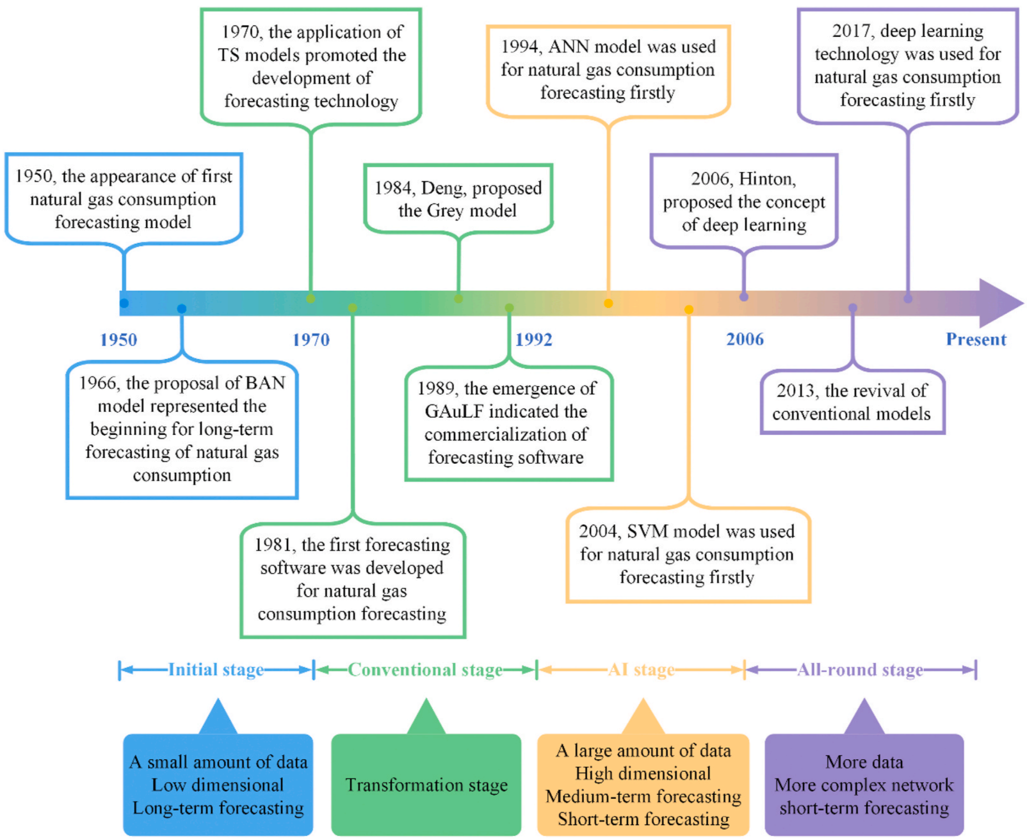

Fig. 2. Development history of natural gas consumption forecasting.

Table 1
Initial Stage-Overview of published papers by years.

Publishing year	References
1950	Verhulst
1956	Hubbert
1965	Berrisford, Ward
1966	Balestra and Nerlove
1968	Elliott and Linden, Johnson
1969	Durrer et al.

effective temperature, etc., it is also necessary to predict the gas equipment sales and central heating to achieve accurate forecasting results. After applying logarithmic logic curve model and Gompertz curve model to forecast the gas equipment sales, multiple regression technology was combined to forecast the natural gas consumption in the next few years in UK Overview of published papers in the initial stage is listed in Table 1.

Limited by the backward computing technology and lack of data, forecasting models at this stage are mainly statistical models, and researchers in this period focused on using a simple mathematical formula to describe the national or global gas consumption trends. However, statistical models can only explain the relationship between consumption and variables with simple structure. It cannot describe the development trend of gas consumption accurately and contain more historical data and variables. Therefore, the earliest consumption forecasting mainly focused on long-term forecasting with low data volume, low dimension and long-time span.

3.2. Conventional stage

Research on natural gas consumption forecasting entered the Conventional stage from 1970 to 1992. The emergence of microcomputers and improvement of calculating capabilities have promoted the development of statistical models (Caton, 1984; Haenel, 1973; Piggott, 1983; Tinic et al., 1973). Many classic forecasting models have emerged, such as TS models and regression models (LR and NLR). Compared to earlier forecasting models, the models appearing in this period have significantly enhanced the processing capabilities of non-linear relationships between data (Berndt and Watkins, 1977; Lyness, 1981, 1984; Taylor and Tomas, 1982; Wang et al., 2019). Therefore, natural gas consumption forecasting is no longer limited to a small amount of data and low-dimensional long-term forecasting, a large number of data, high-dimensional medium-term and short-term forecasting have begun to appear (Tso and Yau, 2007).

In 1970, the book *Time Series Analysis: Forecasting and Control* published by Box and Jenkins, discussed the application of various TS models in forecasting, and unveiled the prelude to forecasting natural gas consumption based on TS models. TS models can predict future trends over a small amount of historical data without external variables (Azadeh and Tarverdian, 2007; Nadimi and Tokimatsu, 2017), including Autoregressive model (AR) (Andersen et al., 2013, 2014), Moving-average model (MA) (Xu and Wang, 2010), Autoregressive moving average model (ARMA) (Pappas et al., 2010), Autoregressive integrated moving average (ARIMA) (Conejo et al., 2005) and other improved TS models (Zhu et al., 2014).

Pepper (1985) built an ARIMA model of multi-dimensional input and output variables based on Box-Jenkins algorithm, which was used to forecast the main energy consumption including oil, electricity and natural gas in UK. Drevna (1985) added a transfer function into ARIMA model. Compared with economic model, the improved ARIMA model reduced the input of model parameters, and presented more accuracy than ARIMA. Nelder and Wedderburn (1972) proposed a generalized linear model that unified LR and logR into one system. Herbert (1987b) established a LR model and introduced economic variables, such as gas price, electricity costs, heating demand, cumulative taxation, etc., to predict the monthly demand of US industrial gas (Herbert et al., 1987)

Table 2
Conventional Stage-Overview of published papers by years.

Publishing year	References
1971	Rodger et al.
1972	Nelder and Wedderburn
1973	Haenel, Tinic et al.
1977	Berndt and Watkins
1981	Lyness
1982	Taylor and Tomas
1983	Piggott
1984	Lyness, Caton
1985	Drevna, Pepper
1987	Herbertet al. (1987a, 1987b)
1989	Jabbour and Meyer
1991	Liu and Lin

and residential gas (Herbert, 1987a). The relative error of forecasting results was low to 0.7%.

Rodger et al. (1971) integrated the forecasting methods of Scottish Gas Board for different forecasting types (industrial, commercial, residential), and established a combined regression forecasting model that can accurately forecast the peak of daily consumption. Grey Model (GM) proposed by Chinese professor Julong Deng in 1984, can describe the development trends vaguely through a small amount of incomplete information. The proposed model led to a fierce discussion in academia, and has been widely used in various research fields.

In 1989, GAuLF (Gas Automated Load Forecaster) has been developed to assist Niagara Mohawk Power Corporation (NMPC) gas operators in estimating short term gas demand by Jabbour and Meyer (1989). As a commercial software developed for natural gas consumption forecasting, the application of GAuLF represented that the forecasting technology was gradually maturing, and its derivative products were becoming more commercialized. Liu and Lin (1991) adopted a linear transfer function model, based on two independent variables of natural gas price and temperature, to forecast medium-term consumption of residential in Taiwan, and performed that temperature was the main factor affecting the accuracy of medium-term forecasting. Overview of published papers in the conventional stage is listed in Table 2.

The emergence of microcomputers and improvement of calculating ability resulted in many improved statistical models, made the models at this stage have stronger nonlinear capabilities than Initial stage. Research directions in this period has also begun to shift towards short-term and medium-term forecasting with more data, higher dimension and shorter time span. However, the calculation of the improved statistical models is still based on a small amount of historical data, and the accuracy of the models largely depends on the size of the selected data set. Therefore, the improved statistical models won't learn enough changes based on a small amount of data set, and cannot reflect the relationship between consumption and variables accurately.

3.3. AI stage

The stage of AI-based models was 1992–2006. The proposal of back propagation algorithm (Rumelhart et al., 1986) and non-linear Support Vector Machine (SVM) (Boser et al., 1992) represented the rise of machine learning in the field of AI (Musilek et al., 2006; Suykens et al., 1996). It also promoted a trend that traditional statistical models and machine learning models going forward together on natural gas consumption forecasting (Magoulès and Zhao, 2016). Compared with statistical models, machine learning models have obvious advantages in the processing of complex non-linear data, especially high accuracy in short-term consumption forecasting (Ivezic, 2006; Peng et al., 2019; Szoplik, 2015). Therefore, machine learning technology was used to forecast natural gas consumption in this period has become research hotspots in academia (Bai and Li, 2016; Lee and Tong, 2011; Pelikan and Simunek, 2005).

Machine learning models are a subclass of AI models, representative models include Artificial Neural Network (ANN) and Support Vector Regression (SVR) (Gerven and Bohte, 2018). In fact, ANN is a framework for many different neural network models to work together and process complex input data, not a specific model. ANN models applied in the field of natural gas consumption forecasting include: Feedforward Neural Network (FFNN) (Azadeh et al., 2013b; Jebaraj et al., 2011; Kermanshahi, 1998; Soldo et al., 2014), Back Propagation Neural Network (BPNN) (Demirel et al., 2012; Miura and Sato, 1998; Peharda et al., 2001; Yu and Xu, 2014), Radial Basis Function Neural Network (RBFNN), Adaptive Network-based Fuzzy Inference System (ANFIS) (Azadeh et al., 2011, 2013a; Kaynar et al., 2011) and Wavelet Neural Network (WNN) (Bhaskar and Singh, 2012; Catalao et al., 2011; Zhang et al., 2018; Zhang and Wang, 2012), etc. As the early ANN models, FFNN and BPNN have the same structure, the difference is only in the calculation method of training error, they are both called ANN models in many forecasting studies (Amber et al., 2018; Jebaraj et al., 2011; Soldo et al., 2014).

Brown et al. (1994) used FFNN model to forecast daily consumption of a certain area in Milwaukee, Wisconsin. The results indicated that the residual mean squared errors of FFNN was 48% of the linear regression models using the same factors (Brown and Matin, 1995). Klema and Kout (1999) combined CBR algorithm, NLR algorithm processed by SVD, and BPNN based on delta rules, proposed a general forecasting algorithm based on AI technology and classic statistical analysis. MAPE of the combined model was about 4%, which can successfully predict the send out in the local gas distribution network.

Khotanzad and Elragal (1999) proposed three two-stage forecasting methods based on ANN. In the first stage of these three methods, two or three adaptive ANN models were used to forecast daily consumption. In the second stage, weighted combination, nonlinear combination of functions and fuzzy genetic combination were applied to combine forecasting results. The forecasting results of these three methods showed that the proposed combined model could provide more accurate results than using a single predictor (Elragal, 2004; Khotanzad et al., 2000).

Gorucu et al. (2004) used BPNN to forecast daily consumption under optimistic (economic stability) and pessimistic (economic crisis) conditions in Ankara, Turkish. The results were satisfactory and logical. Viet and Mandziuk (2005) adopted naive prediction model, linear and quadratic regression models, single feedforward network, combined feedforward neural networks, temperature context networks, working days prediction model, single fuzzy neural network to forecast the consumption of 3 different forecasting horizons in rural and urban areas in Poland. The results showed that the accuracy of neural network models was better than conventional models, and the performance of FNN is better than ANN in neural network models.

Although ANN has better performance in short-term forecasting, it still has inherent defects, such as slow convergence speed, poor generalization ability, local optimization and overfitting, etc. In contrast, the principle of structural risk minimization and kernel function were used to SVR to avoid the defects of ANN effectively (Bai et al., 2018; Beyca et al., 2019). Liu et al. (2004a) considered the influence of temperature and holidays on consumption, and adopted SVM, LS-SVM and SOFM-MLP to forecast daily consumption in Xi'an. The MAPE of the three models were 1.6246%, 1.704% and 3.3059%, respectively. It is indicated that the forecasting method based on SVM is better than neural network method (Liu et al., 2004b). Zhu et al. (2015) proposed an improved SVR for predicting short-term consumption of national gas pipeline network in UK, and proved that the model has a lower error than ARMA and ANN. The lowest MAPE was only 3.4%. Overview of

Table 3
AI Stage-Overview of published papers by years.

Publishing year	References
1994	Brown et al.
1995	Brown and Matin
1996	Suykens et al.
1998	Miura and Sato
1999	Klema and Kout, Khotanzad and Elragal
2000	Al-Fattah and Startzman, Khotanzad et al.
2001	Peharda et al.
2003	Siemek et al.
2004	Elragal, Gorucu et al., Liu et al. (2004a, 2004b)
2005	Viet and Man'dziuk, Pelikan and Simunek
2006	Musilek et al. Ivezić

published papers in the AI stage is listed in Table 3.

Thanks to the advancement of computer science and artificial intelligence, forecasting models at this stage could perform more complex calculations. In particular, the appearance of ANN and SVM has greatly improved the learning ability and nonlinear fitting ability of forecasting models. Moreover, forecasting models in this period could take more variables into consideration, handle the interaction between nonlinear features better, and extract the reasonable rules between input and output automatically to forecast the development trends. Therefore, researchers began to focus on medium-term and short-term forecasting, which require a large amount of data.

Despite these advantages, the models at this stage still have its inherent flaws. The structure and parameters of the forecasting models have always been different, and there is no unified theory to declare how to construct the structure and parameters until now. Trial and error is the only way to solve these problems. In addition, the approximation and promotion capabilities of the model are closely related to the learning samples, and it is a difficult problem to select reasonable samples to form the training set. Furthermore, slow convergence, long computing time, overfitting and underfitting have always been the defects of the forecasting models in this stage.

3.4. All-round stage

Since 2006, research on natural gas consumption forecasting has stepped into a stage of all-round development. Increased awareness of energy conservation and environmental protection, promotion of green economy concepts, outbreak of the shale gas revolution, breakthrough in natural gas hydrate research, etc., all indicated the importance of natural gas in future energy structure. Countries around the world are also vigorously urging the promotion and application of natural gas (Liu et al., 2019). During this period, the number of research papers on natural gas consumption forecasting has surged, and mainly involves three aspects: the appearance of deep learning model, application of combined model and revival of conventional model.

3.4.1. Appearance of deep learning model

In 2006, with the improvement of computing capability, British scientist Hinton established a multi-layer neural network and proposed the concept of deep learning (DL) firstly, marking the research on machine learning stepping into the field of deep learning gradually (Chen et al., 2018). Long Short-Term Memory (LSTM) model is a special form of RNN and also the most popular deep learning model (Ghasemi et al., 2018) currently. It can effectively solve the problem of gradient disappearance of RNN, and the information of previous moment is recorded in each cell through the state variable at the same time, making the information connection between different moments closer. Therefore, it's widely used to solve various time series prediction problems (Graves, 2012; He, 2017).

In 2019, Wei et al. successively employed LSTM model, combined with Feature Analysis Algorithm (Wei et al., 2019b) and Data Denoising Algorithm (Su et al., 2019; Wei et al., 2019c), to forecast daily consumption in different regions. The results showed that LSTM model has higher accuracy and better robustness than machine learning model and regression model. Laib et al. (2019) developed a two-stage Forecasting Monitor-Multilayer Perceptron LSTM model to forecast hourly consumption in Algeria. The average MAPE of this method was 5.48%, which was 16.42%, 14.41%, 13.50% and 56.75% less than MLP, LSTM, SARIMAX and MLR, respectively. Su et al. (2019) combined wavelet transform, multi-layer Bidirectional-LSTM model, GA and LSTM model to establish a robust forecasting model. The results indicated that the established model was superior to the three-layer LSTM and nonlinear autoregressive models.

Merkel et al. (2017) used DNN model based on RBM algorithm to forecast natural gas consumption in 176 operating regions in the United States. The results presented that RBM-DNN has better forecasting performance than ANN and LR models regardless of any conditions, and performed better on highest flow (Merkel et al., 2018). Hafezi et al. (2019) proposed an intelligent forecasting model DmGNn based on DM、ANN and GA algorithm to forecast NG global demand. The results showed that the proposed DmGNn (MAPE 1.69%) was significantly better than MLP (3.8%), ANFIS (1.89%), RBFNN (10.42%) and GRNN (4.17%) models (Liu et al., 2020). Hribar et al. (2019) adopted RNN to forecast residential consumption in Ljubljana, Slovenia. Compared with LR, KM, TRM, TLM and TNM models, RNN has the lowest MAPE (hourly 9.3%, daily 6.8%).

3.4.2. Application of combined model

To overcome the inherent defects of the single model, many optimization algorithms, such as PSO, GA, etc., were proposed to combine with the forecasting model. The related researches have proved that combining model with parameter optimization algorithms, data preprocessing algorithms and feature selection algorithms can effectively improve the accuracy of the forecasting model (Akpinar et al., 2017; Cao and Wu, 2016; Kizilaslan and Karlik, 2008; Wang and Jiang, 2019).

Vitullo et al. (2009) used the MLR, ANN and GD (combined algorithm of MLR and ANN) algorithms to forecast gas consumption in the next 30 days in 14 operating areas. The conclusion showed that the performance of the combined model was significantly better than other models. Azadeh et al. (2013a) proposed an integrated ANFIS-DEA-FDEA algorithm to improve long-term forecasting in five South American countries. The results performed that the combined model was superior to LR algorithm, and it has better superiority and robustness (Azadeh et al., 2015). In the case of predicting natural gas consumption of major cities in Greece, the model proposed by Panapakidis and Dagoumas (2017) combined wavelet decomposition algorithm, GA, ANFIS and FFNN, which can effectively reduce 13.04% of the MAPE of ANFIS.

Fan et al. (2018) combined the annual share changing tendency mechanism with GM (1,1), SIGM and GA algorithms to establish GM-S-SIGM-GA model. The results showed that the combined model was superior to other grey-based models, and has the highest forecasting accuracy in MAPE (4.48%), RMSE (11.59) and MAE (8.41). Qiao et al. (2019) proposed a hybrid forecasting model, which integrated IWOA and RVM algorithms, to forecast hourly gas consumption in Lixin gate station and sanshibu gate station in Anhui, China. The results presented that, compared with RBFNN, GRNN, ELNN, LSSVM and SMOSVM algorithms, the IOWA-RVM model has higher forecasting accuracy, and its MAPE is only 0.02% (Qiao et al., 2020).

Lu et al. (2019) integrated FFOA, SA, CF and SVM algorithms to forecast natural gas consumption in Kunming, China. Compared with PSO-SVM, BPNN, GM (1, 1) and ARIMA, the CF-SA-FFOA-SVM algorithm has the lowest MAPE (3.07%). The life genetic algorithm and SVR were combined by Wei et al. (2019a) to forecast daily consumption in 12 months of the year respectively. The absolute error of the forecasting result was improved by nearly 50% compared with GA-SVR model.

3.4.3. Revival of conventional model

The advent of the era of big data makes researchers prefer AI-based models with powerful data processing capabilities. Although AI-based models have advantages in computing accuracy and efficiency, the disadvantages are also obvious (Liu et al., 2020). As a data-driven model, AI-based models pay more attention to the data itself, and optimize the model parameters through training to obtain the results. During this process, it is difficult for users to observe the relationship between different variables and the specific form of the model, and hard to explain or modify the results. However, traditional statistical models have strong interpretability. In recent years, researches have shown that when the parameters are selected reasonably, the performance of traditional statistical models is comparable to AI-based models (Potočnik et al., 2014). Therefore, despite the rapid development of various AI-based models, traditional statistical models can still have its effect in the field of natural gas consumption forecasting.

Taspinar et al. (2013) employed MLR, SARIMAX, ANN-MLP and ANN-RBFNN models to forecast daily consumption in Sakarya province. The result showed that the performance of the TS model SARIMAX was better than ANN model. Akpinar and Yumusak adopted the daily gas consumption data, provided by AGDAS Company (Erdem, 2020) in Turkish, to verify the forecasting accuracy of MLR (Akpinar and Yumusak, 2013a), ARIMA (Akpinar and Yumusak, 2013b) and exponential regression model (Akpinar and Yumusak, 2017) successively. In their study, the MAPE of ARIMA, MLR and exponential regression model was 11.73%, 14.38% and 14.10%, respectively.

Ozmen et al. (2018) proposed an improved MA model to forecast gas consumption in residential areas. The MAPE was 4.8%. Marziali et al. (2019) used Ridge regression, Gaussian Process, K-nearest neighbor, ANN and a Toroidal model to forecast daily gas consumption of Italy in the next year. The result presented that Gaussian Process performed better than other models, and its lowest MAE was 2.56, 0.05 lower than ANN. Overview of published papers in the all-round stage is listed in Table 4.

Appendix shows an up-to-date overview of published papers in the field of natural gas forecasting, including the forecasting model, applied area, country, forecasting horizon, data size, influencing factor, and performance.

In conclusion, the application of AI technologies, such as “AlphaGo” program, facial recognition systems, driverless cars, etc., promotes the integration of AI and various fields around the world. The forecasting technology that relies on computer science has also been improved. Compared with other stages, forecasting models at this stage can solve more complex problems. Especially with the emergence of deep learning technology, the application of combined model and the revival of conventional statistical models, the nonlinear fitting, self-learning and self-adaptive capabilities have been greatly enhanced.

In spite of these advantages, the models at this stage still have many

Table 4
All-round Stage-Overview of published papers by years.

Publishing year	References
2008	Kizilaslan and Karlik
2009	Vitullo et al.
2010	Xu and Wang
2011	Azadeh et al. Kaynar et al.
2012	Demirel et al. Soldo
2013	Azadeh et al. Taspınar et al., Akpinar and Yumusak (2013a, 2013b)
2014	Soldo et al. Yu and Xu
2015	Szoplik, Zhu et al. Azadeh et al.
2016	Bai and Li
2017	Merkel et al. Panapakidis and Dagoumas, Akpinar and Yumusak
2018	Merkel et al. Fan et al., Ozmen et al. Tamba et al.
2019	Wei et al. (2019a, 2019b, 2019c, 2019d), Laib et al. Su et al., Hafezi et al. Hribar et al., Qiao et al. Wang and Jiang, Beyca et al. Lu et al., Marziali et al.

Table 5
The characteristics in different stages.

Stages	Initial stage	Conventional stage	AI stage	All-round stage
Stage characteristics	A small amount of data, low-dimensional, long-term forecasting	Transformation stage	A large amount of data, high-dimensional, medium-term forecasting, short-term forecasting	More data; more complex structure, high-dimensional, combined models, short-term forecasting, long-term forecasting
Typical models	Statistical models	TS models, MR models (LR and NLR models), GM models	ANNs, SVMs, combined models	ANNs, SVMs, DLs, combined models, improved statistical models
Advantages	Low data volume, simple structure, short computing time	Improved fitting ability, increased variables, low data volume, simple structure, short computing time	Powerful nonlinear fitting ability, self-learning ability, self-adaptive ability, improved generalization and robustness, high data volume	More powerful nonlinear fitting ability, improved self-learning ability, improved self-adaptive ability, powerful generalization and robustness, high data volume, high portability
Disadvantages	Can't describe the development trend accurately, can't contain more historical data and variables	Can't reflect the relationship between consumption and variables accurately, can't contain more historical data and variables	The selection of model structure, parameters, the size of data set, slow convergence, long computing time, overfitting and underfitting	Model structure is difficult to explain, high hardware configuration, the selection of model structure, parameters, the size of data set, slow convergence, long computing time, overfitting and underfitting

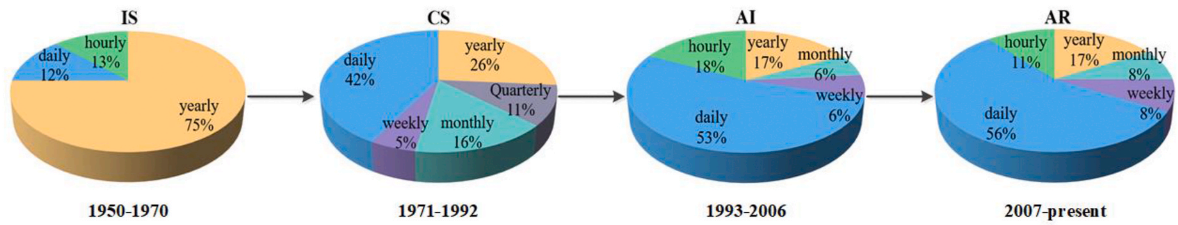

Fig. 3. Transformation for forecasting horizon. Note: IS represents Initial stage, CS represents Conventional stage, AI represents Artificial Intelligence stage, AR represents All-round stage.

Table 6
Influencing factors in different forecasting horizons & stages.

Type	Stage	Influencing factors
Yearly	IS	NG production, industrial/domestic production, weather, effective temperature, gas price, population, sales revenue, revenue, gas fire sales, central heating
	CS	Historical consumption, average temperature, gas/average gas price, HDD
	AI	Historical consumption, gas discovery data, proved reserves, HDD, gas price, number of consumers, exchange rate
	AR	Historical consumption, GDP, CPI, GIP, GDP of the primary/secondary/tertiary industry, population, number of consumers, national income, gas/LPG supply, alternative and nuclear energy, CO_2 emissions, NG production, oil consumption
Quarterly	CS	Historical consumption, average/monthly gas price, GDP, consumers expenditure, monthly temperature
Monthly	CS	HDD, CDD, temperature, gas price, residual fuel oil, price of residual fuel oil, income index
	AI	Temperature, difference between real and expected temperature, oil price, number of consumers, industry consumption
	AR	Historical consumption, monthly/daily average temperature, weather condition, day of the week, holiday, gas price, population, GDP, number of consumers, seasonal index
Weekly	AI	Daily average temperature, day of the week
	AR	Historical consumption, seven-day/daily/maximum and minimum average temperature, weather condition, average number of consumers, day of the week, holiday
Daily	IS	Daily/Previous day's/Exp. weighted temperature, day of the week, rainfall, hours of sunshine, wind speed
	CS	Effective/daily temperature, weather condition, precipitation, cloud cover, humidity, day of the week, season, holiday, the index for manufacturing industries, gas fire sales, central heating, commercial and industrial productivity
	AI	Historical consumption, daily average/daily temperature, wind speed, day of the week/year, holiday, GDP, HDD
	AR	Historical consumption, minimum and maximum/previous day's minimum and maximum/daily average/squared temperature, weather conditions, lowest/average/highest dew point, lowest/average/highest humidity, lowest/average/highest visibility, lowest/average/highest air pressure, lowest/average/highest wind speed, precipitation, moisture, solar, radiation, day of the week/month/year, holiday, the day before/after holiday, the day between public holiday and weekend , number of consumers, gas price, pressure, HDD, geology
Hourly	IS	Historical consumption, hourly temperature, maximum/minimum/average temperature yesterday
	AI	Historical consumption, hourly temperature, day of the week
	AR	Historical consumption, temperature, day of the week, holiday, day between public holiday and weekend, weather condition, climate, gas price

defects. The structure of the DL models is complicate and difficult to explain. Model training requires higher hardware configuration, and needs longer time to calculate. In addition, the selection of best parameters, network topology, and the size of the data set are determined by human experience.

The stage characteristics, typical models, advantages and disadvantages in different stages are summarized in Table 5, as follows:

3.5. Changes in forecasting history

In this review, by summarizing 72 published papers, it can be summarized that forecasting horizon, influencing factor, and forecasting performance have significant changes in four different stages. How these factors have changed in the long forecasting history will be discussed in this section.

3.5.1. Discussion on forecasting horizon

As for natural gas consumption forecasting, forecasting horizon can be divided into three categories: short-term forecasting (weekly, daily, hourly), medium-term forecasting (quarterly, monthly) and long-term forecasting (yearly). The pie chart presents the transformation for forecasting horizon in Fig. 3.

By observing Fig. 3, the Initial stage is dominated by long-term forecasting, which accounts for 75%. Due to the backward technology and lack of data, the earliest consumption forecasting mainly focused on long-term forecasting with low data volume, low dimension and long-time span. To the Conventional stage, the proportion of medium-term (27%) and short-term (47%) forecasting has increased. It illustrates that the emergence of microcomputers and improvement of calculating ability make the models at this stage have stronger nonlinear capabilities, and the research direction has also begun to shift towards short-term and medium-term forecasting.

In the AI stage, research on short-term forecasting keeps increasing, while the long-term forecasting decreased slightly (17%). It performs that the powerful nonlinear fitting capabilities of ANN and SVM make researchers be aware of the potential of AI technology, and have more confidence in improving the accuracy of short-term forecasting models. To the All-round stage, research on short-term forecasting has increased to 75%, followed by long-term (17%) and medium-term (8%) forecasting. It indicates that, with the improvement of computing capabilities and development of DL, the nonlinear fitting and learning ability of the forecasting models has been greatly enhanced. Therefore, research on short-term forecasting with larger data set, higher dimension and shorter time span is getting deeper.

To sum up, research on short-term forecasting has increased from 25% to 75% during the development of forecasting history. It can be concluded that, affected by the development of computer science and AI technology, short-term forecasting is the fastest-growing forecasting horizon, followed by long-term and medium-term. It should be clear that this does not mean other forecast horizons are not important. It just indicates that, compared with other forecasting horizons, short-term forecasting has more space to improve, due to its complex structure and large amount of data.

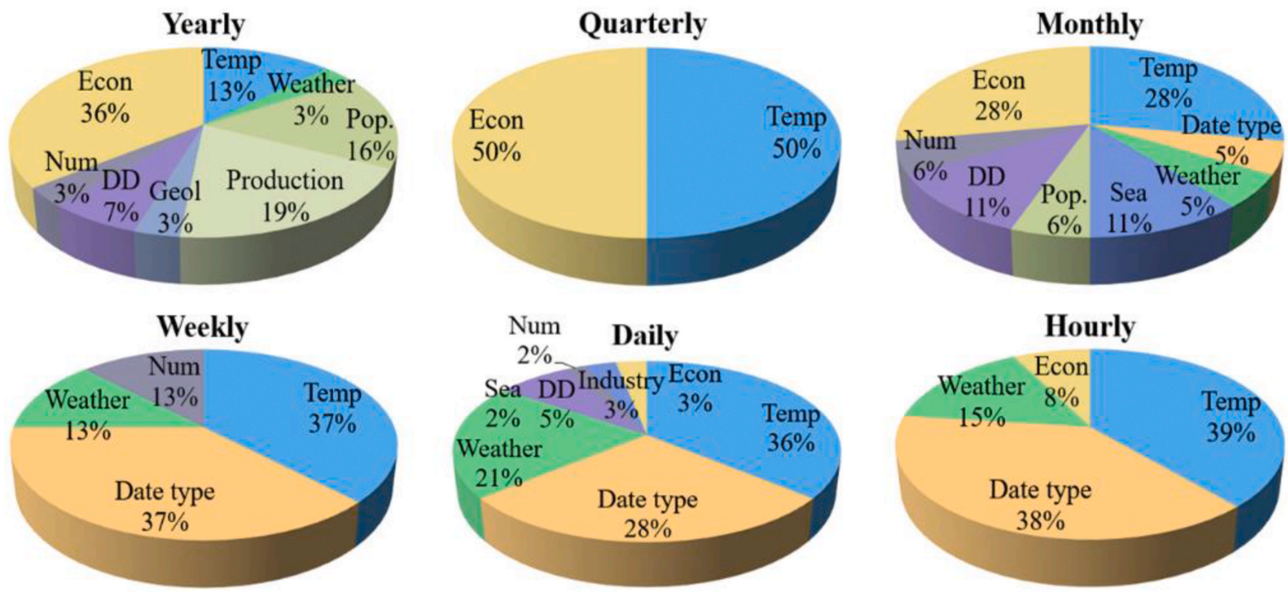

Fig. 4. Proportion of influencing factors in different forecasting horizons. Note: Num represents number of consumers, Sea represents seasonal index, DD represents degree day variables.

3.5.2. Discussion on influencing factor

Influencing factors are one of the factors that have a significant impact on forecasting accuracy. During the history of natural gas consumption forecasting technology, influencing factors of various forecasting horizons considered by the authors at different stages have always been changing. According to the 72 published papers, influencing factors in different forecasting horizons and stages can be summarized as follows (see Table 6).

The proportion of influencing factors in different forecasting horizon is summarized as Fig. 4.

It can be seen from Table 6 that influencing factors, such as production, economy, population, and weather, are mainly considered in the first three stages for yearly consumption forecasting. To the All-round stage, the number of consumers, alternative energy sources, CO_2 emissions and more economic factors have also been taken into consideration. Quarterly forecasting has only been studied in the Conventional stage. The influencing factors include temperature and economic variables. Monthly forecasting regards production, weather and economic variables as the influencing factors in the first three stages. To the All-round stage, factors such as population, number of consumers and date type are added either. Weekly consumption forecasting only considers weather condition and date type in the early stage, and increases number of consumers and temperature variables in the later stage. Weather condition, date type and economic variables are the major influencing factors in the early stage for daily consumption forecasting. To the All-round stage, number of consumers, more complex weather condition and date type are taken into consideration. Influencing factors for hourly consumption forecasting have few changes. Only weather condition and date type are considered in the early stage, and increase temperature and economic variables later.

Fig. 4 illustrates that, for long-term consumption forecasting, production (19%), population (16%) and economic variables (36%) are the major influencing factors. Medium-term (quarterly, monthly) forecasting is mainly affected by economic (50%, 28%) and temperature variables (50%, 28%). Influencing factors of short-term forecasting (weekly, daily, hourly) mainly depend on temperature variables (37%, 36%, 39%), weather condition (13%, 21%, 15%) and date type (37%, 28%, 38%).

In conclusion, since considered into the model, the influencing factors of various forecasting horizons at different stages have always been increasing. To the All-round stage, affected by the development of computer science and AI technology, the influencing factors considered in the model are more than other stages. But generally speaking, long-term forecasting is mainly affected by production, population, and economic variables. Medium-term forecasting is mainly affected by economic and temperature variables. Influencing factors of short-term forecasting mainly depend on temperature variables, weather condition and date type.

3.5.3. Discussion on forecasting performance

During the history of natural gas consumption forecasting, 12 evaluation methods were used to quantify the performance of forecasting models, including: MAPE, MNAPE, MARNE, WMAPE, RMSE, NMSE, R^2, MAE, MSE, ARE, CC, SD. These evaluation methods can be defined as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_i' - y_i|}{y_i} \times 100\% \tag{1}$$

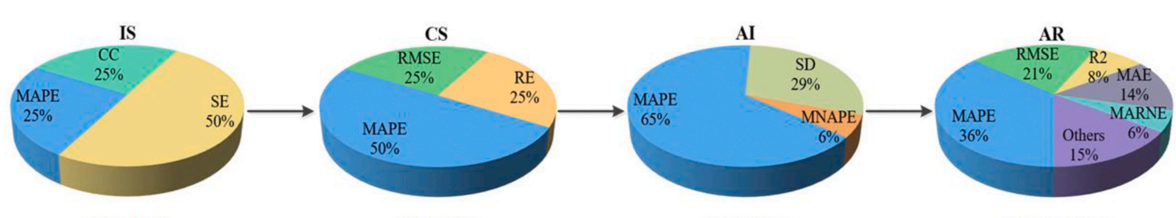

Fig. 5. Transformation for evaluation methods.

Table 7
Summary of the data characteristics of different forecasting models.

Data characteristics	Statistic models			AI-based models		
	TS models	RMs	GMs	ANNs	SVRs	DLs
Data size	Tens to hundreds	Tens to hundreds	Tens	Hundreds to thousands	Hundreds	Hundreds to thousands
Number of factors	Less than ten	Less than ten	None	Less than twenty	Less than ten	Less than twenty
Data type	All	All	Exponential	Periodicity	All	Periodicity

Table 8
Summary of the characteristics of different forecasting models.

Model characteristics	Statistic models			AI-based models		
	TS models	RMs	GMs	ANNs	SVRs	DLs
Advantages	Simple structure, ease of use, Efficient and Economical	Simple structure, ease of use, Efficient and Economical	Simple structure, ease of use, no need for influencing factors	Solve complex nonlinear problems	Good balance between accuracy and calculation time; best stability	Powerful nonlinear fitting ability, generalization and robustness, high portability, best accuracy
Disadvantages	Can't contain more variables	Can't reflect the relationship between consumption and variables accurately	Inability to deal with complex nonlinear problems	Many parameters need to be determined, slow convergence, overfitting, underfitting	The kernel function is crucial and difficult to be determined	Model parameters is difficult to determined, long calculation time, overfitting, underfitting
Complexity	Easy	Easy	Easy	Medium	Medium	Difficult
Computation speed	Fast	Fast	Fast	Medium	Medium	Slow

Table 9
Summary of the average MAPEs of different models in different forecasting horizons.

Horizon	Statistic models			AI-based models		
	TS models	RMs	GMs	ANNs	SVRs	DLs
Long-term	1.90%	3.42%	4.48%	5.31%		2.15%
Medium-termr	2.40%			2.21%	4.93%	
Short-term	14.18%	6.68%		6.52%	4.98%	5.94%

$$MNAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_i' - y_i|}{\bar{y}} \times 100\% \tag{2}$$

$$MARNE = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_i' - y_i|}{\max(y_i')} \times 100\% \tag{3}$$

$$WMAPE = \frac{\sum_{i=1}^{N}|y_i' - y_i|}{\sum_{i=1}^{N} y_i} \times 100\% \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i' - y_i)^2} \tag{5}$$

$$NMSE = \frac{\sum_{i=1}^{N}(y_i' - y_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{6}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i' - y_i)^2}{\sum_{i=1}^{N}\left(\bar{y}_i - y_i\right)^2} \tag{7}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i' - y_i| \tag{8}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i' - y_i)^2 \tag{9}$$

$$ARE = \frac{|y' - y|}{y'} \tag{10}$$

$$CC = \frac{\mathrm{cov}(y_i, y_i')}{\sqrt{D(y_i)D(y_i')}} \tag{11}$$

$$SD = \sqrt{\frac{\sum_{i=1}^{N}(y_i' - \bar{y})}{N}} \tag{12}$$

where N is the dataset size; y_i is the actual natural gas consumption; y'_i is the forecasted value; cov (y_i, y'_i) represents the covariance between the factor of index y_i and y'_i; D(y_i) is the variance of y_i; $\bar{y}$ is the average value of y_i.

Fig. 5 presents the transformation for evaluation methods in the forecasting history. It can be seen that the evaluation method is mainly based on SE (50%) in the Initial stage. To the Conventional stage and AI stage, due to the excellent evaluation ability, MAPE has been better applied. The number of MAPE used in papers accounts for 50% and 65%. To the All-round stage, although MAPE is still the main tool for evaluating model performance (36%), researchers believed that only using a single method to evaluate model performance cannot accurately reflect the forecasting results. Thus, many researchers began to combine MAPE with other evaluation methods at this stage. But generally speaking, MAPE is the most popular evaluation method than others. Moreover, for different datasets, RMSE, R^2, MAE and MARNE have a large difference. Therefore, to compare the forecasting performance with unified criteria, MAPE is introduced as the main evaluation method in the following research.

Forecasting performance is heavily dependent on the model and data characteristics. To screen the best models suitable for different forecasting horizons, the model and data characteristics are summarized in Table 7 and Table 8. It is obviously that, due to the simple structure and high computation speed, statistic models are suitable for long-term forecasting with few recorded data. Among them, TS models have better performance than others. For medium-term and short-term

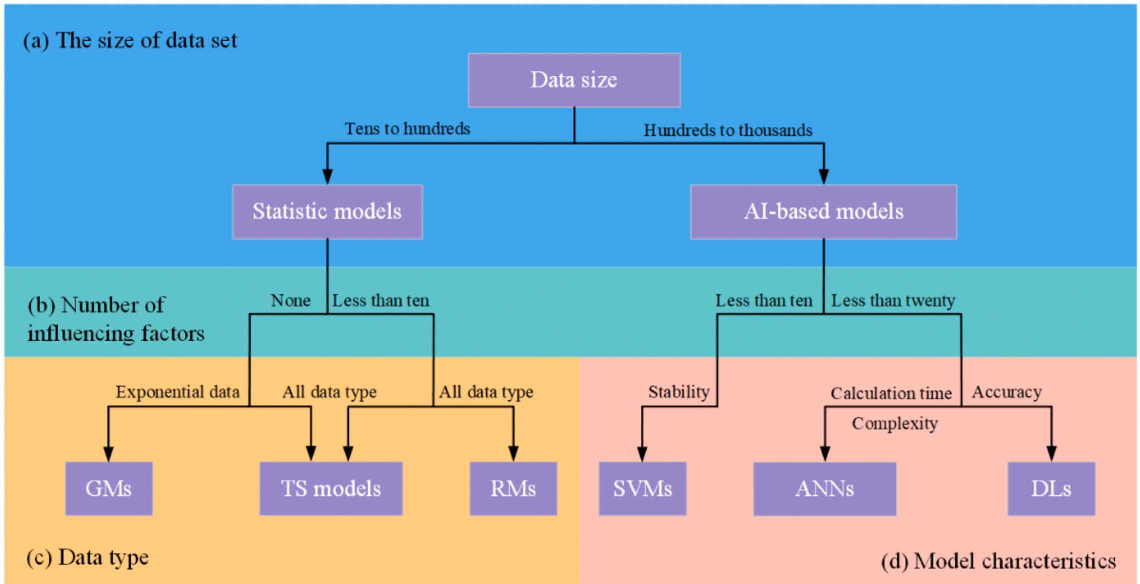

Fig. 6. The process of model selection.

forecasting with a large amount of data, AI-based models perform better. Among them, ANNs can solve the complex nonlinear problems, but many parameters are difficult to determine. DLs have the best accuracy, but the calculation time is longer and model structure is more complex. SVRs can keep a good balance between accuracy and calculation time. It also presents the best stability. Accordingly, SVRs may suitable for short-term forecasting.

To verify the results analyzed above, the statistical analysis of the average MAPEs of the models in different forecasting horizons is summarized in Table 9, according to the 72 published papers. It can be seen that, in long-term forecasting, the average MAPE of TS models is 1.90%, which is lower than RM, GM, ANN, and DL models. ANN models have the lowest average MAPE (2.21%) in medium-term forecasting. The average MAPE of SVR models is 4.98%, which is better than TS, RM, ANN and DL models in short-term forecasting.

It indicated that, TS models are the best models to perform long-term forecasting with a small amount of data. To the medium-term and short-term forecasting with a large amount of data and higher dimension, AI-based models present the best performance. Among them, ANNs are preferred for medium-term forecasting, and SVRs are more suitable for short-term forecasting.

4. Future research directions

Based on the discussion of the forecasting history, the future research directions of natural gas consumption forecasting are summarized as follows.

4.1. Selection of the best model

It can be found from the forecasting history that there are hundreds of models can be used to forecast natural gas consumption, but not all models have excellent performance (Soldo, 2012; Tamba et al., 2018). To achieve better accuracy, the authors will continue to propose new models, which means wasting a lot of time and resulting in many meaningless models (Wang and Srinivasan, 2017). Thus, the selection of the best model has become the most concerned issue for researchers and forecasters.

To solve this problem, all models referred in the published papers are divided into six base models as we discussed in Section 3.5.3, and a model selection framework is proposed based on data and model characteristics. Fig. 6 shows the process of model selection. The specific steps are listed as follows:

Step1: Selecting the model type initially, determining whether your data size is suitable for statistic or AI-based models;

Step2: Selecting models according to the number of influencing factors and the capacity of the model;

Step3: Selecting the specific model based on your needs. For example, if the result needs more stable, SVMs is the best choice, and you can choose DLs if the accuracy is more important;

Step4: Analyzing the characteristics of collected data, and selecting appropriate algorithm to optimize the inherent defects of the base model;

Step5: Comparing the selected base model and optimized model to verify the model performance.

The process proposed above, provides a framework on model selection for researchers, it will be very helpful to simplify the process of model selection. However, the process is only derived based on data and model characteristics without data support. It still needs to be further discussed from a multiple perspective in the future.

4.2. Selection of the model parameters

After selecting the right model, there is still the problem of identifying the best model parameters, and the closest best parameters can only be obtained through trial and error (Liu et al., 2004a). In addition, a better trained model would be only suitable for cities that live in similar consumption structures, climate zones, wealth levels, economic development, and national political systems (Szoplik, 2015). However, researchers in different countries have done their work only based on their own knowledge and experience. Utilizing the same model but different structure and parameters to forecast cannot accurately measure the performance of the model. Therefore, a reliable method and criterion on the selection of model parameters will be essential in the future.

Three methods are suggested for the parameter selection. Firstly, the optimization algorithms, such as PSO, GA et al., could be used to optimize model parameters. Secondly, researchers could divide the process of parameter selection into different stages, and give priority to adjusting parameters that have a greater impact on model performance. Thirdly, researchers could try different parameters on a simplified data set to reduce test time, and then try on the original data set.

Besides, the selection of model parameters is heavily dependent on the data characteristics. Therefore, for the establishment of the criterion on parameters selection, one possible solution is to classify the data with different characteristics, determine the parameter range of different data types through experiments or optimization algorithms, and formulate different forecasting criteria. It will be very beneficial for researchers to simplify the process of parameter selection, and shorten the selection time.

4.3. Establishment of the standard database

Previous studies presented that the data sets used in 72 published papers are always different. Which means there is no unified database to verify the model performance for researchers. The verification of model performance is only based on the data they could collect (Ivezic, 2006). Even if the authors believe that the proposed model has achieved better performance, it is still a problem that whether the model is applicable for other data sets.

Thus, it's essential to establish a standard database including various characteristics of the data, such as, consumption structures, climate zones, wealth levels, national political systems et al., so that researchers can select different characteristics of the data for training. It is very beneficial for the model to learn enough features to improve the forecasting performance. The establishment of the standard database will provide a platform for testing the performance of the model. It will be widely used by researchers all over the world to test the performance of their proposed model.

4.4. Improvement of the feature selection method

As we discussed in section 3.5.2, the influencing factors considered in various forecasting horizons have always been increasing. The increasing influencing factors will not only make the model structure more complicated, but also increase the calculation time. Therefore, feature selection methods, such as PCA, KPCA et al., were developed to screen influencing factors (Hafezi et al., 2019; Wei et al., 2019b). The feature selection methods used in published papers mainly focus on dimensionality reduction, that is, reduce the dimensionality by extracting the main components of the data. However, this filter method has an inherent defect. Although the main components are extracted, and the model structure and calculation time are simplified, it is inevitable that some key information may be lost, which will result in a non-negligible error.

Given this, it is necessary to propose a dimensionality reduction method that won't lose any data information. One possible solution is that, according to the objective function, we can select several features or exclude several features, until the best subset is selected to achieve the better performance. Although the method may be more complicated, it can be used for dimensionality reduction without losing any information.

4.5. Forecasting evaluation benchmark based on multiple perspective

It can be seen from Fig. 5 that the evaluation methods used in 72 published papers are different. Some researchers have realized that there is no united forecasting evaluation benchmark, and proposed various evaluation benchmarks based on their own methods. Lewis (1986) proposed the benchmark for modeling accuracy evaluation based on MAPE, and divided it into four levels, including Highly accurate, Good, Reasonable, and Inaccurate. Wei et al. (2019d) divided the 'Highly accurate' of Lewis into four levels for different forecasting horizons.

Although these benchmarks have been proposed, they are still not recognized and applied by the public. And there is still the problem of how to use various evaluation methods, not just MAPE, to formulate different evaluation benchmarks for different evaluation objects. Therefore, it is essential to formulate a united forecasting evaluation benchmark based on multiple perspective to regulate the forecasting market.

5. Conclusions and suggestions

This paper reviews the history of natural gas consumption forecasting, summarizes the characteristics, typical models, advantages and disadvantages at different stages. Contributions and experiments that proposed by researchers were collected to discuss the changes in forecasting horizons, influencing factors and forecasting performance during the development history. Prospects and suggestions for future have also been analyzed. According to the review results, the main conclusions can be summarized as follows:

1. Research on short-term forecasting has increased from 25% to 75% during the forecasting history. It can be concluded that, affected by the development of computer science and AI technology, short-term forecasting is the fastest-growing forecasting horizon, followed by long-term and medium-term.
2. Influencing factors required by forecasting models have undergone changes that from never considered to a small amount of data and low dimension, and to a large amount of data and higher-dimensional until now. But generally speaking, long-term forecasting is mainly affected by production (19%), population (16%), and economic variables (36%). Medium-term (quarterly, monthly) forecasting is mainly affected by economic (50%, 28%) and temperature variables (50%, 28%). Influencing factors of short-term forecasting (weekly, daily, hourly) mainly depend on temperature variables (37%, 36%, 39%), weather condition (13%, 21%, 15%) and date type (37%, 28%, 38%).
3. The statistical analysis of data characteristics, model characteristics and forecasting results presents that TS models are the best models to perform long-term forecasting. It has the lowest average MAPE (1.90%) in long-term forecasting. To the medium-term and short-term forecasting, AI-based models present the best performance. Among them, ANNs (2.21%) are preferred for medium-term forecasting, and SVRs (4.98%) are more suitable for short-term forecasting.

Moreover, there are still some suggestions for future research: on one hand, consumption data is always considered to be closely related to time. However, Wei et al. (2019c) have proved that geographic location may have an impact on forecasting accuracy, that is, consumption data may not only have a great relationship with time, but also is related to space. Therefore, consumption data should be considered as spatio-temporal data. It should be further discussed from the perspective of spatio-temporal data. On the other hand, some researchers indicated that DL models have better performance than other AI-based models. Nevertheless, according to our research, DL models have been used very few on natural gas consumption forecasting until now. More DL models should be attempted to improve the forecasting performance in the future.

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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Appendix

Table A
The review results of 72 published papers

Stage	Reference	Forecasting model	Applied area	Country	Forecasting horizon	Data size	Influencing factors	Performance
Initial Stage	Hubbert (1949)	Hubbert model	World & national	U.S.	Yearly	1911–1961	Annual statistics of production and estimate	
	Hubbert (1956)	Hubbert model	World	U.S.	Yearly	1911–1961	Annual statistics of production and estimate	
	Berrisford (1965)	Exponentially Weighted model	North Western area		Daily	Apr. 1963	Temperature, Previous day's temperature, Exp. weighted temperature, day of the week, rainfall, hours of sunshine, Wind speed	2–2.5% (SE)
	Ward (1965)	Double-log Multiple Correlations	National		Yearly	1948–1965	Industrial Production, other Domestic Production	0.032 (SE) 0.9570 (Correlation Coef.)
	Balestra and Nerlove (1966)	BAN	Residential and commercial sector	U.S.	Yearly	1957–1962	Weather, gas price, population, sales revenue	
	Elliott and Linden (1968)	Empirical Model	National	U.S.	Yearly	1980–2000	Economy, technology, geology	
	Johnson (1968)	MR	National	U.K.	Yearly	1958–1972	Revenue, effective temperature, gas fire sales, central heating	
	Durrer et al. (1969)	TS	14 residential homes in Northern California	U.S.	Hourly	70 h	Historical consumption, hourly temperature, mean daily temperature yesterday, maximum temperature yesterday, minimum temperature yesterday	0.3–34.8% (MAPE)
Conventional Stage	Rodger et al. (1971)	Combined regression model	National	Scottish	Daily	1962/63–1969/70	Effective temperature, the index for manufacturing industries, gas Fire, central Heating	
	Haenel (1973)	Automatic Interaction Detection	LDC (Southern California)	U.S.	Daily		32 variables include temperature, weather condition, data type, Commercial and industrial productivity et al.	
	Tinic et al. (1973)	Empirical model	Rural region (Alberta)	Canada	Yearly			
	Berndt and Watkins (1977)	BAN	Columbia and Ontario	U.K.	Yearly			
	Lyness (1981)	Monte Carlo method	National transmission system	U.K.	Daily		Temperature, data type	
	Taylor and Tomas (1982)	Adaptive Bayesian method	National transmission system	U.K.	Daily		Temperature, wind speed, precipitation, day of the week, season, holiday	
	Piggott (1983)	Box-Jenkins	LDC		Daily and weekly			
	Lyness (1984)	Box-Jenkins	National transmission system	U.K.	Daily, monthly and yearly		Effective temperature, wind effect, industry variables, economic variables	
	Caton (1984)	S.E.P.	North Thames	U.K.	Daily		Temperature	
	Drevna (1985)	Box-Jenkins	LDC (Columbia)	U.S.	Yearly	1977–1984	Temperature, average gas price, HDD	0.81–4.8% (MAPE)
	Pepper (1985)	Box-Jenkins	National	U.K.	Quarterly	Q1, 1960-Q4, 1983	Average gas price, GDP, consumers expenditure, temperature	3.1–9.4% (RE)
	Herbert et al. (1987)	Regression model	National	U.S.	Monthly		HDD, gas price, residual fuel oil	
	Herbert et al. (1987)	Regression model	National	U.S.	Monthly	Jan. 1980–Dec. 1984	HDD, cooling degree-days, gas price, income index, price of residual fuel oil, temperature	
			LDC	U.S.	Daily			7% (MAPE)

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Table A (*continued*)

Stage	Reference	Forecasting model	Applied area	Country	Forecasting horizon	Data size	Influencing factors	Performance
	Jabbour and Meyer (1989)	Hybrid method based on expert system and pattern recognition					Temperature, wind speed, cloud cover, humidity, holiday, daily variations, weekly variations, seasonal variations	
	Liu and Lin (1991)	Transfer function	Taiwan	China	Quarterly and yearly	Jan. 1975–Dec. 1988	Historical consumption, monthly temperature, monthly price	0.02182–0.0341 (RMSE)
AI Stage	Brown et al. (1994)	ANN	Wisconsin (LDC)	U.S.	Daily		Historical consumption, HDD, temperature, wind speed, day of the week, day of the year	
	Brown and Matin (1995)	ANN	Wisconsin (2 LDCs)	U.S.	Daily	Dec. 21, 1989–Mar. 29, 1994	Historical consumption, HDD, temperature, wind speed, day of the week, day of the year	
	Suykens et al. (1996)	ANN	National	Belgium	Monthly	Jun.1-Oct. 20, 1982	Temperature, difference between real and expected temperature, oil price, number of consumers, industry consumption	
	Miura and Sato (1998)	BPNN	4 LDCs	Japan	Hourly	3 months in winter	Historical consumption, temperature, date type	2.11/2.73/3.32/ 3.35% (MAPE)
	Klema and Kout (1999)	CBR-NLR_SVD-ANN	LDC	Germany	Hourly			4% (MAPE)
	Khotanzad and Elragal (1999)	AFLC	4 LDCs		Daily (One/ Two/three days ahead)		Historical consumption, temperature, wind speed, day of the week	3.94/4.26/4.41% (Average MAPE) 4.09/4.25/4.3% (Average SD)
	AI-Fattah and Startzman (2000)	Hubbert model	World		Yearly	1900–1997	Historical annual production, gas discovery data, proved reserves	
	Khotanzad et al. (2000)	AFF_ANN	6 LDCs		Daily	Period winter of 1994–1997	Historical consumption, day of the week, temperature, wind speed	3.82/5.95% (Average MAPE with actual/forecast weather data) 3.87/5.69% (Average SD with actual/forecast weather data)
		AFL_ANN						3.78/5.89% (Average MAPE with actual/forecast weather data) 3.83/5.76% (Average SD with actual/forecast weather data)
	Peharda et al. (2001)	BPNN	Residential and commercial consumer	Croatia	Hourly	Nov.1-Dec. 15, 2000	Historical consumption, date type, temperature	4.7% (Average MAPE) 4.3% (Average MNAPE) 0.35% (Average SD)
	Siemek et al. (2003)	Hubbert model	National	Poland	Yearly	1970–2001	Historical annual consumption	
	Gorucu et al. (2004)	BPNN	Ankara	Turkey	Yearly	1991–2005	Degree days, selling price, number of consumers, exchange rate	
	Elragal (2004)	FGC	4 LDCs		Daily (One/ Two/three days ahead)	Period winter of 600 days	Historical consumption, wind speed, temperature, day of the week	3.97/4.48/4.85% (Average MAPE) 4.07/4.27/4.63% (Average SD)
	Liu et al. (2004)	SVM	Xi'an	China	Daily	Jan. 1, 2001–Jan. 31, 2003	Average temperature, date type	1.6246% (MAPE)
	Liu et al. (2004)	LS-SVM	Xi'an	China	Daily	Jan. 1, 2001–Jan. 31, 2003	Average temperature, date type	1.7024% (MAPE)
	Viet and Man'dziuk (2005)	FNN	Rural region	Poland	Daily	Jan. 1, 2000–Dec. 31, 2002	Daily average temperature, day of the week	4.24/3.97/4.60% (AVG/MIN/MAX

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Table A (*continued*)

Stage	Reference	Forecasting model	Applied area	Country	Forecasting horizon	Data size	Influencing factors	Performance
								MAPE) 0.0013 (SD)
					Weekly			7.62/7.07/8.87% (AVG/MIN/MAX MAPE) 0.0037 (SD)
					4 Weekly			8.16/7.29/9.10% (AVG/MIN/MAX MAPE) 0.0037 (SD)
			Highly industrialized area		Daily			5.63/5.32/6.28% (AVG/MIN/MAX MAPE) 0.0016 (SD)
					Weekly			10.44/9.57/12.27% (AVG/MIN/MAX MAPE) 0.0059 (SD)
					4 Weekly			11.37/9.80/14.35% (AVG/MIN/MAX MAPE) 0.0092 (SD)
	Musilek et al. (2006)	Hybrid RNN	LDC		Daily	Jan. 1, 2001–Dec. 31, 2004	Daily average temperature, day of the week, holiday, historical consumption	3.6% (MAPE)
	Ivezic (2006)	ANN	City	Serbia	Daily	Oct. 1, 2001–Feb. 7, 2005	Historical consumption, temperature, date type	5.07% (MAPE)
All-round stage	Kizilaslan and Karlik (2008)	ANN	Istanbul	Turkey	Daily	Jan. 1, 2004–Sep. 30, 2007	Minimum and maximum temperature, previous day's minimum and maximum temperature, historical consumption, data type, number of consumers	6.5% (ARE) 0.9915 (Correlation) 0.9826 (R^2)
					Weekly		Seven-day average temperature, average maximum and minimum temperature, average number of consumers, date type	8.2% (ARE) 0.993936 (Correlation) 0.987683 (R^2)
	Vitullo et al. (2009)	ANN-MLR	14 LDCs	U.S.	Daily	Oct. 1, 2009–Jul. 31, 2010	Historical consumption, wind speed, temperature, day of the week, holiday	5.21–19.59% (MAPE)
	Xu and Wang (2010)	PCMACP	National	China	Yearly	1995–2008		3.42% (MAPE)
	Azadeh et al. (2011)	ANFIS-SFA	National	Bahrain Saudi Arabia Syria UAE	Yearly	1980–2007	GDP, population	0.018% (MAPE) 0.014% (MAPE) 0.014% (MAPE) 0.075% (MAPE) 0.016% (MAPE)
	Kaynar et al. (2011)	MLP ANFIS	National	Turkey	Weekly	Jan. 2002–Apr. 2006		5.477% (MAPE) 5.468% (MAPE)
	Demirel et al. (2012)	BPNN	Istanbul	Turkey	Daily	Jan. 1, 2004–Nov. 30, 2009	16 variables include daily average temperature, squared temperature, gas price, number of consumers et al.	0.1833% (MAPE) 0.0347 (RMSE) 0.0376 (MAD)
	Azadeh et al. (2013)	ANFIS-DEA-FDEA	National	Argentina	Yearly	1980–2007	GDP, population	2.9/5.1% (MAPE, original/noisy data) 49.827 (RMSE) 0.994 (R^2)
				Brazil				3.5/7.5% (MAPE) 27.183 (RMSE) 0.95 (R^2)
				Colombia				1.6/4.2% (MAPE) 3.872 (RMSE) 0.99 (R^2)
				Venezuela				6.4/9.3% (MAPE) 67.039 (RMSE) 0.62 (R^2)
				Cuba				

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Table A (*continued*)

Stage	Reference	Forecasting model	Applied area	Country	Forecasting horizon	Data size	Influencing factors	Performance
								1.6/5.3% (MAPE) 0.271 (RMSE) 0.85 (R^2)
	Taşpınar et al. (2013)	ANN-MLP	Sakarya (LDC)	Turkey	Daily	2007–2011	Moisture, atmospheric, wind speed, pressure, ambient temperature	0.441 (RMSE) 0.814% (MAPE) 0.823 (R^2)
	Akpinar and Yumusak (2013)	ARIMA	Household	Turkey	Daily	Jan. 1, 2009–Dec. 31, 2012		9.84–18.51% (MAPE)
	Soldo et al. (2014)	MLP	House	Croatia	Daily	Nov. 6, 2011–Apr. 27, 2012	Temperature, solar, radiation, holiday, day of the week	5.06% (MAPE) 0.635 (R^2)
			LDC			Nov. 8, 2012–Apr. 1, 2013		2.52% (MAPE) 0.908 (R^2)
	Yu and Xu (2014)	CCMGA-BPNN	Shanghai	China	Daily	Nov. 15, 2005–Oct. 13, 2008	Maximum, minimum, average temperatures, date type, weather conditions, historical consumption	7857.5 (MAE) 4.59% (MAPE) 12,582 (RMSE)
	Azadeh et al. (2015)	ELFIS	National	Iran	Yearly	1973–2006	POP, CPI	7.2568% (MAPE) 0.0036 (NMSE) 3.6789s (Time)
							POP, NI	12.3630% (MAPE) 0.0030 (NMSE) 3.5062s (Time)
							POP, GDP	13.6282% (MAPE) 0.00363 (NMSE) 1.5310s (Time)
							POP, NI, GDP	13.7855% (MAPE) 0.0125 (NMSE) 5.0569s (Time)
							POP, NI, GDP, CPI	10.1681% (MAPE) 0.0045 (NMSE) 7.3836s (Time)
							POP, NI, GDP, CPI, demand of previous year	6.7119% (MAPE) 0.0026 (NMSE) 7.6435s (Time)
	Szoplik (2015)	MLP	Szczecin	Poland	Daily	Jan. 1, 2009–Dec. 31, 2011	Month, day of the month, day of the week, hour, temperature	5.5–11.0% (MAPE) 582.2–2166.6 (RMSE)
	Zhu et al. (2015)	SVR-false neighbors filtered	National	U.K.	Daily	Jan. 1, 2009–Dec. 31, 2012	Temperature, wind speed	3.4/3.8% (MAPE) 8.3–9.2 (MAE)
	Bai and Li (2016)	SC-SVR	Anqing	China	Daily	Jan. 2012–Dec. 2012		2.36% (MAPE) 3913.88 (RMSE)
	Merkel et al. (2017)	DNN based on RBM	176 LDCs	U.S.	Daily		Historical consumption, wind speed, temperature, day of the week	
	Panapakidis and Dagoumas (2017)	WT-GA-ANFIS-FFNN	LDC	Greece	Daily	Jan. 1, 2014–Jun. 30, 2016	Daily average temperature, data type	1.87–12.12% (MARNE)
	Özmen et al. (2018)	Multivariate adaptive regression spline	Ankara (residential)	Turkey	Daily	2009–2013	Daily minimum and maximum temperatures, HDD	0.992 (R^2) 0.189 (MAE) 0.295 (RMSE) 0.996 (Correlation Coef.) 4.9% (MAPE)
		Conic multivariate adaptive regression spline						0.992 (R^2) 0.198 (MAE) 0.299 (RMSE) 0.996 (Correlation Coef.) 4.9% (MAPE)
	Merkel et al. (2018)	DNN	62 LDCs	U.S.	Daily	At least 10 years of data for training and 1 year for testing	HDD, dew point, CDD, day of the week, day of the year	5.78% (Average WMAPE)
		Large DNN						5.58% (Average WMAPE)
	Fan et al. (2018)	GM-S-SIGM-GA	National	China	Yearly	2002–2017		4.48% (MAPE) 11.59 (RMSE) 8.41 (MAE)

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Table A (*continued*)

Stage	Reference	Forecasting model	Applied area	Country	Forecasting horizon	Data size	Influencing factors	Performance
	Wei et al. (2019)	LSTM-PCCA	Xi'an	China	Daily	Jan. 1, 2015–Sep. 31, 2017	14 weather factors	3.22% (MAPE) 3.02% (MARNE)
			Athens	Greece		Jan. 1, 2015–Feb. 28, 2018		7.29% (MAPE) 6.66% (MARNE)
	Wei et al. (2019)	ISSA-LSTM	London	U.K.	Daily	Jan. 1, 2015–May. 31, 2018	19 weather factors, day, month, year, gas price	10.01% (MAPE) 4.68% (MARNE)
			Melbourne	Australia				9.94% (MAPE) 5.72% (MARNE)
			Hong Kong	China				14.10%(MARNE)
			Karditsa	Greece				14.37% (MAPE) 5.76% (MARNE)
	Wei et al. (2019)	FSA-LGA-SVR	Athens	Greece	Daily	Jan. 1, 2015–Dec. 31, 2017	19 weather factors	9.06% (MAPE) 1.90% (MARNE)
			Thessaloniki					18.69% (MAPE) 2.26% (MARNE)
			Larissa					12.10% (MAPE) 2.12% (MARNE)
	Laib et al. (2019)	FM-MLP	Residential and industrial sectors	Algerian	Hourly	Jan. 1, 2014–Jan. 1, 2015	Temperature, data type	5.48% (MAPE) 0.0083 (MAE) 0.0108 (RMSE)
	Beyca et al. (2019)	SVR	Istanbul	Turkey	Monthly	Jan. 2005–Oct. 2015	Seasonal index, temperature, gas price, population, historical consumption	5.53% (MAPE) 36,130,270 (MSE)
	Su et al. (2019)	WT-GA-RNN	National	U.S.	Hourly (1 h forecasting)	Summer/Winter data(150 h/150 h)	Data type, weather condition, climate, gas price	19.0497/81.4731 (MAE) 0.0058/0.0061 (MRE) 25.9278/109.5693 (RMSE)
					Hourly (5 h forecasting)	Summer/Winter data(150 h/150 h)		53.9272/124.0326 (MAE) 0.0180/0.0119 (MRE) 69.6089/154.3480 (RMSE)
					Hourly (10 h forecasting)	Summer/Winter data(150 h/150 h)		125.7692/594.2678 (MAE) 0.0584/0.0678 (MRE) 167.149/744.4329 (RMSE)
					Hourly (1 h forecasting)	Summer data (150 h)		10.2701 (MAE) 0.0094 (MRE) 11.8352 (RMSE)
					Hourly (5 h forecasting)	Summer data (150 h)		11.9608 (MAE) 0.0110 (MRE) 14.1134 (RMSE)
					Hourly (10 h forecasting)	Summer data (150 h)		55.1135 (MAE) 0.0501 (MRE) 69.2558 (RMSE)
	Wang and Jiang (2019)	NMGM-ARIMA	Pennsylvania	U.S.	Monthly	Jan. 2012–Dec. 2018		3.16% (MAPE) 0.79% (RMSE)
			Texas					1.64% (MAPE) 0.37% (RMSE)
		ARIMA-ANN	Pennsylvania					2.06% (MAPE) 0.57% (RMSE)
			Texas					1.38% (MAPE) 0.33% (RMSE)
	Hafezi et al. (2019)	DmGNn	World	World	Yearly	1965–2013 (Processed data)	Alternative and nuclear energy, CO_2 emissions, GDP per capita, population, NG production, oil consumption	0.9847 (R^2) 52.19 (MAE) 1.69% (MAPE) 13.54 (MBE) 61.33 (RMSE)
						1965–2013 (Raw data)		0.9679 (R^2) 79.96 (MAE) 2.61% (MAPE) 2.66 (MBE) 94.21 (RMSE)

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Table A (*continued*)

Stage	Reference	Forecasting model	Applied area	Country	Forecasting horizon	Data size	Influencing factors	Performance
	Lu et al. (2019)	CF-SA-FFOA-SVM	Kunming	China	Daily	Jan. 1, 2012–Nov. 30, 2013	Daily mean temperature, weather condition, date type, holiday, historical consumption	3.35% (MAPE) 1.14×10^9 (MSE) 3.38×10^4 (RMSE)
					Weekly			3.59% (MAPE) 1.07×10^{11} (MSE) 3.26×10^5 (RMSE)
					Monthly			4.33% (MAPE) 1.20×10^{12} (MSE) 1.09×10^6 (RMSE)
	Hribar et al. (2019)	RNN	Residential consumer (Ljubljana)	Slovenia	Hourly	The total gas demand in Ljubljana for every hour over the past 8 winter seasons	Historical consumption, temperature, holiday, day between public holiday and weekend	9.3% (MAPE) 0.00106 (MAE)
					Daily			6.8% (MAPE) 0.0183 (MAE)
	Qiao et al. (2019)	IWOA-RVM	Lixin gate station (Anhui)	China	Hourly	360 h		0.02% (MAPE) 82.51 (MAE) 9064.71 (RMSE)
			Sanshibu gate station (Anhui)			2160 h		0.02% (MAPE) 45.60 (MAE) 2515.06 (RMSE)
	Marziali et al. (2019)	Gaussian Process	Residential Gas Demand	Italy	Daily	Jan. 1, 2007–Dec. 31, 2017	Temperature, HDD, day of the week, holiday	2.56 (Average MAE) 4.25 (Average RMSE)

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