# Contribution of the All Data Methodologies for Design of Demand Management Programs in the Industrial Sector

## Contribución de las Metodologías All Data para el Diseño de Programas de Gestión de Demanda en el Sector Industrial

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**ABSTRACT**

Big Data concept is a global trend, creating endless possibilities for the use of data generated by dynamic networks. The challenge is the transformation of this large volume of data into useful information for the electrical system. An example of this is the application of demand management programs (DMP) for the optimization of power system management in real time. This paper presents approach for DMP in Colombia, especially in industrial sector and uses an integrated average value autoregressive model (SARIMA) to create a model in order to propose a PGD according to characteristics of electricity consumption of an industrial user.

**Keywords:** All Data; Demand Management Programs (DMP); Industrial demand; Energy Efficiency; Time Series Analysis.

**RESUMEN**

Big Data es concepto con tendencia mundial, que permite un sinfín de posibilidades para el uso de los datos generados por las redes dinámicas. El desafío es la transformación de este gran volumen de datos en información útil para el sistema eléctrico. Un ejemplo de esto, es la aplicación de los Programas de Gestión de la Demanda (PGD) para la optimización de la gestión del sistema de energía en tiempo real. En este trabajo se explica el concepto de PGD en Colombia, especialmente en el sector industrial y utiliza un modelo autorregresivo de valor medio integrado (SARIMA) para crear un modelo que permita proponer un PGD aplicable a las características de consumo de electricidad de un usuario industrial.

**Palabras clave:** All Data; Programas de Gestión de Demanda (PGD); Demanda Industrial; Eficiencia Energética; Análisis de Series de Tiempo.

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## Introduction

According to International Energy Agency statistics, industrial sector is one of the main electricity consumers, it represents 42.3% of world electricity consumption in the world in 2012 (IEA, 2014). For this reason, PGD implementation at the industrial sector is necessary to balance supply and demand ratios electrical networks and to reduce the cost of electricity for industrial consumers.

In Colombia, regulated demand management programs are not well developed yet, but there is the Law 1715, 2014 that encourages efficient use of electrical energy by means of the implementation of energetic savings strategies and the usage of non-conventional energy, mainly those that are renewable, promotion, stimulus and encouragement to the development of efficient activities are declared public utility and social interest affairs and national convenience.

Article 31 of the current law proposes to establishment of regulatory mechanisms to encourage the demand response, by shifting peak hour's consumption and this way achieving a flattening of the demand curve, responding to reliability requirements (Dyer et al., 2008).

The main motivators to achieve an efficient use of energy at the industrial sector are economic, environmental, political and social, to mention some of them. To improve these aspects, demand control strategies must be implemented, as a result of the accelerated growth of the world`s industry and electrical consumption.

In Colombia, electrical energy demand grew in January 2013 4.5% compared with January 2012 (2.4%). This growth is caused mainly by an increase of regulated demand (residential and small business consumption), result of the high temperatures in the country. Table I shows the growth percentage of electrical energy demand in different regions.

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Table 1. Performance of regional energy demand GWh–January 2013

| REGION | JANUARY 2013 | GROWTH |
|---|---|---|
| Centro | 1256.5 | 0.0% |
| Antioquia | 716.6 | 3.7% |
| Costa Atlántica | 1037.4 | 7.6% |
| Valle | 558.5 | 7.2% |
| Oriente | 515.1 | 6.8% |
| CQR (Caldas, Quindío y Risaralda) | 199.5 | 0.2% |
| THC (Tolima, Huila y Caquetá) | 199.0 | 4.2% |
| Sur (Cauca y Nariño) | 142.8 | 0.0% |
| Chocó | 17.0 | 8.3% |
| Guaviare | 3.9 | 4.3% |

Ref. Behavior in demand for electricity in Colombia 02/25/2013 XM. Market experts

In a similar way, energy demand in the non-regulated market showed a 4.5% increase in January 2013, this growth can be observed in Table 2.

Table 2. Performance of the demand for regulated and unregulated energy for economic activities GWh SIN – National Interconnected

| User type | January 2012 | January 2013 | Growth |
|---|---|---|---|
| REGULATED | 3,172.0 | 3,333.6 | 5.1% |
| UNREGULATED | 1,595.3 | 1,666.6 | 4.5% |
| Manufacturing Industry | 642.3 | 647.4 | 0.8% |
| Mining and Quarrying | 347.2 | 379.4 | 9.3% |
| Social, community and personal services | 217.9 | 213.6 | -2.0% |
| Trade, Repair, Restaurants and hotels | 134.9 | 150.4 | 11.5% |
| Electricity, Gas and Water Town | 120.8 | 123.8 | 2.5% |
| Transport, Storage and Communication | 53.0 | 57.1 | 7.7% |
| Agriculture, Forestry, Hunting and Fishing | 40.6 | 47.9 | 18.1% |
| Financial establishments, Insurance and Real Estate | 35.7 | 43.6 | 22.1% |
| Construction | 2.8 | 3.4 | 20.3% |

Ref. Behavior in demand for electricity in Colombia 02/25/2013 XM. Market experts

With these growth percentages of electrical energy demand in the country it appears a need to perform demand management actions to achieve an important effect on efficient energy consumption, as indicated by law 1715, 2014. Taking into account that industrial facilities demand consumes big amounts of electricity, a strategy for efficient use of energy will be to implement DMP to improve electrical networks reliability (Ding and Hong, 2013). Through strategies possessing the DMP against reduction of load, as well as growth control thereof providing greater flexibility of the electric energy system (Gellings and Smith, 1989).

In figure I, it can be observed the electrical energy demand growth in Colombia during the last 10 years.

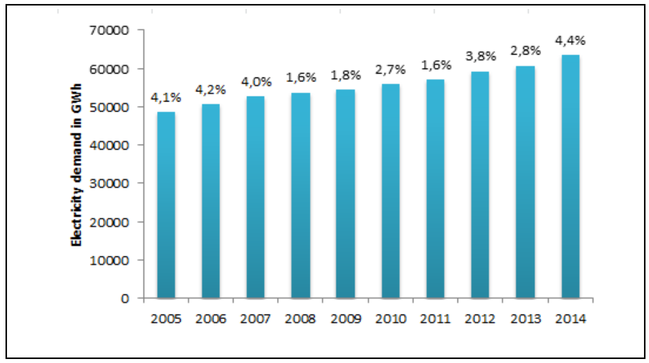


Figure 1. Behavior of energy demand in Colombia for the past 10 years

The first three years, electrical energy demand in Colombia underwent an accelerated growth, becoming less for the following four years and finally it has a more important growth in year 2014 as compared with the immediately previous year.

It is necessary to keep in mind that the main involved in DMP implementation at the industrial sector is the non-regulated user, the success of the execution of such strategies is mainly related to the users participation in such programs, where they gain benefits and no major changes are required, this makes necessary to know the consumption profile of each user.

Data on energy measurement become raw material for analysis, one step to follow is to take advantage of data to transform it into useful knowledge in order to provide answers to operational matters and solve problems with more speed and precision (Potter, 2014).

As study case there are measurement data of a non-regulated user in the manufacturing industry (coffee threshing) (DANE 2015), this is one of the main activities of the CQR region that comprises Caldas, Quindío and Risaralda departments. As noted previously, this activity has shown a 0.8% electrical energy consumption increase in the time between years 2012 and 2013. Compared with the other activities of the manufacturing industry it doesn't contribute with a high percentage. The objective is to implement strategies to reduce the growth of the electrical energy demand in the country or in another way, strategies that allow having more efficient electrical energy consumption.

The approach of this research is focused in proposing a DMP implementation strategy to the Colombian industrial sector, taking into account the different features shown by these users, as well as the variety of factors that may affect their consumption, as weather and the raw materials level changes according to the harvesting conditions, to mention some of them.

The article is organized as follows: Section II describes DMP and their main features. In Section III a general view of All Data methodologies and time series currently used for data analysis are provided. Section IV describes the electrical series demand of an industrial user whose main activity is coffee threshing. In Section V results are analyzed and conclusions close the article.

## DMP Overview.

Demand Management is a portfolio of strategies to improve the electrical energy system from a consumption standpoint. It goes from improving energetic efficiency by means of the use of better materials, smart energy fees with stimulus for certain consumption patterns to a sophisticated real time control of distributed energetic resources (Palensky and Dietrich, 2011). This can be clearly observed in Figure 2.

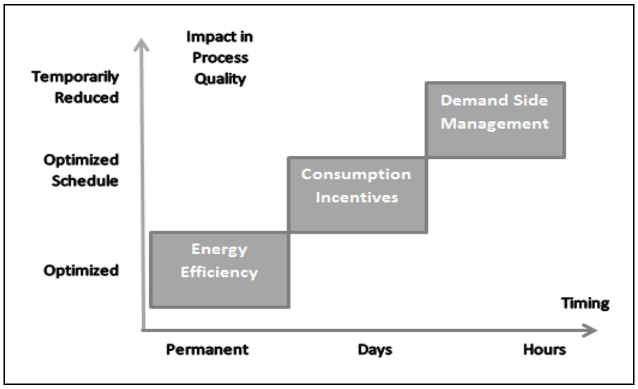


Figure 2. Definition of Demand Side Management

DMP are oriented to the regulation of the electrical energy market, these can design a specific model for each hour of the day, perform a balance and participate in an active way in the market (Martinez and Rudnick, 2012). In addition, they are directed to the reduction of the electricity cost; solve transmission lines congestion because it can delay inversions in transmission networks and increase reliability indexes in electrical systems.

DMP have been implemented to achieve a best participation of demand facing the cost or the needs to improve reliability levels of the electrical system, searching to mitigate power restrictions in an electrical system or to get a more efficient handling of this resource, obtaining also economic benefits for trading companies as well as for the end user (Baratto, 2010).

The need to have balanced and coordinated systems brings an interest to the network operators to participate in DMP. A bidirectional market allows buyers and sellers to find and negotiate the type of market in which they want to participate enjoying mutual benefits (Aalami et al., 2008).

Basically DMP are divided in two main categories, called time based programs and stimuli based programs. Time based programs are: use times programs (Aalami et al., 2008), critical peaks prices and real time prices. Stimuli based programs are: demand response programs in emergency times, load direct control, interruptions/reductions programs, market capacity, demand offer programs and random services programs, as can be seen in Figure 3.

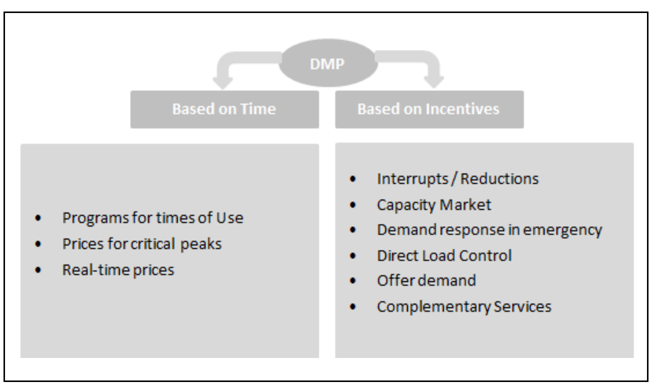


Figure 3. Distribution of DMP

Time based programs feature is that prices change during different periods according to the cost to provide electricity, for example:

- High prices on peak times
- Moderate prices on out of peak periods
- Low prices on low load periods

These types of programs don't receive stimuli or penalties.

Stimuli-based programs can be voluntary or mandatory.

Consumer's demand depends on the elasticity of electricity costs as well as on the stimuli and the penalty costs determined by DMP (Aalami et al., 2008).

DMP were created to obtain utilities treating reductions of maxim demand peaks as an alternative for the capacity from a perspective of the integrated planning of resources. Since the 80's, DMP have evolved to incorporate efficiency as well as load management (Spees and Lave, 2007).

The load side management plans, implements and monitors the activities that influencing consumer in the electricity use so that they can produce desired changes in forms of load, as well as in the time patterns and magnitude of the same (Gellings, 1985). The active management of load transforms the demand curves, driving to stability or providing programed peak and valley, so that the power system it can effectively plan and control the generation and the expansion of both systems transmission and distribution. Also it contribute at the decongestion of system, emergency support and backing when the users they have active participation and they possess elements of cogeneration and autogeneration (UPME, 2014).

Demand management is divided mainly in two parts, passive demand management and active management. Passive demand management includes educational material, auditing for the customers amidst other passive forms where the end user is trained about the value of performing an efficient use of the energy, as well as the consumers' knowledge of the benefits they could obtain participating on a DMP. Active demand management is the inclusion of more important changes in the typical demand behaviour, for example, change or implementation of a new technology or the active participation of an user into a DMP where the consumer in a voluntary or obligatory way makes the pertinent consumption reductions and receives stimuli for his participation.

Electricity reductions, according to a recent study of the Economic Board for Latin America and Caribbean, estimates that the savings potential is important, establishing that 25% of the electrical energy consumption can be avoided with the active demand participation (Merril, 2014).

## Overview Methodologies All Data in Data Analysis.

The volume and complexity of the available information overwhelm human and computer resources. Different approaches, technologies and tools are dealing with different data types as for example mining, learning and management of existing information which is growing more and more. From small data understanding (Small Data), academy and industry recently embraced big data (Big Data), linked data (Linked Data) and open data (Open Data). Each one of these concepts has specific foundations, algorithms and techniques and is appropriate and successful for different application types. While every concept is approached from a standpoint that allows a better understanding (and potential optimization), there is no application or service that can be developed without taking into account all the data types mentioned above, which are grouped in All Data (Pineda et al., 2015) as it can be seen in Figure 4.

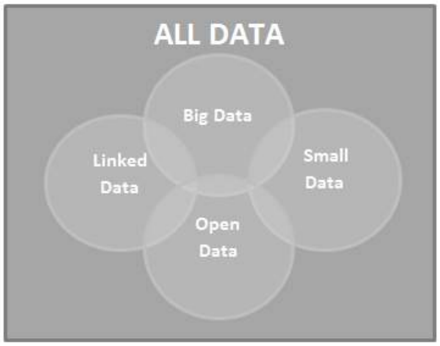


Figure 4. Grouping methodologies All Data

Next, different data types are described in a more specific way:

Big Data: Refers to big data volumes, where all the information is collected and it is associated with the immediacy to apply over advanced analytics technics (Joyanes, 2013) (McAfee and Brynjolfsson, 2012) (Piatetsky, 2014).

Small Data: It refers to the use of small data to make inferences obtained from polls; these are not closely related to immediacy in the statistic answers.

Open Data: It is understood as the opening of digital data, there is also place for physical data. Data opening is requested more and more to complement analytic studies. Access promotion is then linked to the process transparency.

Linked Data: It refers to data obtained through internet, on this approach there is a close relationship with the internet of things (IOT), it collects the information produced by all types of electronic devices communicated through internet, as for example electronic measurement devices, domotics, etc. They can easily become a Big Data.

Management of this type of tools to analyse big amounts of data requires identifying, mixing and managing multiple data sources, as well as the capacity to build advanced analytics models to predict and optimize results. Taking into account that the most critical component is related to the capacity to transform the passive contribution of energy demanders to an active contribution and in real time to achieve the DMP purposes of the industrial users, then a strategy for the DMP would be the design of a LOBS's model as it can be seen in Figure 5.

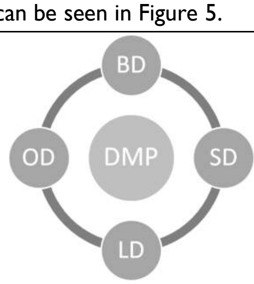


Figure 5. Grouping methodologies All Data

This model links All Data to improve the reliability of the information you have and then migrate to scenarios with big amounts of information to offer alternative schedules to industrial users according to scales stablished for an electrical energy consumption classification and subsequently identify the specific DMP.

The design and implementation of DMP efficient required in first term of the recognition of complex phenomenon as it is the energy market and its multiple impacts in a world amply interdependent and articulate.

It is therefore of assume a theoretical position that recognize inherent multidimensionality at a DMP and hence it is not just a problem of technical character that pretend modify the consumption habits, and, in the actual condition of Colombia voluntary decrease and considerably, the energy demand.

The sustainability of programs of this magnitude a demand consider aspects that go from environmentally to the political, including economic issues and social. That implies in ultimately an ethical dimension.

However, the strategy of associated information with a DMP queries this dimensionality and offers its answers considering the various possible sources. In the case of the experience currently it develops in the industrial sector of Manizales it has with a first source of supplies automatic data through smart meters capable of making telemetering (Article 3, Resolution CREG 131/1998) (linked data) which bring volumes increasing of data (big data) about the periodic consumption of energy. This should be collated with the information on the industrial characteristics of production regarding at activities each of the process where it presents an energetic expenditure as the type of engines, refrigerators, illumination, among others, as well as know volumes and variety of production, size, among others externalities that affect directly the processes of production. The latter usually come from the application of polls and studies inside of industry in question (small data) and contextualized with information of the biggest database that offered the government entities which provide rates of variation in the production, classification of different industries as well reports on capacity of the industrial sector for practice to energy efficiency (ISO 50001, 2011) (DANE, 2015) (UPME, 2015) (open data).

La integración de estas cuatro fuentes, junto con una analítica apropiada es la Conduce a una propuesta de todos los datos promovidas por la primera conferencia en Barcelona, con el interés de calificar la decisión procesa anuncio en particular los relacionados con la energía (ALLDATA, 2015).

The technic that will be used refers to the study of the Time Series originated in the periodic data collection on electrical energy consumption, this is the foundation to build the demand curve, to build consumption models and to predict demand, and the technic will be explained in more detail next.

### *Time Series Analysis*

The analysis of experimental data that have been observed for different time points leads to new problems in statistic modeling. Correlation by time-adjacent points sampling may be restricted by the applicability of some traditional statistic methods, depending that this adjacent observations are independent and distributed identically. The approach answers mathematical and statistical questions posed by such time correlations that commonly referred as time series analysis (Shumway and Stoffer, 2010).

(Box and Jenkins 1976) (Box 1994) develop a systemic models class called Autoregressive integrated moving average ARIMA to handle a modeling of correlated time and prediction, this model includes a prediction for the processing of more than one series entry at a time through the multivariate ARIMA or through the transfer function model.

## Series of electricity demand of an industrial user (coffee processing)

The series of electricity demand of the industrial user consists of hourly time series of the electricity consumption of the coffee threshing specialized facility located in Manizales city; this is one of the main agricultural activities in the city. A collection of the electrical energy consumption in MWh was collected in the time between September 2014 and January 2015, all the data were used to estimate the parameters.

In Figure 6 it can be seen a graph of the time series that covers the time from September 1, 2014 to January 30, 2015; days are identified by 24 hours periods.

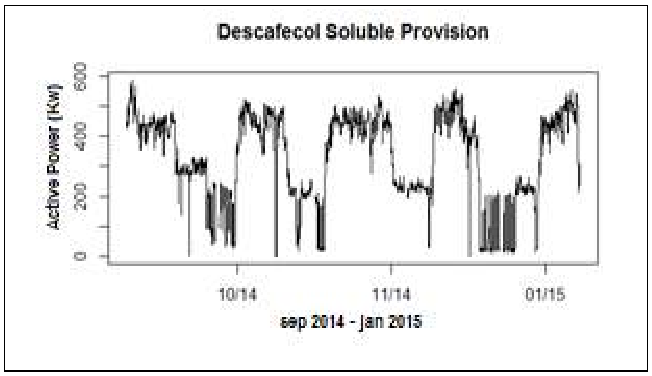


Figure 6. Active power consumption of the Industrial Company

It is clear that the first days of the month show similar demand patterns, while the last days of the month have the lowest peaks of electricity demand and then show different demand patterns, this is caused by the variation of the agricultural production because there are different factors that affect the production and then the threshing variates in time.

It can be observed that there is an important variation as sampling time goes, in Figure 7 the first sampling week consumption can be observed.

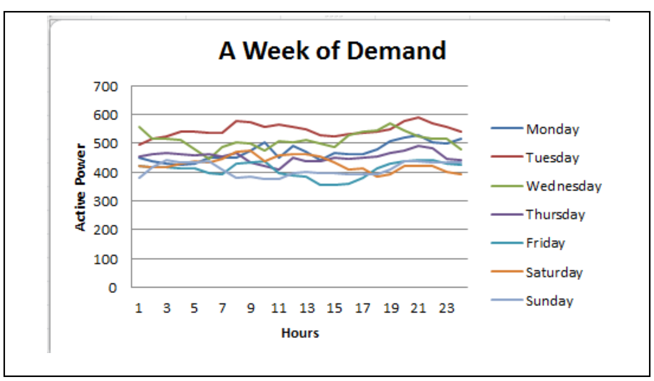


Figure 7. Active power consumption of the Industrial Company

It can be seen that consumption every day has a different behaviour, being higher starting the week, by the end of the week, electrical energy demand decreases. Consumption in an industrial user doesn't have a typical curve as the home user.

### *Model Applied*

The Seasonal Autoregressive integrated moving average - SARIMA model is introduced by (Box and Jenkins, 1976) to analyze the pattern of the individual time series. The SARIMA model is noted as ARIMA $(p,d,q)(P,D,Q)s$, where $p$ and $P$ express the orders of the autoregressive terms non-seasonal and seasonal respectively; $d$ and $D$ are the orders of the differentiation non-seasonal and seasonal respectively; while $q$ and $Q$ are the orders non-seasonal and seasonal of the mobile average component and $s$ is the seasonal period.

SARIMA can be expressed as:

$$\emptyset_p(B)\Phi_P(B^s)\nabla^d\nabla_s^D y_t = \theta_q(B)\Theta_Q(B^s)\,\varepsilon_t, \qquad (1)$$

Where $\nabla^d$ and $\nabla_s^D$are the non-seasonal and seasonal differentiation operators respectively; $B$ is the backwards displacement operator; $\varepsilon_t$ is a White noise process with zero mean and constant variance; $\emptyset_p(B)$ and $\Phi_P(B^s)$, are the $p$ y $P$ order polynomials, they represent the non-seasonal and seasonal autoregressive components respectively; $\theta_q(B)$ and $\Theta_Q(B^s)$ are the $q$ y $Q$ order polynomials, they represent the mobile average non-seasonal and seasonal respectively.

If the data series of the industrial user is non-stationary differences and/or transformations must be done to make it stationary (Ismail et al., 2015).

## Results

Different SARIMA models are used to predict or Project the electricity demand of an industrial user. Results have been obtained using R software (Chambers, 2015). They indicate a 2 order polynomial in the non-seasonal component and 1 order in the seasonal component that has a 24 hours period; it is necessary to make a difference in the non-seasonal component and it is not necessary to difference in the seasonal component and finally there is a 2 order polynomial in the mobile average component, for the non-seasonal as well as for the seasonal part.

SARIMA (2, 1, 2) (1, 0, 2) [24]

The output with the results provided by the R software is shown next.

```
ARIMA (2, 1, 2) (1, 0, 2) [24] with drift

Coefficients:
         ar1      ar2      ma1      ma2    sar1     sma1    sma2    drift
      0.9665  -0.0795  -0.8117  -0.1286  0.8976  -0.7432  0.0042  -0.0730
s.e.  0.1056   0.1080   0.1057   0.1093  0.0158   0.0240  0.0200   0.5179

sigma^2 estimated as 559.7:  log likelihood=-15708.69
AIC=31435.38   AICc=31435.43   BIC=31490.9
```

The coefficients of each one of the SARIMA method variables can be observed with its corresponding standard deviation, where `ar1` corresponds to $\emptyset_1$, `ar2` corresponds to $\emptyset_2$, `ma1` corresponds to $\theta_1$, `ma2` corresponds to $\theta_2$, `sar1` corresponds to$\Phi_1$, `sma1` corresponds to $\Theta_1$, `sma2` corresponds to $\Theta_2$, and finally the term `drift` refers to the $\varepsilon_t$ constant.

The terms `AIC=31435.38` `AICc=31435.43` `BIC=31490.9` are AIC the Akaike's information criterion, AICc is the AIC with deviation corrected and BIC is the Bayesian information criterion, these terms are defined in (Shumway and Stoffer, 2010), they refer to the criteria to choose the best model, being the best model the one that has the lowest AIC.

The steps to follow are the model refining that will allow predicting the electricity consumption based on a series of data to identify how convenient is the model.

Then build on the basis of the depurated model the scenarios of DMP that can be applied according to the behavior of the consumption curves, also, with new data information, modify the model to make it more precise.

Also find in other All Data methodologies useful information that allow to identify new models that will enrich the investigation, as for example small polls to industrial users and national polls that provide useful open data to influence electricity consumption inter alia.

Finally it is proposed to the local network operator the possibility to perform an individualized information treatment to predict the behavior of industrial customers, given that the electricity consumption varies depending on multiple factors according to the economic activity accomplished, which brings complexity by the diversity of DMP implementation strategies to industrial users.

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## Conclusions

SARIMA model was investigated in this work for electricity demand prediction of an industrial user from Caldas specialized in coffee threshing, that through a time series, a prediction of the electricity consumption behavior can be realized and will be presented to the user immediately after that will allow to reduce the decision making time and then reduce the times to apply appropriate DMP strategies.

This work has raised concerns about the behavior of the industrial user because this one doesn't present a typical behavior day after day, this is reflected thanks to the change in raw material levels according to the changing conditions presented by the coffee harvest, among other factors that can affect directly the consumption as the weather, time of the year, demand of the elaborated product, etc.

As it can be seen in Figure 7, the electricity consumption curve for this specific type of industrial user doesn't show critical peaks during the day and then it can be inferred that the success of DMP application to this type of users focuses mainly on stimuli based programs.

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