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A Gaussian Process Regression for Natural Gas Consumption Prediction Based on Time Series Data

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***Abstract*—For several economical, financial and operational reasons, forecasting energy demand becomes a key instrument in energy system management. This paper develops a natural gas forecasting approach, which consists of two major phases: 1) it classifies the natural gas consumption daily pattern sequences into different groups with similar attributes. 2) the design and training of multiple autoregressive Gaussian Process models phase is carried out using the Algerian natural gas market data together with exogenous inputs consisting in weather (temperature) and calendar (day of the week, hour indicator) factors. The main novelty in this work consists of the investigation of multiple different clustering techniques for better analysis and clustering of natural gas consumption data. The impact of the obtained clusters, by each technique, is then summarized and evaluated with respect to the prediction accuracy.**

***Index Terms*—time series classification, gaussian process, load forecasting, natural gas consumption**

I. Introduction

The development of energy modeling for short term forecasting of the patterns such as periodicity or seasonality on the energy demand can leads to significant saving especially on dispatch scheduling and maintenance planning. Subsequently, this development became extremely important since it stimulates analysts, economists and other experts to use computational intelligence techniques as a supporting tool for decision making in order to increase the efficiency in the energy distribution.

Natural gas is a primary energy source in Algeria where its demand fluctuates over time. Furthermore, it is difficult to predict the demand, due to the variations and non-stationarity of the load series. Other factors that have an influence on the gas consumption are the thermal energy that is depleted for heating of residential areas, for generating electricity and for the industrial sector.

The variety of customer profiles, the high dependence on seasonal and climate aspects, together with the actual gas consumption limit the maximum accuracy that classical single model prediction approaches [1] can provide. To overcome this limitation there are techniques that rely on multiple models. Multiple models are often combined with the divide-and-conquer approaches for solving such complex problems [2].

The literature is rich with forecasting approaches for natural gas and energy consumption forecasting in a short term. Some of the most widely used methods which have been successfully applied are: artificial neural networks [3] and a long short-term memory (LSTM) recurrent neural network (RNN) for electrical load forecasting. In [4], neural networks with multilayer perceptrons are proposed, to forecast the natural gas consumption in Szczecin, Poland. Fuzzy approaches are proposed in [5] [6] and autoregressive integrated moving average (ARIMA) algorithms in [7].

However, another nonparametric machine learning method for regression, the Gaussian process regression has been successfully applied to many different areas such as electricity forecasting [8] [9], wind power forecasting [10] and groundwater level time-series forecasting [11].

This paper investigates several divided-and-conquer approaches for the purposing of forecasting the natural gas consumption. Inspired from [12], This approach is based on splitting the Algerian natural gas hourly consumption of 2014 into multiple subsets using different kinds of clustering methods. The dataset division is made by regrouping the daily pattern sequence of the 24 hours load using three powerful methods. After the division process, multiple local autoregressive Gaussian Process (AR-GP) models are developed for a specific variation of similar daily curves according to each clustering method. Finally, the results obtained by several non-supervised classifiers are compared over the problem for load consumption prediction.

The rest of this paper is organized as follows: Section II presents data for the case study, Section III introduces the proposed methodology upon which the paper is based on, Section IV provides a brief overview of the theory of Auto-Regressive Gaussian Process, Section V shows and analyses the results of the experiment for natural gas load forecasting. Finally, conclusion and discussion are summarized in Section VI.

II. Data Description

This study is based on the Algerian natural gas consumption for both residential and industrial sectors data and a corresponding weather data recorded by a meteorological service company.

Actual hourly consumption of gas during 2014 data is provided by the Algerian Company of Electricity and Gas

SONELGAS for the year of 2014. Fig. 1 shows fluctuation in gas consumption through the entire observed year along with temperature. Besides, there are many other exogenous factors that could be used for this type of forecasting like weather factors (wind speed, humidity, nebulosity) and calendar information (day of the week, is a holiday day, season) [13]. There are various factors which may influence the rate of natural gas consumption. These include : oil prices, number of clients, GDP, natural gas price, etc [14]. However, for a daily or hourly based forecasting horizon, this kind of data does not have any impact on the outcome of the short term consumption like in the current research.

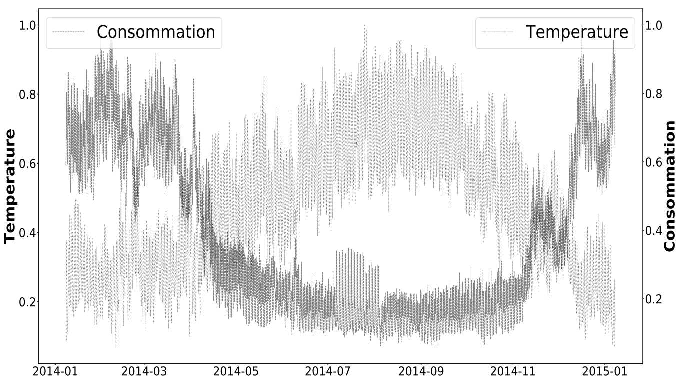


Fig. 1: Hourly recorder natural gas consumption and temperature during 2014.

III. DAILY LOAD CURVES CLASSIFICATION

The first step of the proposed approach is to classify samples of historical segments $H_{2014}\big[D_0 \ldots D_{364}\big]$ into K clusters containing identical daily load curves, where each historical segment (day x) is represented in 24 hours consumption vector $D_x = \{C_0, C_1 ... C_{23}\}$ with C_h is the consumption at a specific hour h. As the number K is unknown in this case, from a statistical point of view this issue is considered as an unsupervised curves classification problem. To group the daily consumption curves, different techniques are applied.

A. K-Means

First, a centroid based KMeans is used, but with the need of evaluating the K we suppose that there is a daily consumption and meteorological variables correspondence. Therefore, we assume that K could be equal to 3 (winter, summer, and spring-autumn) clusters.

B. HDBSCAN

Secondly, a hierarchical density-based clustering method is used. The current method was firstly introduced by Campello et. al in [15] and [16], where it improves the DBSCAN method by transforming it into a hierarchical clustering algorithm. Thus, it generates a complete density-based clustering hierarchy from which a simplified hierarchy composed only of the most significant clusters can be easily extracted. This method requires only one parameter which represents the minimum size of the cluster.

C. MOHGP

Another non-parametric clustering method is used, but unlike the HDBSCAN the mixture of hierarchical Gaussian Process is specialized on structural time series. MOHGP is proposed by James Hensman in [17] which is a combination of two Bayesian non-parametric algorithms, where it combines Gaussian processes (GPs) approach to model time-series and Dirichlet processes (DPs) to perform clustering.

D. Mixture of K-means and HDBSCAN

The last clustering technique is a result of two combined methods (HDBSCAN and KMeans): where it keeps the 3 clusters obtained by the KMeans and add another two clusters which get recognized by the HDBSCAN. There is a significant difference between the obtained clustering results. The reason is due to the fact that these clusters represents two different time periods in of the year: the first is the period of the Ramadan and the second one is the period of national and religious holidays. During these holiday periods the consumption patterns are unique.

IV. GAUSSIAN PROCESS REGRESSION METHOD FOR TIME-SERIES MODELING:

Once daily curves are regrouped, an AR-GP model is trained to learn the data for each cluster. Hence, every model handles the forecasting task for all hourly load in the corresponding cluster. By each GP model a single value C_t is predicted depending essentially on the following inputs: First, the previous lagged observations $C_{t-1}, C_{t-24}, C_{t-168}$ which represent the consumption of the previous hour, the same hour of the previous day and the same hour of the previous week. Then, meteorological factors corresponding to the temperature T_t, the maximum T_{max} and the minimum T_{min} temperature of the day are considered.

Fig. 3 presents the computation procedure for the proposed gas demand prediction method.

Gaussian Process models are considered as a collection of random variables that predict C_t at time t for a given input x_t. Assume that f is a latent function, which provides the values for each data point according to:

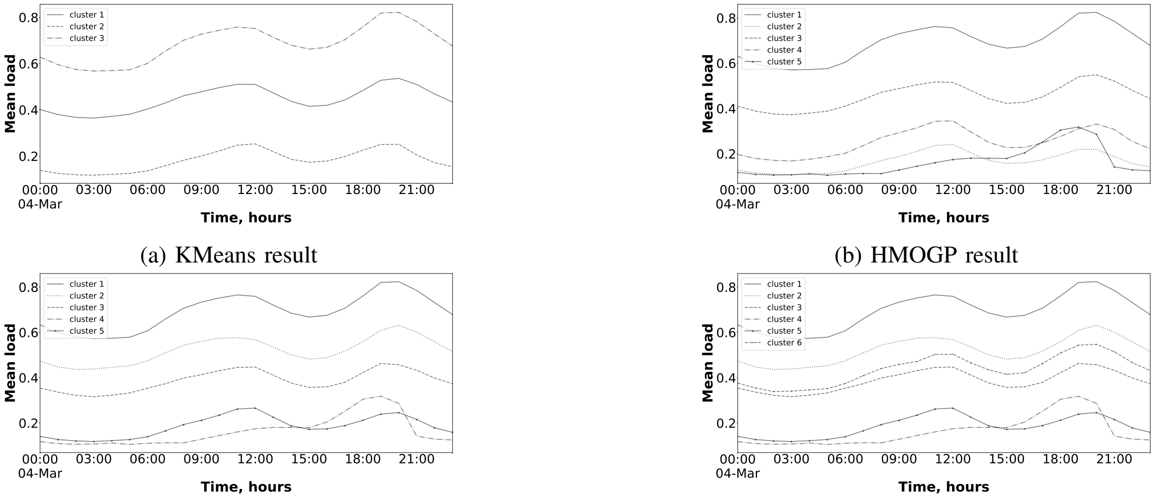
$$C_t = f(t) + \alpha \tag{1}$$

where $\alpha \sim N(0; \sigma^2)$ is a Gaussian noise with a zero mean and a variance σ^2. Noting that a Bayesian inference is performed and hence the posterior predictive distribution of f can be written as follows:

$$f(x) \sim GP(m(x), k(x, x')) \tag{2}$$

where $f(x)$ is the real process to model, x and x' are two different points. Here $m(x)$ is the mean value which is equal to zero in this case and $k(x, x')$ is the kernel function. Because of the dependence of the performance of the GPs on the chosen kernel, a radial basis function (RBF) kernel is adopted, also known as the squared exponential. The RBF kernel is given by:

$$k(x, x') = \ exp\bigg(\ -\frac{1}{2} d\Big(\frac{x}{l}, \frac{x'}{l}\Big)^2 \ \bigg) \tag{3}$$



(a) KMeans result

(b) HMOGP result

(c) Mixed of KMeans and HDBCAN result

(d) HDBSCAN result

Fig. 2: Average load for clusters obtained by each method.

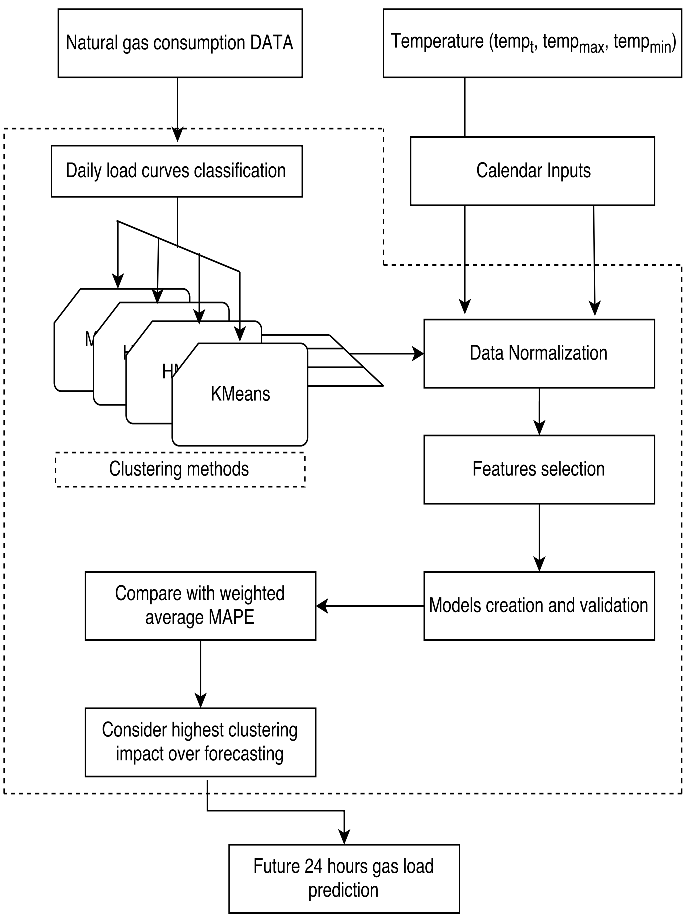


Fig. 3: Main steps of the proposed framework.

The radial basis function provides an expressive kernel to model smooth functions. The hyper-parameters l (called the length-scale) can be varied to increase or reduce the correlation between points and consequentially the smoothness of the resulting function.

Depending on the hyper-parameters of the kernel function, predictions are correlated with already observed values that have been recently observed. However, the influence of different variables on gas consumption is defined by the hyper-parameters of the covariance function which can be derived by maximizing the marginal likelihood. The log-marginal likelihood (LML) is defined as:

$$log(p|X,\theta) = -\frac{1}{2}C_T k_{-1} C - \frac{1}{2}log|K| - \frac{n}{2}log 2\pi \quad (4)$$

where the first term is the data-fit, the second term is a complexity penalty and the last term is a normalizing constant with n being the number of training samples.

The dataset is separated then into two partitions, the first partition (70 %) is for the fitting and optimizing of the GP's hyper-parameters, the rest (30 %) is for the test to evaluate the model quality.

In order to achieve a better estimation of hyper-parameters of covariance functions, using an appropriate approach to normalize the time series data is critical before feeding it to the GP model. The outputs and inputs data are normalized to an interval between [0, 1]. Hence, a value of X is normalized to X' by computing:

$$X' = \frac{X}{X_{max}} \quad (5)$$

where X' is the new value, X is the old value and X_{max} is the largest consumption value in the year.

V. Experimental results

A. Clustering

In order to make a clear visualization of the classification process, the next figures (a, b, c, d) in Fig. 2 show the mean daily load curve in each cluster obtained by the four clustering methods. At the end of the clustering, 365 daily curves of in the dataset H_{2014} are all labeled with its correspondent cluster K_x.

$$H_{2014} \begin{bmatrix} D_0[C_0...C_{23}] & K_x \\ \vdots & \vdots \\ D_{364}[C_0...C_{23}] & K_x \end{bmatrix}$$

TABLE I: Season's day count per cluster

Clustering Method	Cluster ID	Seasons			
		Winter	*Spring*	*Summer*	*Autumn*
KMeans	C 1	85	0	0	18
	C2	3	19	0	30
	C 3	0	74	94	42
HMOGP	C 1	82	3	0	18
	C 2	0	31	65	40
	C 3	6	15	0	25
	C 4	0	44	0	7
	C 5	0	0	29	0
HDBSCAN	C 1	79	3	0	18
	C 2	5	8	0	4
	C 3	4	0	0	23
	C 4	0	0	29	0
	C 5	0	74	64	40
	C 6	4	4	1	5
Mixture	C 1	82	0	0	18
	C 2	2	15	0	27
	C 3	0	74	64	40
	C 4	0	0	29	0
	C 5	4	4	1	15

These numbers represent days included in each cluster.

In order to be able to compare results obtained in each clustering method in Table. I, the clusters are related to a season which represented the most number of days, this is determined by the seasons of the year. The comparison of results is therefore based on the labeled seasons.

B. Features selection

The most appropriate features must be determined in order to enhance the prediction accuracy. The investigation started using only 3-dimensional input vector containing the historical load ($C_{t-1}, C_{t-24}, C_{t-168}$). Furthermore, other features were added sequentially as indicated in Table. II to observe its impact on estimating one hour ahead.

To measure the error in estimated loads, the models are evaluated based on the Mean Absolute Percentage Error calculated according to the following formula:

$$MAPE = \frac{100\%}{N} \sum_{i=1}^{N} \left| \frac{A_i - P_i}{A_i} \right| \tag{6}$$

Because of the complexity of the load time series, the experiments show that every time the AR-GP injected with exogenous variables, it provides a significantly better forecasting results. The correlation of natural gas consumption with temperature is -0.70 which means that there is no strong relevance between the two variations. However, adding the temperature variables reduced the MAPE in all clusters especially in the winter period. The unexpected improvement is also in the summer period which leads to the fact of the AR-GP is not influenced by the temperature as an indicating value for hotness or coldness but influenced by value that indicates the period in the day which corresponds the load.

TABLE II: Mean Absolute Percentage Error according to features combination

Experiments	Exp 1	*Exp 2*	*Exp 3*	*Exp 4*	*Exp 5*	*Exp 6*
Historical Inputs	x	x	x	x	x	x
Temp		x			x	x
Day Ind			x			x
Hour Ind				x	x	x
Kmeans method						
C1 MAPE	3.48	3.89	3.55	2.41	2.25	**2.05**
C2 MAPE	4.54	4.94	4.39	3.16	**2.90**	2.68
C3 MAPE	7.64	6.18	7.31	5.79	**5.88**	4.84
HDBSAN method						
C1 MAPE	5.16	4.93	4.81	4.27	**3.01**	3.10
C2 MAPE	6.24	4.68	4.54	2.94	2.66	**3.28**
C3 MAPE	8.29	6.00	6.08	5.49	4.06	**4.00**
C4 MAPE	7.91	6.60	7.43	6.94	6.24	**5.78**
C5 MAPE	8.25	5.68	6.09	6.42	3.57	**4.23**
C6 MAPE	10.12	7.83	18.34	10.02	**3.48**	1.59
HMOGP method						
C1 MAPE	5.26	5.13	4.87	4.37	3.41	**3.21**
C2 MAPE	8.35	5.89	7.63	5.90	3.96	**3.58**
C3 MAPE	6.45	4.38	5.40	4.72	**4.07**	4.20
C4 MAPE	8.68	7.70	8.19	7.44	**6.84**	6.23
C5 MAPE	8.25	5.68	6.09	6.42	3.57	**4.23**
Mixed method						
C1 MAPE	5.16	4.93	4.81	4.27	3.37	**3.07**
C2 MAPE	8.76	5.37	5.66	6.15	**3.92**	3.51
C3 MAPE	7.99	6.68	7.50	7.03	6.32	**5.70**
C4 MAPE	8.25	5.68	6.09	6.42	3.57	**4.23**
C5 MAPE	10.12	7.83	18.34	10.02	**3.48**	1.59

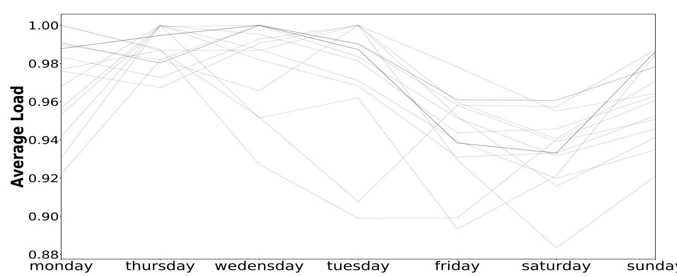


Fig. 4: The daily average natural gas consumption per week.

Apart from using historical and exogenous attributes, the experiments also involved two different kinds of calendar variations. The first is a daily indicator, to identify the day of the week which related to the predicted load. Identifying the day for which forecast is performed can help the model to distinguish between working days and holidays and also to recognize the first day of the week from the last ones. Fig. 4 shows the variety of daily average load per week on the generated clusters. The second calendar inputs is an hourly indicator which is considered as a very strong intraday periodic pattern.

Despite the effectiveness of the models on the training process, generalization and good performances on test and validation data is not straightforward. There are two main causes that occur the inconsistency of the model's performance through training and testing sets: the first cause is when the influence of an exogenous factor doesn't cover the entire period of the correspondent cluster, like in the case of KMeans clusters: C2 and C3, the best input combination is (Exp 5) because the error during test is lower than in (Exp 6) 4.5%, 4.2% respectively. The hyper-parameters of the kernel are optimized during the fitting of the AR-GPR by maximizing the LML. As the LML have a multiple local optima, this means that the model may fall in the over-fitting phenomena, which is the second cause that makes the covariance function will tend to have a poor predictive performance on the test unlike on training where is it the case in (Exp 6) with HDBSCAN C5, the MAP-Errors in training and test are (1.59% and 395.72% respectively) thus, the feature combination in (Exp 6) will be ignored.

C. Load forecasting results

After selecting the most convenient features, Table. III reports the mean absolute percentage error for AR-GP based on the proposed clustering methods.

Injecting predicted load in every iteration is the main concept for the stepwise forecasting. Furthermore, AR-GP models are extremely sensitive to the historical consumption, thus, a non-accurate estimation will definitely lead to a very bad performance along the rest of the 24 hours ahead, and this is the case when the AR-GP model is constructed basing on a load prior to the desired one (C_{t-1}). Meanwhile, we should note that under some circumstances an AR-GP regress according to the prior load could distort its performance. Therefore, the previous load will not be used in the forecasting process. Table. III obviously expresses seven cases where the prior load is ignored (C3), (C3, C4, C5), (C2, C4) and (C4) in KMeans, HMOGP, HDBSCAN and Mixture clusters respectively. Consequently, the 1 step forecasting error will be exactly the same as the 24 steps forecasting error.

Each cluster deserved a particular consideration, and Because of the high distinction in the generated daily load curves by each clustering approach, there is no general indication of how effective a daily load curves classification procedure can be given without applying a relevant comparative evaluation.

The weighted arithmetic mean is applied instead of the ordinary mean to calculate an average MAPE that represents the error for a clustering method.

$$\overline{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\sum_{j=1}^{4} w_j MAPE_i}{\sum_{j=1}^{4} w_j}\right) \tag{7}$$

Equation (7) expresses the weighted average of the mean absolute error ($\overline{MAPE}$), where w_j is the number of days per season j (winter, spring, summer and autumn) counted in each cluster i.

A summarized comparison between actual and forecast gas consumption in terms of mean absolute percentage error shown in Table. IV. The results indicate that the AR-GP

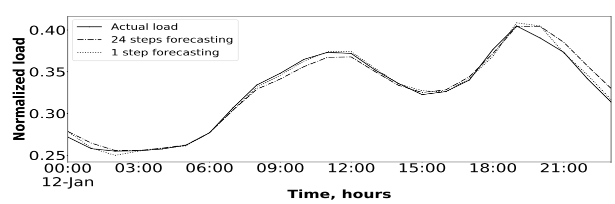
TABLE III: Forecasting MAPE based on the clustering approaches

Method	Cluster (season)	1 step training MAPE	1 step test MAPE	24 step training MAPE	24 step test MAPE
KMeans	C1 winter	1.33	1.34	2.05	3.33
	C2 sp & au	1.88	1.99	2.90	4.25
	C3 summer	5.88	7.10	5.88	7.10
HM-OGP	C1 winter	1.33	1.50	3.21	5.42
	C2 spring	1.73	2.24	3.96	5.00
	C3 autumn	4.20	7.25	4.20	7.25
	C4 summer	6.84	7.32	6.84	7.32
	C5 ramadan	4.23	6.72	4.23	6.72
HDB-SCAN	C1 winter	1.26	1.48	3.10	4.31
	C2 spring	3.28	4.53	3.28	4.53
	C3 autumn	2.09	1.97	4.00	4.11
	C5 summer	3.82	3.42	5.78	7.35
	C4 ramadan	4.23	6.27	4.23	6.27
	C6 sp-days	2.31	2.72	3.48	5.56
Mixture	C1 winter	1.26	1.48	3.07	4.31
	C2 sp & au	1.70	2.15	3.92	4.81
	C3 summer	3.24	3.31	5.70	4.72
	C4 ramadan	4.23	6.27	4.23	6.27
	C4 sp-days	2.31	2.72	3.48	5.56

sp & au: spring and autumn
sp-days: special days

performs much better on the Mixture method amongst all other clustering methods on the test period. The reason of choosing the Mixture method is because of the performance stability of AR-GP through training and testing sets compared to its performance on KMeans, HMOPG and HDBSCAN clusters. Additionally, the $\overline{MAPE}$ obtained of Mixture method clusters on test is 4.77%, which is an improvement over the KMeans, HMOPG and HDBSCAN by 16.53%,19.83% and 25.91% respectively.

The results of the forecasts for gas demand for the Algerian market reported with the use of Mixture clustering method clusters are illustrated in Figures. 5, 6, 7, 8 and 9. The labeled figures (a) and (b) presented the results through learning and test period respectively.



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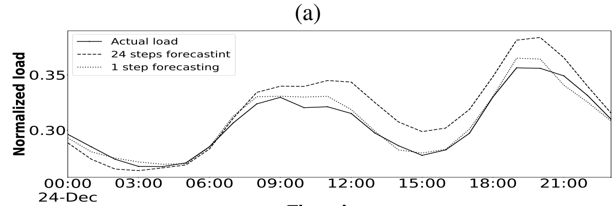
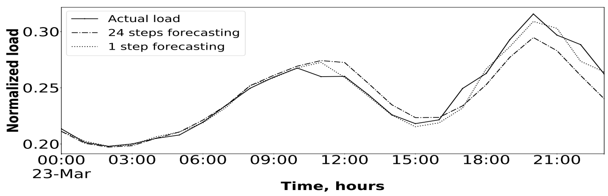


(b)

Fig. 5: 24 hour forecast through training and testing winter period



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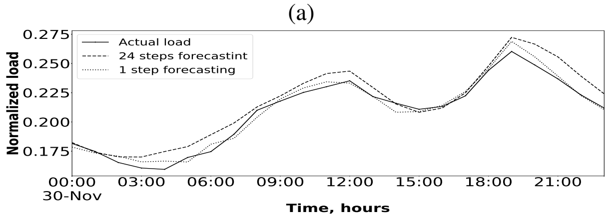
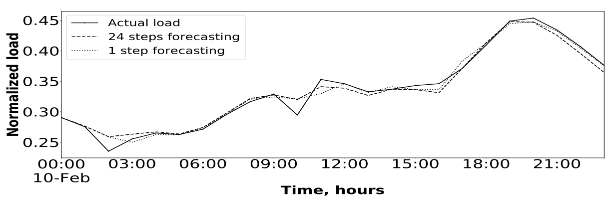
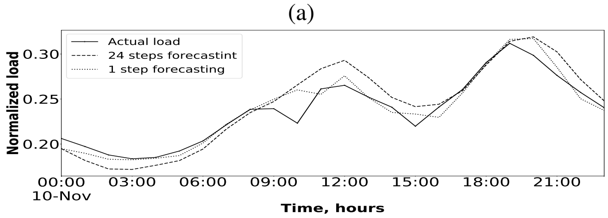


(b)

Fig. 6: 24 hour forecast through training and testing Spring and Autumn period

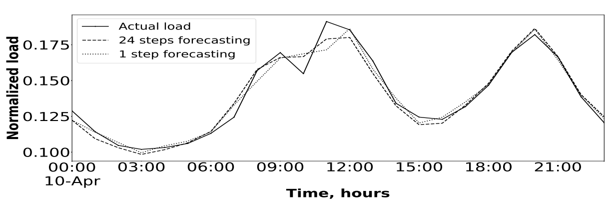


(a)



(b)

Fig. 7: 24 hour forecast through training and testing special days period



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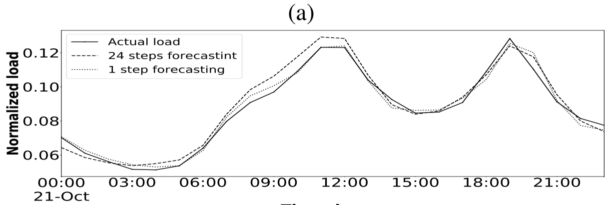
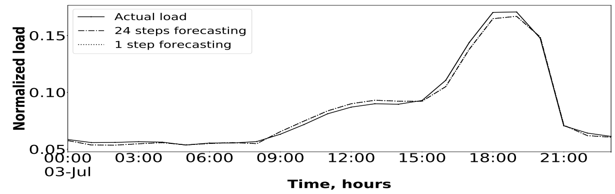


(b)

Fig. 8: 24 hour forecast through training and testing summer period



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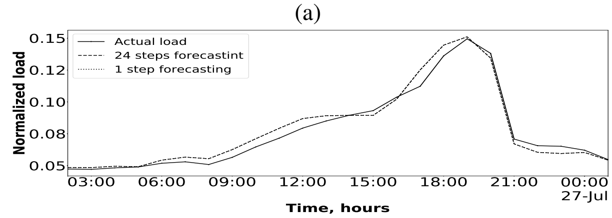

(b)

Fig. 9: 24 hour forecast through training and testing ramadan period

TABLE IV: $\overline{MAPE}$ based on the clustering approaches

Approach	**Train** $\overline{MAPE}$	**Test** $\overline{MAPE}$
KMeans	4.37%	5.63%
HMOGP	4.20%	5.82%
HDBSCAN	4.58%	6.19%
Mixture	4.56%	4.77%

As a test-bench experiment, a noise can be added to the inputs to cover different kinds of uncertainties in the measurement. Three levels of simulated random noise were added to inputs vectors: 1%, 3% and 5%. Because of the prior data normalization from [0,1], the inputs noise values was randomly generated from -0.01, -0.03 and -0.05 to 0.01, 0.03 and 0.05 respectively according the noise percentage. Occurring prediction with this uncertainties should definitely lead to an increase in the $\overline{MAPE}$. Unexpectedly, AR-GPs models show a very powerful ability of handling the noisy inputs, where even 5% added noise did not inadequately effect the prediction accuracy and results error increasing by 8% only and barely increases after 1% of noise is added. Fig. 10 illustrates the $\overline{MAPE}$ increase with regard to the noise level.

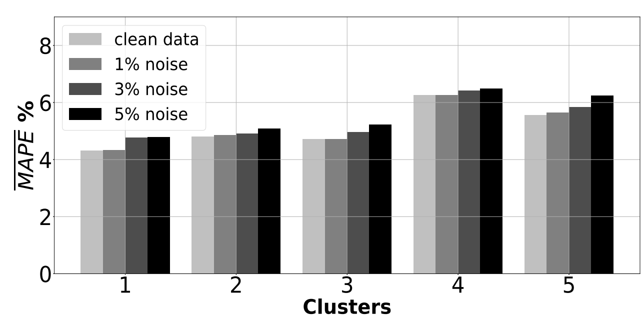

Fig. 10: GP models performance on test dataset with respect to noise level.

TABLE V: Models and Months

Model Name	Data Months
Model 1	January, February
Model 2	March
Model 3	April
Model 4	June, July
Model 5	August, September, October
Model 6	November, December

To evaluate the results obtained by the proposed approach, a comparison with another two divide-and-conquer approaches are conducted. The first method was developed in [18] is considered in the preliminary analysis for energy forecasting, where the dataset is split according to the holiday (i.e., Friday, Saturday and other holidays), to working days, to pre-holidays and to special days.

A second proposed by Mustafa Akpinar in [19], the data is split into six monthly subsets shown in Table. V.

TABLE VI: Average prediction $\overline{MAPE}$ for every cluster according to each approach

Cluster	Training $\overline{MAPE}$ %			Test $\overline{MAPE}$ %		
	MIX	APP1	APP2	MIX	APP1	APP2
Cluster 1	3.92	5.08	4.76	4.31	7.82	6.18
Cluster 2	3.92	4.83	8.63	4.81	6.16	10.68
Cluster 3	5.70	2.72	4.03	4.72	5.56	9.87
Cluster 4	4.23	5.65	10.09	6.27	4.90	11.48
Cluster 5	3.48	/	6.91	5.56	/	6.50
Cluster 6	/	/	5.72	/	/	5.60
Average	**4.56**	5.25	6.95	**4.77**	5.96	8.13

MIX: prediction based on Mixture clustering method.
APP1, APP2: prediction based on first and second benchmark approaches.

From comparison results shown in Table. VI, it can be noticed that the proposed method gives a very accurate forecast for practical needs even when compared with the two benchmark methods.

VI. CONCLUSION

This paper investigates the practical aspects of development of forecasting the Algerian natural gas consumption. There is a strong correlation of the natural gas load with meteorological elements which is mainly represented by temperature for the residential sector and physical and statistical factors like season of the year, day of the week for the industrial sector. Load data of 2014 is analyzed and clustered using different clustering methods in order to classify daily load profiles according to the similarity measures of each clustering method.

Based on the grouped daily load curves and using temperature with calendar inputs, multiple models construction are conducted by several experiments to determine the most influential factor. Forecasting results of 2014 are summarized and expressed in mean absolute percentage error. The average calculated $\overline{MAPE}$ on training and test datasets is 4.56% and 4.77%, which was achieved using mixture of KMeans and HDBSCAN method.

Classifying load curves into a huge amount of groups or adopting many different models does not necessarily improve the forecasting results, even in the case of using powerful clustering techniques. Contrarily, properly segmented and classified clusters can enhance the overall quality of the developed models considerably.

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