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# A method for natural gas forecasting and preliminary allocation based on unique standard natural gas consumption profiles

J. Ravnik, M. Hriberšek*

*Faculty of Mechanical Engineering, University of Maribor, Smetanova Ulica 17, SI-2000, Maribor, Slovenia*

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A B S T R A C T

The paper reports on the development of unique standard gas consumption profiles for the end gas consumers and the preparation of a method for the implementation of the developed profiles for forecasting and preliminary gas allocation. Four years of gas consumption and temperature measurements were used to develop eight types of consumption profiles for 17 gas consumer groups, which were grouped according to their professional activity. As an alternative to the exponential, Gompertz or logistic model functions, frequently used in gas consumption model developments, the sigmoid model function is implemented and model constants for the eight types of profiles are developed based on the knowledge of the temperature independent portion of the gas consumption and separate treatment of workdays/weekends. Based on these profiles, a method was developed for the preliminary allocation of the gas consumption. The developed profiles and the gas consumption allocation method were validated on the available set of gas consumption data for the Slovenian gas market, proving the sigmoid model function based gas consumption allocation as an accurate and viable means of gas consumption forecasting.

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## 1. Introduction

Natural gas is one of the main energy sources used in modern society. As the majority of natural gas is supplied to the end consumers through a pipeline based distribution system, there is a need to forecast the gas demands in the future as accurately as possible. In the case of a pipeline system, the main challenge is to balance the supply and demands for the end consumers on a daily basis, with the need to forecast the gas consumption within a day and for the next day accurately. In addition to forecasting, temporary allocation of consumed gas among consumers is an important part of the daily operation of the gas transmission system. (see Fig. 12)

In order to predict the behaviour of a large number of energy consumers, several methods have been used in the past. Statistical approaches were employed to analyse gas consumption quite some time ago by Herbert [1]. More recently, several algorithms were used to make forecasts, such as the grey model, statistical models, econometric models, neural network models, genetic algorithms, mathematical models, and their combinations [2]. The Hubbert curve model has also been extensively used for supply forecasts.

Zeng and Li [3] used a self-adapting intelligent grey model for forecasting the natural gas demand in China. They focus on annual estimates and predict China's gas demands until 2020. Ma and Liu [4] also predicted the growth of annual natural gas consumption in China until 2020. They showed, that predicting the behaviour of very large groups of consumers using the grey model, is accurate. In contrast, prediction of gas used by consumers of a single gas supplier for a single day, which is the purpose of this paper, is more challenging. Similarly, natural gas consumption was studied by Xie and Li [5], who proposed the usage of the grey model in combination with a genetic algorithm for prediction of annual gas consumption totals. Also, Azadeh et al. [6] proposed an adaptive network-based fuzzy inference system-stochastic frontier analysis algorithm for long-term natural gas consumption forecasting and applied it to Bahrain, Saudi Arabia, Syria, and the UAE.

Wadud et al. [7] used a econometric model to study natural gas demand in Bangladesh. They include gas price, GDP and number of consumers to fit a relationship giving an estimate of total gas usage. Such a method also works for large scale only, and it is useful for developing energy polices and not appropriate for day-to-day allocation and prediction of gas demands. Neural networks were

* Corresponding author.
*E-mail addresses:* jure.ravnik@um.si (J. Ravnik), matjaz.hribersek@um.si (M. Hriberšek).

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used by Farzaneh-Gord and Rahbari [8] to perform unsteady simulations of response of natural gas distribution pipeline networks to ambient temperature variation. They are able to estimate daily gas demands. They successfully demonstrate that neural networks are capable of predicting the response of gas users to temperature variations. In this work, we develop a similar algorithm, based of fitting a sigmoid curve. The main advantage of our approach is it simplicity, which makes it easy for gas supply companies to implement in their work flow, after the coefficients, presented in the appendix of the paper, are published within the legislative framework of a country they operate in.

Several other researchers focused on China. They follow the same agenda, obtain measurements of gas usage for a chosen country and implement a numerical method to forecast future usage. A wide rage of methods is used, for example, Zeng [9] used the grey model for modelling of natural gas demand in China. Similarly, Shaikh et al. [10] used optimized nonlinear grey models for forecasting China's natural gas demand. Rui et al. [11] used a genetic algorithm to improve the least squares approach and study natural gas consumption in China. Shaikh et al. [12] also studied the gas demand in China using logistic modelling analysis, while Zhang and Yang [13] used the Bayesian model averaging. A model for short-term natural gas prediction using support vector regression was presented by Zhu et al. [14]. Bai and Li [15] proposed a structure-calibrated support vector regression approach to forecast the daily natural gas consumption. Zhang et al. [16] considered the impact of natural gas supply on infrastructure development in China. Some of this studies optimise their model for predicting annual averages, some focus on short term forecasting.

In this paper, we develop a model, which is aimed at day-ahead and within-day forecasting of gas demand. When implemented on national scale, it will enable a fair preliminary allocation of gas consumption between gas supply companies operating in the same market. Day-ahead forecasting was the focus of research conducted by Panapakidis and Dagoumas [17] who proposed a model using a combination of wavelet transform, genetic algorithm and neural network techniques. They confirm that accurate forecasts of natural gas demand can be essential for utilities, energy traders, regulatory authorities and decision makers. They worked on data from Greece and predict gas usage at distribution points. In our work, presented in this paper, we make predictions at consumer level, giving gas supply companies a possibility to predicts the behaviour of all customers in their portfolio. Short term forecasting was the focus of Yu and Xu [18], who used a combination of optimized genetic algorithm and neural networks to develop a short-term load forecasting model of natural gas. Similarly, the use of genetic algorithms to predict short-term usage of natural gas in houses was proposed by Aras [19], however they focused on monthly averages only. The split the gas consumption to temperature dependent and independent parts. This approach is also taken in this paper.

Natural gas demand in Turkey was studied by Erdogdu [20]. Their objective was to estimate short and long run price and income elasticities of sectoral natural gas demand in Turkey and to forecast future growth in this demand using ARIMA modelling and compare the results with official projections Fagiani et al. [21] reviewed several forecasting techniques aimed at developing smart natural gas and water grids.

Pelikan and Simunek [22] used a genetic algorithm as an optimising tool in risk management of the natural gas consumption. Karadede et al. [23] developed a breeder hybrid algorithm for natural gas demand forecasting and used it in Turkey to forecast natural gas demand from 2001 to 2014. They claim that the breeder hybrid model is superior to other models and can be used as general natural gas demand forecasting tool with daily, monthly and annually data with error close to zero.

Apart from natural gas forecasting, solar [24] and wind energy [25] demands have been studied extensively. Chen et al. [26] proposed a novel method based on nonlinear-learning ensemble of deep learning time series prediction based on long short term memory neural networks, support vector regression machine and extremal optimization algorithms. Thaler et al. [27] have developed an empirical model for prediction of energy consumption in a distribution system. They used a normalised radial basis function neural network to find an economically optimal energy distribution. Day-ahead forecasting of the electricity market was studied by Koltsaklis et al. [28]. Li et al. [29] studied the relationship between gas demand and electricity production for gas-to-power systems. Qiao et al. [30] built a comprehensive system model of a natural gas and electricity coupled network. Oliver et al. [31] developed a method for peak-day gas consumption for gas transmission system operators. Baldacci et al. [32] used natural gas forecasting in order to detect anomalies on the gas distribution network.

An econometric model for forecasting both the short and long-term dynamics of natural gas consumption in Pakistan was used by Khan [33]. They provide estimate until 2020. Taspinar et al. [34] used artificial neural networks to forecast natural gas consumption based on four years of data in Turkey. The ant colony algorithm was employed by Toksari et al. [35]. A degree-day concept was used by Gumrah et al. [36] to study the gas demands of Ankara city. Ervural et al. [37] also considered gas demand forecasting in Turkey using autoregressive moving average, while Akpinar et al. [38] used ABC-based neural networks and the sliding window approach for day-ahead natural gas demand forecasting. In comparison to using the sigmoid model, as proposed in this paper, the authors admit that the coding of the neural network algorithm is difficult, however claim that the use for companies should be easy. They stress that the decision makers can use the natural gas demand forecasting results obtained from forecasting models as decision support systems. In this work, we extent this hypothesis and claim that an well defined and easy implementable model can serve as a basis for preliminary allocation of gas consumption between supply companies on a national level.

Nonlinear programming and genetic algorithms were employed in Iran by Forouzanfar et al. [39] to forecast natural gas usage. They introduce the sigmoid curve, which is a special case of the logistic equation, as a good model for many different contexts such as demographics, T biology, economics, etc. The curves are used because of their ability to describe these processes and display typical phases of, among others, gas consumption: the low gas usage in summer, the logarithmic growth in the winter months and saturation when extreme cold limits gas consumption. In this work we also employ the sigmoid curve to model gas consumption.

In Poland, Siemek et al. [40] have used an adaptation of the Hubbert model to derive a model of future gas demand. They used the Newton-Gauss algorithm to determine the model constant. In our work, we use the Levenberg-Marquardt algorithm for the same task. Liu et al. [41] used a time-series approach to model gas consumption in Taiwan. Vondracek et al. [42] used a nonlinear regression model with individual customer effect, typical time-dynamics part and the temperature correction for natural gas usage estimation in the Czech Republic. Sabo et al. [43] investigated the natural gas usage in Croatia on the basis of hourly temperature and gas usage measurements. A review paper on the topic of forecasting natural gas consumption was prepared by Soldo [2], who summarised the approaches used by researchers based on the forecasting area (world, national, individual consumer), forecasting horizon (hourly, daily, monthly), gas data measurements used and the model applied. An overview of forecasting methods for energy demand was prepared by Ghalehkhondabi et al. [44]. Potočnik et al. [45] investigated risks associated with forecasting models and exposed the Slovenian economic incentive model that motivates natural gas distributors to forecast their future consumption. Potočink and Govekar [46] presented practical results of forecasting for the natural gas market where they stress the importance of incorporating the proper influential variables into the model, and by properly understanding the underlying principles of energy consumption. Potočnik et al. [47] also considered short-term residential natural gas forecasting in Croatia. The same research group studied the influence of solar radiation on the gas forecasting models ([48]). Artificial neural networks combined with the Levenberg-Marquardt training algorithm were used to produce short-term natural gas consumption forecasts in Serbia by Ivezic [49]. Gascon and Sancez-Ubeda [50] used generalised additive models for short-term natural gas demand forecasting. Aguilera and Ripple [51] employed the Variable Shape Distribution model to estimate the total endowment of conventional gas in Asia Pacific. Azadeh et al. [52] propose to use an integrated emotional learning fuzzy inference approach for optimum training of forecasting models for natural gas demand.

Apart from modelling gas consumption at the consumer level, models have been prepared that attempt modelling of the global natural gas supply (Crow et al. [53]). These types of models represent the natural gas market as a system of nodes and connections with prices and flows, and seek an equilibrium solution in the whole network (Busch [54]). Several mathematical approaches are utilised: Linear programming, nonlinear programming, or agent based economic modelling. Bianco et al. explore the relationship between the residential [55] and nonresidential [56] gas consumption and the Gross Domestic Product of Italy. They find strong correlation between the two. A similar result was reported by Apergis et al. [57], who considered economic growth in 67 countries, and by Karasalihovic et al. [58] for Croatia. Chavez-Rodriguez et al. [59] modelled long-term natural gas dynamics in the south of Latin America. They employed a combination of a simulation model LEAP (Long range Energy Alternatives Planning System), and the TIMES model was used to optimise the natural gas supply. Horschig et al. [60] prepared a biomethane market simulation model, which was used in Germany to explore the future relationship between the natural gas market and the biomethane market. In order to find the most efficient way of distributing gas, optimization of transmission networks has been considered as well. Uster et al. [61] developed an integrated large-scale mixed-integer nonlinear optimization model for design and operation of natural gas transmission networks. Rios-Mercado et al. [62] give a state-of-the-art review of optimization problems in natural gas transportation systems. On a smaller scale, Lo Cascio et al. [63] developed a multiobjective optimization model for urban integrated electrical, thermal and gas grids.

In this paper, we propose a method, which, when coupled with a mathematical forecasting model, enables gas transmission system operators to forecast or preliminarily allocate consumed gas fairly and uniquely. The development of the proposed model was initiated by the initiative of The Energy Agency of the Republic of Slovenia, with a clear goal to derive a model that would be accurate, yet easy to use, whether used by the gas distributors for forecasting the consumers demands or system operators for balancing purposes, and therefore would be widely accepted when set into the legislative framework, that had to be used by all members in the Slovenian gas market. The developed model and its method of use is simple to implement, and can be applied at the level of balance group leaders, members of a balance group, the operator of the gas market, the operator of the transport system, as well as at distribution system operators. The proposed method is not geographically restricted and can also be implemented in other countries, if the modelling assumptions are met. When adopted at a national or a regional level, it may serve as a legislative tool, which enables fair preliminary allocation of consumed gas and helps to avoid conflict between balance group leaders or transmission system operators. The underlying mathematical forecasting model should, naturally, be prepared separately for each region, since specific local, regional and climate characteristics must be taken into account.

The consumption of natural gas in a specific time period depends on many factors (for example temperature of the surroundings, other environmental elements, the purpose of usage, etc). Certain groups of users exhibit similar usage characteristics, which make it possible to predict the future usage based on the known or estimated environmental parameters. Such estimates are expected to work well only when used for a large number of users, so those single individual users who do not follow the statistical behaviour of the group completely, do not influence the estimate to a large extent.

In order to make it possible for the natural gas suppliers to have a unified, fair, and dependable model for estimating the natural gas usage, the Unique Standard Consumption Profiles (USCP) for individual groups of users are developed in this paper. The USCPs are developed in the form of a mathematical model, which includes several model constants which are fitted to the usage data of individual gas users. In this paper, we present the development of gas consumption profiles based on the influence of the outside temperature on the natural gas usage. The developed USCP can be used in combination with a method for preliminary allocation of consumed gas, which gives a unique and fair way of preliminary allocation. Gas usage data was obtained from measuring consumption of end users from individual characteristic groups in the time frame of 2009–2013, provided by the Energy Agency of the Republic of Slovenia. The USCPs in this work are prepared using the sigmoid model function, which presents an alternative to the exponential, Gompertz (Gutierrez et al. [64]), linear (Spoladore et al. [65]), support vector regression (Bai et al. [15]), and logistic model functions (Melikoglu [66]) used by other authors (Sabo et al. [43]).

The basic requirement for the models and methods prepared in this paper is to provide a simple algorithm for allocation of gas between gas suppliers on a short-term scale, i.e. within a day, or for the next day (Cui et al. [67]) based on forecasted climate conditions. The models and method are meant to be published in a legislative framework, and serve as a fair and standard method of performing preliminary allocation of gas consumption among gas suppliers. Since official temperature forecast is available, and since the number of gas consumers to which the model will be applied is expected to be large (i.e. all consumers within a country/region), we chose the sigmoid regression model. It is simple, quick and works well when used to model a large number of consumers. It can be defined uniquely by publishing only four parameters. We were able to establish, that the sigmoid model performs better than other regression models. Furthermore, as time passes and new measurements become available, the techniques developed in this paper can be used to update the forecasting models and, thus, provide a fairer and more accurate allocation of consumed gas among gas suppliers.

The developed method for preliminary gas allocation is applicable worldwide regardless of the forecasting models. The gas consumption forecast models we present in this paper have been developed based on four year long measurements of gas consumers all around the country. Slovenia has very diverse climate conditions (the Mediterranean in the south-west, alpine in the north, and continental in the east). Thus, the developed models (published in the Appendix), can be used in similar climate conditions around the world. Alternatively, if a region possesses a several years long gas consumption measurement dataset, only the method and the model derivation can be employed to recalibrate the model parameters for a specific region. The developed preliminary allocation method, in combination with the presented forecast model, can be used immediately after the adoption into the legislative framework. Implementation within either a spreadsheet software or a website is trivial, and can be done with minimal effort. The method requires data on average annual gas consumption of each consumer. This dataset (or at least an estimate) is usually readily available at gas providers.

The original contribution of this paper is twofold. Firstly, we present a method for preliminary (day-ahead) and within-day gas consumption allocation, which enables a fair and standardised distribution among gas suppliers. The developed method is applicable worldwide, and is not limited to a single region. Secondly, we propose the use of a sigmoid model function (as opposed to the exponential, Gompertz or logistic model functions proposed by other authors) in support of the allocation method.

The paper is organised as follows. Section 2 presents the measurements of gas consumption and temperature. Section 3 describes the development of consumption profiles and the method for their use. Section 4 the presents the validation of the developed profiles and the analysis of their applicability and accuracy. The paper ends with the conclusions and an acknowledgement.

## 2. The experimental dataset

The Energy Agency of the Republic of Slovenia performed hourly gas consumption measurements at 260 consumers (end users) in Slovenia. The measurements were taken during the period 1.9.2009–31.5.2013. At the same time, 18 meteorological stations recorded climate conditions.

### 2.1. Gas usage data

For each of the 260 consumers, 32856 hourly measurements were made during the observation period. The consumers were chosen in such a way, that they represented several Consumer Groups (CG), as listed in Table 1. The consumers were chosen on the basis of their type of activity (e.g. Agriculture, Civil Engineering, etc.), reported in the standardised Business Registry and, secondly, in such a way, that they were located in different local climate regions.

The chosen gas consumers use gas in a temperature dependent manner and are located in different climate regions. Such arrangement of consumers into groups enabled us to produce USCPs for individual groups, as well as the average USCP for all consumers.

Given the gas consumption dataset, we first performed statistical analysis in order to determine the consumption variation within the dataset. For each consumer, we calculated the average daily consumption and standard deviation using the following formulae:

$$m_i > 0 \quad \Rightarrow \quad \overline{m} = \frac{1}{N}\sum_i m_i, \qquad \sigma = \sqrt{\frac{1}{N}\sum_i m_i^2 - \overline{m}^2},$$

where $m_i$ is the consumption data, $\overline{m}$ is the average, $N$ the number of all measurements and $\sigma$ the Standard Deviation. In order to exclude erroneous gas consumption data, the measurements that exceeded the $7\sigma$ interval were eliminated from the dataset. This meant eliminating 378 measurements.

Furthermore, due to equipment failure or other unforeseen circumstances, all of the consumers do not have a complete four year dataset of the measurements available. The majority of the 260 consumers had between 70% and 90% of the maximum number (each day with full 24-h resolution) of measurements. Based on this analysis, the measuring points with less than 10% of the maximum number of measurements possible were eliminated from the final dataset. Thus, the final dataset included 231 consumers and 6.7 million measured gas consumption data points. The dataset is presented in Fig. 1 and is available to readers upon request.

Within a specific Consumer Group there are several measuring points (consumers) with different total annual gas consumption. In order to create a single dataset for a group, first the daily sum of the gas consumption of an individual consumer was calculated, $P_i^j$, followed by calculation of the average daily consumption, $P_g^j$, which served as the denominator in the calculation of the normalised daily consumption:

$$P_i^j = \sum_{6am}^{6am} m_i, \qquad P_g^j = \sum_{i=1}^{N_g} P_i^j, \tag{1}$$

where $P_i^j$ is the daily (from six in the morning until six in the morning) gas consumption of an $i^{th}$ consumer on $j^{th}$ day, $P_g^j$ is the total daily gas consumption of the $g^{th}$ Consumer Group and $N_g$ is the number of consumers in a group. In Fig. 2 the average hourly gas consumption measurements are presented and compared with the market gas price in the same time period. Although the market gas price exhibits some variation during the time period, we do not observe a strong correlation between the price and consumption. Furthermore, we assume that during the measurement period the

**Table 1**
List of Consumer Groups showing the Consumer Group Code, the number of consumers and the number of measurements in the data set.

| Code | Consumer Groups | No. of consumers | No. of measurements |
|---|---|---|---|
| A | Agriculture and hunting, wood industry | 5 | 153187 |
| C | Processing industries | 13 | 336731 |
| F | Civil engineering | 7 | 192378 |
| G | Retailing | 18 | 548512 |
| H | Logistics and storage | 10 | 304994 |
| I | Catering | 11 | 327122 |
| J | Information and communication | 7 | 207574 |
| K | Financial, insurance, advisory services | 11 | 341154 |
| O | Public administration | 11 | 317935 |
| P | Education | 13 | 399056 |
| Q | Health and social service | 12 | 377169 |
| R | Cultural and recreational services | 10 | 318867 |
| S | Others | 11 | 303297 |
| W | Individual residences | 53 | 1573217 |
| Zx | Apartment buildings | 67 | 1954071 |
| HEA | Heating use only | 40 | 1098167 |

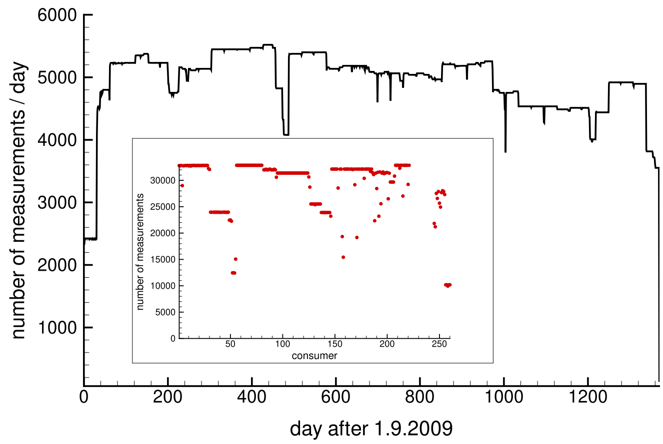


**Fig. 1.** Number of available gas consumption measurements for each day in the dataset. For most days, about 90% of the total $231 \cdot 24 = 5544$ measurements per day are available. The inserted panel shows the total number of measurements for each consumer, exposing the consumers which were eliminated due to small number of available measurements.

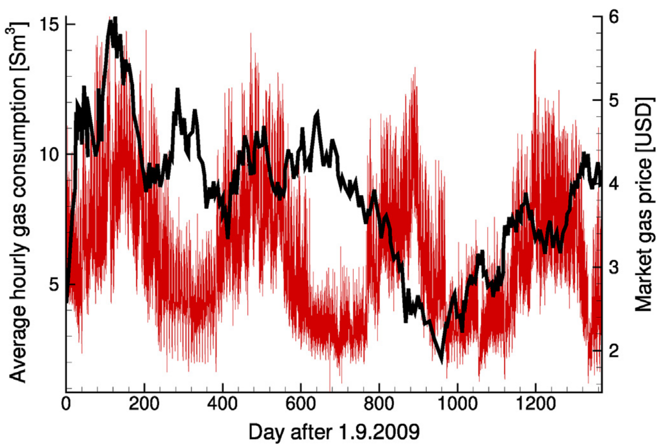


**Fig. 2.** Comparison of the average hourly gas consumption measurements and market gas price. Correlation between the price and the consumption is not observed.

variation of natural gas price is small in comparison with Slovenia's gross domestic product, thus the natural gas price was not considered as a variable in modelling.

### 2.2. Temperature data

The Slovenian Environmental Protection Agency (ARSO) measures climate conditions at several meteorological stations around the country. For the period in question, the temperature data was made available to us from 18 meteorological stations. Locations of the stations, along with the locations of gas consumers, are shown in Fig. 3.

To develop the consumption profiles, we used average daily temperatures. Due to regulations imposed on the gas market, we define a gas day to last from six in the morning until six in the morning. Since the meteorological stations report average temperature measurements for calendar days only, the gas day temperature is calculated as

$$T = \frac{18}{24} T_{day} + \frac{6}{24} T_{day+1}, \tag{2}$$

where $T_{day}$ is the average measured or forecasted daily temperature and $T_{day+1}$ is the average daily temperature for the next day measured in $[^\circ C]$. Each gas consumer is paired with a representative meteorological station, from where temperature measurements and temperature forecasts are taken. Instead of average gas day temperature, heating degree days could be used as a measure for heat demand and as a basis for model development. We chose average temperature, due to the gas market requirements of using gas days and not calendar days.

Since information on the end use of gas for a specific consumer was not available, we performed a simple check to identify the consumers, who use gas for heating purposes only. Based on this analysis, a new end group of users with 40 individual consumers was created - heating (HEA) with end consumers, that do not use natural gas at temperatures exceeding $20^\circ C$.

## 3. Unique standard consumption profiles

In this section development of unique standard usage profiles, forecasting method and preliminary allocation method are described.

### 3.1. Mathematical background

The temperature measurements from meteorological stations were averaged to give a gas day average temperature $T_j$ for each gas day and for each consumer. Next, for each Consumer Group $g$ a normed daily gas consumption $P_g^j$ dataset was prepared.

The decision on which numerical model to implement was taken based on the review of the measurement dataset and by taking into account that the developed should be easily publishable in legislative framework and its use enforced by the government to all stakeholders in the gas market. Considering the fact that the gas usage is high and constant at low temperatures, decreases approximately linearly with increasing temperature for mid-range temperatures, and is constant and low at high temperatures, we decided to fit a model curve in the form of a sigmoid (Hellwig [68]). The sigmoid curve is a tilted $S$-shaped curve that resembles trends in the lifecycle of living things and phenomena [39]. Its $S$ shape gives it unique properties suitable for modelling the gas consumption characteristics, described above, similarly to polynomial, exponential, Gompertz and logistic model functions (Sabo et al. [43]).

To confirm, that the sigmoid is the best possible choice, we compare linear, parabolic, exponential and sigmoid models for a single consumer in Fig. 4. The exponential function was defined as $P_g^m = A + (B - A)\exp(-C(T + D))$. We observe best performance using the sigmoid model for virtually all consumers. Thus, we employed the sigmoid model for further analyses.

The sigmoid describing the relationship between gas consumption and temperature $P_g(T)$ can be defined by four parameters $A$, $B$, $C$ and $D$. Its formula is:

$$P_g^m = \frac{A}{1 + \left(\frac{B}{T-40}\right)^C} + D, \tag{3}$$

where $T$ is the temperature in $[^\circ C]$ defined in eq. (2). Fitting of these parameters in a least squares sense is a non-linear problem. The Levenberg-Marquardt method (Press et al. [69]) was chosen to perform the least squares fitting. The Levenberg-Marquardt method requires the knowledge of derivatives of the sigmoid with respect to the four parameters. These are:

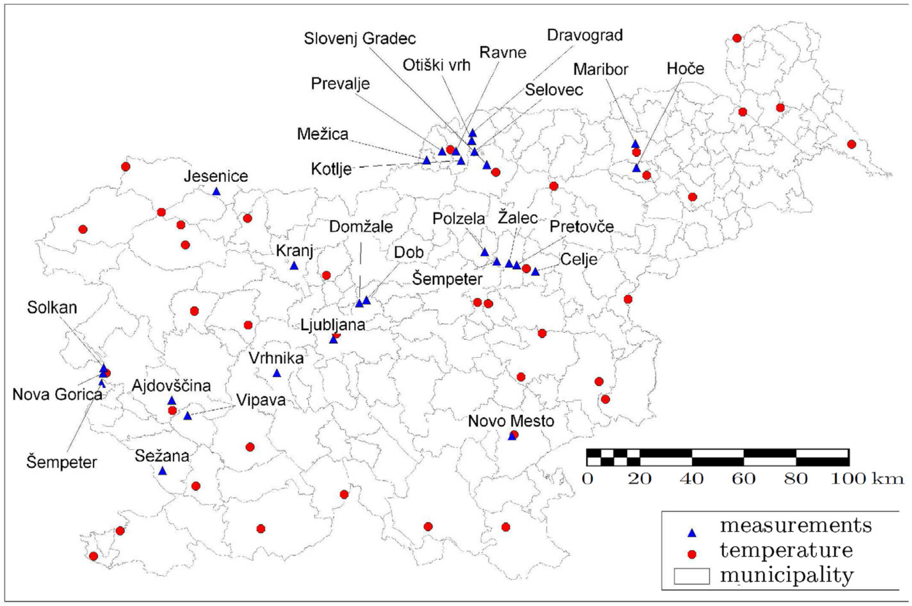


**Fig. 3.** Locations of the weather stations (red circles) and locations of gas consumers (blue triangles) in Slovenia. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

$$\frac{\partial P_g}{\partial A}=\frac{1}{1+\left(\frac{B}{T-40}\right)^C},\qquad \frac{\partial P_g}{\partial B}=-\frac{AC\left(\frac{B}{T-40}\right)^C}{B\left(1+\left(\frac{B}{T-40}\right)^C\right)^2}, \tag{4}$$

$$\frac{\partial P_g}{\partial C}=-\frac{A\left(\frac{B}{T-40}\right)^C}{\left(1+\left(\frac{B}{T-40}\right)^C\right)^2}\ln\frac{B}{T-40},\qquad \frac{\partial P_g}{\partial D}=1. \tag{5}$$

An example of the sigmoid curve fitted to the gas consumption dataset is shown in Fig. 5. In order to have a mathematically based assessment of the quality of the fit, the following sample correlation coefficient $r$ was employed [68],:

$$\overline{P_g}=\sum_j P_g^j,\qquad \overline{P_g^m}=\sum_j P_g^{m,j},\qquad r=\frac{\left(\sum_j P_g^j P_g^{m,j}-n\overline{P_g}\,\overline{P_g^m}\right)^2}{\left(\sum_j\left(P_g^j\right)^2-n\overline{P_g}^2\right)\left(\sum_j\left(P_g^{m,j}\right)^2-n\overline{P_g^m}^2\right)}, \tag{6}$$

where $P_g^j$ is the measured gas consumption for a consumer in the group $g$ on the day $j$, while $P_g^{m,j}$ is its modelled counterpart and $n$ is the number of data points. The sample correlation coefficient $r$ takes values between 0 and 1, with a higher value describing a better fit.

### 3.2. Types of unique standard usage profiles produced

Looking at the model results and analysing the measurements, we discovered that the gas consumption of some consumers is independent of temperature. For those modelling makes no sense, thus in the forecasting algorithm described below, we recommend using their annual average to forecast their consumption.

The gas consumption of temperature dependent gas consumers is usually composed of two parts: A smaller temperature independent part (for example, gas used for cooking), and a temperature dependent part (for example, gas used for heating). The gas distribution companies may or may not know the temperature independent part of the gas consumption of their consumers. Thus, we devised two types of models. The first, that takes all data into account is applied when the temperature independent part of the consumption is not known. The second applies to the situation where the temperature independent part of the consumption is known. For these models, we calculated the average consumption in days when the outside temperature was above $20^\circ C$. This value was then subtracted from the daily gas consumption measurements and, thus, the second set of models was constructed.

Looking at the raw gas consumption and taking into account the social interaction patterns, we decided to make models which would additionally take into account variation of the consumption due to the day of the week. Thus, we prepared separate models for workdays and weekends, as well as models which do not distinguish between the days of the week.

A final subdivision of the models was made based on the assumption whether the classification of the consumer into a specific Consumer Group was known. Thus, models were made for each group of consumers, as well as for all Consumer Groups together. A decision tree for choosing one of the developed models is shown in Fig. 6. The model constants are listed in the Appendix in Tables 2–9

### 3.3. Forecasting method

The developed unique standard usage profiles are to be used by taking the steps in the following calculation steps:

1 For each temperature dependent gas consumer one should provide:
  1a Average annual temperature dependent gas consumption (*PLTOP*).
  1b Average annual temperature independent gas consumption (*PLTNP*). If the temperature independent share of the

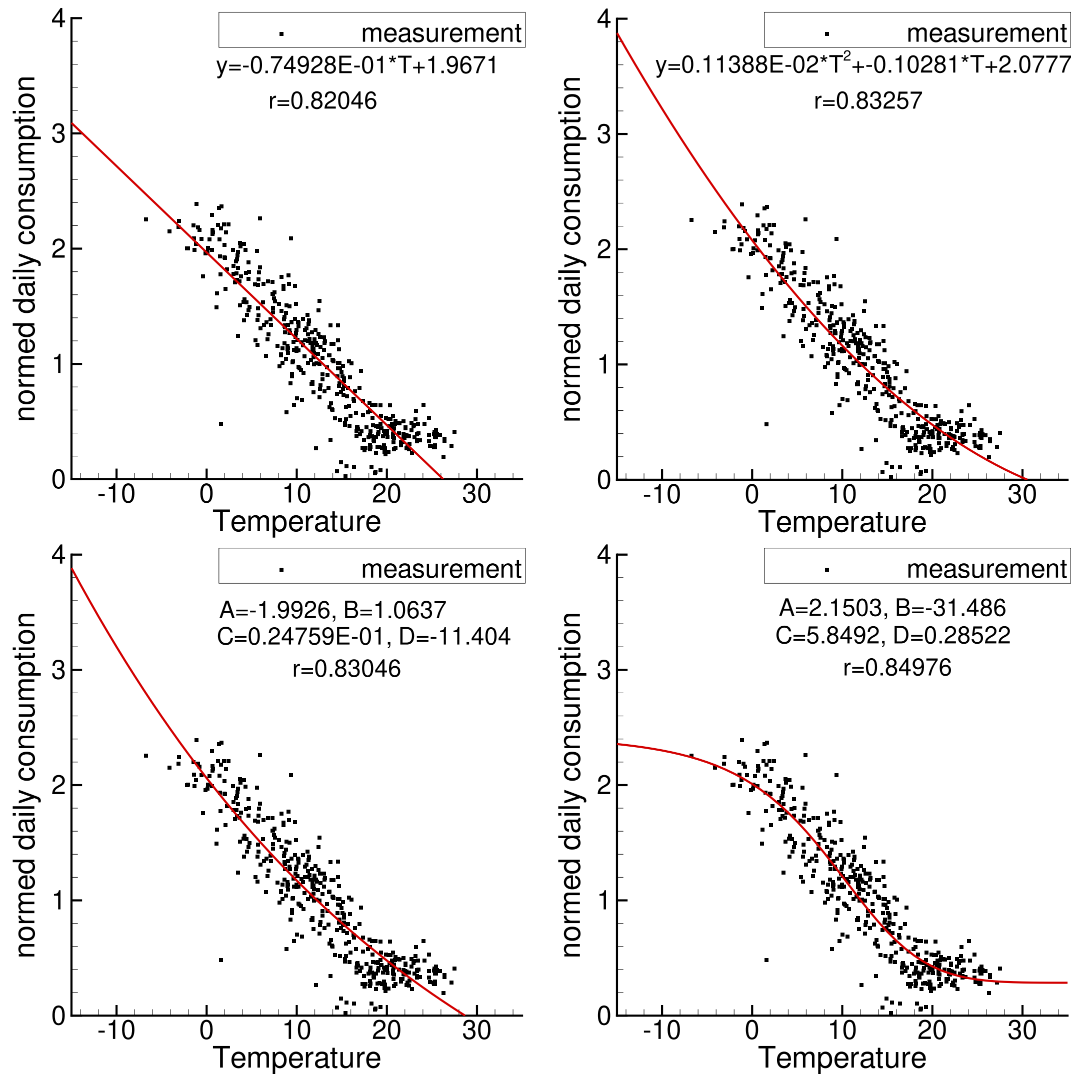


**Fig. 4.** Comparison between linear, parabolic, exponential, and sigmoid regression curves showed the best result for the sigmoid model. Panels show measurements at a single consumer modelled with linear (top left), parabolic (top right), exponential (bottom left) and sigmoid (bottom right) regression models.

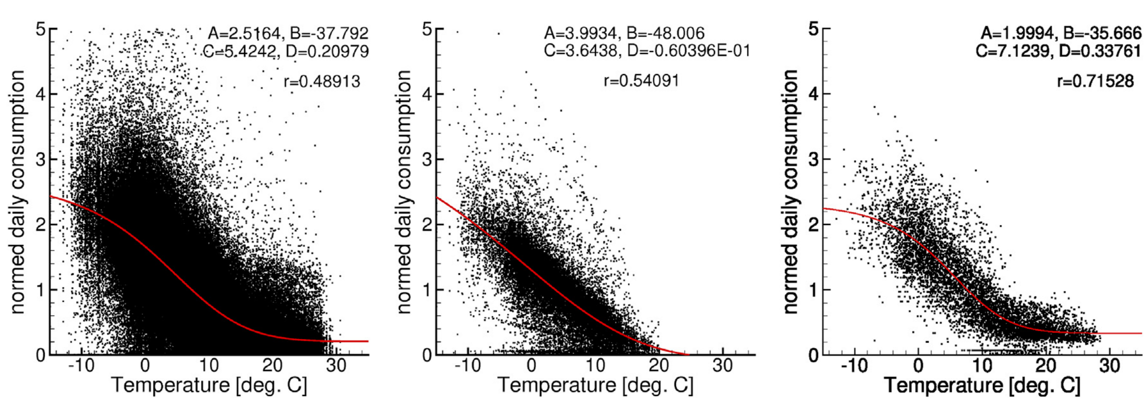


**Fig. 5.** Examples of fitted model curves. For the left panel the whole dataset was used, HEA consumer group for the middle panel and catering group for the right panel.

consumption is unknown, use $PLTNP = 0$, while $PLTOP$ is equal to the total annual average gas consumption.

1c Number of days per year the consumer uses gas ($DVL$).

2 Based on the decision tree shown in Fig. 6 decide on the appropriate model and choose the model constants $A, B, C$ and $D$.

3 The user should next obtain a forecast for the temperature data from the relevant meteorological station. The temperature for

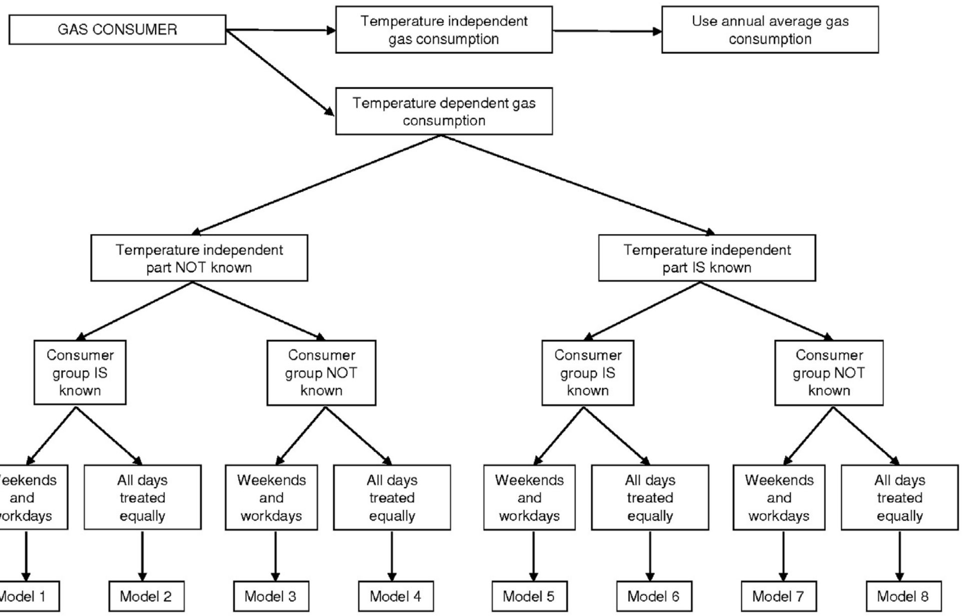


**Fig. 6.** A decision tree showing the eight types of the derived models.

the day for which forecasting is made ($T_1$) is needed as well as the temperature for the next day ($T_2$).

4 Using the following equation estimate the gas consumption *NPP* for each gas consumer:

6 Make a sum of all forecasts to obtain the total forecast for all consumers.

$$NPP_1 = \frac{A}{1+\left(\frac{B}{T_1-40}\right)^C} + D$$

$$NPP_2 = \frac{A}{1+\left(\frac{B}{T_2-40}\right)^C} + D$$

$$NPP = \frac{PLTOP}{DVL} \cdot \frac{16 \cdot NPP_1 + 8 \cdot NPP_2}{24} + \frac{PLTNP}{DVL}$$

### 3.4. Preliminary allocation method

When the total gas consumption for a hydraulic cell in the gas distribution network is known, it is necessary to make a preliminary allocation of the gas consumption of individual consumers based on the application of the USCPs. The method proposed here provides a unified and fair way of determining the preliminary allocation and when it is introduced into the legislative framework ensures smooth operation and helps to avoid conflict between gas suppliers.

Let the total quantity of gas which needs to be allocated be denoted by $S$. For each of the consumers, a forecast is made, based on the USCPs provided in this paper. Let the number of consumers be $n$ and let the predicted gas consumption of $i-th$ consumers be $P_i$. Due to the inaccuracy of the USCP forecast, we notice that the total measured gas consumption is not equal to the sum of all forecasts for all consumers, $\sum_{i=1}^{n} P_i \neq S$. We want to calculate preliminary gas consumption allocation $A_i$ in such a way that $\sum_{i=1}^{n} A_i = S$. In order to achieve this, the preliminary gas consumption allocation $A_i$ is calculated using the following formula:

$$A_i = \frac{P_i}{\sum_{i=1}^{n} P_i} S. \tag{7}$$

## 4. Results and discussion

Accurate predictions of the daily consumption for the distribution system on the national level could be obtained by the adoption of the proposed preliminary allocation method through each of the gas market operators, providing that the latter have a detailed database of their users within the consumer groups. The accuracy of these predictions depends strongly on the correct use of the developed USCPs. In the following, the analysis of the performance of the forecasts made by USCPs is made, and recommendations are given on the usage of the developed USCPs.

### 4.1. Analysis of the correlation coefficient

The sample correlation coefficient $r$ (Eq. (6)) gives a mathematical indication of the quality of the representation of the gas consumption by the developed USCP. The correlation coefficient was estimated for all Consumer Groups and all models by modelling each consumer separately and averaging the results. The results are shown in Fig. 7. We observe a poor correlation for Consumer Group *F* and a good matching for the group *Q*, while all other Consumer Groups exhibit similar values of *r*. It has to be noted that the poor correlation for the Group *F* was caused by the fact that the number of data points in the Group *F* was small.

### 4.2. Forecasting a single gas consumer

The objective of developing USCPs is to have a reliable forecast of the gas consumption for a given day for a large number of consumers. The forecasting party, which will use the developed method in this paper, is expected to run the model for all consumers in its portfolio; on average at least a thousand or more consumers. Using the USCP to forecast the gas consumption of a single consumer, which is shown in Fig. 8, reveals a poor agreement

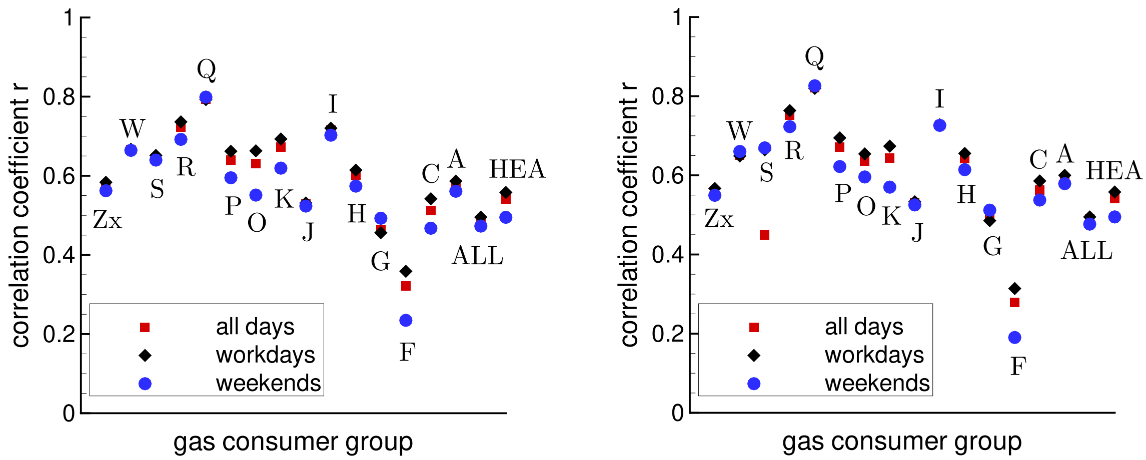


**Fig. 7.** Comparison of the correlation coefficient *r* for models (1–4) (left panel) and models (4–8) (right panel).

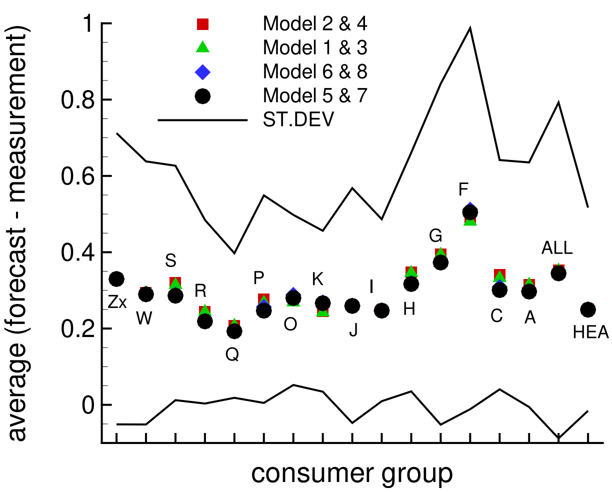


**Fig. 8.** Absolute difference between forecast and measurement based on the analysis of each individual gas consumer for each day. The value on the ordinate axis is in normed daily consumption.

between the forecast and the actual consumptions. The disagreement is expected since there is no way of knowing when the consumer will stop using gas in a normal/average way due to the equipment malfunction, vacations or other unforeseen circumstances. Fig. 8 shows the average difference between the model forecast and measurement for each day and for each gas consumer within a Consumer Group. The average difference is expressed in normed daily consumption. We observe that, when forecasting a single gas consumer for a single day, we can expect an average error of about 0.3±0.3 average daily consumption.

### 4.3. *Forecasting average consumption*

Focusing on a day with a specific temperature, we calculate the average measured gas consumption of each Consumer Group and compare it with model predictions for this Consumer Group. The prediction is obtained by averaging model forecasts of each individual consumer in the group. Comparisons for the whole dataset, the heating group and the residences group, are shown in Fig. 9. We observe good agreement in almost the whole temperature spectrum. Discrepancies are noticeable at a very low temperature, where consumer behaviour becomes more chaotic, and the differences in gas consumption on such days are larger than during the warmer days. All models perform similarly, but models 5 & 7, which have the advantage of a known temperature independent part of the consumption, outperform the other models on warm days. We can conclude from this analysis that the models perform very well when used to forecast consumption of a large enough number of gas consumers.

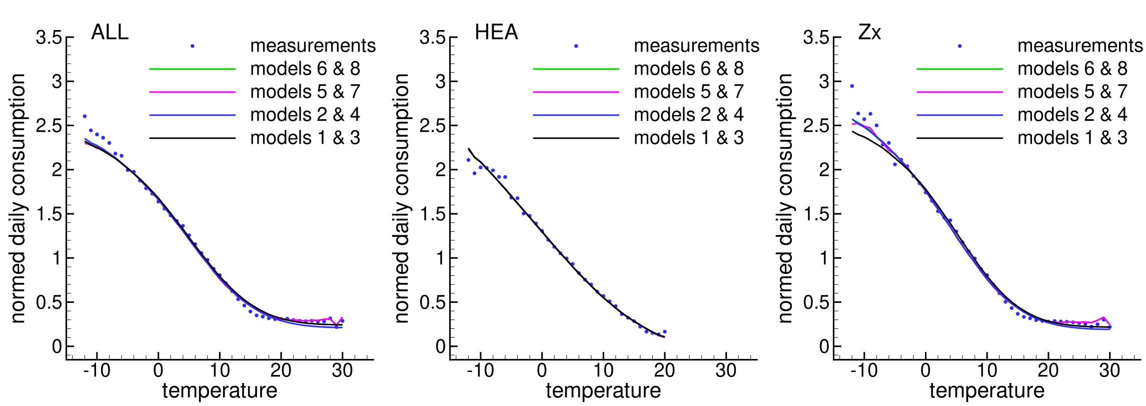


**Fig. 9.** Comparison of the measured average gas consumption versus temperature and model forecast; for the whole dataset (left), the Heating Consumer Group (middle) and Zx Consumer Group (right).

### .4. Forecasting daily totals

The developed method and the associated models are supposed to be used for within day or day-ahead forecasting for all consumers in a large region. In this subsection, we try to estimate the dependence of the error of the total consumed gas forecast on the number of consumers. Since measurements are available for only 231 consumers per day, we extend the dataset over a longer period of time and predict totals for such periods. In this way, we are able to assess the forecast inaccuracy for a large number of consumer - days.

Fig. 10 shows the difference in predicted and measured total gas consumption for a single day, for a total of one year (2012), and for a total of the whole period 2009–2013. We observe that the model prediction is good (in the range of ±1% of the measured data) for the case of the four years time period, while the prediction is worse for a single day or a single year case. These results were expected,

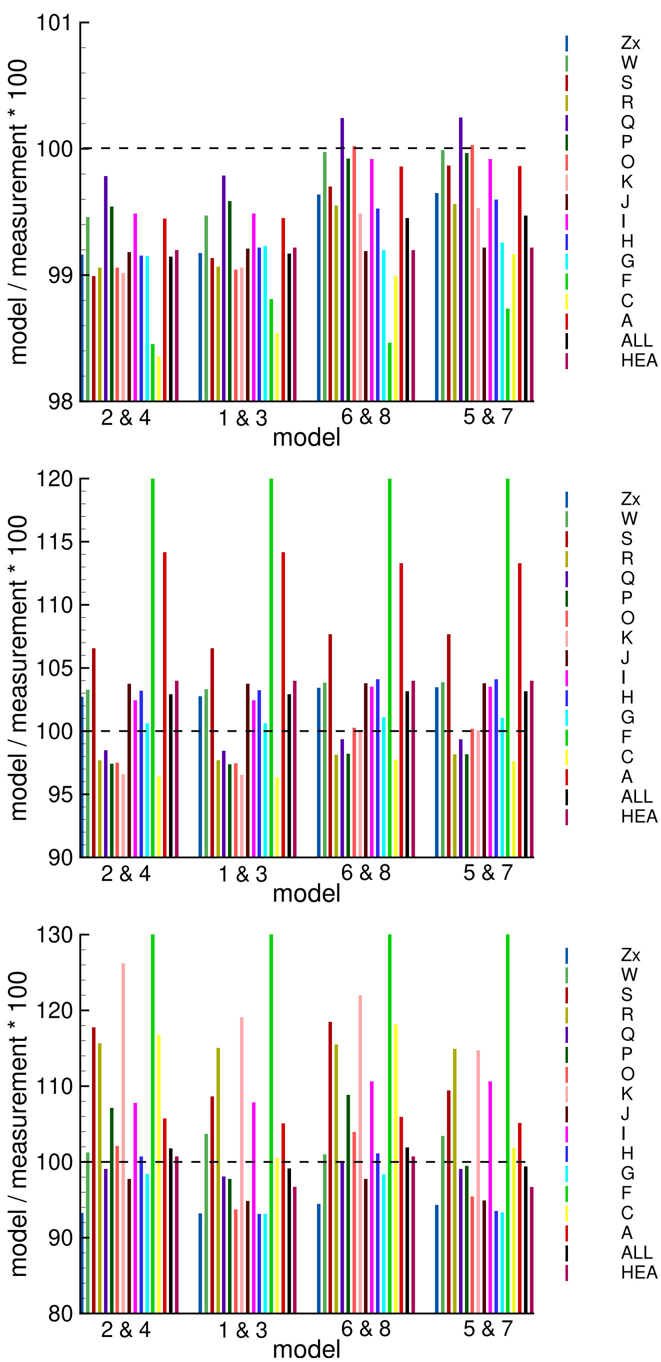


**Fig. 10.** Comparison of the total gas consumption predictions for a four year time span (top), a single year (middle) and a single day (bottom).

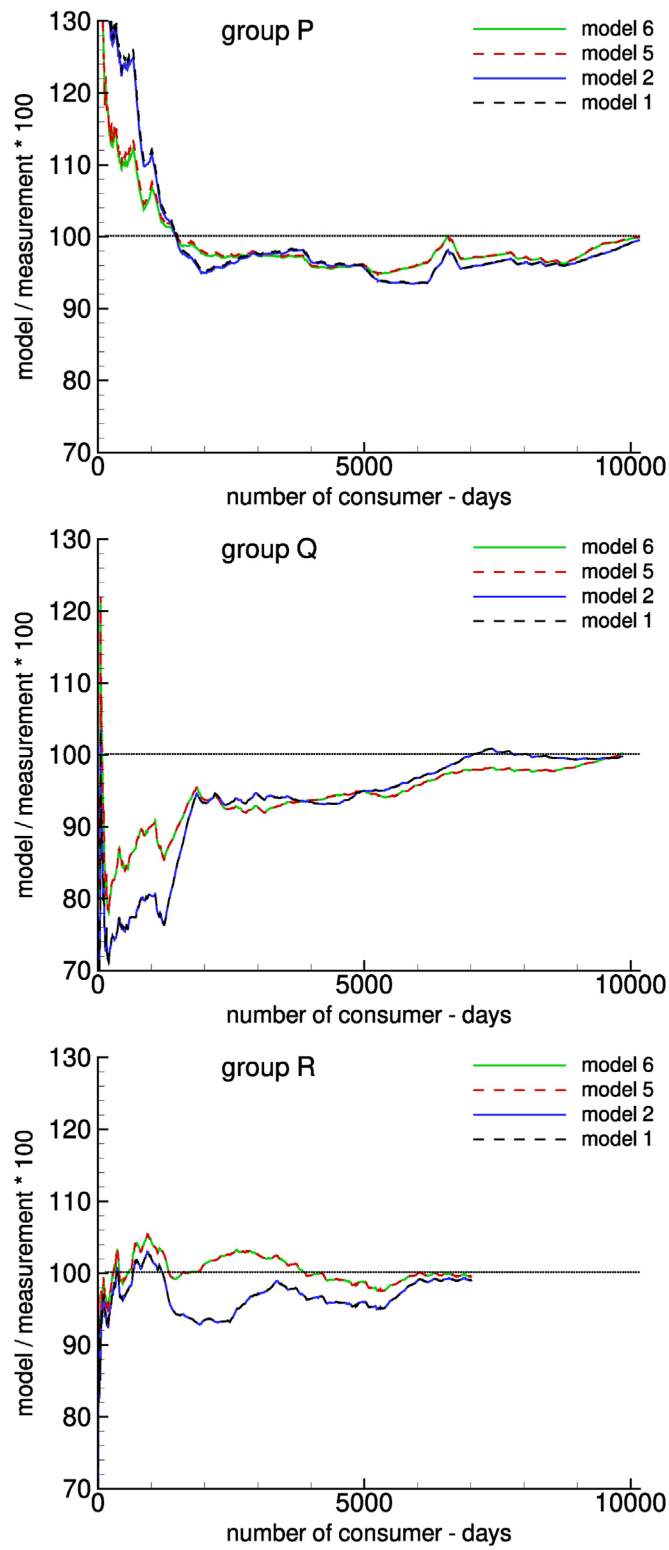


**Fig. 11.** Improvement of the total gas consumption predictions with increasing number of consumer-days. Results for Group P (top), Q (middle) and R (bottom) are shown.

and gave us an indication of the model performance on a real-world large dataset. Since only 231 consumers were predicted in the singe day case, the accuracy is only within ±20%, while, when a larger dataset is considered (231 times 4 years) the accuracy is improved to ±1%. We observe that similar accuracy is obtained for each Consumer Group which includes about 10 consumers. Thus, we may conclude that $\approx 10 \cdot 365$ are needed to have ±5% accuracy of the total daily consumption. For ±1% accuracy, at least $\approx 10 \cdot 365 \cdot 4$ consumers are needed. The proposed accuracy estimates are verified in Fig. 11, where we present the improvement of the total gas consumption predictions with increasing number of consumer - days for three Consumer Groups. We observe clear improvement of prediction accuracy with the number of consumer - days. The results show a clear difference between models for consumers for which the temperature independent portion of consumption is known and models for consumers for which the temperature independent portion of consumption is not known. Difference between all-day models and weekend-workdays models is noticeable only for a small number of consumer - days.

### 4.5. Validation of the preliminary allocation

Finally, we validate the method for preliminary allocation. For each day we use USCPs to forecast gas consumption of all gas consumers in the dataset. The accuracy of the preliminary allocation was assessed using the available gas consumption measurements.

Let $M_i^j$ be the actual measured gas consumption of the $i-th$ consumer on the $j-th$ day and $n$ be the number of consumers. Thus, on the day $j$ we must allocate

$$S^j = \sum_{i=1}^{n} M_i^j \tag{8}$$

Let $A_i^j$ be the preliminary allocation for the $i-th$ consumer on the $j-th$ day, which was estimated using calculation steps described in Section 3.4 (eq. (7)). For each day we calculate the root mean square (RMS) norm $R_j$ between the preliminary allocation and actual measurements using

$$R_j = \sqrt{\frac{\sum_{i=1}^{n}\left(A_i^j - M_i^j\right)^2}{\sum_{i=1}^{n}\left(M_i^j\right)^2}} \tag{9}$$

Fig. 12 shows the average RMS norm for the whole time period for all consumer groups. The results indicate clearly that the most accurate allocations are obtained when using models 5 & 7, i.e. when the temperature independent portion of the consumption is known, and when weekends and workdays are treated separately. Comparing the results for different Consumer Groups, we observe similar results except for Group *F*, and, to a lesser extent, for the groups *J* and *K*, where the lack of data did not enable us to make a reliable USCP. Based on the fact that the model which is valid for all consumers performs similarly well as the models for individual Consumers Groups, we recommend its usage in practice.

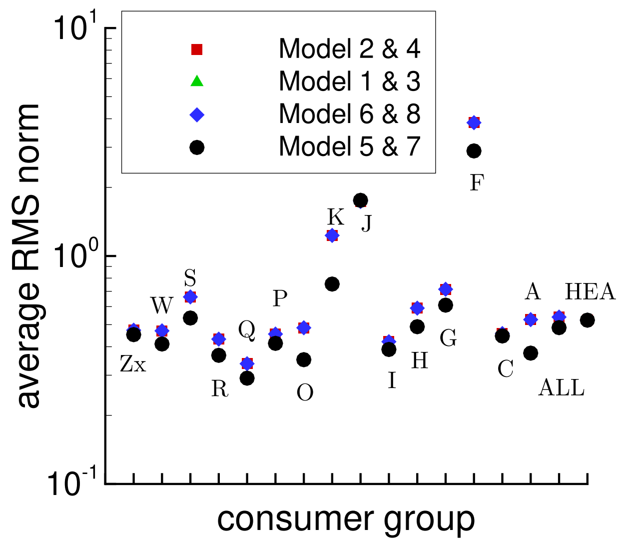


**Fig. 12.** Average RMS norm between the preliminary allocation based on the USCP forecast and the actual measurements.

## 5. Conclusions

Unique standard gas consumption profiles were developed for several Consumer Groups based on the measurement of gas consumption and air temperature. The sigmoid model function was implemented as the basis for the consumption profiles' derivation. Eight different types of consumption profiles were developed, based on the separate treatment of workdays/weekends, and based on a priori knowledge of the temperature dependent portion of the gas consumption. Furthermore, a method was developed which enables gas providers to allocate preliminary gas consumption among consumers.

The developed profiles were tested and validated on the gas consumption and temperature measurements data in a four year period. The most accurate results were obtained when using the profile which uses information on the temperature independent portion of the consumption, and when weekends and workdays are treated separately. As anticipated, the developed gas consumption forecasting leads to accurate results when used on a sufficiently large number of consumers. Since the use of all consumers' profiles produced similar accuracy of the predictions as using the profiles for individual groups of consumers, a recommendation can be given that, when the number of consumers in a certain Consumer Group is not sufficient for statistically reliable results, the usage of the averaged profile is recommended. Even though the knowledge of the temperature independent part of the consumption yield better estimates of the gas consumption, its use should be avoided when the data on temperature independent gas consumption is not known reliably.

The preliminary allocation method developed in this paper is applicable worldwide. Since Slovenia has a very diverse climate, and since measurement were taken all around the country, the models published in the Appendix may be employed as a first approximation in other regions as well. When a 4-year span of gas consumption measurement is available for a certain region, the preliminary allocation method and the model development, presented in this paper, can be used to prepare a dedicated preliminary allocation strategy for a given region.


## Acknowledgements

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## Appendix. Values of model constants

**Table 2**
Model constants for gas consumers for which the temperature independent part of the consumption is not known and the consumer group is known. Model constant are shown for workdays and weekends.

| CG | *A* | *B* | *C* | *D* |
|---|---|---|---|---|
| workdays | | | | |
| A | 2.797662121 | −38.24962866 | 4.505060696 | 0.1045862894E-01 |
| C | 2.290237548 | −35.54801194 | 5.418553819 | 0.1144397072 |
| F | 2.051814347 | −39.57611862 | 9.629336345 | 0.4455177847 |
| G | 3.664103285 | −42.71567369 | 4.580427091 | 0.3526982928E-01 |
| H | 2.612077544 | −36.65626061 | 5.845160781 | 0.5605792755E-01 |
| I | 2.008469717 | −35.71425854 | 7.059833825 | 0.3382810258 |
| J | 2.644637222 | −36.72444718 | 4.213866757 | −0.1644022043 |
| K | 2.423635417 | −37.01550427 | 5.499923050 | 0.1279426654 |
| O | 4.175551021 | −48.45465280 | 3.811653925 | 0.1829635148 |
| P | 2.925388740 | −39.63687302 | 4.912728179 | 0.1301499672 |
| Q | 2.812187747 | −37.80007356 | 4.682350393 | 0.1246898485 |
| R | 3.008399667 | −38.69689550 | 4.815927442 | 0.8298815399E-01 |
| S | 2.361808877 | −34.65784705 | 6.421446681 | 0.9432060294E-01 |
| W | 2.272966041 | −33.88938227 | 6.668914307 | 0.1479208016 |
| Zx | 2.699474732 | −37.81317242 | 5.722124803 | 0.1927017108 |
| HEA | 3.659508835 | −45.74863788 | 3.816625682 | −0.5583642253E-01 |
| weekends | | | | |
| A | 2.869851781 | −39.17742432 | 4.438008632 | 0.3543419633E-01 |
| C | 3.707181321 | −47.79404135 | 4.206468327 | 0.1266689639 |
| F | 1.343753647 | −38.48568462 | 12.30978518 | 0.3701725487 |
| G | 4.757786435 | −48.68465977 | 3.820053085 | −0.4813105520E-01 |
| H | 3.019844968 | −40.26813674 | 5.024342518 | 0.3349812007E-01 |
| I | 1.971430302 | −35.51839160 | 7.307392273 | 0.3361228149 |
| J | 2.980688355 | −39.99604175 | 3.793043982 | −0.1536884454 |
| K | 2.837958451 | −40.08894586 | 4.368162014 | 0.6057728561E-01 |
| O | 4.507854032 | −52.82681602 | 4.033255733 | 0.2644000136 |
| P | 2.564417888 | −39.87974740 | 5.268750863 | 0.1433415237 |
| Q | 2.808886719 | −38.09131994 | 4.744539368 | 0.1256552603 |
| R | 3.428670178 | −40.94848931 | 4.436268283 | 0.6910469370E-01 |
| S | 2.236630967 | −35.70078584 | 6.094857438 | 0.1037380508 |
| W | 2.466661467 | −34.30474504 | 6.242718753 | 0.1345745024 |
| Zx | 3.346144249 | −40.93206201 | 4.999775325 | 0.1767613074 |
| HEA | 8.275196589 | −71.50339408 | 2.730103727 | −0.1626721227 |

**Table 3**
Model constant for gas consumers for which the temperature independent part of the consumption is not known and the consumer group is known. Model constant are for all days of the week.

| CG | *A* | *B* | *C* | *D* |
|---|---|---|---|---|
| all days | | | | |
| A | 2.817655100 | −38.51097068 | 4.484561557 | 0.1755472659E-01 |
| C | 2.541605297 | −38.07759219 | 4.864008888 | 0.1084081827 |
| F | 1.895293833 | −39.59187866 | 10.25905647 | 0.4319338099 |
| G | 3.894241227 | −43.99427654 | 4.372662003 | 0.1395732935E-01 |
| H | 2.693756733 | −37.48128807 | 5.624553075 | 0.5130747762E-01 |
| I | 1.999370756 | −35.66633049 | 7.123878203 | 0.3376091369 |
| J | 2.728515665 | −37.56567940 | 4.086045102 | −0.1609271926 |
| K | 2.505546484 | −37.62998396 | 5.200211127 | 0.1116260365 |
| O | 4.370662652 | −50.23406085 | 3.838470476 | 0.2069612404 |
| P | 2.900182045 | −40.11365910 | 4.930399321 | 0.1324826762 |
| Q | 2.817307427 | −37.91884005 | 4.693703095 | 0.1248122210 |
| R | 3.100196806 | −39.20567817 | 4.718827452 | 0.7980621517E-01 |
| S | 2.349617873 | −35.06353739 | 6.266707488 | 0.9601397164E-01 |
| W | 2.314349011 | −33.94517749 | 6.577639958 | 0.1450774434 |
| Zx | 2.825833312 | −38.44908321 | 5.538440185 | 0.1893304664 |
| HEA | 3.993433742 | −48.00639731 | 3.643751180 | −0.6039593603E-01 |

**Table 4**
Model constant for gas consumers for which the temperature independent part of the consumption is not known and consumer group is also not known. Model constant are shown for workdays and weekends.

| day | *A* | *B* | *C* | *D* |
|---|---|---|---|---|
| weekends | 2.801042542 | −39.69944287 | 4.941970845 | 0.1899869845 |
| workdays | 2.430900634 | −37.19153478 | 5.614144797 | 0.2168963858 |

**Table 5**
Model constant for gas consumers for which the temperature independent part of the consumption is not known and consumer groups is also not known. Model constant are for all days of the week.

| day | *A* | *B* | *C* | *D* |
|---|---|---|---|---|
| all days | 2.516363414 | −37.79199079 | 5.424167096 | 0.2097926381 |

**Table 6**
Model constant for gas consumers for which the temperature independent part of the consumption is known and the consumer group is also known. Model constant are shown for workdays and weekends.

| CG | *A* | *B* | *C* | *D* |
|---|---|---|---|---|
| workdays | | | | |
| A | 2.902661073 | −37.36421461 | 4.234911898 | −0.1898197150 |
| C | 2.519453999 | −35.14399053 | 4.955334677 | −0.8831554064E-01 |
| F | 2.418577069 | −39.17820665 | 6.966474250 | −0.7611851803E-01 |
| G | 3.830051506 | −42.58141137 | 4.402630890 | −0.1097956369 |
| H | 2.803649027 | −36.64910850 | 5.468291388 | −0.8742413743E-01 |
| I | 2.068288073 | −35.11539972 | 6.838570872 | −0.3258564445E-01 |
| J | 2.658774803 | −36.73593124 | 4.194643086 | −0.1731702797 |
| K | 2.583993071 | −36.75462029 | 5.003084733 | −0.1005292940 |
| O | 6.400906175 | −57.98018175 | 2.769831022 | −0.2645523978 |
| P | 3.251882747 | −40.30839300 | 4.451333348 | −0.1098004477 |
| Q | 2.914418421 | −37.50625037 | 4.531415322 | −0.1221025369 |
| R | 3.138635684 | −38.55169864 | 4.602981935 | −0.1148705816 |
| S | 2.501129039 | −34.85959236 | 6.044477345 | −0.6745998083E-01 |
| W | 2.268016151 | −33.70125240 | 6.727159007 | −0.6110378412E-01 |
| Zx | 2.716219318 | −37.50708202 | 5.654223725 | −0.7493394114E-01 |
| HEA | 3.659508835 | −45.74863788 | 3.816625682 | −0.5583642253E-01 |
| weekends | | | | |
| A | 3.083245268 | −38.65307435 | 3.991477171 | −0.1934197995 |
| C | 5.064251518 | −53.57912042 | 3.375922292 | −0.1106958990 |
| F | 1.323026329 | −37.88984228 | 10.72263327 | 0.3642880088E-01 |
| G | 4.750587989 | −47.80261770 | 3.766548160 | −0.1745236258 |
| H | 3.291703554 | −40.59546695 | 4.650654201 | −0.1149214944 |
| I | 2.037914648 | −34.95385322 | 7.054650244 | −0.3642859203E-01 |
| J | 2.997784564 | −40.02663370 | 3.775420339 | −0.1623190806 |
| K | 3.019823533 | −39.73762725 | 3.944139757 | −0.1924279771 |
| O | 21.98950993 | −119.9136061 | 2.394916941 | −0.2278786669 |
| P | 2.899539334 | −40.73223105 | 4.719552851 | −0.9018026003E-01 |
| Q | 2.872169507 | −37.65766910 | 4.635999030 | −0.1140092365 |
| R | 3.565475521 | −40.86958730 | 4.253502236 | −0.1255101602 |
| S | 2.411378431 | −35.90133018 | 5.687008442 | −0.7615448428E-01 |
| W | 2.461088416 | −34.11017064 | 6.297608912 | −0.7535926786E-01 |
| Zx | 3.365342773 | −40.63964718 | 4.900019789 | −0.9487361914E-01 |
| HEA | 8.275196589 | −71.50339408 | 2.730103727 | −0.1626721227 |

**Table 7**
Model constant for gas consumers for which the temperature independent part of the consumption is known and the consumer group is also known. Model constant are for all days of the week.

| CG | *A* | *B* | *C* | *D* |
|---|---|---|---|---|
| all days | | | | |
| A | 2.950691734 | −37.70853923 | 4.164194073 | −0.1907738367 |
| C | 2.837035441 | −37.92514524 | 4.360975513 | −0.1031301831 |
| F | 2.185907678 | −39.32855651 | 7.491156037 | −0.3985900125E-01 |
| G | 4.038575005 | −43.77553668 | 4.225571128 | −0.1265567701 |
| H | 2.901142595 | −37.53182249 | 5.247133684 | −0.9344816687E-01 |
| I | 2.061190371 | −35.07672010 | 6.893117353 | −0.3382554242E-01 |
| J | 2.743141906 | −37.58071093 | 4.067673353 | −0.1696075822 |
| K | 2.676226396 | −37.37889602 | 4.717332124 | −0.1225646785 |
| O | 7.876570152 | −66.39090333 | 2.653895722 | −0.2538320343 |
| P | 3.246899222 | −40.91952369 | 4.449124122 | −0.1064646040 |
| Q | 2.910084178 | −37.59325728 | 4.552951691 | −0.1200301512 |
| R | 3.231527450 | −39.07526856 | 4.513887959 | −0.1171139411 |
| S | 2.502329856 | −35.27840313 | 5.881063629 | −0.7128292102E-01 |
| W | 2.309869243 | −33.75773384 | 6.633448103 | −0.6431415401E-01 |
| Zx | 2.844138010 | −38.14629066 | 5.459306373 | −0.7937059158E-01 |
| HEA | 3.993433742 | −48.00639731 | 3.643751180 | −0.6039593603E-01 |

**Table 8**
Model constant for gas consumers for which the temperature independent part of the consumption is known and the consumer group is not known. Model constant are shown for workdays and weekends.

| day | $A$ | $B$ | $C$ | $D$ |
|---|---|---|---|---|
| workdays | 2.535858418 | −36.61568014 | 5.393126978 | −0.8145854682E-01 |
| weekends | 2.873157235 | −38.89400882 | 4.773060939 | −0.1076673249 |

**Table 9**
Model constant for gas consumers for which the temperature independent part of the consumption is known and the consumer group is not known. Model constant are for all days of the week.

| day | $A$ | $B$ | $C$ | $D$ |
|---|---|---|---|---|
| all days | 2.617690720 | −37.17940604 | 5.212215141 | −0.8866374719E-01 |

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