# MITIGATION OF UNCERTAINTY IN FORECASTS OF GENERATORS WITH RENEWABLE ENERGY SOURCES IN MEXICO

**TANIA ARISTA-SALADO GELER[1] AND**

**ADRIAN HERNANDEZ-DEL-VALLE[2]**

**Abstract:** Mexico has the natural conditions and the need to continue promoting the use of renewable energy sources for electricity generation. But since 2019 there has been no provision by market regulators to increase capacity at these sources. Among the main reasons given is the uncertainty associated with the forecast of its generation. With this research, it was sought to evaluate an alternative to reduce the forecast error in electricity generation to make electricity dispatch easier, the planning of the energy supply to satisfy the demand, and maintain the reliability of the users in the system. national electric. ARIMA and VAR models were used to perform this analysis. With them, the demand and local marginal prices in the electricity market of the day in advance and in the one hour in advance were estimated and the average error was calculated for each estimate, resulting in a decrease in forecasting one hour in advance forecast error significantly.

**Keywords:** Mexican wholesale electricity market, forecast uncertainty, renewable sources of energy, one hour ahead market.
JEL: C53, E37, L94, Q47

## 1. INTRODUCCIÓN

Renewable energy resources, RES, are one of the most efficient and effective long-term solutions to the environmental problems that we face today. They are a key element to attain sustainable development [see, e.g. Bradley, Watts and Williams (1991), Norton (1991), MacRae (1992), Levin and Lin (1993), Dincer and Dost (1996), Rosen (1996), Im, Pesaran and Shin (1997), Dincer and Rosen (1998), Dincer (1998a), Stiglitz (2002), Perman and Stern (2003), Sari and Soytas (2004), Bugaje (2006), Kaygusuz, Sadorsky (2009), Apergis and Payne (2010), Frondel, Ritter, Schimdt and Vance (2010), Munasinghe (2010), Pereira, Freitas and Silva (2010), Fang (2011), Menegaki (2011), Moselle (2011), Tugcu, Ozlturk and Aslain (2012), Hu, Hernandez-del-Valle and Martinez-Garcia (2017), Liu, Zhang and Bae (2017), Solarin, Usama and Ozturk (2017), Taner Güney (2019)].
First, they are a solution to the fact that fossil fuels have finite availability in the long-term and this causes them to be involved in continuous political conflicts.

[1] Corresponding autor: SEPI-ESE-Instituto Politécnico Nacional. E-mail: taniaristageler@gmail.com. Dirección: Felipe Carrillo Puerto 179, Col. Popotla, C.P. 11400. Teléfono: 5561624960

[2] SEPI-ESE-Instituto Politécnico Nacional. E-mail: ahdv@hotmail.com. Dirección: Jalapa 164ª, Depto. 107, Col. Roma, C.P. 06700. Teléfono: 5572039533

Second, the constant variability of the prices of these fossil fuels negatively affects the good performance of economies. Mainly those dependent on the import of coal and other hydrocarbons such as Mexico, which in 2018 was the fourth consecutive year in showing dependence on energy imports to satisfy their demand, data obtained in the SENER, 2019.

In addition, when a large part of the Revenue from the Mexican government also depends on the export of crude oil, this income can be seriously affected if a sudden drop in the prices of hydrocarbons, as has just happened at the beginning of 2020 after declaring the COVID-19 pandemic.

Third, its use counteracts the growing and constant deterioration of the global and local environment, which occur as a result of the process of extraction and transformation of fossil fuels and greenhouse gas emissions (GHG).

Mexico has great potential to generate energy through clean sources and as a consequence it opens the possibility to take advantage of new market opportunities. It has abundant solar energy, areas with intense and constant winds, steam and water for the impetus of geothermal fields (ExpokNews, 2018), seas to take advantage of the seawater energy, and the generation of hydroelectricity, although the latter hydroelectric plants are recommended, by the negative impacts it brings.

That is why it has been reflected on numerous occasions, the interest of the country in developing the FRE in conjunction with the increase of the energy supply and its reliability, and the sustainability of the environment. But, although a greater use of clean technologies has been promoted in recent years, the desired levels in accordance with the global trend have not yet been reached.

As of 2019, investments in new capabilities in FRE have been limited. And the proposal for reform of the Law of the Electrical Industry in March 2021, represents a great recoil in: the scope of the FRE, the enlargement of the electricity, in compliance with international and commercial agreements, and in environmental terms, well, bet on the use of fossil fuels. Hence the present and relevance of carrying out this research topic.

Among the main causes that have been raised to limit greater investment in FRE, is the uncertainty associated with its prognosis. This uncertainty is fundamentally presented with solar and wind energy because of its condition of being variable sources, because they have an intermittent generation.

Being able to derive that the forecast of the amount of electricity that is expected to be produced by generators with is not reliable[3], and cause insecurities in the electrical system, a suboptimal dispatch and difficulties in controlling voltage regulation[4]. As well as cause distortions in the prices of the Wholesale Electricity Market (MEM). For ensuring the supply of energy before imbalances of demand and generation, they are compensated with plants powered by fossil fuels at a much greater cost.

The above translates into a decrease in the reliability of the National Electrical System (SEN). Therefore, the problem of this research is to evaluate an alternative in the wholesale electricity market to mitigate uncertainty in energy generation forecasts with renewable sources in Mexico. So, it

3 Also on occasions, the quantity produced in real time has been greater than the forecast supply, limiting its use to its generation potential in the purchase and sale of the energy market.

4 To see an example of the problems caused by errors in generation forecasts with FRE, consult: ESTA International, Independent Monitor of the Electricity Market. (2020).

is important to analyze examples such as the Independent Operator of Systems of California (CAISO), which has managed to overcome and reduce these prognostic uncertainties that can be served as a study for FRE projects in Mexico.

The CAISO implements the second stage market (forecast every 45, 15 and 5 minutes) that allows it to continuously adjust its offer and enables you to gain time to face any unforeseen non-compliance in the power supply.

From the above, the **objective** of this research is to simulate forecasts with one day and one hour in advance in the short-term energy market, to compare the deviations of forecast errors, and see the need to implement the second stage market to mitigate the uncertainty in the generation of energy with renewable sources.

The **hypothesis** is that if the second stage of the wholesale electric market is implemented, specifically the markets of one hour of advancement, this will reduce the uncertainty generated by the deviations of the forecasts of renewable energy sources.

The implementation of the Market with one Hour of Advance (MHA) would also decrease the uncertainty that exists in the SEN, due to the differences between what is expected to be demanded (predicted) and real demand. Which causes ignorance from the actual reserves margin necessary to support imbalances between demand and generation, and instability in electricity distribution networks (affecting the sufficiency, quality and continuity of electricity supply). As the blackout occurred in December 2020, product of an imbalance in the national interconnected system between the load and the generation of energy.

The geographic framework of the research includes the National Interconnected System (SIN) of Mexico and the Baja California Sur Interconnected System (BCS), based on the experience of the Independent Operator of Systems of California, in the United States to apply a simulation in the BCS.

To carry out the simulation, an integrated self-regressive model of mobile stockings (ARIMA) and self-regressive vector models (VAR) is used. The variables used are the Demand of the day market in advance (MDA) and the Average Local Marginal Price of the MDA. With a research period covered by January 1, 2019 to October 1, 2020, it allows analyzing the main problem of the FRE: its prognosis.

For the elaboration of this thesis, several foreign authors were used as reference and domestic Entities such as SENER, CRE, CENACE, and thesis work carried out previously carried out in the Higher School of the National Polytechnic Institute were also consulted.

The research comprises introduction, 3 sections, conclusions and bibliography. In section 2, is spoken about the participation that the FRE have in the Mexican market. Subsequently, the electric sector and the structure that this market has is regulated in Mexico. Mainly the functioning of the short-term energy market is described, which is divided into the first stage market and the second stage. Finally, a brief description of the Baja California Sur System is made, which is the one on which the data is collected to carry out the research analysis.

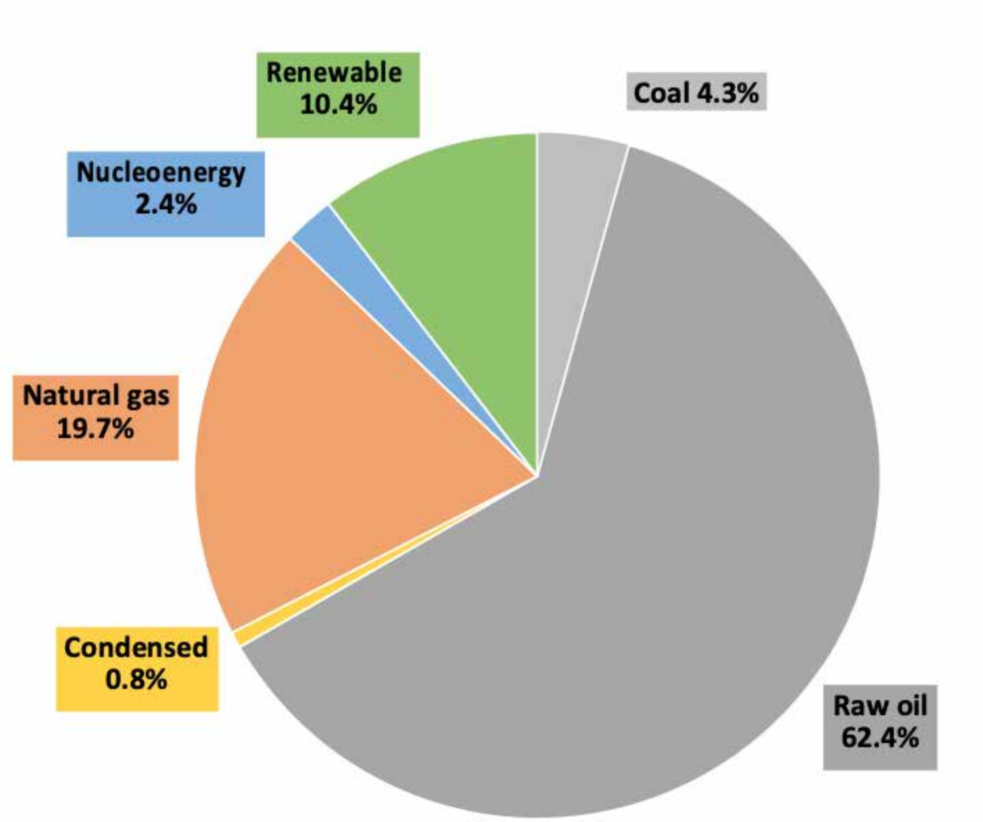
Section 3 we present the methodology, and a brief introduction to VAR and ARIMA models, which will be used to predict a day of advancement and one hour in advance with BCS data that were collected by the independent market monitor. The formal demonstration of forecasting one hour ahead is developed, and so on until the result of forecasting 24 hours ahead is obtained. The database to be used is described.

Finally, in Section 4 we present the analysis carried out and the results obtained. Where it was sought to replicate the second stage of the short-term electricity market in Mexico. Seeking to demonstrate that if this second stage market is put into operation, that is, forecasting one hour in advance instead of 24 hours in advance, it is effective in obtaining a more accurate forecast of expected demand, and in reducing variability or forecast errors during power generation, mainly when using renewable sources.

## 2. THE MEXICAN ENERGY SECTOR

The activity of the Mexican economy, over time, has grown, and with it the demand for energy has also been increasing. However, in recent years, primary energy production has gradually decreased since 2007 until 2018 according to the latest data published officially by the National Energy Balance (SENER, 2019). During 2018, energy imports increased by 15.51% compared to 2017. This was mainly reflected in an increase in the importation of hydrocarbons, especially liquefied gas, gasoline and naphtha, diesel, dry gas[5], among others.

In Graph 1 shows the production of primary energy in the country according to the source. It can be seen that the highest production is from hydrocarbons with 82.9% and within this, the use of crude oil occupies 62.4%, so that thermoelectric plants that burn fossil fuels (gas, oil and coal) predominate. And energy production with renewable sources occupies 10.4%.




Source: Own elaboration with data from the National Energy Balance (SENER, 2019). All Petajoule data were converted to Gigavatio hour.

GRAPH 1. PRIMARY ENERGY PRODUCTION, MEXICO 2018 IN GWH

Although, since 2014, a reform was approved in Mexico energy that allowed you to create a wholesale electricity market and several measures were also approved. Among them, to promote generation through renewable sources through long-term auctions. The main objectives of this reform were: 1) the generation of reliable energy to guarantee the supply, 2) that is more competitive economically, and 3) that is friendly with the environment (ENERGIAHOY, 2019).

Subsequently at the International Conference on Climate Change (COP21) in 2015, Mexico is committed to reducing greenhouse gas (GHG) emissions to 22% by 2030. and established that this decrease would be given through the addiction of 36.7 GW of clean and renewable energies, the reconversion of dual thermal power plants, the establishment of state-of-the-art technologies, and the improvement of the efficiency of power plants.

Also, in the Act of Energy Transition approved in 2015 in Mexico, goals were established in renewable and clean energy installation. Where by 2024, the country must have 35% of the generation of electricity through clean technologies. And by 2050, it must reach 50% of the generation of electricity through renewable energy (ENERGIAHOY, 2019).

In the same way, it was necessary to strengthen and expand the transmission and distribution infrastructure of electricity, strengthen the instruments and competences of the institutions responsible for energy efficiency, and combat climate change. All these agreements brought an increase in long-term auctions in FRE, and therefore a clean energy development as shown in Graph 1, although up to date the growth of the auctions has not been constant.

However, the current government at the beginning presented the willingness to follow and strengthen the development of the FRE within the electricity sector[6], but a change of direction has been observed aimed at safeguarding the Mexican hydrocarbon and oil sector (PEMEX).

This change has focused on rescuing Pemex and the oil industry, focusing on refining to achieve "fuel sovereignty" and reduce dependence on imports. In the rehabilitation of existing refineries, based on the existence of potential potentials by determining hydrocarbons and stable natural gas prices (ENERGIAHOY, 2019).

Also, in the idea that FRE can have a negative impact on the country's energy security due to the lack of reliability they have to meet the demand of end users, mainly variable sources of energy for the difficulty in their prediction for the calculation of daily demand.

These limitations faced by FRE, has been mainly by the way of making energy policy by the Government, which must legislate the alliance between the Federal Electricity Commission and private companies, so that the two invest and contribute to the modernization of the Mexican system with the infrastructure of generation, transmission and distribution. And continue with the Commitment to reach a sustainable electricity, to mitigate the dependence on imported gas.

An example to promote non-Mexico's non-dependence of hydrocarbons may be the blackout occurred in February 2021, due to low temperatures that prevented from importing natural gas from the United States to meet energy demand. It could be thought, that maybe the impact would have been less,

[6] The 2018-2024 Nation Project presented by AMLO, when he was a candidate for the Presidency, proposed to establish as one of his goals: to increase the "effort of exploration and production of natural gas", "to expand the gas pipeline networks to the regions that still they do not have access to energy", and to substitute natural gas for renewable energies in the production of electricity during the six-year term.

if it was counted on a diversified energy matrix and with a much greater presence of own clean technologies.

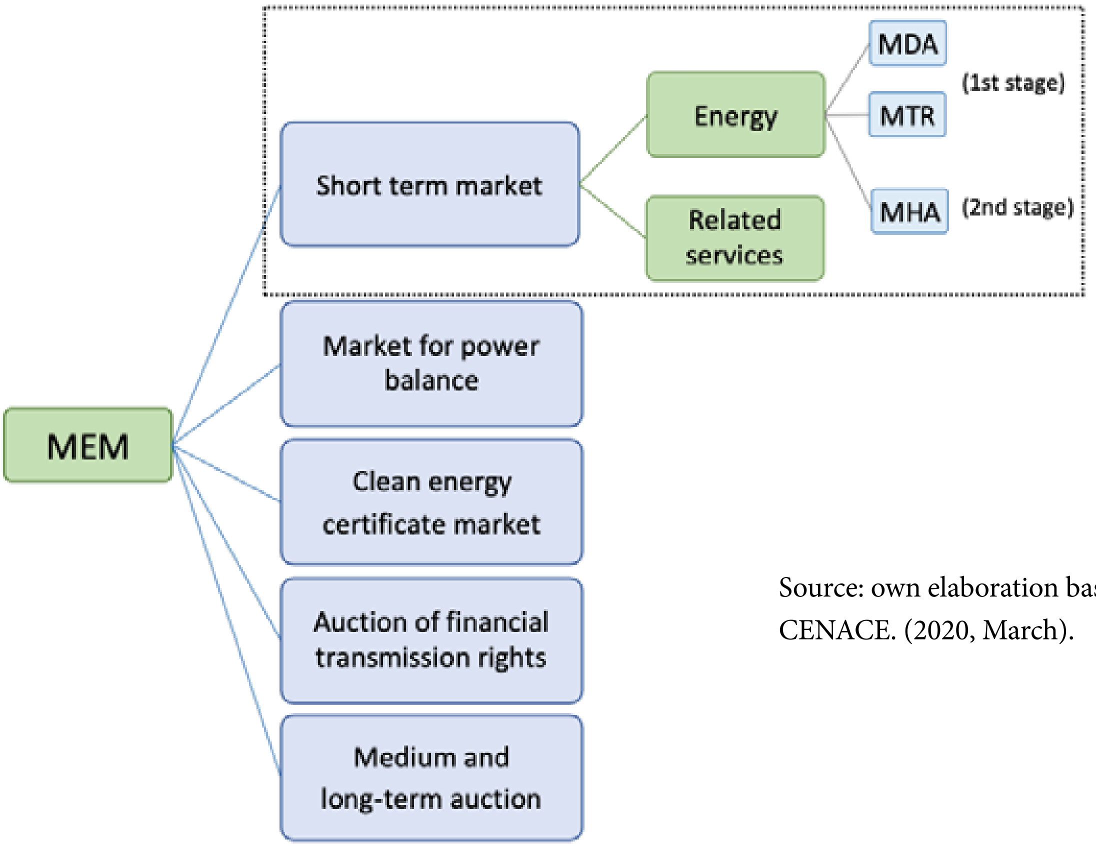
Also, the current state of the transmission and distribution infrastructure has been a very low growth in the last 10 years, less than 1% since 2013. Only growing 1 kilometer in the period of 2019-2020 due to the decrease in auctions in the long term, becoming an increase in the congestion of the electrical system, in the imbalances, increase of the MEM PML and therefore the system remains highly stressed (Business Coordinating Council, forum carried out in 2021).

So, the question we should ask ourselves is really the answer to achieve Mexico's energy security is to achieve the independence of the import of hydrocarbons, and the road is developing fossil fuels? The fact that the greater volume of electricity continues to be obtained from generation models with hydrocarbons, without investing in new technologies and infrastructures, violates confidence in the Mexican electrical system.

The energy reform that was carried out in Mexico allowed the transition from a centralized and controlled scheme by the Federal Electricity Commission, to a competitive market structure based on the interaction of the supply and demand forces, regulated by CRE and the CENACE.

This transformation brought the need to have a model of assignment and dispatch of own units of a wholesale electricity market based on five new markets in which electric power, clean energy certificates, power, and other products that are required for the Operation of the SEN.

Within these markets is the short-term energy market, which is where the investigation of this thesis focuses. Next, in Figure 1 the structure of the MEM is shown summarized.




Source: own elaboration based on CENACE. (2020, March).

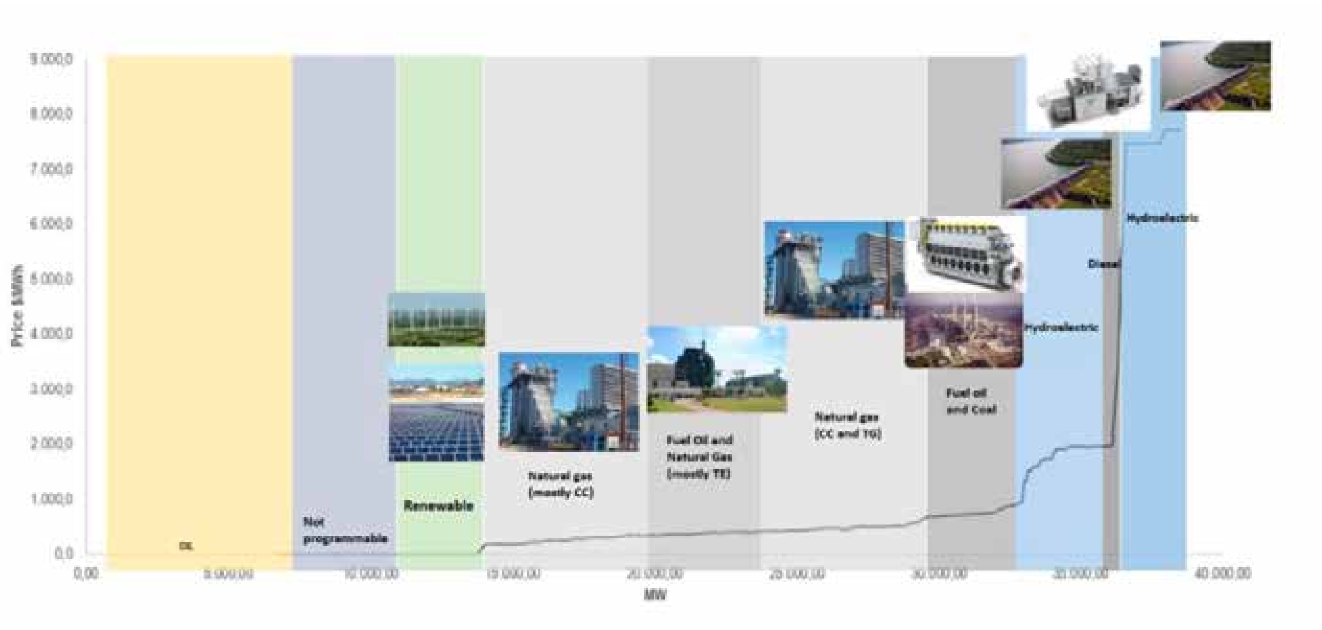
FIGURE 1. STRUCTURE OF THE WHOLESALE ELECTRICITY MARKET (MEM)

This short-term market is formed by the energy market and related services. In it the participants make offers of purchase-sale of energy and related services in order to provide enough energy at the lowest possible cost. Qualified users and their suppliers determine the demand for electric power, while the offer is determined by the variable costs of each electricity generator.

In the case of Mexico, the lowest cost offers are first approved in tenders and are priority of dispatch, usually power plants with lower variable costs are clean energy generators. The cost is associated with the type of technology that the participant uses as can be observed in Figure 2, the merit curve of energy sales offers.

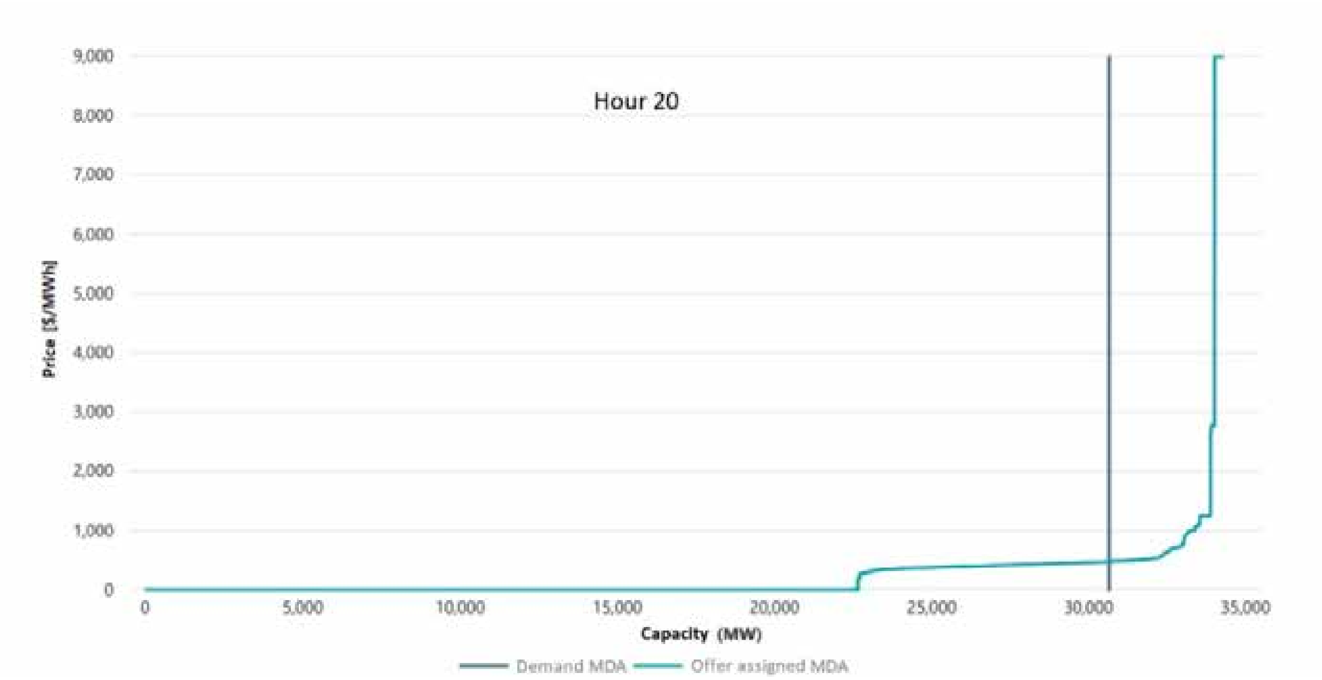
The cost market is expressed in the offer of electric markets, which depend on the costs of generation of plants, and the expects of profits of economic agents to recover investment costs and obtain profitability. These costs will be depending on the type of technology that is used. The balance price will be equal to the final price of the last central used to comply with the demand[7].

[7] In Mexico, the market operator is CENACE, and there are price markets and cost markets. The price markets are given by the condition of being multinodal markets, it occurs when there is a price for each node of the system due to the restrictions of the transmission network or the situation of the generators and consumers. It can also be expressed in a single-node market, which does not consider all the limitations during the transmission at the closing of the market, and there is only one price for the entire market.




GRAPH 2. MERIT CURVE OF ENERGY SALE OFFERS

Balance determines the amount of energy needed to meet the demand as can be seen in Figure 3 below:




GRAPH 3. SALE CURVE ASSIGNED AND DEMAND, PEAK HOUR (SIN)

Source: CRE. (2020). Daily report of the day market in Advancement (MDA), December 31, 2020.

The generator dispatched with higher cost is the one that will set the purchase-sale price in the wholesale electricity market, therefore, those of lower costs are those that They will get greater profits. In a price market, participants offer price while in a cost market they offer costs. In Mexico, CENACE verifies that the costs offered by the participants are effectively the production costs based on the technology they use, the type and antiquity of the machines and the type of fuel they require.

As shown in Figure 1, the short-term energy market is divided into two stages depending on the temporary horizon of the transaction. The first stage market is made up of the operation of the Advance Day Market (MDA) and the Real Time Market (MTR). And the second stage is formed by the Hour Market in Advancement (MHA).

If the energy is marketed a day before its generation, the transaction is performed in the MDA. If the energy is marketed on the same day of its generation, it is done on the MTR. And if the energy is marketed an hour before its generation, it is done in the MHA.

In Mexico, the MDA initiated its operations for the interconnected system of Baja California on January 27, 2016, for the National Interconnected System on January 29, 2016, and for the Baja California Sur Interconnected System on March 23, 2016 (CENACE, 2020, March).

Once the CENACE receives the purchase and sale offers, it carries out an Economic Office of the UCE for each of the markets. As a consequence of this office, the PML of energy is obtained in each distributed node (loading area or a generation zone) of the national electrical system.

The nodal PML obtained in the MDA are formed from the energy component, component by Electrical network congestion and active power loss component on the network. The PML is the incremental cost to satisfy a load change in a given node, respecting the physical restrictions of the network.

The PML methodology is essential to calculate the price of energy in some electrical markets. And it is defined as the "price of electrical energy in a given node of the national electrical system for a defined period, calculated in accordance with the rules of the market and applicable to electrical energy transactions carried out in the wholesale electricity market" (CENACE, 2020, April).

## BAJA CALIFORNIA SUR (BCS) SYSTEM

Baja California Sur is one of the states of Mexico rich in natural beauty both in marine and terrestrial life, and therefore is one of the places where tourism has been largely promoted. Contradictorily, due to the geographical characteristics presented by Baja California Sur, has had one of the most pollution and expensive electrical systems in the country (SECFIN BCS, 2016).

The way for electricity generation in South California has been liquid fuels that can be transported by sea, and this together with the presence of a non-abundant population as in other states, limited the development of the technologies of the energy generation systems.

The unwanted consequences of the above mentioned were high generation costs and the emission of pollutants that negatively impact the health of their inhabitants and climate. Therefore, alternatives were raised that were mostly materialized, but other alternatives as including FRE allowed to cover the demand for very competitive costs and without affecting the environment.

The Southern California Baja California (BCS) is an electrical system that geographically comprises from Loreto to Los Cabos, in Baja California Sur. It is an isolated electrical system of the National Interconnected System (SIN), the Baja California Interconnected System and the Interconnected System of Mulege, but all of them together make up the National Electrical System (SEN), as shown in Figure 4.


FIGURE 4. INTERCONNECTED SYSTEMS OF THE SEN

Source: Taken HR Ratings from Mexico, SA (2018).

The BCS has three large power generation power plants with fuel and diesel, with maximum generation capacity of 104 MW, 113 MW and 210 MW respectively (Ramírez Cabrera, Víctor F., 2020). There are also 3 units of renewable power plant (UCE) solar generation. Two of them are Legacy Interconnection Contracts (CIL) of 30 and 25 MW each, and their market participant is a CFE intermediation generator.
The third is a private UCE of 0.5 MW cataloged as an exempt generator, and represents it ampere energy. This is known as a distributed generation and is defined as the generation of electrical energy that is interconnected to a distribution circuit and includes the one that is carried out by an exempt generator, which is a power plant with a capacity lower than 0.5 MW (can also be by citizens who buy and install solar panels) so they do not require permission before CRE to generate electricity in the market. The distributed generation can be located at the installations of the loading centers or independently (SENER, 2016).
Because the BCS incorporates and uses the FRE for the generation of electricity, it is exposed to presenting the same problems that are mentioned in chapters before using variable clean energies. And it is that these sources for its features of intermittent generation could negatively influence the reliability and stability of the SEN, and as a consequence to derive in a decrease in the participation of the FRE within the electrical system.

Therefore, real data from the BCS of the day energy market in advance (MDA) are taken to apply the model of the second stage of the MEM short-term market. And observe the behavior and variation of the average error by forecasting the demand for electric power and its local marginal prices.

This is expected to obtain a more precise prognosis to the real-time market (MTR) where generators and consumers carry out the purchase-sale of energy, with more balanced and righteous prices.

## 3. METHODOLOGY

The self-recruitment vectors (VAR) are a statistical model that is used to represent the relationship between multiple amounts as they change over time. Var is a series of time and therefore is a stochastic (random) process indexed by time. Var are widely used for analysis in economics given its predictive power[8].
In this type of model, each variable has an equation that models its evolution over time, and allows to treat very well with endogeneity / simultaneity, where a variable is explained by another and at the same time that other variable is explained by the previous one, that is, they are explained each other. Hence, we use it in this research to predict each hour of a given day until you reach the hour 24.
This equation includes the laggard (past) values of the variable and an error term. Then to develop this type of models, it requires prior knowledge of a list of variables that can be hypothesized to affect each other over time, and not as much knowledge of the forces that influence a variable as structural models with equations Simultaneous.
ARIMA is a statistical model that uses variations and regressions of statistical data with the aim of finding patterns for a prediction to the future. Like Var is a dynamic model of temporary series, that is, future estimates are explained by past data and not by independent variables.
This model allows to describe a value as a linear function of previous data and errors due to chance, and may also include a cyclic or seasonal component. So, you must contain all the necessary elements to describe the phenomenon.
The development of the formal demonstration of why the forecast is better just one step forward, and not the forecast with several hours in advance is shown below, because this justification is the most important step to demonstrate our hypothesis, and later it will be taken to the practice.

[8] To deepen on autoregressive vector models, see: Novales, Alfonso (2017, November).

Be Model AR (1):

$$Yt = \varphi\, Yt{-}1 + \mathcal{E}t \qquad (10)$$

Under the assumptions that $\mathcal{E}t \sim^{iid} (0, \sigma^2)$, $Y_t$ is weakly stationary, and Cov $(\mathcal{E}_s, Y_t) = 0 \; \forall \; t \neq s$.

Forecast one step forward (h + 1):

1) $Y_{h+1} = \varphi\, Y_h + \mathcal{E}_{h+1}$

2) Punctual forecast.

$E(Y_{h+1}/F_h) = \varphi\, E(Y_h/F_h) + E(\mathcal{E}_{h+1}/F_h)$ (11) As $E(\mathcal{E}h{+}1/Fh) = 0$, is obtained:

(11)

$$E(Yh{+}1/Fh) = \hat{Y}h{+}1 = \varphi\, Yh \qquad (12)$$

$\varphi\, Y_h$: This is the last real value observed in the database.

3) Forecast error.

Substituting:

$$e_{h+1} = Y_{h+1} - \hat{Y}_{h+1} = \varphi\, Y_h + \mathcal{E}_{h+1} - \varphi\, Y_h = \mathcal{E}_{h+1} \qquad (13)$$

$$e_{h+1} = \mathcal{E}_{h+1} \qquad (14)$$

4) Error variance.

$$Var(e_{h+1}) = Var\,(\mathcal{E}_{h+1}) = \sigma^2 \qquad (15)$$

Forecast Two steps forward (h + 2):

1) $Y_{h+2} = \varphi\, Y_{h+1} + \mathcal{E}_{h+2}$

2) Punctual forecast.

$$E(Y_{h+2}/F_h) = \varphi\, E(Y_{h+1}/F_h) + E(\mathcal{E}h_{+2}/F_h) \qquad (16)$$

$$E(Y_{h+2}/F_h) = \hat{Y}_{h+2} = \varphi\, \hat{Y}_{h+1} \qquad (17)$$

It can be seen that the forecast two steps forward use the forecast a step forward previously $\hat{Y}_{h+1}$.

3) Forecast error.

Substituting:

$$e_{h+2} = Y_{h+2} - \hat{Y}_{h+2} = \varphi Y_{h+1} + \varepsilon_{h+2} - \varphi \hat{Y}_{h+1} \quad (18)$$

$$e_{h+2} = \varphi (Y_{h+1} - \hat{Y}_{h+1}) + \varepsilon_{h+2} \quad (19)$$

$$e_{h+2} = \varphi \varepsilon_{h+1} + \varepsilon_{h+2} = \varphi e_{h+1} + \varepsilon_{h+2} \quad (20)$$

4) Error variance.

$$\begin{aligned}\mathrm{Var}\ (e_{h+2}) = \mathrm{Var}\ (\varphi \varepsilon_{h+1} + \varepsilon_{h+2}) = \varphi^2\ \mathrm{Var}\ (\varepsilon_{h+1}) + \mathrm{Var}\ (\varepsilon_{h+2}) + \\ \mathrm{Var}\ (\varepsilon_{h+2})\ 2\varphi\mathrm{Cov}(\varepsilon_{h+1}, \varepsilon_{h+2})\end{aligned} \quad (21)$$

As $2\varphi\mathrm{Cov}(\varepsilon_{h+1}, \varepsilon_{h+2}) = 0$

$$\mathrm{Var}\ (e_{h+2}) = \varphi^2\ \mathrm{Var}\ (\varepsilon_{h+1}) + \mathrm{Var}\ (\varepsilon_{h+2}) = \varphi^2 \sigma^2 + \sigma^2 = \sigma^2(\varphi^2 + 1) \quad (22)$$

Unlike of the variance calculated with a step forward in equation 15, the variance obtained with only two steps forward grows in the magnitude of ˆ ^ 2 ( ^ 2 + 1), equation 22. With what is concluded, as of These results, we can expect a much greater increase in the variance of the error using a forecast with 3, 4 and up to 24 steps forward. In this case the variance of the error with 24 steps of advance is:

$$Var\ ( e_{h+24}) = \sigma^2(1 - \varphi^{48}/1 - \varphi^2) \quad (23)$$

## DESCRIPTION OF THE DATABASE

The Database used in this research is provided by the National Center for Energy Control (CENACE). It contains real information regarding the demand of the day market in advance (MDA) of the BCS and the average local MDA marginal prices.

The database covers a period of January 1, 2019 until October 1, 2020. It takes a day to forecast between the period from May to September, since it is considered the critical stage of BCS demand, and therefore It is the most difficult to predict.

The database according to its type[9] is a series of temporary data. It means that it is a succession of data measured at certain times and ordered chronologically. The data is spaced at equal intervals, and for the analysis of the time series, methods that allow them to interpret them and extract representative information on the underlying relationships between the data of the series are used.

They make it possible to extrapolate or interpolate the data to predict the behavior of the series at times not observed in the future (predictive extrapolation), in the past (retrograde extrapolation) or at intermediate moments (interpolation).

Within the period covered by the database, there are 693 days and you have the detailed information of 24 hours of each day, so there are 16,632 data. But from the previously explained, it was decided to take a sample with a temporary horizon of January 1, 2019 until May 20, 2020, that is, 506 days, 12,144 data. With this information, the 24-hour model of advancement of May 21, 2020 and the one-hour model of ahead is estimated from the time 1 to the time 24 of that same day. And then make a comparison between MDA and MHA, and observe which has the least average prognostic error.

The variables to be used are the total MDA demand and the MDA average PML. It should be specified that the MDA PML are averages, because as set out in sub-item 2.3, the Node PML depends on the injection or physical withdrawal of energy and the components of loss and congestion in each location where these nodes are found, Therefore, the PML that make up without, may vary within a region. Also, because according to the bases of the electricity market (SENER, 2015), section 4.3.3, subsection (c) - (iv), its calculation should include the historical average of 7 days before.

The variable of the demand is expressed in megawatts per hour, MWh, and the PML in Mexican pesos by MWh, $ / MWh.

When using the extrapolation method to predict in the MDA, it consists of supposing that the series will behave in the future in the same way that is being developed, and this is established as a rule to reach a new conclusion. The basis for extrapolation will be about the recent knowledge that is of the development of a phenomenon, and it is required of at least two sequential observations made in a specific time in the past to perform it.

Extrapolation is to create a tangent line at the end of the known data and extend it beyond that limit. Linear extrapolation will provide good results only when using to extend the graph of a linear function approximately or not far away from the known data.

If the two points that will be extrapolated close to the $x*$ point, are $(xk-1, yk-1)$ and $(xk, yk)$, the linear extrapolation gives us the function:

$$y(x_*) = y_{k-1} + \frac{x_* - x_{k-1}}{x_k - x_{k-1}}(y_k - y_{k-1})$$

[9] Remember that, depending on the type, there are data: temporal, cross section, spatial and panel.

The disadvantage that is, that when you want to continue with the prognosis at times of time in the future, (24) for example, when we forecast the variables of our research from the 3 hours, you are reached at the point where you are no longer available with data Real for the forecast, and the obtained values begin to give zero as a result.
Then we must go through an interpolation on the prognosis. That is, we will continue to perform the same calculation that it has been developed, but with the predicted values. If already by itself, the extrapolation represents the obtaining of a data with some uncertainty, we can expect that with interpolation, the more we get away from the observation, the worse the prognosis.
But if we predicted in the MHA, which means forecasting only one step forward, the models continue to use real information to predict, and the margin of error will be much lower.
Therefore, it can be summarized, that the fundamental difference between the current market and that of the second stage is the forecast horizon. When a VAR model and / or ARIMA predicts begins to lose real data and you should start predicting the forecasts. The farther is the forecast horizon, the predictions will have a greater error, on the other hand, when only one step forward is forecast, the models continue to use real information.

## 4. SIMULATION OF THE SECOND STAGE MARKET IN THE BCS INTERCONNECTED SYSTEM

To perform the econometric analysis of the database and its statistical tests, the statistical package of EViews 10 was used, and to perform the prognosis calculation and waste variations. Use Excel. An ARIMA model and 24 VAR models is used.
Beginning with the econometric analysis, you must first know if the series of variable D (demand) is stationary or not. For this we check the T-Statistic, and compared the estimate against statistics in tables, all in absolute value. We propose that the series is stationary if |t estimated | > |t-Statistic on Table 1.
For this, the unitary root test is applied in EViews, in this case you have to apply the first difference to make it stationary, and as | 21.20862 | > | T-statistic on Table | the stationary is met. The results are shown in Table 2.

TABLE 3. PARKING TEST OF THE VARIABLE PML

| | | *t-Statistic* | *Prob.** |
|---|---|---|---|
| *Increased Statistical Test of Dickey-Fuller* | | **-21.20862** | **0.0000** |
| *Test Critical Values* | 1% Level | -3.958790 | |
| | 5% Level | -3.410173 | |
| | 10% Level | -3.126823 | |

Source: Own elaboration obtained in the EViews estimate of the model.

TABLE 4. ESTIMATED PARAMETERS OF THE ARIMA MODEL (2, 1, 0) OF THE VARIABLE DEMAND PREDICTED

| *Parameters* | $c$ | $\varphi_1$ | $\varphi_2$ |
|---|---|---|---|
| *Poefficients* | 0.001691 | 0.933651 | -0.235482 |
| *p-value* | 0.9938 | 0.0000 | 0.0000 |

Source: own elaboration obtained in the EViews estimate of the model.

When observing the sign of the first coefficient of regression, a direct relationship (positive sign) is observed between the variables, that is, if the demand for a previous period is increased in an MWh, the present demand will increase in 0.0065 MWh (corresponds to the value of Std. error).

From the estimate of the model also get relevant statistics that are presented in Table 5.

TABLE 5. RELEVANT STATISTICS OF THE ESTIMATION

**Table 5. Relevant statistics of the estimation**

| | | | |
|---|---|---|---|
| **R-squared** | **0.594905** | **Mean dependent var** | **0.002334** |
| **Adjusted R-squared** | 0.594804 | **S.D. dependent var** | 10.85012 |
| **S.E. of regression** | 6.906643 | **Akaike info criterion** | 6.703253 |
| **Sum squared resid** | 579528.2 | **Schwarz criterion** | 6.705690 |
| **Log likelihood** | -40728.31 | **Hannan-Quinn criter.** | 6.704070 |
| **F-statistic** | 5947.154 | **Durbin-Watson stat** | 2.004131 |
| **Prob (F-statistic)** | 0.000000 | | |

Source: Own elaboration obtained in the EViews estimate of the model.

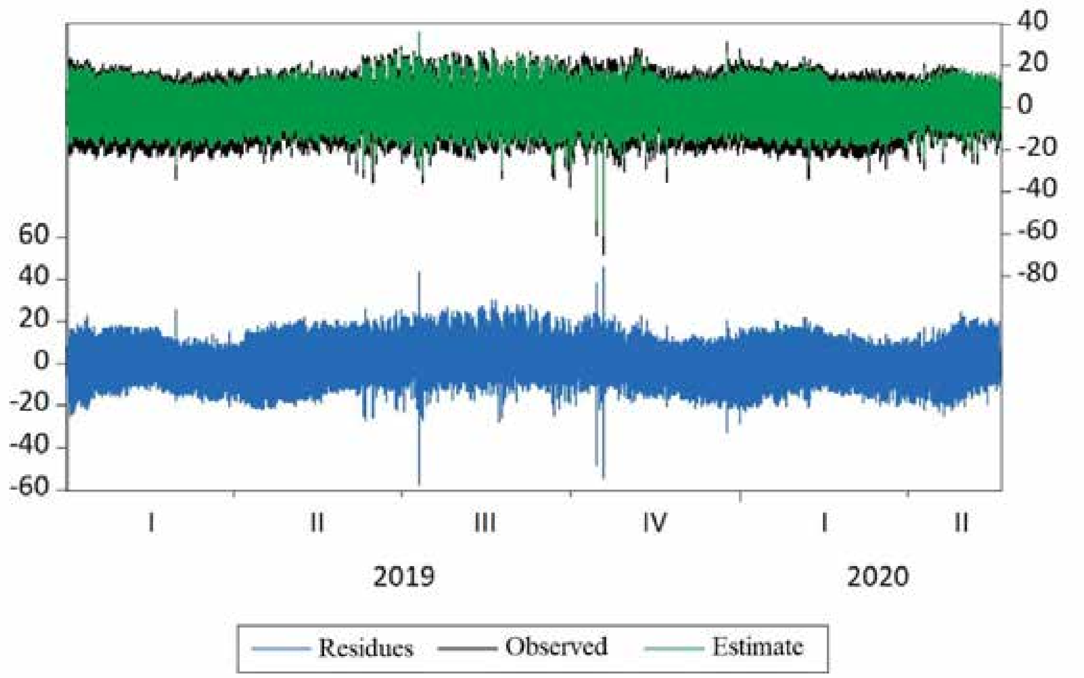
To know the kindness of the model adjustment, the multi-determination coefficient $R^2$ is used. With a R-squared = 0.594905 it can be said that the model is good because the value of $R^2$ is close to one. This is a sign of good fit and as it is a model with constant, this result indicates that 59% of the variability of demand (Yt), is explained by the model. The same is explained for the corrected determination coefficient of the model.

Another relevant statistic is Durbin-Watson = 2,004131. The null hypothesis of the statistic tells us that there is serial autocorrelation of 1st order, it means that in the t-1 (today) there is information that can improve the model. Ho: $\varphi \neq 0$ $y$ $c \neq 0$ mean that if they explain. Therefore, as DW approaches 2, there is no serial and express autocorrelation that there is nothing in t-1 that serves to improve the model.

It can also be determined if the model is stationary, when examining the value of the roots of the estimated AR delays: Inverted AR Roots = .47-.13i and the roots are less than the module of 1, and consequently, the value of the estimated coefficients guarantees the stationarity.

Continuing with the verification of the kindness of the model setting, it is used to compare the estimated or adjusted series (fitted in EViews) with the observed (current in EViews), and the residues of the model are examined. The foregoing gives us information about the goodness of the adjustment. If the model is good, the adjusted series will be very similar to that observed, and the waste will be small in relation to the observed values.

Below is a Graph 4 to double scale of these series. The observed and adjusted series is observed at the top. Both series are very similar, which indicates that the model is adjusted well. Below the series of waste is represented, which fluctuates around 0 randomly. As can be seen, the residues are small in relation to the value of the observed variable, which also informs us of the goodness of the model.




GRAPH 4. WASTE OF THE D SERIES (DEMAND)

Source: Own elaboration obtained in the EViews estimate of the model.

Therefore, the best estimated model describing the time series of MDA demand is an ARIMA model (2, 1, 0) and is represented as follows, with the series of waste from the model:

$$D(Demand) = 0.001691 + 0.933651 * D(Demand)_{t-1} - 0.235482D(Demand)_{t-2} + e_t \quad (25)$$

Applying the Formula presented by the SENER (2017) in the manual of Forecast, the multiple linear regression methodology is used, which consists of the existence of a set of independent variables and a dependent variable. The variation of the independent variables is used to predict the dependent variable. A straight line is the simplest graphic model to relate a dependent variable with one or several independent variables.
The formula of the multiple linear regression model is as follows:

Where:

$$Y = B_0 + B_1X_1 + B_2X_2 ... + B_nX_n + e \quad (26)$$

Y: dependent variable, in this case, demand that you want to know.
$X_1$, $X_2$: independent variables, real demand values in previous periods.

$B_0$, $B_1$, $B_2$: parameters obtained in the model made in EViews.

n: numbers of independent variables.

e: random disturbance.

Then using the previously obtained coefficients, the predicted D (Demand) lawsuit is extrapolated, and interpolated on the prognosis, since in theory to carry out this exercise we assume that we only have the total real demand until the full day of 20 May 2020. The results of D (Demand) predicted, can be found in Annex 3.
Now it is passed to estimate the coefficients of the D variable (average PML) with the VAR model in EViews. It is done in general mode, the same procedure that has been done so far. To this end, the model is estimated and the following parameters are obtained from Table 6.

TABLE 6. ESTIMATED PARAMETERS OF THE VAR MODEL FOR THE PML VARIABLE AVERAGE PREDICTED

| | *D(PML(-1))* | *D(PML(-2))* | *D(DEMAND(-1))* | *D(DEMAND(-2))* | *C* |
|---|---|---|---|---|---|
| *D(PML)* | -0.225932 | -0.031618 | 9.916062 | -0.121381 | -0.051569 |

Source: Own elaboration obtained in the EViews estimate of the model.

And the best estimated model to predict in the MDA is represented as follows:

$$D(PML) = C(1,1) * D(PML(-1)) + C(1,2) * D(PML(-2)) + C(1,3) * (DEMAND(-1)) + C(1,4) * D(DEMAND(-2)) + C(1,5) + e_t \tag{27}$$

$$D(PML) = -\ 0.225932 * D(PML(-1)) - 0.031618 * D(PML(-2)) + 9.916062 * D(DEMAND(-1)) - 0.121381 * D(DEMAND(-2)) - 0.051569 + e_t \tag{27.1}$$

Once the parameters are obtained, they are used to estimate the average PML error or residue that are expected for the next day. This is solved extrapolating over the current values of the residues of the demand and the PML itself that were obtained in EViews of the ARIMA model. Then this column of estimated PML errors will be added with the actual PML of one day before, and as a consequence it gives us the estimated PLM with 24 hours of advancement, that is, of the MDA.

Of course, that to continue forecasting from two hour, on May 21, no real data are already being counted, and therefore you will have to start using the estimated demand data and the errors of the PML, to find the new values of estimated PML with 24 hours of advancement. All these data can be found in Annex 3.

Why are residues used? A good prognostic error estimate in a passage of time, it can be useful to make better predictions. Add the expected forecast error to a prediction serves to correct it and, in turn, improve the skill of the model.

Waste is useful for verifying whether a model has adequately captured information in the data. If the waste patterns are observed, the model can probably improve. A good prognosis method will produce waste with the following properties: waste is not correlated, if there are correlations between residuals, then there is still information on waste to be used to calculate forecasts (Hyndman, RJ and Athanasopoulos, G., 2016).

The residues are average zero, if the waste has a different than zero average, the forecasts are biased. In addition to these essential properties, it is useful but not necessary, that waste also have the following two properties: waste has a constant variance, and waste is normally distributed (Hyndman, R. J. and Athanasopoulos, G., 2016).

As a result of the calculations carried out, a percentage variation is obtained for an average error predicting with a var and the 24-hour model in advance of 205.6%.

Subsequently, it is proceeded to estimate the remaining 23 var models in EViews for the MHA, that is, to predict one hour of advancement. It consists of adding the real time observed of a period prior to the new estimate. The coefficients that are obtained from the models are in the following estimated equations:

$$VAR2\text{: D(PML)} = -\ 0.225935 * \text{D(PML(}-1)) - 0.031621 * \text{D(PML(}-2)) + 9.916682 * \text{D(DEMAND(}-1)) - 0.121369 * \text{D(DEMAND(}-2)) - 0.055876$$

$$VAR3\text{: D(PML)} = -\ 0{,}225942 * \text{D(PML(}-1)) - 0{,}031606 * \text{D(PML(}-2)) + 9{,}916041 * \text{D(DEMAND(}-1)) - 0{,}124404 * \text{D(DEMAND(}-2)) - 0{,}0302936$$

$$VAR4\text{: D(PML)} = -\ 0{,}225934 * \text{D(PML(}-1)) - 0{,}031605 * \text{D(PML(}-2)) + 9{,}915838 * \text{D(DEMAND(}-1)) - 0{,}124758 * \text{D(DEMAND(}-2)) - 0{,}026329$$

$$VAR5\text{: D(PML)} = -\ 0{,}225939 * \text{D(PML(}-1)) - 0{,}031651 * \text{D(PML(}-2)) + 9{,}915419 * \text{D(DEMAND(}-1)) - 0{,}121673 * \text{D(DEMAND(}-2)) - 0{,}049261$$

$$VAR6\text{: D(PML)} = -\ 0{,}225935 * \text{D(PML(}-1)) - 0{,}031651 * \text{D(PML(}-2)) + 9{,}915353 * \text{D(DEMAND(}-1)) - 0{,}121511 * \text{D(DEMAND(}-2)) - 0{,}051578$$

$$VAR7\text{: D(PML)} = -\ 0{,}225935 * \text{D(PML(}-1)) - 0{,}031649 * \text{D(PML(}-2)) + 9{,}915334 * \text{D(DEMAND(}-1)) - 0{,}121483 * \text{D(DEMAND(}-2)) - 0{,}052089$$

$$VAR8\text{: D(PML)} = -\ 0{,}225935 * \text{D(PML(}-1)) - 0{,}031649 * \text{D(PML(}-2)) + 9{,}915328 * \text{D(DEMAND(}-1)) - 0{,}121508 * \text{D(DEMAND(}-2)) - 0{,}050649$$

$$VAR9\text{: D(PML)} = -\ 0{,}225934 * \text{D(PML(}-1)) - 0{,}031649 * \text{D(PML(}-2)) + 9{,}914651 * \text{D(DEMAND(}-1)) - 0{,}120907 * \text{D(DEMAND(}-2)) - 0{,}056896$$

$$VAR10\text{: D(PML)} = -\ 0{,}225924 * \text{D(PML(}-1)) - 0{,}031645 * \text{D(PML(}-2)) + 9{,}912949 * \text{D(DEMAND(}-1)) - 0{,}120121 * \text{D(DEMAND(}-2)) - 0{,}068377$$

$$VAR11\text{: D(PML)} = -\ 0{,}225912 * \text{D(PML(}-1)) - 0{,}031634 * \text{D(PML(}-2)) + 9{,}911847 * \text{D(DEMAND(}-1)) - 0{,}120471 * \text{D(DEMAND(}-2)) - 0{,}079841$$

$$VAR12\text{: D(PML)} = -\ 0{,}225908 * \text{D(PML(}-1)) - 0{,}031629 * \text{D(PML(}-2)) + 9{,}912064 * \text{D(DEMAND(}-1)) - 0{,}121270 * \text{D(DEMAND(}-2)) - 0{,}085275$$

$$VAR13\text{: D(PML)} = -\ 0{,}225906 * \text{D(PML(}-1)) - 0{,}031626 * \text{D(PML(}-2)) + 9{,}911906 * \text{D(DEMAND(}-1)) - 0{,}121437 * \text{D(DEMAND(}-2)) - 0{,}089601$$

$$VAR14\text{: D(PML)} = -\ 0{,}225907 * \text{D(PML(}-1)) - 0{,}031627 * \text{D(PML(}-2)) + 9{,}911861 * \text{D(DEMAND(}-1)) - 0{,}121231 * \text{D(DEMAND(}-2)) - 0{,}086869$$

$$VAR15\text{: D(PML)} = -\ 0{,}225907 * \text{D(PML(}-1)) - 0{,}031631 * \text{D(PML(}-2)) + 9{,}913861 * \text{D(DEMAND(}-1)) - 0{,}121798 * \text{D(DEMAND(}-2)) - 0{,}061319$$

$$VAR16\text{: D(PML)} = -\ 0{,}225950 * \text{D(PML(}-1)) - 0{,}031640 * \text{D(PML(}-2)) + 9{,}913957 *$$

$$\mathrm{D(DEMAND(-1))} - 0{,}122857 * \mathrm{D(DEMAND(-2))} - 0{,}084510$$

$$VAR17\text{: } \mathrm{D(PML)} = -0{,}225977 * \mathrm{D(PML(-1))} - 0{,}031620 * \mathrm{D(PML(-2))} + 9{,}914866 * \mathrm{D(DEMAND(-1))} - 0{,}122796 * \mathrm{D(DEMAND(-2))} - 0{,}070022$$

$$VAR18\text{: } \mathrm{D(PML)} = -0{,}225974 * \mathrm{D(PML(-1))} - 0{,}031625 * \mathrm{D(PML(-2))} + 9{,}914835 * \mathrm{D(DEMAND(-1))} - 0{,}122598 * \mathrm{D(DEMAND(-2))} - 0{,}067501$$

$$VAR19\text{: } \mathrm{D(PML)} = -0{,}225969 * \mathrm{D(PML(-1))} - 0{,}031606 * \mathrm{D(PML(-2))} + 9{,}914259 * \mathrm{D(DEMAND(-1))} - 0{,}121828 * \mathrm{D(DEMAND(-2))} - 0{,}054402$$

$$VAR20\text{: } \mathrm{D(PML)} = -0{,}225958 * \mathrm{D(PML(-1))} - 0{,}031603 * \mathrm{D(PML(-2))} + 9{,}912937 * \mathrm{D(DEMAND(-1))} - 0{,}120805 * \mathrm{D(DEMAND(-2))} - 0{,}044922$$

$$VAR21\text{: } \mathrm{D(PML)} = -0{,}225951 * \mathrm{D(PML(-1))} - 0{,}031593 * \mathrm{D(PML(-2))} + 9{,}912435 * \mathrm{D(DEMAND(-1))} - 0{,}120877 * \mathrm{D(DEMAND(-2))} - 0{,}037792$$

$$VAR22\text{: } \mathrm{D(PML)} = -0{,}225944 * \mathrm{D(PML(-1))} - 0{,}031599 * \mathrm{D(PML(-2))} + 9{,}908113 * \mathrm{D(DEMAND(-1))} - 0{,}116988 * \mathrm{D(DEMAND(-2))} - 0{,}048231$$

$$VAR23\text{: } \mathrm{D(PML)} = -0{,}2259426 * \mathrm{D(PML(-1))} - 0{,}031594 * \mathrm{D(PML(-2))} + 9{,}908871 * \mathrm{D(DEMAND(-1))} - 0{,}118296 * \mathrm{D(DEMAND(-2))} - 0{,}053475$$

$$VAR24\text{: } \mathrm{D(PML)} = -0{,}225942 * \mathrm{D(PML(-1))} - 0{,}031594 * \mathrm{D(PML(-2))} + 9{,}908235 * \mathrm{D(DEMAND(-1))} - 0{,}117679 * \mathrm{D(DEMAND(-2))} - 0{,}049592$$

For calculation the new D (Average PML) estimated in Excel, the residuals from previous periods D (Demand) and from D (Average PML), in this case always go to being the residues of current values because the model is updated every hour.
Then the value of the estimated average PML for each hour, is the sum of the D residue (average PML) estimated earlier for the actual average period and PML of a previous hour. With what the variation of the residue that gives an average error predicted with one hour of advance of 1.1% is obtained, as can be seen in Annex 4.
It can be concluded that when making a comparison between the two variations obtained from the MDA and the MHA, give a prediction error of 205.6% and 1.1% respectively, so there is a big difference. Therefore, hypothesis is accepted, which applying the second stage in the short-term energy market, mainly that of predicting one hour of advancement, helps obtain a more successful prognosis by decreasing estimation errors and generation uncertainty, mainly for the FRE.

## 5. CONCLUSIONS

With this research it is concluded that the energy sector is fundamental for the economic growth and social development of a country. Access to electricity is considered a basic service and a right to which the entire population should have access. Therefore, the need to maintain an energy offer safely and reliably.
Also, in Mexico, the main route to generate electricity is by importing fuels, and in 2018 continued to increase, mainly in liquefied gas, gasoline and diesel. However, the coun-

try has a great potential to generate in the electric market with FRE, those that occupied 10.4% in 2018 in the total generation of electricity.

In the same way, it can be concluded that the FRE can contribute great benefits for the Mexican economy, among them having a drag capacity of the national industry, the generation of employment, allow the electrification of urban areas of more difficult access, to develop tourism Ecological, and open up to new market opportunities (in clean technology) in which most economies of the world are accelerated in an accelerated way.

One of the most important benefits, is that to increase the generation with FRE the PML stabilize and the energy prices are picked up. For the projects with FRE are the lowest variable cost and until March 2021, they have placement priority in the MEM, this being a competitive advantage with respect to generation projects with fossil fuels.

It is also summarized that the development of the FRE can be limited by technical, economic and regulatory barriers. One of the obstacles presented by the FRE for deployment, is that at certain occasions they can be difficult to forecast, because of their condition of being intermittent, they associate with them to bring insecurities during the energy dispatch in the SEN.

Due to the above it is established that in Mexico, the fundamental difference between the energy market of short term of the first stage and the second stage market, is the forecast horizon, that is, predicted with a day in advance or predict with one hour in advance in the MHA.

To face prognostic uncertainty, it can be based on the methodology of forecasting with one hour of advance the demand for energy. This allows you to activate the lower cost generator to the system to supply the demand, and be able to respond in shorter time to unforeseen and system failures.

For this reason, the prediction of the price of electricity becomes an important task in the operation and planning of the electrical system. A forecast with one hour in advance provides market participants prices upon shipping for the next hour, and a planning in the generation of energy closest to real demand.

The simulation carried out in this investigation, gives us a clear example of the differences of forecasting with a day or an hour in advance, and therefore on the difference of information on which market operators will take decisions at MEM. If decisions are made with furthest data from reality, there will be greater possibility that imbalances occur in the national electrical system, and that on the other hand the FRE remains relegated to unreliable sources.

When a VAR model and / or ARIMA predict with one day before the next 24 hours, they begin to lose real data to be forecast and therefore must begin to predict the forecasts. This means that the data obtained will have a lower veracity regarding the actual behavior of the electricity market and the amount of energy that is expected to be inserted into the electrical system. Therefore, the forecast horizon is the farther, the predictions will have a greater mistake.

Instead, when only one step forward is forecast, that is, only one hour in advance, it will constantly be contrast to what is obtained against reality, and then the models will continue to use accurate information.

## 6. BIBLIOGRAPHY


Anon. (1987). Our common future, World Commission on Environment and Development, Oxford University Press, Oxford .

Anon. (1989). Energy and the environment: policy overview. *International Energy Agency* (IEA). Anon. (1995a). Anon. GlobalEnergy perspectives to 2050 and beyond. Technical report. London: World Energy Council.

Anon. (1995b). Urban energy handbook. Paris: Organisation for Economic Co-Operation and Development (OECD).

Apergis, N., & Payne, J. (2010). Renewable energy consumption and economic growth: evidence from a panel of OECD countries. *Energy Policy,* 656–660.

Bradley, R., Watts, E., & Williams, E. (1991). Limiting net greenhouse gas emissions in the United States. *US Department of Energy.*

Bugaje, I. (2006). Renewable energy for sustainable development in Africa: a review. *Renew. Sust. Energ. Rev, 10*, 603–612.

Cobb, C. D. (1928). A theory of production. *Am. Econ. Rev., 18*, 139-165.

Dincer, I. (1998a). Energy and environmental impacts: present and future perspectives. Energy Sources , 20(4), 27–53.

Dincer, I. (2000). Renewable energy and sustainable development: a crucial review).Renewable and Sustainable Energy Reviews.

Dincer, I., & Dost, S. (1996). Energy analysis of an ammonia-water absorption refrigeration system (ARS). *Energy Sources, 18*(6), 727-733.

Dincer, I., & Rosen, M. (1998). A worldwide perspective on energy, environment and sustainable development. *International Journal of Energy Research, 22*(15), 1305-1321.

Fang, Y. (2011). Economicwelfare impacts fromrenewable energy consumption: the China experience. *Renew. Sust. Energ. Rev., 15*, 5120–5128.

Frondel, M., Ritter, N., Schimdt, C., & Vance, C. (2010). Economic impacts from the promotion of renewable energy technologies: the German experience. *Energy Policy, 38*, 4048–4056.

García-Álvarez, M. T., & Moreno, B. (2016). La liberalización en la industria eléctrica española. El reto de lograr precios competitivos para los hogares. *Gestión y política pública, 25*(2), 551- 589. doi:http://www.scielo.org.mx/scielo.php?script=sci_arttext&pid=S1405-10792016000200551&lng=es&tlng=es

Hu, J.Q., Hernandez-del-Valle, A. and Martinez-Garcia, M.A. (2017) Environmental Pollution and Economic Growth in China: A Test of the Environmental Kuznets Curve. Journal of Geoscience and Environment Protection, 5, 92-100. https://doi.org/10.4236/gep.2017.510008

Im, K., Pesaran, H., & Shin, Y. (1997). Testing for unit roots in heterogeneous panels. Discussion Paper. *University of Cambridge, Cambridge*.Im, K., Pesaran, M., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *J. Econ., 115*, 53–74.

IPCC. (2007). Fourth Assessment Report of the Intergovernmental Panel on Climate Change.

Jian, Z., Cencen, X., Xiaohua, L., & Ziang, Z. (2017). Electric load forecasting in smart grids using Long-Short-Term-Memory based Recurrent Neural Network. Department of Electrical and Computer Engineering.

Kaygusuz, K. (2007). Energy for sustainable development: key issues and challenges. Energy Sources B Econ. Plan. Policy, 2, 73–83.

Kaygusuz, K., Yuksek, O., & Sari, A. (2007). Renewable energy sources in the European union:markets and capacity. *Energy Sources*

*B Econ. Plan. Policy, 2*, 19–29.
Lei, Z., Linghui, Y., Chengyu, G., & Da, L. (2020). LSTM-based Short-term Electrical Load Forecasting and Anomaly Correction. *International Conference on Power, Energy and Electrical Engineering (CPEEE 2020), 182*. doi:https://doi.org/10.1051/e3sconf/202018201004
Levin, A., & Lin, C. (1993, December). Unit root tests in panel data: asymptotic and finite-sample properties. *Discussion Paper. University of California.*
MacRae, K. (1992). Realizing the benefits of community integrated energy systems. *Canadian Energy Research Institute, Alberta .*
Mahmoud A., H., Borut, J., Bojan, R., & Dejan, D. (2020). Methods and Models for Electric Load Forecasting: A Comprehensive Review. L*ogistics & Sustainable Transpor, 11*(1), 51-76. doi:http://dx.doi.org/10.2478/jlst-2020-0004
Menegaki, A. (2011). Growth and renewable energy in Europe: a random effect model with evidence for neutrality hypothesis. *Energy Econ, 33*, 257–263.
Moselle, B. (2011). Why Support Renewables? . *EPRG Spring Research Seminar University of Cambridge, UK.*
Munasinghe, M. (2010). Rural electrification in the Third World. *Power Eng. J*, 189–202.
Norton, R. (1991). An overview of a sustainable city strategy and Municipalities. *Report Prepared for the Global Energy Assessment Planning for Cities.*
Pablo, d. R., & Mercedes, B. (2008). Assessing the Impact of renewable energy deployment on local sustainability: Towards a theoretical framework. *Renewable and Sustainable Energy Reviews, 15*(5), 1325-1344. doi:https://doi.org/10.1016/j.rser.2007.03.004
Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels withmultiple regressors. *Oxf. Bull. Econ. Stat., 61*, 653–670.
Pedroni, P. (2004). Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis: new results. *Econ. Theory, 20*, 597– 627.
Pereira, M., Freitas, M., & Silva, N. (2010). Rural electrification and energy poverty empirical evidences from Brazil. *Renew. Sust. Energ. Rev., 14*, 1229–1240.
Perman, R., & Stern, D. (2003). Evidence from panel unit root and cointegration tests that the environmental Kuznets curve does exist. *Aust. J. Agric. Resour. Econ., 47*, 325–347.
Rodríguez Padilla, V. (2016). Industria eléctrica en México: tensión entre el Estado y el mercado. *Problemas del desarrollo, 47*(185), 33-55. doi:http://www.scielo.org.mx/scielo.php?script=sci_arttext&pid=S0301-70362016000200033&lng=es&tlng=es
Rosen, M. (1996). The role of energy efficiency in sustainable development Technology and Society. *CrossRefView Record, 15*(4), 21-26.
Roula, I.-L. (2016). The impact of renewable energy consumption to economic growth: A panel data application. *Energy Economics*, 58-63. doi:https://doi.org/10.1016/j.eneco.2015.01.003
Sadorsky, P. (2009). Renewable energy consumption and income in emerging economies. *Energy Policy, 37*, 4021–4028.
Sari, R., & Soytas, U. (2004). Disaggregate energy consumption, employment, and income in. T*urkey. Energy Econ., 26*, 335–344.
Staudemeyer, R., & Morris, E. (2019). *Understanding LSTM - a tutorial into Long Short-Term Memory Recurrent Neural Networks.*
Stigllitz, J. (2002). Globalization and Its Discontents. *Penguin Books Ltd., London, UK.*

Taner, G. (2019). Renewable energy, non-renewable energy and sustainable development. *International Journal of Sustainable Development \& World Ecology, 26*(5), 389-397. doi:DOI: 10.1080/13504509.2019.1595214

Taylor, & Francis. (1996). Environmental technology handbook.

Tester, J., Wood, D., & Ferrari, N. (1990). Energy and the environment in the 21st Century. *MIT, Massachusetts.*

Tugcu, C., Ozlturk, I., & Aslain, A. (2012). Renewable and non-renewable energy consumption and eocnomic growth revisited: evidence from G7 countries. *Energy Econ., 34*, 1942–1950.