A novel model for predicting natural gas consumption

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ABSTRACT: We present a novel model intended to predict mainly the residential and commercial natural gas consumption in urban areas, for the short and intermediate ranges of time. In the short range, the model has been successfully used to forecast the daily gas consumption of major cities of Argentina. It is able to predict the consumption 1 to 5 days in advance with 10% of uncertainty. In the intermediate range (1 to 5 years), the model allows us to estimate the annual peak consumption, load factors and the optimal transportation capacity for a given region of interest. We also present a novel procedure to obtain the distribution of daily consumption from the monthly consumption derived from the monthly billing.

I.- INTRODUCTION

The prediction of natural gas consumption is crucial for the gas distribution and transportation companies as well as for the government agencies associated to the natural gas sector. In particular, the short range prediction, 1 to 5 days, is important to ensure the normal supply of natural gas to a given city or community. This type of prediction is particularly important for countries like Argentina, where the production sites are far from the major centers of consumption. In the case of Argentina, these distances are of about 2000 km. This circumstance and the lack of large reservoirs make it necessary to develop reliable models to predict the gas consumption a few days in advance. The present study addresses the issue of residential, commercial and Natural Gas Vehicle Service Stations (NGV-SS), that have non-interruptible gas services (firm contract). Most large industries and electric plants in Argentina have interruptible contracts. Therefore their consumption patterns are different to the non-interruptible component and will not be discussed in this paper. We will use the terms firm and non interruptible to designate this type of component of consumption.

There is also a need to predict the firm component of consumption in the intermediate range of time, within 1 to 4 years, in order to adapt and upgrade the infrastructure of transportation and distribution. This type of prediction is also useful for all the sectors of the gas industry that need to plan their production and optimize their anticipated purchase.

The most important factors that affect the gas consumption of residential and commercial users are temperature, day-of-the-week (holiday or working day) and prevailing scenario of consumption. Other factors that may also influence the consumption are: wind speed and its direction, humidity, etc. Due to the lack of reliable information on these parameters, we have not included them in our model.

We herein present the basic characteristics of a simple model to perform short-range predictions and its generalization for intermediate range predictions. In line with the criterion of parsimony, the model has basically 6 parameters that are easy to obtain and interpret physically. This approach allows us to develop a novel formalism to obtain the main parameters of the model from monthly consumption data. This feature of the model allows us to infer the daily distribution of consumption, based on the monthly consumption. This association is important, not only because the monthly consumption is often a known piece of information, available from billing, but also because it allows us to better define the parameters of the model and to obtain the load factors for different types or segments of consumers. Furthermore, since the information from billing is often well known for different types of consumers, i.e. residential, commercial, etc., it is possible to obtain the daily distribution of consumption for each type of consumer. The load factors are important parameters to determine the transportation cost of natural gas for different types of consumers.

The outline of our paper is as follows. First we describe the short-range version of the model to predict the firm component of the consumption and compare the results of the model with the observed values. We then present the extension of the model to the intermediate range. We apply this model to predict the maximum annual consumption. We also discuss a novel procedure to obtain the daily distribution of consumption using the monthly consumption obtained from billing. This procedure is quite general and can be used to obtain the distribution of daily consumption for the different types of consumers. We used the firm component of the consumption as a benchmark to validate the procedure. Technical details are reported separately.[1]

II.- HABITS OF CONSUMPTION

In this section we present the results of our observations on the habits of gas consumption for the case of Argentina. Some of these characteristics may be valid for other regions. However, it is necessary to check the validity of these habits prior to the application of the model to a new region of interest.

Throughout this work, we will concentrate mainly on the firm component of consumption. The cost of natural gas in Argentina, in the period of study (1994 to 2003), has been very stable, with variations in the order of or less than 1% per year. The average annual consumption per user, for different consumer types, during the period of time studied here, has been almost constant, with a slight tendency to decrease. Figure 1 illustrates this situation for the case region of GBA, supplied by MetroGas, for both residential (R) and commercial (C) users. The situation for all the regions analyzed and other types of users shows a similar trend. This behavior can be described by the following linear expression:

$$Q_{usr}^{(i)}(t) = Q_{usr\_0}^{(i)} \cdot \left(1 + f_{usr}^{(i)} \cdot (t - t_0)\right), \tag{1}$$

where $Q_{usr}^{(i)}(t)$ represents the average annual consumption per user, corresponding to the component i (Residential, Commercial, etc.) at the time t. $Q_{usr\_0}^{(i)}$ is the corresponding value at the reference time t_0 and $f_{usr}^{(i)}$ is the parameter that determines the annual variation of $Q_{usr}^{(i)}$.

Figure 2 shows the annual variation in the number of consumers for the GBA, supplied by MetroGas. Here again we find a linear variation in the number of users with time, i.e.:

$$N^{(i)}(t) = N_0^{(i)} \cdot \left(1 + f_N^{(i)} \cdot \Delta t\right) \tag{2}$$

where $N^{(i)}(t)$ represents the number of users type (i) for the year indicated by t, $N_0^{(i)}$ is the number of users type i for the year t_0 taken as reference, $\Delta t(=t\text{-}t_0)$ is the number of years between t and t_0. $f_N^{(i)}$ is the factor that describes the increase in the number of users type (i) for the region of interest. The parameters $N_0^{(i)}$ and $f_N^{(i)}$, as well as $Q_{usr\_0}^{(i)}$ and $f_{usr}^{(i)}$ can be obtained from least square fit of the data.

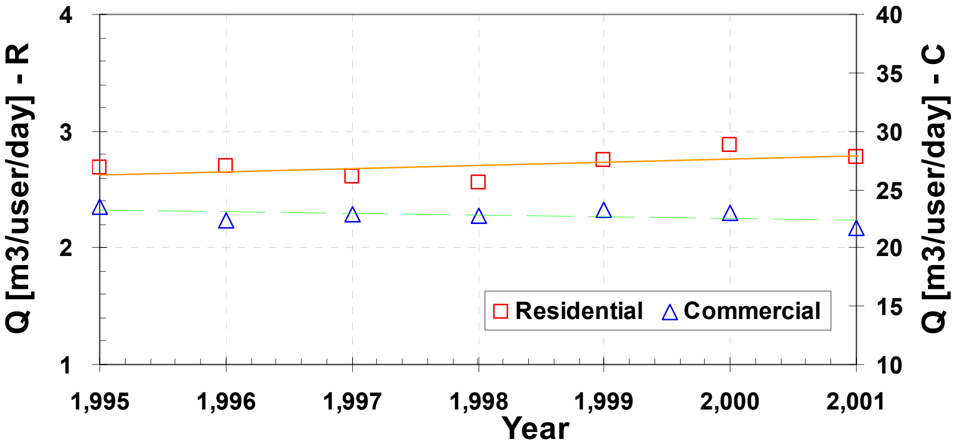

Figure 1: Average annual consumption per user, for residential (R) and commercial (C) users, for the region of GBA supplied by the distribution company MetroGas. The values presented here are the average daily consumption for each year. We observe an almost constant behavior, with a slight decreasing trend. The lines are fits to the data using expression (1).

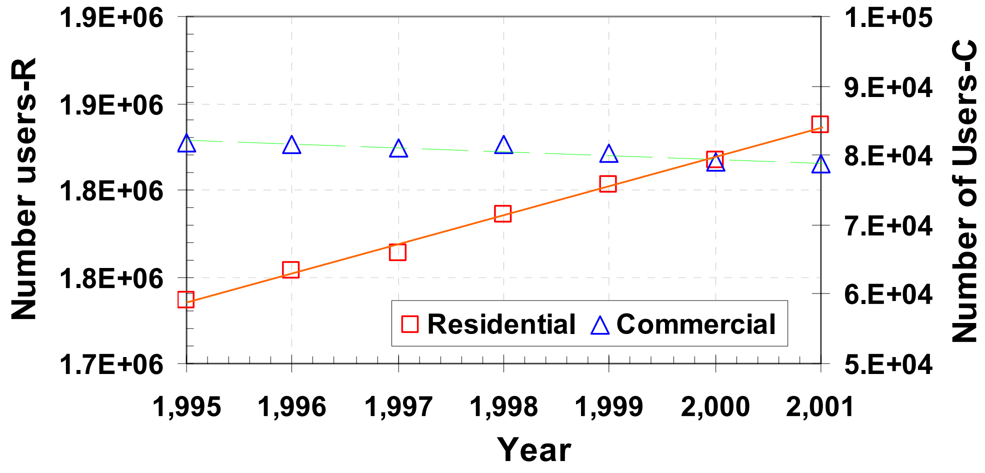

Figure 2: Variation in the number of users, Commercial (C) and Residential (R), as a function of time. These data correspond to the region of GBA supplied by MetroGas. The lines are fits to the data using expression (2).

Combining expressions (1) and (2) it is possible to obtain the total average variation of consumption for each region and for the different types of users. i.e.:

$$Q_{annual}{}^{(i)}(t) = Q^{(i)}_{usr\_0} \cdot N^{(i)}_0 \cdot \left(1 + f^{(i)}_{usr} \cdot \Delta t\right) \cdot \left(1 + f^{(i)}_N \cdot \Delta t\right) \approx Q^{(i)}_{annual\_0} \cdot \left(1 + \left[f^{(i)}_{usr} + f^{(i)}_N\right] \cdot \Delta t\right), \quad (3)$$

where $Q_{annual\_0}{}^{(i)} = Q^{(i)}_{usr\_0} \cdot N^{(i)}_0$. We have also defined $f^{(i)}_Q = f^{(i)}_{usr} + f^{(i)}_N$. This parameter characterizes the total variation in consumption, in a given region and for the particular segment of users indicated by *i*. Therefore it is possible to write the total average variation of consumption for each region as:

$$Q_{annual}{}^{(i)}(t) = Q^{(i)}_{0\_annual} \cdot \left(1 + f^{(i)}_Q \cdot \Delta t\right) \quad (4)$$

This last expression will be useful to make projections of consumption in the intermediate time range. In the cases analyzed here, the time dependency of the consumption per user and the number of users turned out to be linear. This particular dependence is not a requirement for the validity of the model. However, these relations must be known.

III.- MODEL OF PREDICTION – SHORT RANGE

The prediction of the firm components (residential, commercial, etc.) of natural gas consumption is made profiting from the correlation that usually exists between the daily consumption and the temperature. The model we have developed[1,2,3] is based on the observation that the users do not respond only to the current temperature but also to the preexisting thermal scenario. This statement can be confirmed by the observation that usually the consumption of gas is greater, for the same mean temperature, on a day in winter than on a day in summer or spring. This inertia is evidenced by the fact that the users usually do not turn on their heating until the temperature has remained low for a few days. Similarly, users do not turn their heating off until the increase in temperature has persisted for a few days. This effect of inertia in the consumption can be taken into account by introducing the concept of effective temperature, T_{eff}, that is defined as the linear combination between the mean $<T>$ of the day under consideration and the moving average of the mean temperature, $<T\_n>$, of the n previous days. Usually n varies between 3 and 5. More specifically:

$$<T\_n> = \frac{1}{n} \cdot \sum_{i=-n-1}^{i=-1} <T>_i \,, \tag{5}$$

where i represents the different previous days: $i=0$ refers to today, $i=-1$ refers to yesterday, $i=-2$ the day before yesterday, etc.

$$T_{eff} = w \cdot <T> + (1-w) \cdot <T\_n> . \tag{6}$$

Here w is a weighting factor between 1 and 0, that is obtained from the best fit of the data. $<T>$ represents the mean temperature of the day of interest.

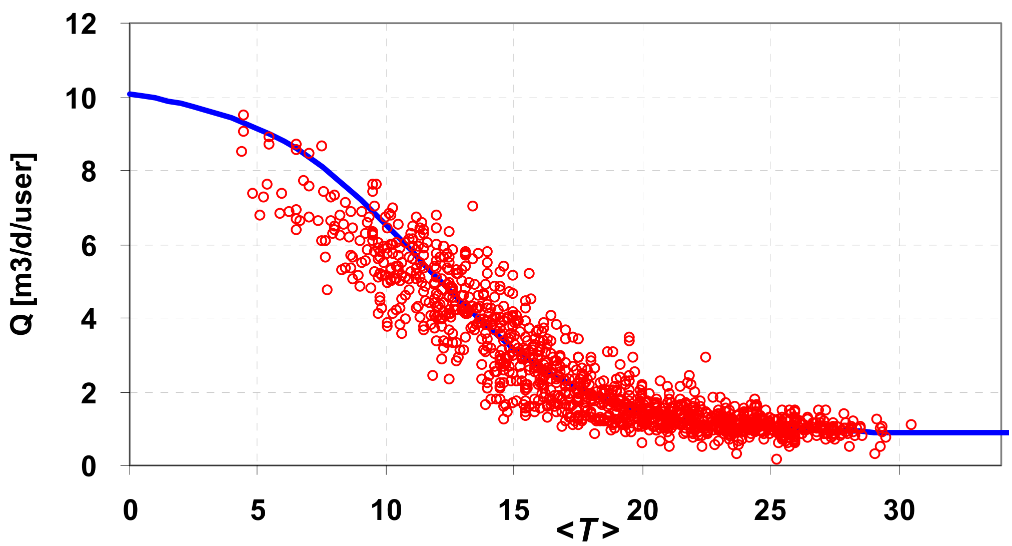

Figure 3: Variation of the daily total firm consumption (residential, commercial, etc.), represented by Q_i, as a function of the mean temperature, $<T>$, for the region of GBA supplied by MetroGas, for all the working days over the years 1996 to 2000. The circles are the measured data and the continuous curve is a fit to the data using expression (7).

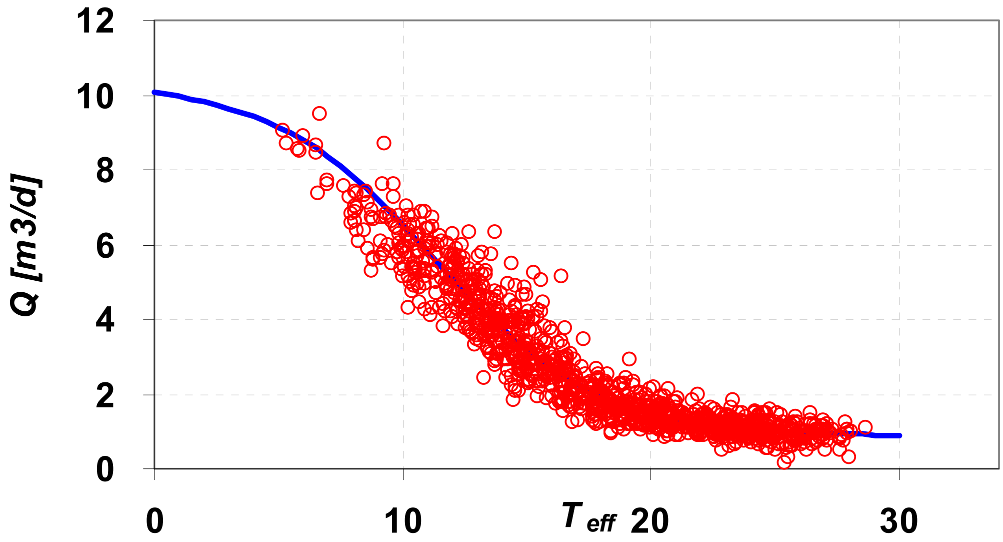

Figure 4: Variation of the daily total firm consumption, Q_i , as a function of the effective temperature, T_{eff}, for the region of GBA supplied by MetroGas, for all the working days over the years 1996 to 2000. The symbols (circles) are the measured data and the curve is a fit to the data using expression (7).

The importance of the effective temperature, is that it automatically incorporates the effects of inertia or hysterisis that is characteristic of the consumption of gas. Using this parameter it is possible to describe the relation of the consumption $Q^{(i)}$ versus T_{eff} by the function:

$$Q^{(i)}(T_{eff}) = Q_0^{(i)} \cdot \left(1 + f_c^{(i)} \cdot tanh\left(\frac{T_{eff} - T_0}{\Delta T}\right)\right). \quad (7)$$

In this expression, all the parameters T_0, ΔT, $f_c^{(i)}$ and $Q_0^{(i)}$ depend on the particular region under consideration and the type of user under consideration, the superindex *(i)* indicates these two situations. For simplicity we have not included the superindex in the parameters T_0, ΔT, but they are implicit. As can be seen in figures (3) and (4), expression (7) does provide an adequate description of the data. Also the dispersion of the data points representing the daily consumption per user show less dispersion around the model, when we plot $Q^{(i)}$ as a function of T_{eff}. The meaning of the four parameters appearing in expression (7) can be easily understood. The inflection point of the curve characterized by the coordinates (T_0, $Q_0^{(i)}$), $Q_0^{(i)}$, represents the consumption at T_{eff}=T_0 and is related to the average annual daily consumption, discussed previously. The product $Q_0^{(i)} \cdot f_c^{(i)}$ represents the asymptotic difference in consumption between the lowest (hottest) days and the highest (coldest) days. Our study reveals, as expected, that the parameters T_0, ΔT and $f_c^{(i)}$, do not change in time. They are in a way characteristic of the inhabitants of the region. On the other hand, the time dependence shown by expressions (1), (2) and (4) can be directly applied to $Q_0^{(i)}$, i.e.

$$Q_0^{(i)}(t) = Q_{00}^{(i)} \cdot \left(1 + f^{(i)} \cdot (t - t_0)\right) \qquad (8)$$

The parameter $f^{(i)}$ represents $f_{usr}^{(i)}$ or $f_Q^{(i)}$ depending on whether we are considering the consumption per user , Eq. (1) or the total consumption of the region, Eq.(4). In this manner, we see that the present model can incorporate intermediate range variations of the consumption with time. In fact, our model can reproduce the consumption of a given region for a period of time spanning 4 to 7 years with the same parameters. A final consideration for predicting the short-range daily consumption is the inclusion of the effects of weekends and holidays. From the analysis of the data we were able to reproduce the data for most of the regions of Argentina by using a factor that reduces the prediction of the model by about 10% on Saturdays and by about 15% on Sundays and holidays. Figure 5 shows the comparison between the prediction of our model and the observed consumption for the total firm consumption of gas for the region of the GBA supplied by MetroGas. This type of agreement is representative of the quality of fit obtained for most of the regions studied. We observed that on 95% of the days the agreement between the model and the real data is of the order of 10%. It is interesting to note that the prediction of the model is more robust than the prediction based solely on the temperature. This is because the effective temperature depends only partially on forecasted temperatures, which involve uncertainties, and partially on temperatures of previous days that have already been measured.

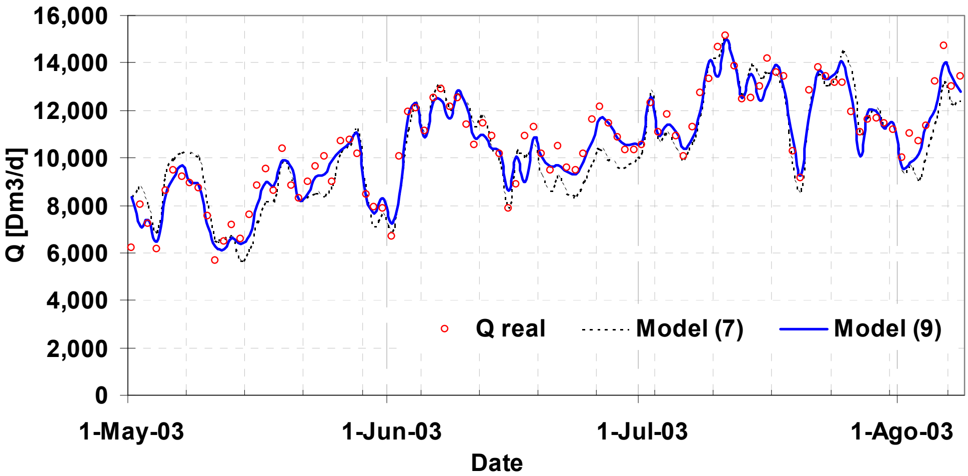

Figure 5: Comparison of the observed total firm consumption of natural gas in (open circles) for the region of GBA supplied by GasBan and the predictions of the model (curves). The dashed curve is the prediction of the model without correlation, expression (7). The blue solid curve is the prediction of the model including correlations, expression (9). The vertical grid corresponds to the beginning of the week (Sundays). The interval of time presented in this plot (from May to September, 2003) spans the Autumn and the Winter. Dm^3 represent thousand of standard m^3.

In the short range the accuracy of the model can be greatly improved by including correlations that correct the prediction of the model based on the deviations observed on previous days. In particular it was useful to introduce correlations with the previous day and the corresponding day of the previous week. More specifically, to predict the consumption on a given day *i*, we use the expression:

$$Q_{corr}(T_{eff},i) = Q_0(T_{eff},i) + C_1\left[Q_{real}(i-1) - Q_0(T_{eff},i-1)\right] + \\ + C_7\left[Q_{real}(i-7) - Q_0(T_{eff},i-7)\right] \quad (9)$$

Here, $Q_{real}(i)$ is the consumption actually observed for the day *i*, $Q_0(T_{eff},i)$ is the consumption predicted for the day *i* by expression (7). C_1 and C_2 are two constants chosen to optimize the fit to the data. In this manner the errors are reduced to 5% on 95% of the days.

IV.- MODEL OF PREDICTION – INTERMEDIATE RANGE

In principle the model described in the previous section can be used to make intermediate range predictions of consumption. However, due to the basic impossibility of making long-term temperature forecasts, in practice, the usefulness of the model as described this far is limited to 1 to 5 days.

In the case of the natural gas industry, what we usually are interested in is not necessarily predicting the consumption for a given day, one or two years from now, but rather the probability of occurrence of a given scenario of consumption. The probability distribution of temperatures for a given region can be obtained from the historical database of temperatures. In particular if we have access to a database of daily maximum and minimum temperatures for 10 or more years, it is possible to obtain a reliable distribution of future temperatures for that region. The rationale of this statement is that the temperatures that have occurred in the recent past can also occur in the future with the same probability. Here we assume that possible global temperature changes have negligible effect in the time ranges studied here, 1 to 10 years. This type of global changes is expected to be of the order of 1^0C per century.[4] Perhaps more relevant to our study is the so-called “urban heat island” effect. It is well known that metropolitan areas are significantly warmer than their surroundings. This occurs because in urban areas, there are fewer trees and other natural vegetation than in the countryside. Trees and vegetation cool the air by evaporation of water from the surfaces and the soil. In contrast, buildings and roofs with low reflectivity absorb more heat, causing an overall temperature increase in urban areas. As an urban area expands, its mean temperature also increases. In the GBA this effect is expected to be of the order of 0.25 ºC per decade. Therefore, for the range of time in consideration here, this effect can also be ignored.

Employing a historical database of temperatures, we can obtain the effective temperature for an extended period of time, 10 to 30 years. From a histogram of frequency of occurrence of temperatures, see figure 6, we can easily obtain the probability of occurrence of a given temperature in the future. Combining these probabilities with the model of prediction, with parameters adjusted as discussed in the previous section, we can obtain the probability of occurrence of a given scenario of consumption for any year in the near future. The evolution of consumption with time is already contained in the parameter indicated by expressions (1), (2), (4) and (7). Therefore, we are able to predict, for any region and for any year in the intermediate range, the probability distribution of consumption and most probable magnitude of the uncertainty of this distribution.

The model therefore allows us to determine optimum values of gas that may be adequate to celebrate contracts (reserved capacity) with producers and transporters. This type of distribution is also useful to estimate the Load Factors[1], since the model allows us to obtain both the average consumption $<Q>$ and the maximum consumption, Q_{max}, for a given year.

IV.- RELATION BETWEEN DAILY AND MONTHLY CONSUMPTION DISTRIBUTION

In this section we present a novel procedure that establishes the relation between the daily and monthly consumption distribution. This association allows us to estimate the load factors and peak consumptions for future years, from the information obtained from the monthly billing. Furthermore, this procedure allows us to obtain load factors for different segments of users in a given region. The formalism proposed here is based on the assumption that the daily consumption of natural gas can be described by a model that depends on the temperature as described by the expression (7) and that the number of users in the future can be predicted. We will also assume that for each month of the year, the daily mean temperatures have a probability distribution that is well approximated by a normal distribution, with a mean value, T_{month}, that depends on the month of the year and a standard deviation, σ_{month}, that can also depend on the month in discussion. For the major cities of Argentina that we have studied, this assumption in well justified. In figure 6 we present the histogram of daily mean temperatures for the month of July for the Greater Buenos Aires, taking the data of the observed temperatures for this month from 1944 to the year 2000. In this figure we also plotted the corresponding normal distribution. We see that the normal distribution closely approximates actual data. This agreement holds true for all the months of the year. In Figure 7 we present the distribution of the mean value, T_{month}, as a function of the month for the Greater Buenos Aires using the same database as in figure 6. The error bars in this plot represent the value of the standard deviation, σ_{month}. In this case, σ_{month} was almost constant (σ_{month}=3.1 ºC ± 0.6 ºC).

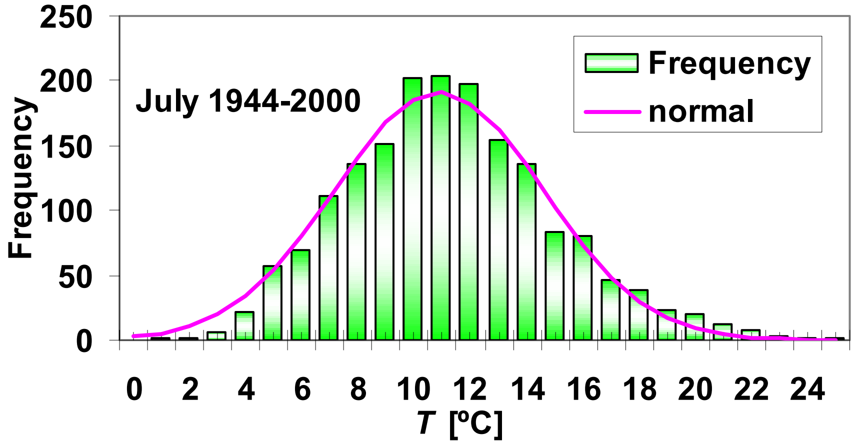

Figure 6: Distribution of daily mean temperatures for the month of July for the GBA. This histogram was obtained using all the observed temperatures for this month for the years 1944 to 2003. The continuous curve is a fit to the data using a normal distribution.

If we use the effective temperature instead of the mean temperatures, we obtain the same result. Thus, all the results discussed here can be applied to both distributions: daily mean and effective temperature.

Algorithm: If the daily consumption of gas is described by a model as represented by expression (7) and the daily mean temperatures are well approximated by a normal distribution, with a mean value and a standard deviation given by (T_{month}, σ_{month}), then it is possible to obtain the monthly consumption, represented by the variable Q_{month}. This quantity is the average daily consumption for the month under consideration. Clearly this magnitude can be obtained by taking the weighted average of the daily consumption *Q(T)*, with the corresponding normal weight, *i.e.*

$$Q_{month}(T_{month}) = Q_0 \cdot \frac{1}{\sqrt{2\pi} \cdot \sigma_{month}} \cdot \int_{-\infty}^{\infty} \left[1 - f \cdot tanh\left(\frac{T - T_0}{\Delta T}\right)\right] \cdot \left[\exp - \left(\frac{T - T_{month}}{\sqrt{2} \cdot \sigma_{month}}\right)^2\right] \cdot dT \quad (10)$$

The integral in expression (10) can be solved easily using the convolution theorem of the Fourier Transform, see Ref. 1 for details. The result is given by:

$$Q_{month}(T_{month}) \cong Q_0 \cdot \left[1 - f \cdot tanh\left(\frac{T_{month} - T_0}{\Delta T_{month}}\right)\right] . \quad (11)$$

Here T_{month} represents the average monthly temperature and the parameter ΔT_{month}, which determines the width of the distribution, is:

$$\Delta T_{month} = \sqrt{\Delta T^2 + 1.382 \cdot \sigma^2_{month}} . \quad (12)$$

The value of Q_{month} is the average daily consumption for the month. The total consumption for the whole month will be the product of Q_{month} by the number of days in the corresponding month. The expressions (11) and (12) indicate that there is a connection between the daily distribution of consumption and the monthly consumption. This last information can be obtained from the monthly billing.

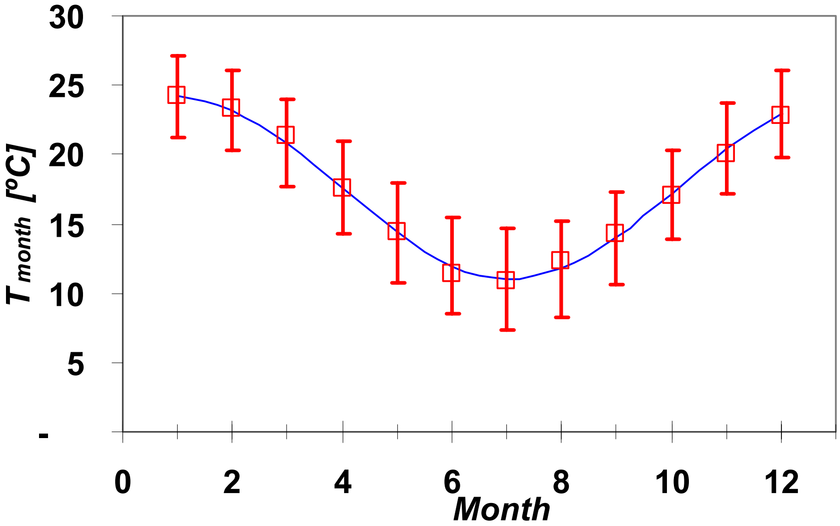

Figure 7: Distribution of the monthly mean temperatures for the GBA, the vertical error bars represent the values of the corresponding standard deviation, σ_{month}. The curve is a fit of the data using the function: $T_{month}=a+b.cos(c.month+d)$.

From the plot of Q_{month} versus T_{month} , it is possible to test the validity of expression (11) and to obtain the parameters of the model (Q_0, f, T_0, and ΔT_{month}). Once the monthly distribution is well characterized, using equation (12) and the known daily temperatures for each day in the month, we can use expression (7) to estimate the daily consumption distribution.

In particular, the daily distribution is useful to estimate the maximum daily consumption for a given year, Q_{max}, which is the crucial parameter to determine the load factor for each segment of users and optimize the purchase of reserved capacity. To carry out this estimation, the procedure is the following: from the data of billing we can obtain the parameters that characterized expression (11). Then, employing equation (12) we obtain the daily consumption distribution. The value of Q_{max} can be calculated from the minimum effective temperature, T_{min}, in the period under study, using the expression:

$$Q_{max} \cong Q(T_{min}) = Q_0 \cdot \left[1 - f \cdot tanh\left(\frac{T_{min} - T_0}{\Delta T} \right) \right]. \qquad (13)$$

From the billing information for the period of time in consideration, it is also possible to obtain the daily maximum consumption.

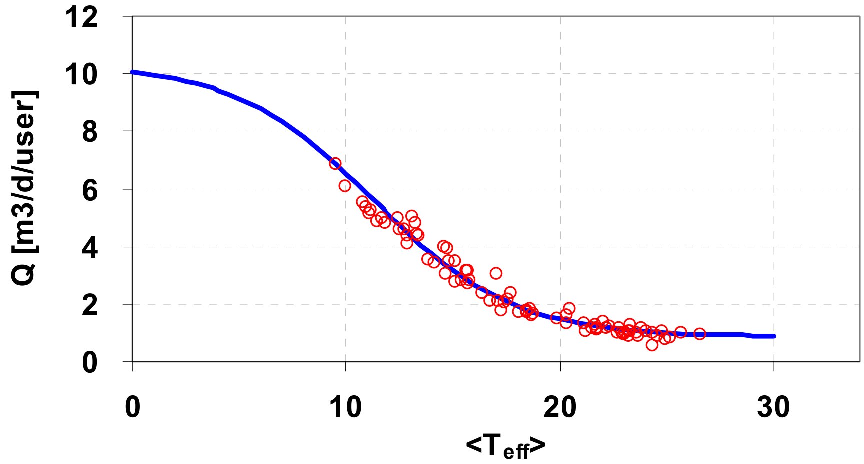

Figure 8. Monthly distribution of consumption (firm component) for the case of GBA supplied by MetroGas (symbols) as a function of the monthly average effective temperature, for all the working days over the years 1996 to 2003. The continuous curve is a fit obtained using expression (11).

In order to test the validity of the present formalism, we have applied the model to the case of the firm consumption of the region of GBA supplied by MetroGas. For this case the total daily consumption is known from direct measurements. The monthly consumption and the daily temperature are also known. The data of the daily consumption as a function of the effective temperature are shown in Figure 4, together with the fit obtained using expression (7). The data plotted here are the values of daily consumption per user, expressed in terms of standard m^3/day, using the information for the years 1996 to 2000. In Figure 8, we present the corresponding monthly consumption, expressed in terms of the average daily consumption for the month in consideration (working days) as a function of the average effective temperature for the month. It is useful to point out that when we take the average monthly temperature, the result is basically the same whether if we use the average daily or the effective temperature. In figure 8, we have also included the model prediction obtained using expressions (11) and (12). As can be seen, the agreement between the model and the data in this figure is excellent. This type of agreement was also found in the other cities of Argentina where the model was tested. This agreement gives support to the formalism presented here. Furthermore, it is clear from figure 8, that the dispersion of the data around the model, is much smaller than in the case of the daily consumption (Fig. 4). Therefore it is a more convenient and robust way of extracting the parameter of the model.

In summary, the validity of the model to establish the relation between the daily and monthly distribution of consumption has been established by two procedures. a) By mathematical manipulation of the analytical distribution using the convolution theorem of the Fourier transform, and b) by direct comparison of real data of consumption, using the firm consumption for the case of GBA. In a separate publication we discuss a third procedure to validate this connection based on the Monte Carlo simulation.[1] By all the three methods, we have confirmed the validity of the proposed formalism to establish the relation between the daily and monthly distributions.

V.- CONCLUSIONS

In this work we present a model we developed to predict natural gas consumption in the short (2 to 5 days) and intermediate range (1 to 5 years). The model can be applied to predict the consumption of different segments of consumption and is also useful to predict the maximum consumption in the intermediate range. The predictions of the model have been successfully applied to all the major cities of Argentina. The short-range prediction agrees with the observed consumption within 10% on 90% of the days. The uncertainties of the intermediate range prediction are in the order of 10%. This model can be regarded as a first order approximation. The accuracy of the model can be greatly improved by including correlations that correct the prediction of the model based on the deviations observed on previous days. In this manner the errors are reduced to 5% on 95% of the days.

The model presented here, reveals a useful association between the daily and monthly distribution of consumption. This relation is useful to develop predictive models of consumption when the only available information is the monthly consumption for a given region or segment of users. It also allows us to estimate the peak consumption in the intermediate range and to extract the load factors from the monthly billing information. This alternative is very attractive economically, since it does not require costly additional measurements.

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