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Practical results of forecasting for the natural gas market

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1. Introduction

The need for natural gas consumption forecasting is rooted in the requirements to balance the supply and consumption of natural gas. For daily operation of natural gas suppliers and distributors, short-term forecasting with the forecasting horizon of several days is required. Forecasting resolution is required on daily and also on hourly basis. Since the natural gas market is very dynamic, many factors influence the consumption and consequently, the natural gas demand forecasting becomes very challenging. The restrictive economic policies that drastically penalize the forecasting errors only increase the forecasting challenge.

Various approaches to energy consumption forecasting have been investigated in the literature. Forecasting methods include time series and regression methods (Ediger et al., 2006; Ediger & Akar, 2007), nonlinear regression (Vondráček et al., 2008), expert systems (Smith et al., 1996; Chandrashekara et al., 1999; Petridis et al., 2001; Tzafestas & Tzafestas, 2001), stochastic models (Hubele & Cheng, 1990, Vajk & Hetthéssy, 2005), artificial neural networks (Mihalakakou et al., 2002; Beccali et al., 2004; Gonzalez & Zamarreno, 2005; Karatasou et al., 2006; Hamzaçebi, 2007), wavelets (Benaouda, 2006) and support vector machines (Pai & Hong, 2005a; Pai & Hong, 2005b).

Based on our experience, the forecasting solution can be considerably improved by incorporating the proper influential variables into the solution, and by properly understanding the underlying principles of energy consumption. Consequently, the forecasting approach was developed based on the understanding the underlying natural gas consumption cycles (Potočnik et al., 2007a) and the forecasting system for the Slovenia energy market was developed (Potočnik et al., 2005; Potočnik et al., 2007b; Potočnik et al., 2008). The proposed forecasting approach was embedded into stand-alone forecasting applications for various companies and natural gas distributors in Slovenia. This chapter presents an overview of practical results for a larger gas distributing company, obtained during the last three years of online operation. The forecasting requirements for the Slovenia natural gas market are explained in section 2, section 3 presents data for the case study, development and validation of the model are presented in section 4, section 5 is devoted to the presentation and discussion of practical forecasting results, obtained through the several years of operation, and the last section 6 draws some conclusions.

2. Forecasting requirements

The forecasting requirements that motivate the forecasting efforts of energy distribution companies vary from country to country and are also subject to modifications according to the legislation. Slovenia's economic incentive model is briefly described in this section. Currently, companies in Slovenia are motivated to accurately forecast their daily gas consumption for the next "gas consumption" day. Slovenia's gas consumption day is defined as the period from 8.00 AM until 8.00 AM the following day. The forecast should be delivered approx. at 9.00 AM for the gas consumption day starting tomorrow, therefore the forecasting horizon is H = 2 days. Currently, the incentive model only refers to forecasting on daily resolution, therefore hourly forecasting is only required by the company for online optimization of their resources and operation strategies. Both, daily and hourly forecasting results are considered in this chapter. Daily forecasting requirements are shown in Fig. 1, and expanded hourly forecasting requirements are plotted in Fig. 2.

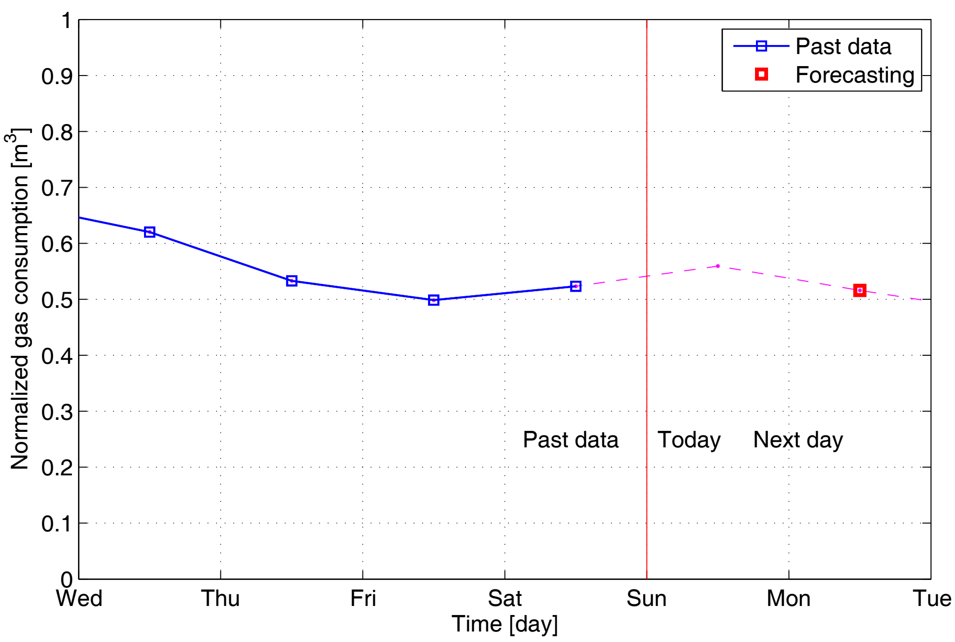


Fig. 1. Forecasting requirements for Slovenia's gas market on daily resolution.

The economic incentive model in Slovenia currently regulates the transfer of savings based on daily forecasting results. Daily natural gas consumption forecast y_F with the forecasting horizon H = 2 days is compared with actual (measured) gas consumption y_M, and the forecasting error E is expressed through a percentage of the maximum transport capacity (MTC) of the distribution system:

$$E = 100(y_F - y_M)/MTC \quad [\%] \tag{1}$$

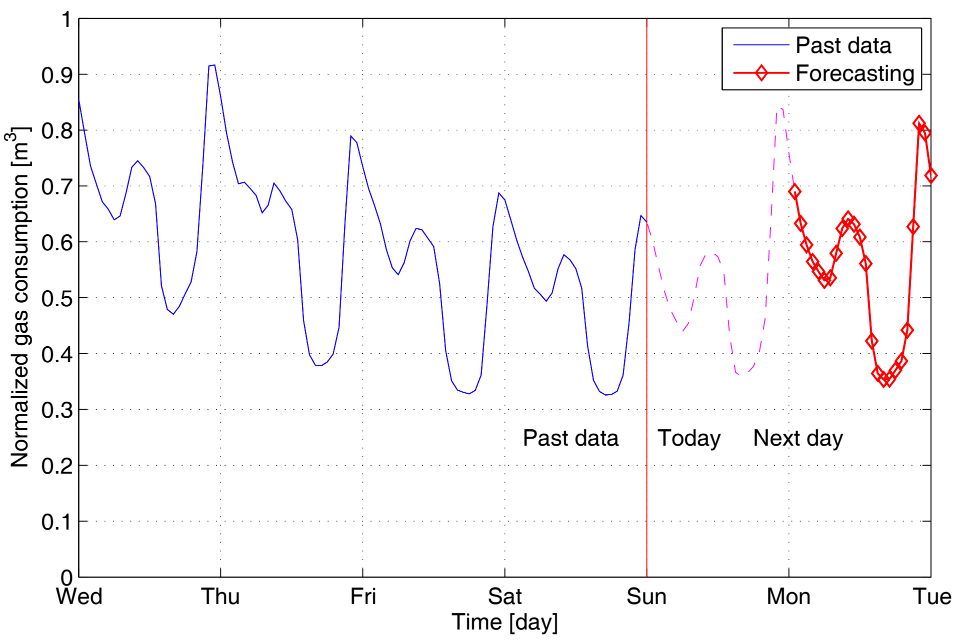


Fig. 2. Forecasting requirements for Slovenia's gas market on hourly resolution.

Two error levels are particularly important for the economic evaluation of the forecasting model:

E3: defining the relative forecasting error *E* = 3% MTC
E8: defining the relative forecasting error *E* = 8% MTC

The economic incentive model is schematically shown in Fig. 3 and is defined by the following rules:

E < *E3* :	distributor receives a positive daily profit,
E > *E3* and *E* < *E8* :	daily profit is 0,
E > *E8* :	daily profit is negative.

For negative errors (forecasted consumption less than actual) of more than *E8*, the negative daily profit increases more rapidly than for positive errors of more than *E8*. Absolute values of daily profits depend linearly on the size of the distribution system (defined by MTC value). In addition to the economic evaluation relative to the *E3* and *E8* levels, distributors that decide to forecast their gas consumption also obtain an extra stimulation directly proportional to the daily gas consumption. This is an important measure that further encourages distributors to take the risk of natural gas consumption forecasting.

For the case study considered in this chapter, the customer's forecasting requirements were defined as follows:

1. forecasting is required only during the winter season, since consumption during the summer season is quite simple,
2. forecasting is required both in daily, and in hourly resolution.

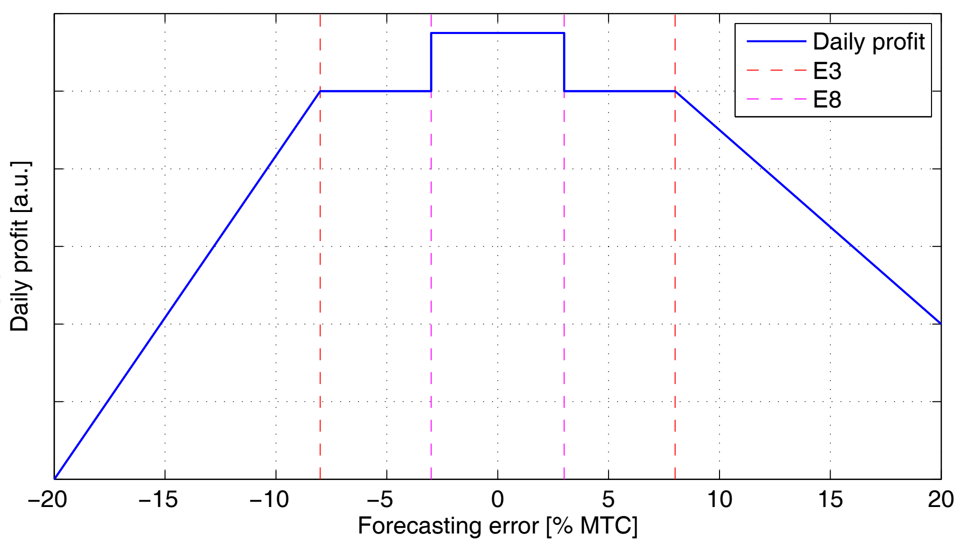


Fig. 3. Economic incentive model for natural gas consumption forecasting

According to the confidentiality policy of the company, its identity and the absolute values of the natural gas consumption data should not be revealed. Consequently, relative gas consumption data, normalized to the maximum transfer capacity (MTC) of the distribution system, are considered throughout this chapter.

3. Data

The initial forecasting model was developed based on natural gas consumption data, as shown in Fig. 4. Only data for incomplete two winter seasons were available. The consumption data are shown in relative units, expressed as a percentage of MTC. Fig. 4. shows daily gas consumption data, and Fig. 5. shows the 2007 portion of the data in hourly resolution. The hourly data exhibit wild fluctuations, therefore the zoom of the hourly natural gas consumption data is displayed in Fig. 6 for the period of three weeks of March 2007.

Beside the past consumption data, various meteorological data and past weather forecasts were also available. Based on the expert knowledge, it was known that the outside temperature heavily influences the natural gas consumption, therefore the temperature data were collected as the most important influential inputs. But when forecasting for the future, weather data are not available and the forecasting model must rely on the weather forecast. For the geographical region of Slovenia, the ALADIN weather model is applied daily by the The Environmental Agency of the Republic of Slovenia (ARSO). The model provides daily forecasts of the most important meteorological parameters, including the temperature, for the forecasting horizons up to 72 hours which suffices for the short-term natural gas consumption forecasting requirements.

Fig. 7 shows comparison of measured temperature and ALADIN weather forecast. Forecasting horizons are defined according to the requirements for the natural gas forecasting. Discrepancy (E_T) between measured and forecasted temperatures on daily basis for the winter season 2008-2009 are as follows: mean(E_T) = -0.93 ^{o}C, std(E_T) = 1.68 ^{o}C. Fig. 7

also reveals several data errors both on measured temperature as well on the temperature forecast. Such obvious outliers can be easily detected and removed but more subtle errors are much more difficult to detect by automated signal processing methods.

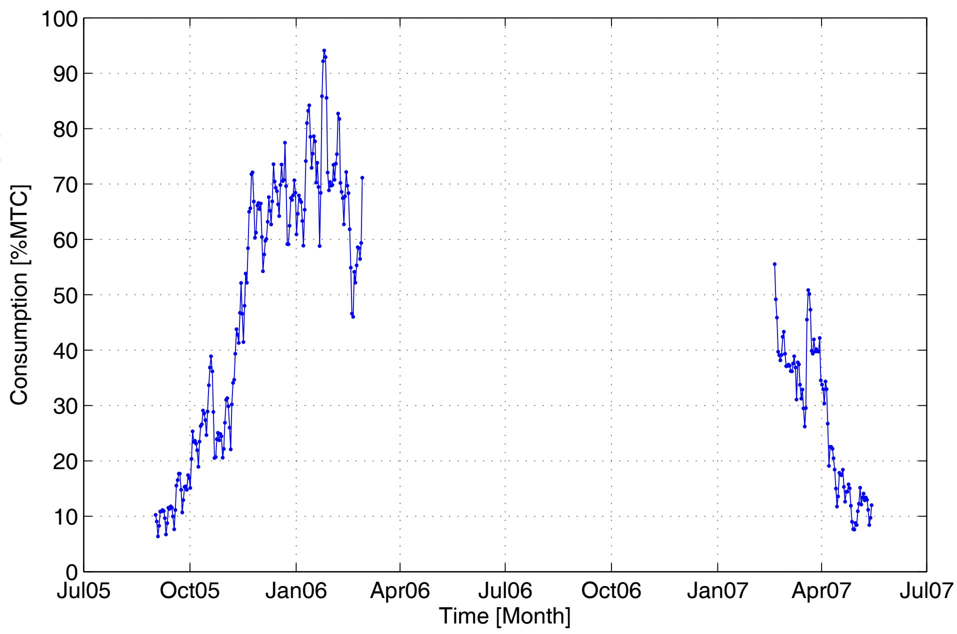


Fig. 4. Daily past natural gas consumption data, available for the development of the model

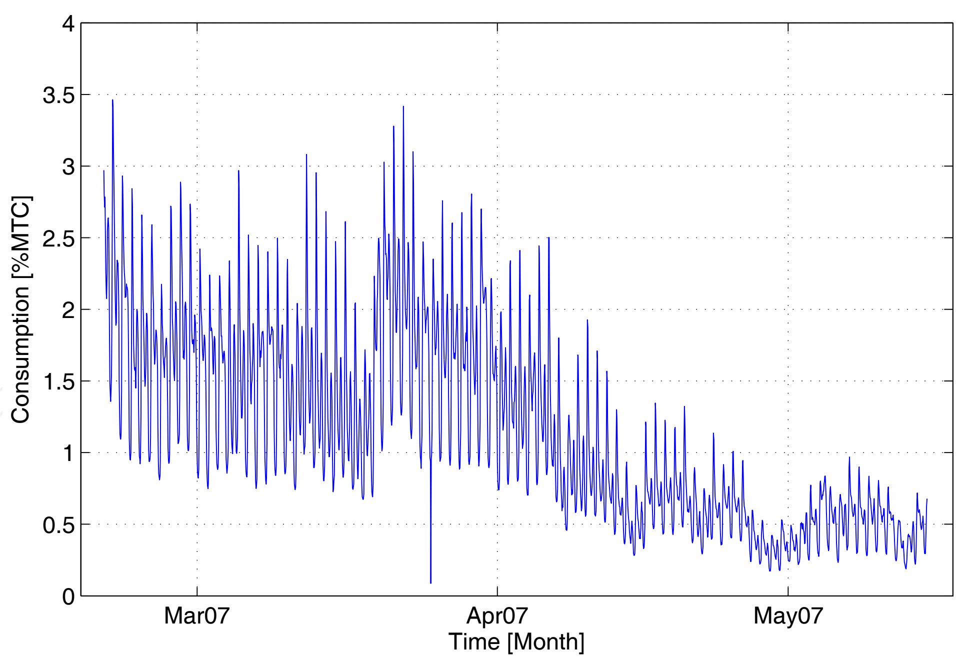


Fig. 5. Hourly past natural gas consumption data for the 2007 period

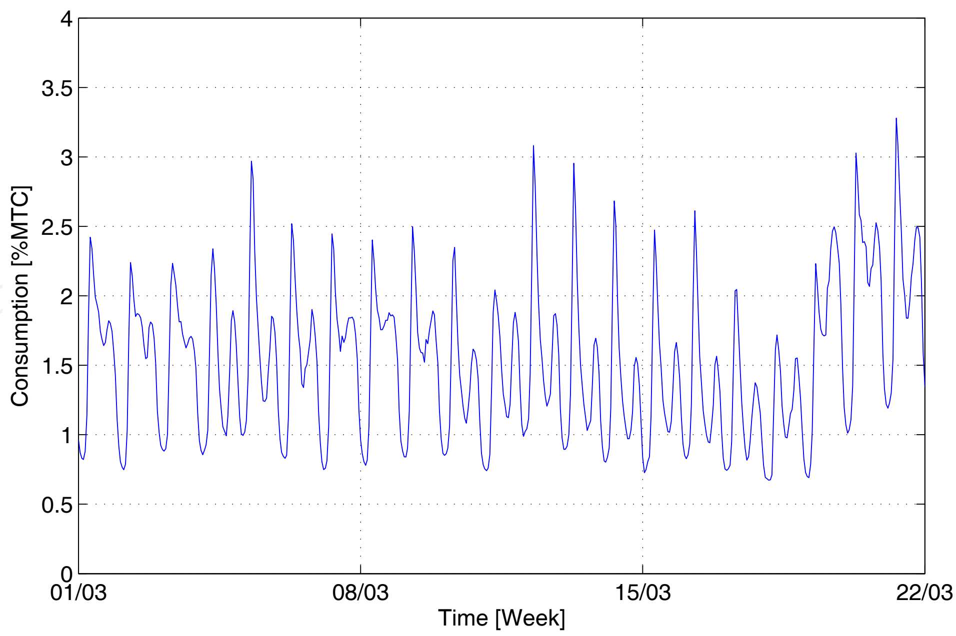


Fig. 6. Hourly past natural gas consumption data for March 2007

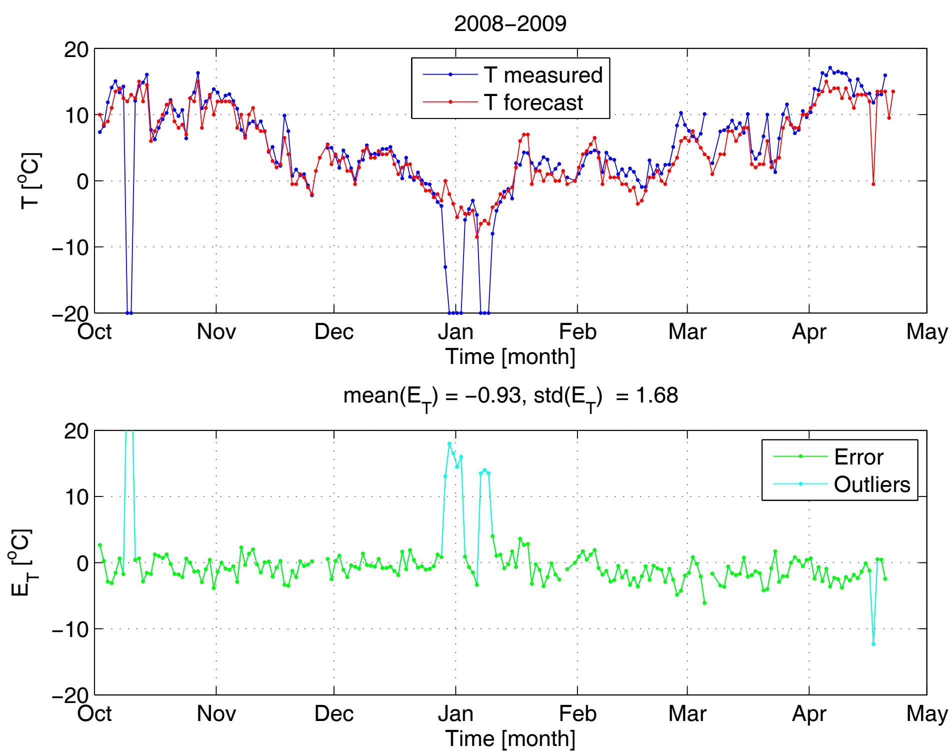


Fig. 7. Comparison of measured temperature and ALADIN weather forecast

4. Model formation and validation

The natural gas consumption data exhibit complex dynamics both on daily, and even more on hourly scale. Therefore it is advantageous to decompose the forecasting task into subdomains (daily and hourly resolution) and construct the forecasting models separately for daily and for hourly forecasting. This results in decreased complexity of the forecasting submodels compared to the single forecasting model (Potočnik et al., 2008). The proposed approach comprises a daily forecaster and a series of hourly forecasters, each for the particular hour of the day. The output of the daily forecaster is a single forecast for the next gas consumption day. The outputs of hourly forecasters are relative hourly consumptions (hourly profiles) that can be combined with a daily forecast to obtain absolute values of natural gas consumption forecast in hourly resolution. The distributed forecasting approach is schematically shown in Fig. 8.

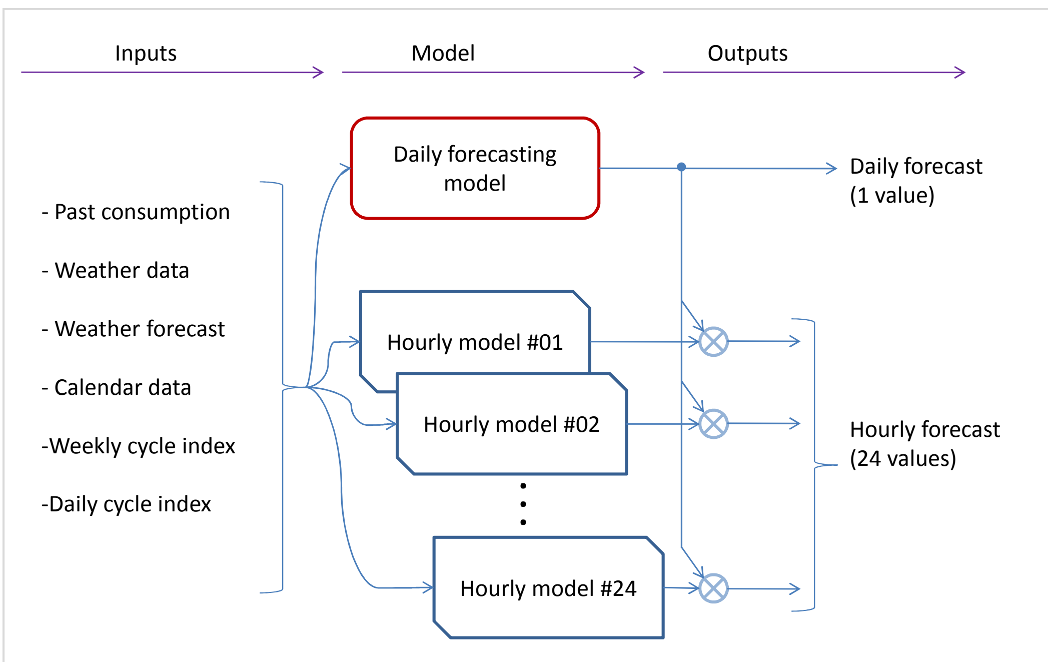


Fig. 8. Complete forecasting solution for combined daily and hourly forecasting

The absolute natural gas consumption values are only forecast by the daily model. The task for the hourly models is simplified by substituting the absolute requirement by the relative one, therefore hourly models are designed to provide normalized daily profiles which are then multiplicatively combined with the daily forecast to obtain final absolute gas consumption forecasts in hourly resolution. The development of daily and hourly submodels are described in the following subsections.

4.1 Development of a daily forecasting model

Natural gas consumption during the winter season is highly correlated with the outside temperature, since the major natural gas consumption in cities is governed by the heating patterns of a residential and business part of the population. The correlation with the temperature can be captured by an ordinary linear regression.

Some portions of the consumption depend nonlinearly on the activity pattern of the population and consequently, nonlinear modelling structures should be applied for proper modelling of the consumption. An interesting solution to avoid nonlinear modelling is to extract features that capture the nonlinear relationships and therefore enable further simplification of the modelling procedure. As proposed in (Potočnik et al., 2007a), natural gas consumption cycles can be efficiently calculated from the available data and offer powerful solution to feature extraction of nonlinear patterns of calendar-based consumption activity.

For the application in a daily forecasting model, a weekly gas consumption index (*WGCI*) was calculated in order to obtain a typical consumption pattern through the days of the week. The weekly cycle is mainly governed by the proportions of residential, business and industrial consumption. It can be calculated through the normalisation of daily consumption data $y(t)$ by the mean of the current week (starting at the current day minus three days, and ending at the current day plus three days):

$$WGCI(d) = \frac{1}{N_W} \sum_{n=1}^{N_W} \frac{y(d+7n)}{\frac{1}{7}\sum_{k=-3}^{3} y(d+7n+k)}, \quad d = 1,2,\ldots,7 \tag{2}$$

Weekly gas consumption index is calculated from daily data for each day of the week (d=1, Monday; d=2, Tuesday; ...; d=7, Sunday) by averaging through the number of available weeks N_W. When the weekly-normalised daily consumption data are collected for each day of the week, a weekly cycle with confidence intervals can be obtained, as shown in Fig. 9.

Characteristically lower consumption can be observed on Friday, Saturday and Sunday. The variations of *WGCI* within each day of the week are small enough compared to the variation of *WGCI* across the week, therefore a complete weekly cycle represents an important nonlinear feature that can be helpful in building the daily forecasting model. WGCI can be included into the forecasting model as an input either directly:

$$WGCI(t+H), \tag{3}$$

or indirectly by weighting the last measured daily gas consumption $y_M(t)$ by the ratio of weekly gas consumption cycle for the forecast day $WGCI(t+H)$ and the current day $WGCI(t)$:

$$\frac{WGCI(t+H)\, y_M(t)}{WGCI(t)}. \tag{4}$$

H denotes the forecasting horizon (H=2) and t the current day (the last day with available measured data). Both possible regressors are defined by Eq. (3-4) with respect to the day $t+H$ for which the forecast should be given.

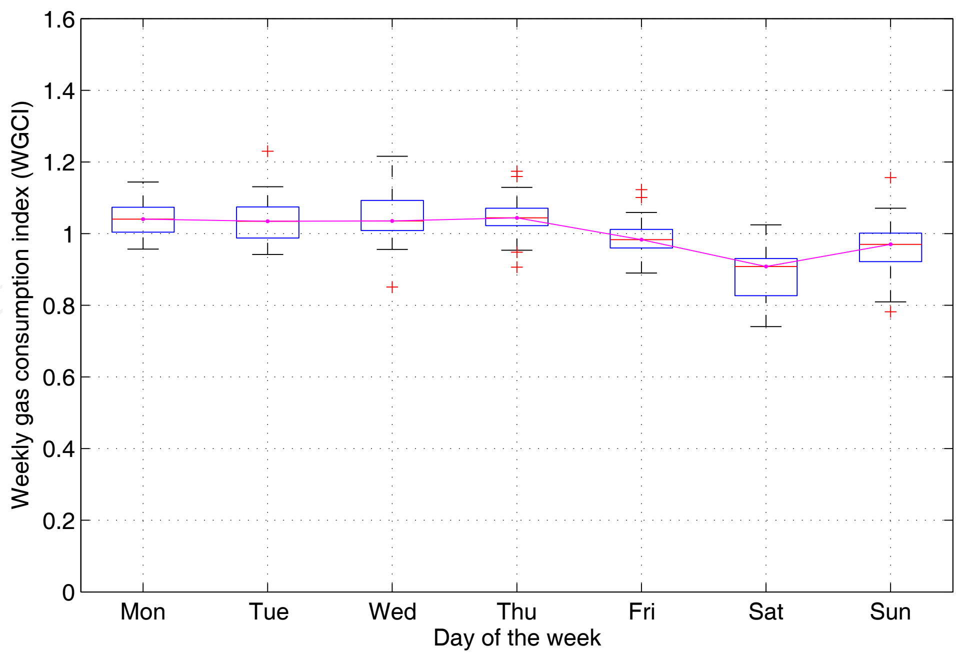


Fig. 9. Weekly gas consumption index (*WGCI*)

Population activity that depends on calendar data, such as holidays, can also be expressed through *WGCI* indexes where the preliminary study should be performed to obtain the appropriate clusters of similar days. For example: holidays can be encoded as Sundays, the day after holiday as Monday, etc.

The other possible regressors for the forecasting model include:

- past natural gas consumption $y_M(t)$, $y_M(t\text{-}1)$, ...,
- past weather data, such as temperatures $T_M(t)$, $T_M(t\text{-}1)$, ...,
- weather forecasts, such as temperature forecasts $T_F(t+H)$, $T_F(t+H\text{-}1)$, ...

The regressors can be specified on various resolution scales, e.g. hourly or daily resolution, therefore the list of possible regressors can grow very large.

Consequently, an optimization approach should be applied to select the most informative subset of regressors that yield the best model structure. We constructed the forecasting model as a liner combination of possible regressors, and the best subset of regressors was determined through the stepwise regression procedure. The final version of the daily forecasting model that was a result of the feature selection optimization based on the available data was defined in the following form:

$$
\begin{aligned}
y_F(t+H) = \quad & a_0 + a_1 WGCI(t+H) + \\
& + a_2 \frac{WGCI(t+H)\, y_M(t)}{WGCI(t)} + \\
& + a_3 T_F(t+12h) + a_4 T_F(t+30h) + \\
& + a_5 T_F(t+36h) + a_6 T_F(t+42h) + \\
& + a_7 T_F(t+54h),
\end{aligned}
\tag{5}
$$

Subscripts F denote the forecasted value and M the measured value. Weather forecasts such as T_F are obtained from the corresponding Environmental Agency. Both weekly gas consumption features, as defined by Eq. (3-4), were included in the forecasting model. Past weather data were surprisingly not included in the model but forecasted temperatures T_F were included on the hourly resolution, as specified by the forecasting horizons $T_F(t+12h)$, ..., $T_F(t+54h)$.

Daily forecasting model, optimized by the stepwise regression procedure as described above, was tested on available past data. The results on past data are shown in Fig. 10. Note that past weather forecasts and not past weather data were used in order to estimate the industrial applicability of the model. In order to compare various forecasting results, we express the forecasting error of the model with the mean absolute error (*MAE*):

$$
MAE = \frac{100}{MTC} \frac{1}{N} \sum_{t=1}^{N} \left| y_F(t) - y_M(t) \right| \quad [\%] \tag{6}
$$

For the training results, shown in Fig. 10, the forecasting error amounts to <u>*MAE* = 2.4 %</u>. This result is very good from the practical perspective and helps the company to generate extra savings due to forecasting accuracy. Taking into consideration various unknown uncertainties and unknown future natural gas consumption network dynamics, the estimate about the future online performance was proposed as $MAE \approx 3$ %.

For better alignment with online forecasting conditions, the complete model formation procedure was accomplished on past weather forecasts and not on past measured data. However, by using the past measured weather data, the model's forecasting capacity can be estimated. If past weather data and not past weather forecasts were applied to the natural gas consumption forecasting model (Eq. 5), the forecasting error of *MAE* = 1.5 % is obtained. This shows high forecasting capacity of the proposed model but is of little help for online application due to the fact that weather data for the future are not available.

The final step in preparing the forecasting model for online application was fine-tuning of model parameters according to the policy that favours higher forecasting accuracy toward the newest data. This is specially important when several years of available data exist. Usually the oldest data are less relevant but still useful for the construction of the forecasting model.

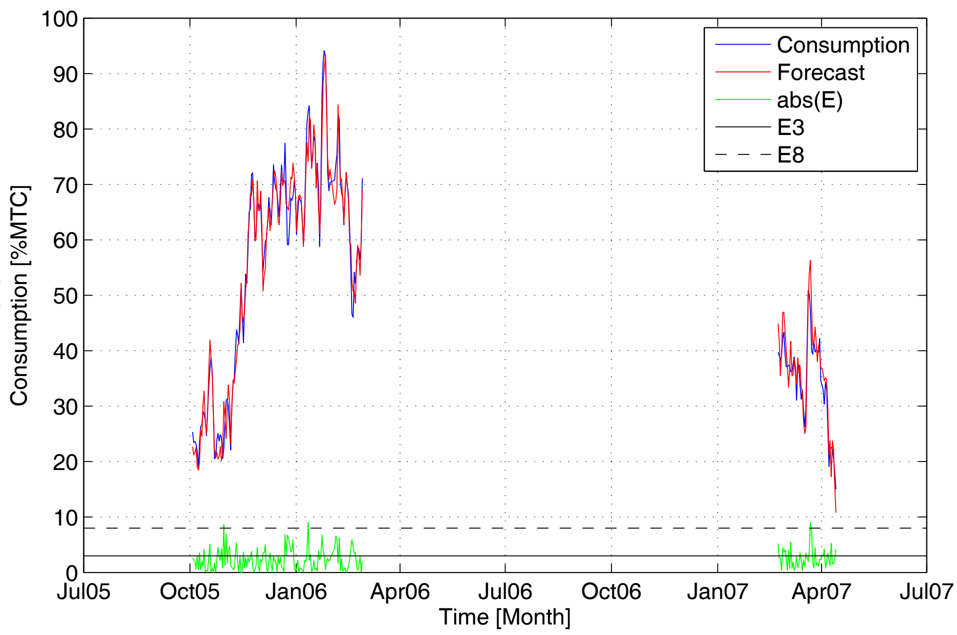


Fig. 10. Daily forecasting model applied on past training data

We propose the following fine-tuning strategy that can be realised through the following two steps:

1. Amplification of the error function, as obtained by the basic forecasting model, according to the desired amplification function (linear, quadratic, sigmoid, ...).
2. Numerical optimization of the basic forecasting model in order to minimize the amplified error function.

By using any of the amplified error functions, as shown in Fig. 11, the original error function is transformed into an amplified error function. The second step is then to numerically optimize model parameters to minimize the transformed error function.

We applied the linear error function that linearly increases the importance of newer data and obtained the fine-tuned forecasting error *MAE* = 2.6 %. This error is higher compared to the basic model (2.4 %) but the optimized model is expected to be more relevant for online application on new data. Fig. 12 shows the comparison of initial and optimized model parameters for the daily model (Eq. 5) according to the fine-tuning strategy.

By performing the described steps, the daily model is prepared for online application. An online application of the daily model should be supported by periodical model updates based on newest data, followed by fine-tuning as described above.

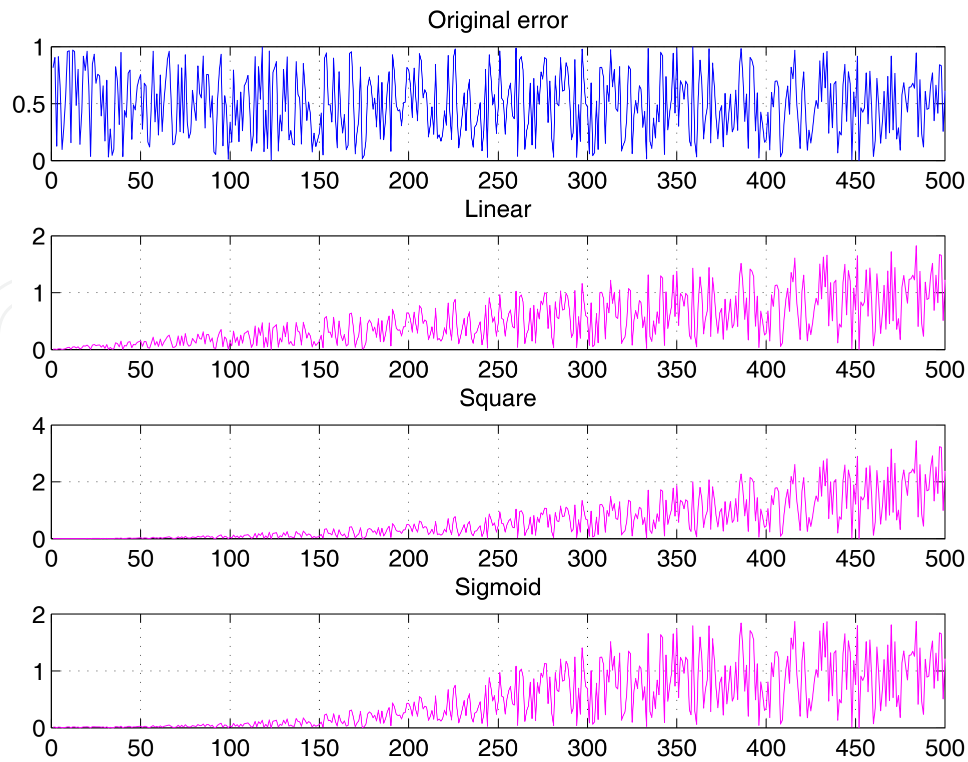


Fig. 11. Examples of amplified error functions for model fine-tuning

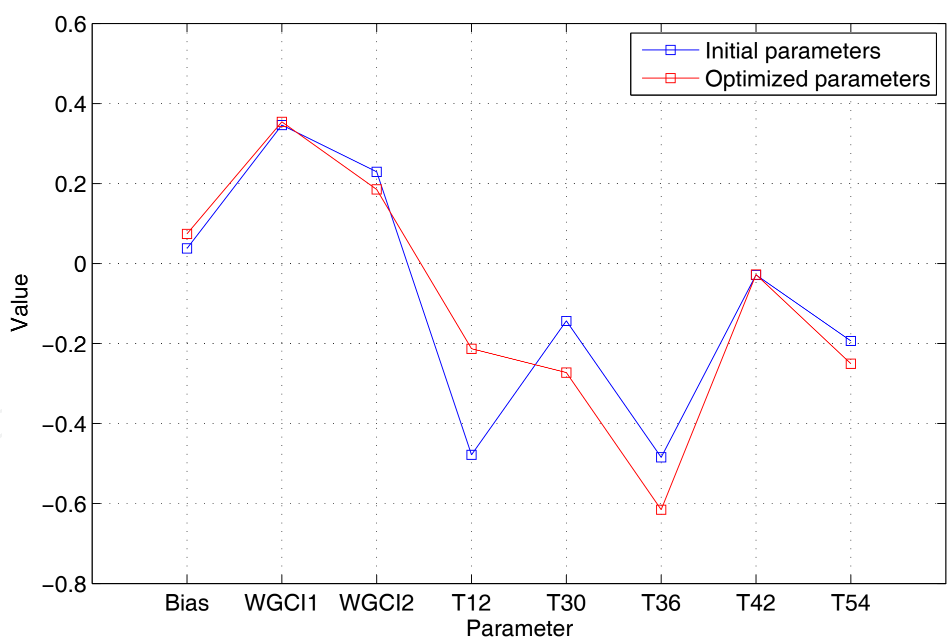


Fig. 12. Initial model parameters and optimized model parameters

4.2 Model formation for hourly forecasting

In this section, the development of an hourly forecasting model is described. The hourly model is designed to forecast the relative hourly profile and this information is then multiplicatively combined with daily forecast as shown in Fig. 8 to obtain final forecasting solution for combined daily and hourly forecasting.

In accordance with the daily model strategy, where a weekly gas consumption index (*WGCI*) was calculated in order to obtain a typical consumption pattern through the days of the week, we derive a similar feature for the hourly model. A daily gas consumption index (*DGCI*) describes a typical consumption pattern through the hours of the day and can be calculated by normalisation of hourly consumption data by the mean of hourly consumption for the current day:

$$DGCI(h) = \frac{1}{N}\sum_{n=1}^{N}\frac{y(h+24n)}{\frac{1}{24}\sum_{k=-12}^{11} y(h+24n+k)}, \quad h = 1,2,\ldots,24 \qquad (7)$$

Daily gas consumption index is calculated from hourly data for each hour of the day (h=1, 2, …, 24) by averaging through the number of available data days *N*. When the daily-normalised hourly consumption data are collected for each hour of the day, a daily cycle with confidence intervals can be obtained, as shown in Fig. 13. Morning and evening consumption peaks, as well as the low-consumption night period, can easily be observed.

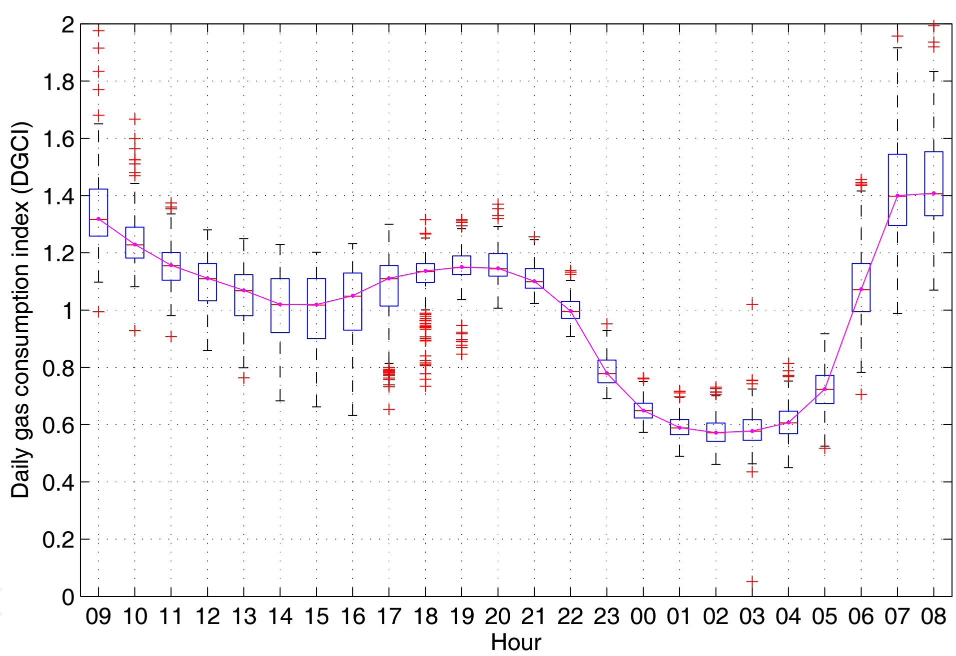


Fig. 13. Daily gas consumption index (*DGCI*)

Daily gas consumption index can be further specialized for particular days of the week by applying the basic equation (Eq. 7) to particular days or groups of the days only, as shown in Fig. 14. If daily cycles are similar enough across various days of the week, it is not necessary to specialize the *DGCI* for particular days of the week and a basic equation (Eq. 7) can be utilized. Daily gas consumption index represents an important nonlinear feature that facilitates the construction of a simplified hourly model which is linear in the parameters.

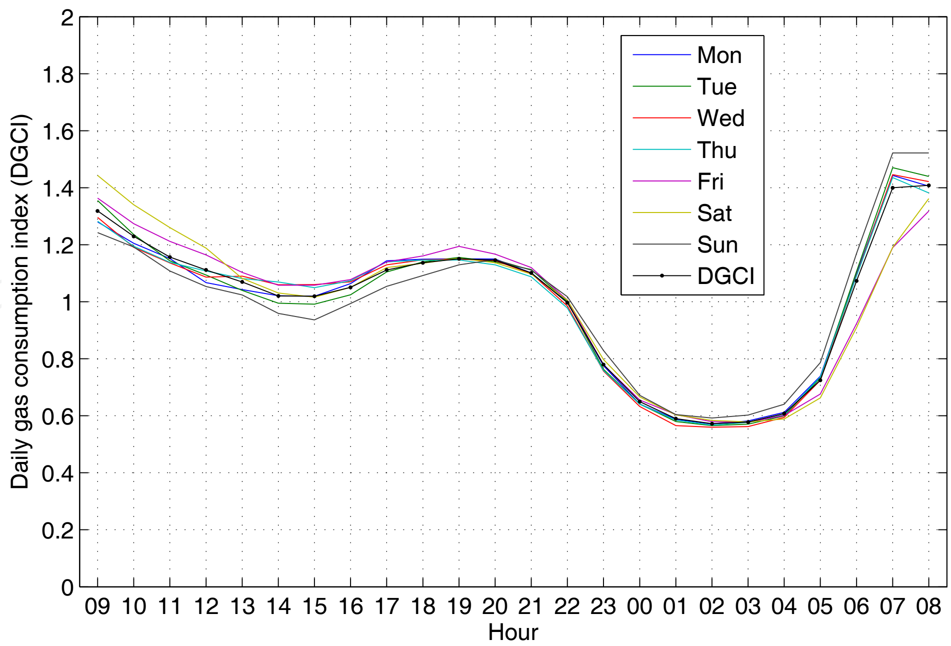


Fig. 14. Daily gas consumption index for particular days of the week

Hourly model can be constructed either as a single model or as a set of 24 submodels for each hour separately. In our case study, the later approach is applied in order to slightly increase the forecasting accuracy of hourly forecasting. The hourly model is composed of 24 submodels, each forecasting normalized consumption for a specific hour of the day. Inputs and parameters for each hourly submodel are optimized through a stepwise regression from a pool of a larger set of available regressors. This results in optimized model structures for each hourly submodel. The pool of possible regressors includes the variables available to the daily model and additional daily gas consumption index.

The stepwise regression procedure automatically selects the most appropriate set of relevant regressors for each hourly submodel, as shown in the following few examples denoting the hourly forecasts for the hours *hrs* = {09, 15, 21}:

Hourly model, *hrs* = 09:

$$\begin{aligned} y_F(t+hrs) = \; & b_0 + b_1 DGCI(hrs) + b_2 y_M(t-1, hrs) + \\ & + b_3 T_F(t+30h) + b_4 T_F(t+36h) + \\ & + b_5 T_F(t+42h) + b_6 T_F(t+54h) \end{aligned} \tag{8}$$

Hourly model, *hrs* =15:

$$\begin{aligned} y_F(t+hrs) = \; & b_0 + b_1 DGCI(hrs) + \\ & + b_2 T_F(t+12h) + b_3 T_F(t+30h) + \\ & + b_4 T_F(t+36h) + b_5 T_F(t+42h) + \\ & + b_6 T_F(t+48h) + b_7 T_F(t+54h) \end{aligned} \tag{9}$$

Hourly model, *hrs* =21:

$$
\begin{aligned}
y_F(t+hrs) = \quad & b_0 + b_1 y_M(t-1, hrs) + \\
& + b_2 T_F(t+12h) + b_3 T_F(t+18h) + \\
& + b_4 T_F(t+36h) + b_5 T_F(t+48h) + \\
& + b_6 T_F(t+54h)
\end{aligned}
\tag{10}
$$

Automatic selections of regressors for each hourly submodel shows that the most informative regressors include:

- *DGCI(hrs)*: daily gas consumption index for the particular (forecasted) hour,
- $y_M(t-1,hrs)$: past normalized hourly consumption for the forecasted hour,
- $T_F(t+Xh)$: temperature forecast for various forecasting horizons.

A complete hourly forecast is composed from values of all 24 hourly submodels and thus an output of an hourly model is a normalized hourly profile, specified for each hour of the day.

4.3 Complete forecasting model

The complete natural gas consumption forecast is finally obtained by a daily forecast, multiplicatively combined with an hourly normalized profile. This results in a final forecast in an hourly resolution, as shown in Fig 8. An example of a complete forecast for the training data is shown in Figures 15-16 for two weeks of January 2006 and March 2007.

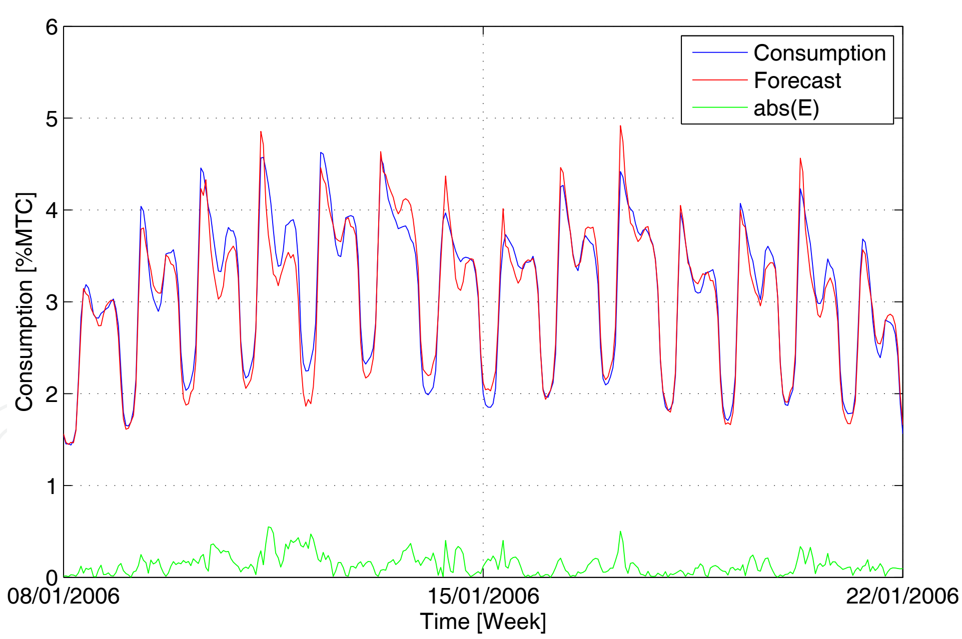


Fig. 15. Complete forecast (daily + hourly), January 2006, training data

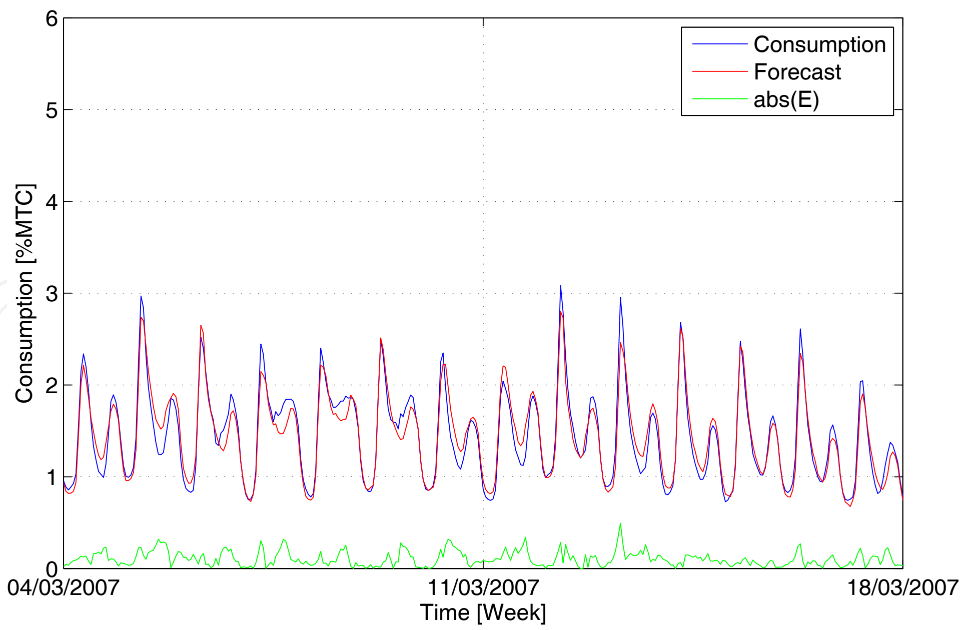


Fig. 16. Complete forecast (daily + hourly), March 2007, training data

5. Practical forecasting results

The proposed forecasting solution was installed in September 2007 and operates online since then. The system is designed as a software package composed from the data acquisition module, the forecasting module and the output module. Input data are parsed from various data sources, such as weather forecasts and autoregressive time series data. The forecasting module is responsible for data preprocessing and for daily generation of natural gas consumption forecasts. The output module provides for integration of forecasting results with the company's SCADA (supervisory control and data acquisition) system. During the last three seasons of operation (2007/2008, 2008/2009, 2009/2010), the forecasts failed few times due to system errors or missing values in input data. The forecasting results, obtained through online operation, are shown and discussed in the following sections.

5.1 Daily forecasting results

Forecasting results based on online operation of the forecasting system are shown in Fig. 17-19 for last three seasons of operation. Results are obtained in daily resolution by forecasting with the horizon H=2 days. Daily forecasting results are summarized in Table 1.

Season	Forecasting days	MAE [%MTC]	E<E3 [%]	E<E8 [%]
2007/2008	191	3.60	51	94
2008/2009	199	2.82	64	96
2009/2010	188	3.05	54	97
Totals	578	3.15	56	96

Table 1. Daily forecasting results

The average mean absolute error for all seasons amounts to $MAE = 3.15\ \%$ for a complete set of 578 forecasting days. On average, 56% of forecasting errors were below E3 margin (error < 3% MTC), and 96% of forecasting errors were below E8 margin (error < 8% MTC). The result is in accordance with the initially estimated $MAE \approx 3\ \%$. The obtained forecasting result is beneficial to the company and is therefore considered as very positive. There were several days without forecasts which is mainly due to errors in input data or missing inputs.

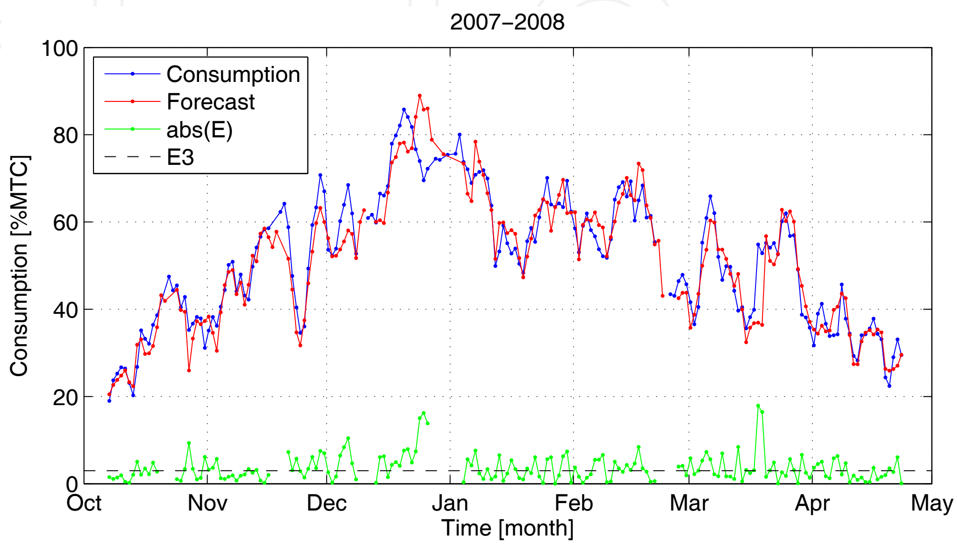


Fig. 17. Daily forecasting results for winter season 2007/2008

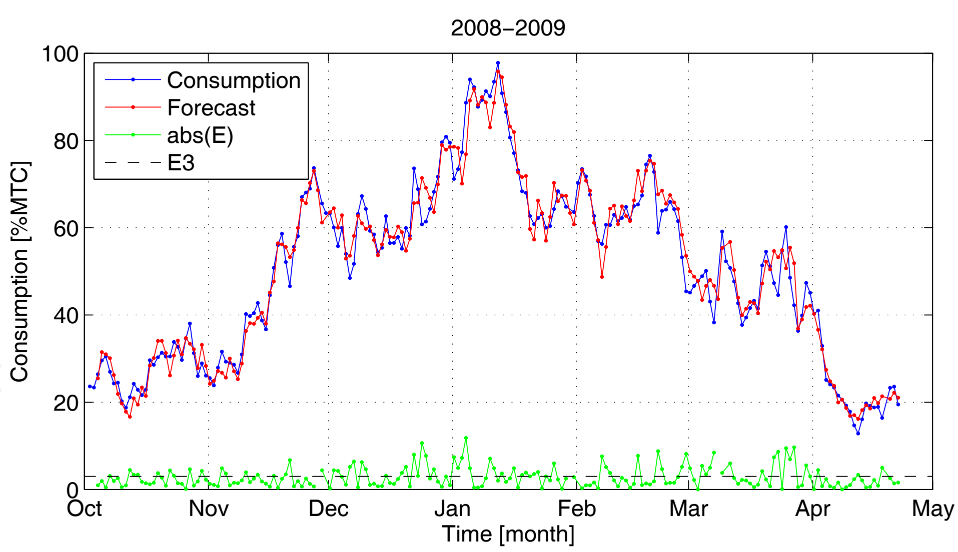


Fig. 18. Daily forecasting results for winter season 2008/2009

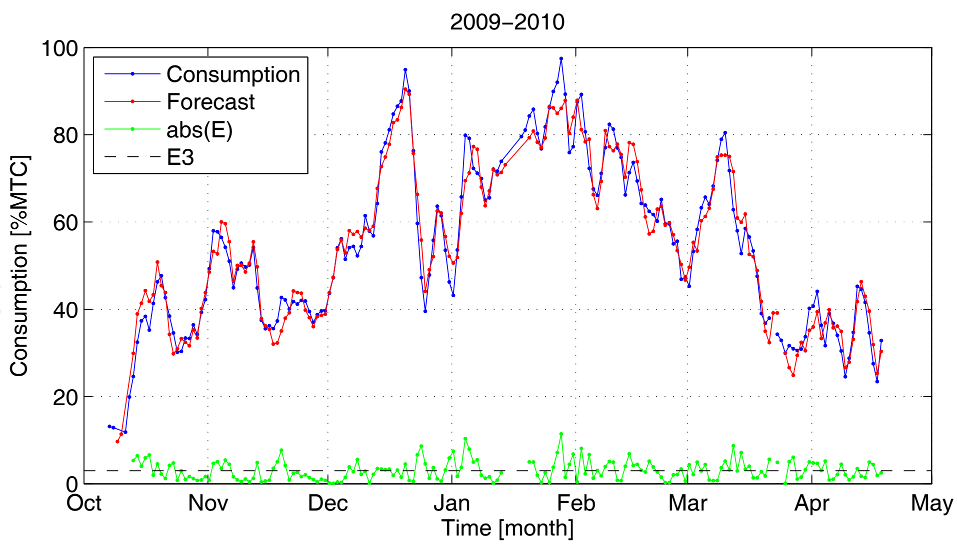


Fig. 19. Daily forecasting results for winter season 2009/2010

5.2 Hourly forecasting results

Whereas daily forecasting results are reflected directly in the cash flow due to economic incentive model, the hourly forecasting results are only utilized by the company's internal resource optimization strategies. Fig. 20-22 show several weeks of hourly forecasting for each forecasting season. Hourly forecasting results are collected in Table 2.

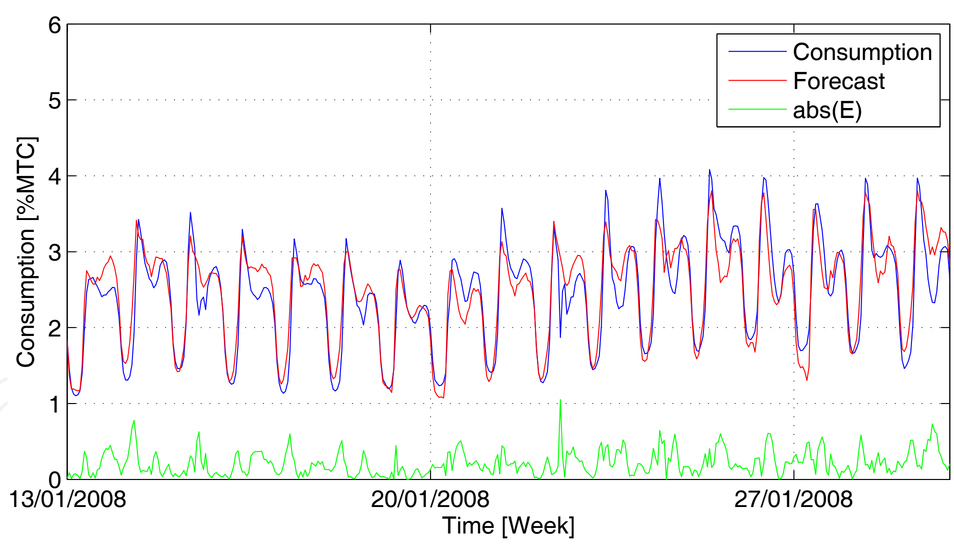


Fig. 20. Hourly forecasting results for winter season 2007/2008 (detail)

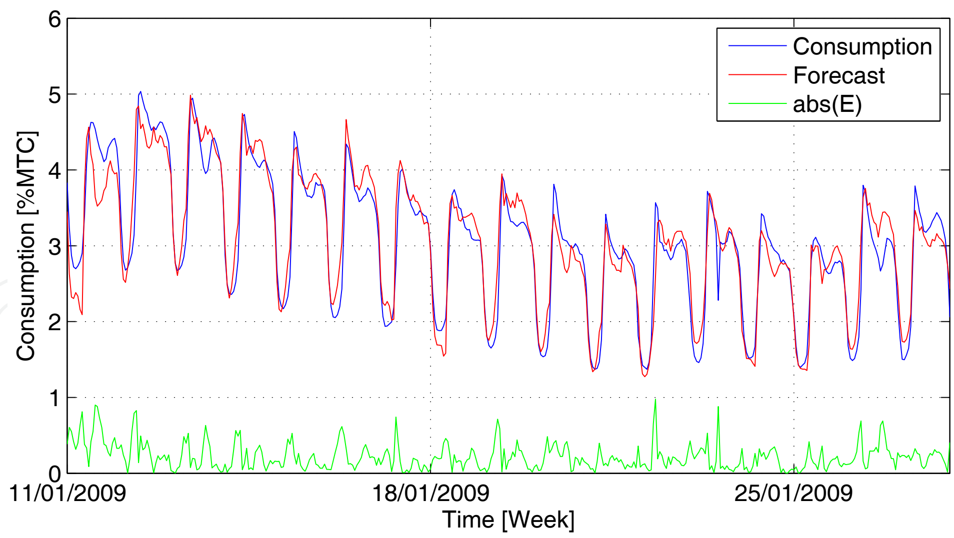


Fig. 21. Hourly forecasting results for winter season 2008/2009 (detail)

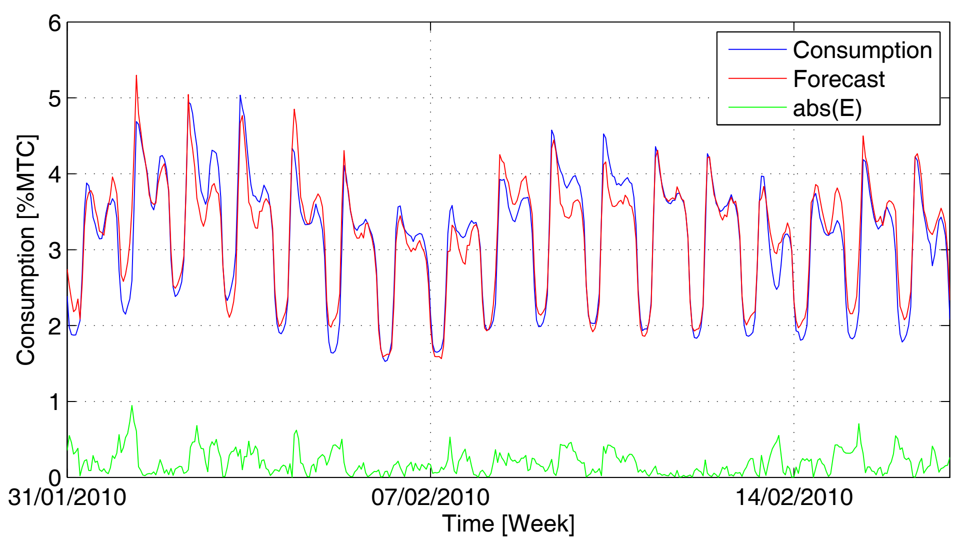


Fig. 22. Hourly forecasting results for winter season 2009/2010 (detail)

Season	Forecasting days	MAE (hourly) [%MTC]	MAE (daily sum) [%MTC]
2007/2008	191	0.24	5.85
2008/2009	199	0.20	4.69
2009/2010	188	0.17	4.05
Totals	578	0.20	4.87

Table 2. Hourly forecasting results

The third column in Table 2 shows hourly forecasting accuracy averaged per hour and expressed in percentage of MTC. The last column scales the hourly error to the daily resolution for comparison with the daily forecasting model. The average daily error amounts to 3.15% and the average hourly forecasting amounts to 4.87%. Consequently, this means that the hourly forecasting model increases the daily model error by 1.72% due to expansion of the daily forecast into hourly forecast, and this result can be interpreted as expected and appreciated. Such results are very useful to the company for planning in advance proper operating actions and optimization strategies of heating and natural gas distributing resources.

6. Conclusions

Natural gas consumption forecasting is required to balance the supply and consumption of natural gas. Companies and natural gas distributors are motivated to forecast their consumption by the economic incentive model that dictates the cash flow rules corresponding to the forecasting accuracy. The rules are quite challenging but enable the company to gain positive cash flow by forecasting accurately their short-term natural gas consumption.

In this chapter, some practical forecasting results for the Slovenia natural gas market are presented. In 2007, an online forecasting system was developed and installed for a larger gas distributing company in Slovenia (according to the confidentiality policy of the company, its identity should not be revealed). The chapter presents the development of the forecasting models for both daily and hourly forecasting and summarizes the practical forecasting results, obtained during the last three years of online operation (winter seasons 2007/2008, 2008/2009, and 2009/2010).

Average daily forecasting result, expressed over three successive forecasting winter seasons as a mean absolute error, amounts to $\underline{MAE = 3.15\ \%}$. The result is considered as very successful and confirms the applicability of such an approach. The results obtained also enable the company to gain benefits according to the economic incentive model. Based on the presented case study, some practical conclusions can be drawn:

- An initial small data set of two incomplete winter seasons (Fig. 4) suffices for a construction of an adequate forecasting model.
- Extraction of specific natural gas consumption features, such as *WGCI* (Eq. 2) and *DGCI* (Eq. 7) is highly recommended in order to construct simple (linear in the parameters), robust and effective forecasting models.
- Stepwise regression procedure proved to be successful in extraction of informative inputs for both daily and hourly forecasting models. The simple forecasting models, as presented by Eq. 5 for the daily forecasting and Eq. 8-10 for hourly forecasting, proved to be quite robust and successful for the considered case study.
- During the online operation of the forecasting model, its performance can be successfully improved by regular model adaptation on new data. Applying the proposed weighting error function (Fig. 11) is essential for proper adaptation of the model through longer operation periods.
- Finally, it should be mentioned that natural gas forecasting results rely heavily on available weather forecasts. Therefore, the accuracy of the forecasts of influential data should be taken into account for each case study and the eventual natural gas forecasting efficiency estimated in order to gain the full perspective of possible natural gas forecasting outcomes.

7. References

Beccali, M.; Cellura, M.; Lo Brano, V. & Marvuglia, A. (2004). Forecasting daily urban electric load profiles using artificial neural networks. *Energy Conversion and Management*, 45, 2004, 2879–2900.

Benaouda, D.; Murtagh, F.; Starck J.-L. & Renaud, O. (2006). Wavelet-based nonlinear multiscale decomposition model for electricity load forecasting, *Neurocomputing, 70,* 1-3, 2006, 139-154.

Chandrashekara, A.S.; Ananthapadmanabha, T. & Kulkarni, A.D. (1999). A neuro-expert system for planning and load forecasting of distribution systems. *Electrical Power and Energy Systems*, 21, 1999, 309–314.

Ediger, V.Ş.; Akar, S. & Uğurlu, B. (2006). Forecasting production of fossil fuel sources in Turkey using a comparative regression and ARIMA model, *Energy Policy*, *34,* 18, 2006, 3836-3846.

Ediger, V.Ş. & Akar, S. (2007). ARIMA forecasting of primary energy demand by fuel in Turkey, *Energy Policy*, *35,* 3, 2007, 1701-1708.

Gonzalez, P.A. & Zamarreno, J.M. (2005). Prediction of hourly energy consumption in buildings based on a feedback artificial neural network. *Energy and Buildings,* 37, 2005, 595–601.

Hamzaçebi, C. (2007). Forecasting of Turkey's net electricity energy consumption on sectoral bases, *Energy Policy*, *35,* 3, 2007, 2009-2016.

Hubele, N.F. & Cheng, C.S. (1990). Identification of seasonal short-term forecasting models using statistical decision functions. *IEEE Transactions on Power Systems*, 5, 1990, 40–45.

Mihalakakou, G.; Santamouris, M. & Tsangrassoulis, A. (2002). On the energy consumption in residential buildings, *Energy and Buildings*, *34,* 7, 2002, 727-736.

Karatasou, S.; Santamouris, M. & Geros, V. (2006). Modeling and predicting building's energy use with artificial neural networks: Methods and results. *Energy and Buildings, 38,* 8, 2006, 949-958.

Pai, P.F. & Hong W.-C. (2005a). Support vector machines with simulated annealing algorithms in electricity load forecasting, *Energy Conversion and Management*, *46,* 17, 2005, 2669-2688.

Pai, P.F. & Hong W.-C. (2005b). Forecasting regional electricity load based on recurrent support vector machines with genetic algorithms, *Electric Power Systems Research*, *74,* 3, 2005, 417-425.

Petridis, V.; Kehagias, A.; Petrou, L.; Bakirtzis, A.; Kiartzis, S.; Panagiotou, H. & Maslaris, N. (2001). A Bayesian multiple models combination method for time series prediction. *Journal of Intelligent and Robotic Systems*, 31, 2001, 69–89.

Potočnik, P.; Thaler, M., Poredoš, A. & Grabec, I. (2005). Risk estimation of excess energy demand in a distribution system based on energy consumption prediction, In: *Physics of risk*, Second annual meeting COST Action P10, Toledo, Spain, April 23-26, 2005.

Potočnik, P.; Govekar, E. & Grabec, I. (2007a). Short-term natural gas consumption forecasting, *Proceedings of the 16th IASTED International Conference on Applied Simulation and Modelling*, Palma de Mallorca, Spain, August 29-31, 2007, 353-357.

Potočnik, P.; Thaler, M.; Govekar, E.; Grabec, I. & Poredoš, A. (2007b). Forecasting risks of natural gas consumption in Slovenia. *Energy Policy*, 35, 2007, 4271-4282.

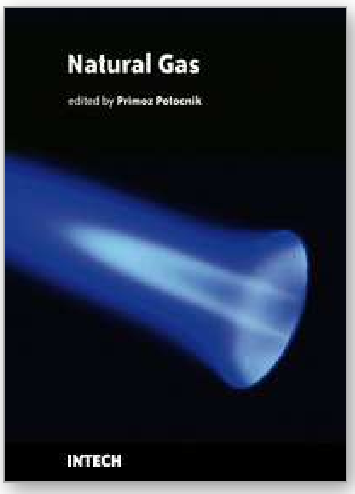
Potočnik, P.; Govekar, E. & Grabec I. (2008). Building forecasting applications for natural gas market, In: *Natural gas research progress*, Nathan David (Ed.), Theo Michel (Ed.), New York, Nova Science Publishers, 2008, 505-530.

Smith, P.; Husein, S. & Leonard, D.T. (1996). Forecasting short term regional gas demand using an expert system, *Expert Systems with Applications*, *10,* 2, 1996, 265-273.

Tzafestas, S. & Tzafestas, E. (2001). Computational intelligence techniques for short-term electric load forecasting. *Journal of Intelligent and Robotic Systems*, 31, 2001, 7–68.

Vajk, I. & Hetthéssy, J. (2005). Load forecasting using nonlinear modelling, *Control Engineering Practice*, *13,* 7, 2005, 895-902.

Vondráček, J.; Pelikán, E.; Konár, O.; Čermáková, J.; Eben, K.; Malý, M. & Brabec, M. (2008). A statistical model for the estimation of natural gas consumption. *Applied Energy*, 85, 5, May 2008, 362-370.



Natural Gas

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The contributions in this book present an overview of cutting edge research on natural gas which is a vital component of world's supply of energy. Natural gas is a combustible mixture of hydrocarbon gases, primarily methane but also heavier gaseous hydrocarbons such as ethane, propane and butane. Unlike other fossil fuels, natural gas is clean burning and emits lower levels of potentially harmful by-products into the air. Therefore, it is considered as one of the cleanest, safest, and most useful of all energy sources applied in variety of residential, commercial and industrial fields. The book is organized in 25 chapters that cover various aspects of natural gas research: technology, applications, forecasting, numerical simulations, transport and risk assessment.

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