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Constructing a Bayesian Network for Solar Energy in Egypt Using Life Cycle Analysis and Machine Learning Algorithms

Rawaa H. El-Bidweihy, Hisham M. Abdelsalam, Ihab A. El-Khodary

***Abstract*—**In an era where machines run and shape our world, the need for a stable, non-ending source of energy emerges. In this study, the focus was on the solar energy in Egypt as a renewable source, the most important factors that could affect the solar energy's market share throughout its life cycle production were analyzed and filtered, the relationships between them were derived before structuring a Bayesian network. Also, forecasted models were built for multiple factors to predict the states in Egypt by 2035, based on historical data and patterns, to be used as the nodes' states in the network. 37 factors were found to might have an impact on the use of solar energy and then were deducted to 12 factors that were chosen to be the most effective to the solar energy's life cycle in Egypt, based on surveying experts and data analysis, some of the factors were found to be recurring in multiple stages. The presented Bayesian network could be used later for scenario and decision analysis of using solar energy in Egypt, as a stable renewable source for generating any type of energy needed.

***Keywords*—**ARIMA, auto correlation, Bayesian network, forecasting models, life cycle, partial correlation, renewable energy, SARIMA, solar energy.

I. Introduction

ENERGY is considered to be one of the main pillars of any society, as well as one of the most important components of economic development in the country. As the population and urbanization increases, the energy consumption increases, nowadays 75% of the energy we use is from non-renewable resources such as coal, oil and natural gas, the other 25% is from renewable resources such as; solar, water, wind, geothermal and biomass [1].

The main advantages of renewable energy sources over the non-renewables ones that they are environmentally friendly and virtually limitless; on the other hand, one of the main problems of the renewable resources is the high cost in the short run. As the technology improves and more people use renewable energy, the prices may come down. Whereas, as more people use non-renewable energy, the prices go up and become more expensive. So, at some point in the long run, even if the renewable energy is expensive now, the non-renewable energy will be even more expensive.

Solar energy is the radiant light and heat that comes naturally from the sun and then converted into energy using some technologies. It is the most important natural source of energy on the planet.

Although the solar radiation outside the earth's atmosphere reaches 5.961×10^7 kg·s^{-3}, it drops to about 1316 kg·s^{-3} on the surface of the earth in the afternoon on a sunny day, where the solar radiation is perpendicular to the surface of the earth, and then it falls in the remaining daylight hours [2]. The clouds also reduce the solar energy falling on the surface of the earth. Thus, there are two basic difficulties in taking advantage of the solar energy; the low density of the energy and changing the amount of energy that can be used.

Egypt is geographically located between the latitudes 22 and 31.5 north which makes it at the center of the global solar belt. Thus, Egypt is one of the richest countries with the solar energy.

Different studies and researches analyzed and discussed the positive impacts of using renewable energy sources [3]-[7], also they discovered a range of potential factors from different types, whether economic, policy, environmental, political, institutional or security, that may affect the use of a renewable energy source as an alternative for generating energy or electricity. Factors identification techniques that are usually used in constructing an experiment may include questioning experts, literature review, surveys, knowledge-based systems, data-based systems or other techniques.

Motivated by the need of using renewable energy and overcoming their disadvantages, this study is interested in using analytical, statistical and machine learning algorithms, to construct a dynamic Bayesian network that will be used later in predicting the market share and the cost of the solar energy in Egypt by 2035, which may help people to start using or investing in renewable energy now, once they ensure that the cost of their investments will be much lower than the other option.

II. Methodologies

Bayesian network is a machine learning algorithm which is in the form of structured, statistical and graphical model that represents a collection of random variables and their relationships via conditional dependencies and independencies. It is a tool to analyze the complex structures, which allows observation of the current structure and basic consequences of any strategic change. They are usually useful for diagnosis, prediction, classification, decision making and in cases of missing data and uncertainty

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Each node in the network represents a random variable with a probability distribution function that takes as input a set of values from the node's parents and gives as output the probability of the variable represented by the node. Those that model time series or sequence of variables are called dynamic Bayesian networks.

Bayesian network is much better than full joint probability distribution (FJPD) technique, as it only computes the values from smaller distributions based on the dependencies between the nodes, instead of computing all the possible combinations that could take place in a network. Lots of studies [8]-[14] showed that Bayesian networks are considered to be a promising tool for the field of the renewable energy with potential applications.

ARIMA (auto regressive integrated moving average)/ SARIMA (seasonal auto regressive integrated moving average) models are considered to be machine learning algorithms that are used for non-stationary time series data forecasting based on multiple parameters. The parameters of ARIMA model are (p = trend auto regression, d = trend difference, q = trend moving average), whereas the SARIMA model includes 4 additional parameters which are P = seasonal auto regression, D = seasonal difference, Q = seasonal moving average, m = the time steps for a seasonal period as it deals with data that include seasonality. Determining the parameters is usually based on observing the autocorrelation function (ACF) plot and the partial autocorrelation function (PACF) plot.

ACF plot provides along x-axis, the lag number (correlation between each observation in a time series & observations of previous time steps) and the correlation coefficient value between -1 and +1 on the y-axis, to indicate the moving average value based on sharp peaks above the confidence interval whereas, PACF plot shows the direct relationship between an observation and its lag, indicating the auto regression value by managing the peaks passing the significant area [15].

III. Collecting and Analyzing Factors

The first step in our research was surveying past papers and studies, which covered all the possible factors that may affect the solar energy's production and consumption compared to the other energy sources [16]-[26]. This process resulted in collecting 37 factors that were later categorized into 3 main classes, which are; general, environmental, and economical/ political, shown in Table I. The environmental class covered 8 factors that define the weather and the atmosphere conditions. The economical/political class covered 13 factors which are responsible for the financial state of the economy, imports, exports, and the government's interventions or decisions that affect the energy usage. And, the general class covered the remaining 16 factors.

After the preliminary step of finding the factors affecting the use of solar energy through a literature review, we needed to make sure of the suitability of these factors to the Egyptian market. Hence, some field experts from the faculty of Engineering, Cairo University were questioned to provide us with their feedback and opinion about which factors could be more effective according to the characteristics and the situation of the energy in Egypt. This process resulted in omitting 10 factors from the ones mentioned in Table I. The deleted factors are: *shading & aerosols* from the environmental class, *financial speculations* from the economical/political class, and *transport (gas pipeline &electrical transmission), siting & transmission, market entry of the solar energy, size of solar panels, maintenance of solar panels, tilt angle of solar panels and battery capacity* from the general class. The final factors are shown in Table II.

In step 2, a questionnaire was designed to identify the most important factors throughout the life cycle of the solar energy's production. We made sure to get the basic information and contact of the respondents, to ensure their experience in the field of energy.

First, the respondents were asked to indicate the stage(s) at which each factor will be effective, namely, *(1 = Construction, 2 = Operational, 3 = Disposal*).

TABLE I
Factors That Could Affect Solar Energy Obtained From Past Papers and Studies [16]-[26]

Environmental	Economical/Political	General
Humidity	GDP	Technological advancements
Shading	Oil price	Energy cost
Atmospheric pressure	Personal income tax rate	Average electricity price
Irradiance	Oil reserves	Prices of raw materials
Air mass	Energy imports & exports	Energy supply
Global climate change	Government regulations	Energy inventory
Aerosols	Financial speculations	Energy generation changes
Pollution & sand storms	International agreements	Transport (gas pipeline & electricity transmission)
	Population	Nuclear power availability
	Industrialization	Energy consumption
	GDP per capita	Siting & transmission
	Capital costs	Market entry of solar energy
	Oil production	Size of solar panels
		Maintenance of solar panels
		Tilt angle of solar panels
		Battery capacity

Next, they were asked to indicate the likelihood of occurrence/rate of change of each factor on a scale from 1 to 5 (1 = very low, 5 = very high) and the severity of consequence of each factor on the market share of the solar energy in Egypt, on a scale from 1 to 5 (1 = very low impact, 5 = very high impact).

Building upon the responses, to determine the level of importance of each factor, the significance score method was applied [27]. The main idea is calculating a score that is given by each respondent to each factor by multiplying the level of occurrence/rate of change and the severity of consequence given by this respondent (1):

$$SS_{ij} = \alpha_{ij}\, \beta_{ij} \quad (1)$$

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where SS_{ij} is the significance score given by respondent j to factor i, $i \in (1, m)$; m is the number of factors, $j \in (1, n)$; n is the number of respondents, α_{ij} is the likelihood of occurrence/ rate of change given by respondent j to factor i, and $\beta_{ij}$is the severity of consequence given by respondent j to factor i.

TABLE II
FACTORS THAT COULD AFFECT SOLAR ENERGY AFTER EXPERTS' FILTRATION

Environmental	Economical/Political	General
Humidity	GDP	Technological advancements
Atmospheric pressure	Oil price	Energy cost
Irradiance	Personal income tax rate	Average electricity price
Air mass	Oil reserves	Prices of raw materials
Global climate change	Energy imports & exports	Energy supply
Pollution & sand storms	Government regulations	Energy inventory
	International agreements	Energy generation changes
	Population	Nuclear power availability
	Industrialization	Energy consumption
	GDP per capita	
	Capital costs	
	Oil production	

A numerical value for each factor was needed to be given in order to compare the importance between them. So, a significance index is calculated by averaging the significance scores given before, to each factor by all the respondents (2):

$$SI_i = \frac{\sum_{j=1}^{n} SS_{ij}}{n} \tag{2}$$

where SI_i is the significance index of factor i.

We choose the factors with significance index greater than or equal to the average which was approximately 11.88, to be represented in the Bayesian network as the most significant factors in our model. This resulted in 12 factors that are illustrated in Table III.

TABLE III
FINAL FACTORS THAT AFFECT SOLAR ENERGY IN EGYPT AFTER ANALYSIS

Environmental	Economical/Political	General
Irradiance	Oil price	Prices of raw materials
Humidity	Personal income tax rate	Energy Consumption
Pollution & sand storms	Oil reserves	
	Government regulations	
	GDP per capita	
	Capital costs	
	Oil production	

Concerning the life cycle stages of producing the solar energy, the probability of a factor being effective in one or more stages, was calculated (3):

$$ST_{ik} = \frac{N_{ki}}{j} \tag{3}$$

where ST_{ik} is the probability of factor i being effective in stage k, $k \in (1, p)$; p is the number of stages, and N_{ki} is the number of respondents who chose factor I to be effective in stage k.

The distribution of the factors among the stages is shown in Fig. 1, they were determined based on those who had probability greater than or equal to 0.5. The construction stage included prices of raw materials, the operational stage included energy demand, energy consumption, irradiance, global climate change, and pollution & sand storms, whereas oil price, taxes, oil reserves, government regulations, GDP per capita, and capital costs were chosen to be effective in both construction and operational stages, the disposal stage did not include any effective factors.

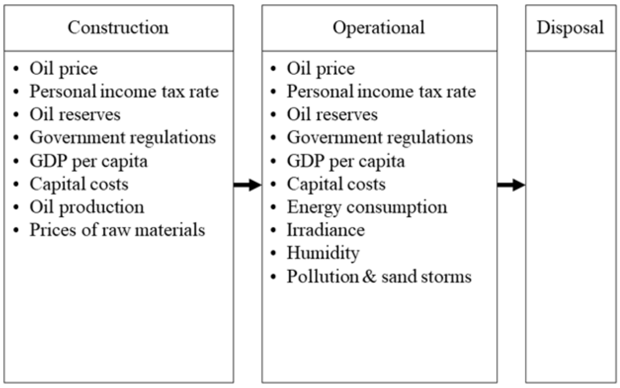

Fig. 1 Effective factors distributed among solar energy's life cycle production

IV. CONSTRUCTING THE BAYESIAN NETWORK

With the help of some experts in the field and going through past studies, the dependency of the relationships between the factors was derived [28]-[39]. We have added 3 more destination nodes that will help later in the scenario and the decision analysis, which are: water saving, agriculture production, and market share of the solar energy. We have also merged the 2 factors; prices of raw materials and capital costs into one node, named *total costs* that will act as another destination node. Fig. 2 shows the final structure of the Bayesian network.

Using the selenium and chromium libraries in python, we scrapped the historical data of 8 factors, which are energy consumption, oil production, oil price, oil reserves, GDP per capita, personal income tax rate, global climate change, and pollution & sand storms, with different timestamps shown in Table IV [40]-[46]. The main aim at this point was forecasting the states of each factor by 2035, in order to add them in the nodes of the Bayesian network. In our study, we have adopted the ARIMA/SARIMA models according to the behavior and the historical patterns of the data of each factor accordingly. Concerning, the data of the factors related to the weather condition; humidity, pollution & sand storms, they were derived specifically for Cairo.

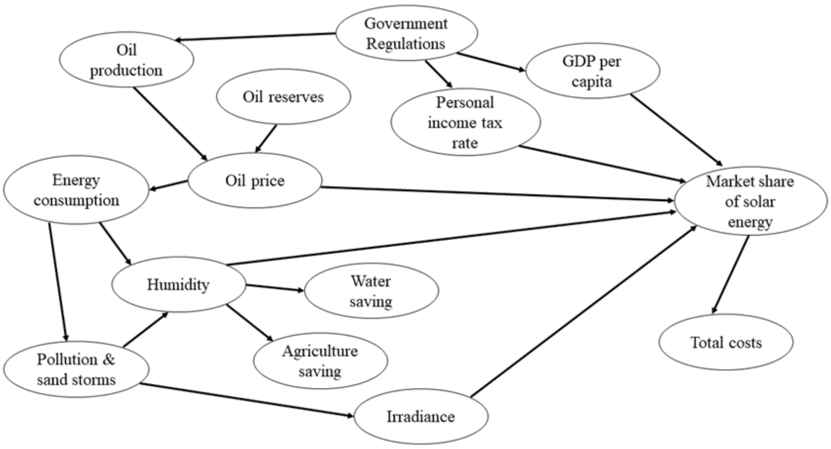

Fig. 2 Structure of the Bayesian network

TABLE IV
FACTORS AND THEIR SCRAPPED TIMESTAMPS DATA TYPE

Factor	Timestamp Data
Energy consumption	Annually
Oil production	Annually
Oil price	Monthly
Oil reserves	Annually
GDP per capita	Annually
Personal income tax rate	Annually
Pollution & sand storms	Daily
Humidity	Daily

A. Energy Consumption

Figs. 3-5 show the historical data curve, the ACF plot, and the PACF plot of the *energy consumption factor*, respectively. According to the behavior of the data, an ARIMA (0,1,0) model was constructed, which will lead to a normal distribution graph of the residuals with mean around zero and approximately 1182 MSE value. Also, the crucial lags at the ACF and the PACF plots have been eliminated and the adjusted data points are now within the range with no pattern in higher-order lag. The forecasted value of the *energy consumption* in Egypt by 2035 using the constructed model is believed to be an average of 2440 kW.h/person.

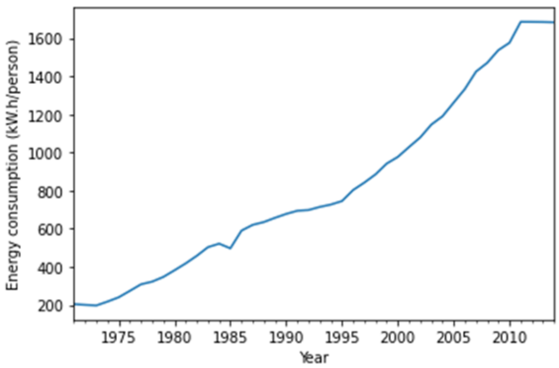

Fig. 3 Energy consumption (kW.h/person) in Egypt vs year, in time frame from 1971 to 2014

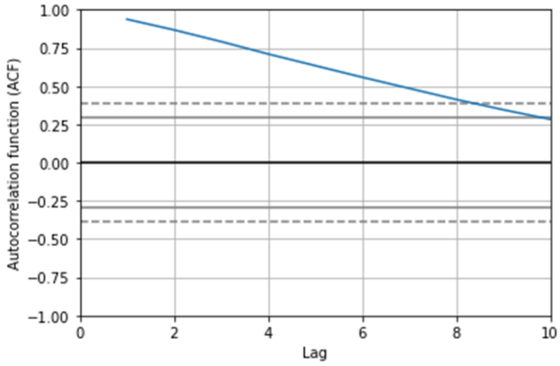

Fig. 4 Autocorrelation coefficient value of energy consumption vs lag, grey lines indicating the 95% confidence area & dashed lines indicating the 99% confidence area

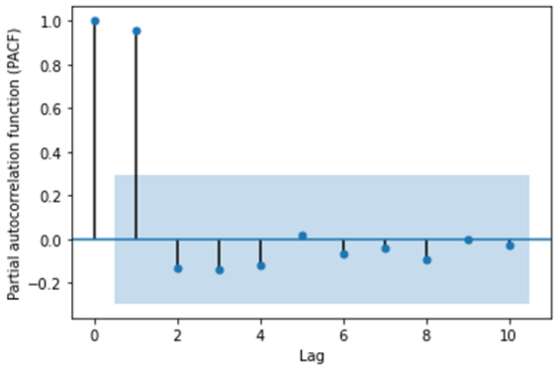

Fig. 5 Partial autocorrelation coefficient value of energy consumption vs lag, shaded part showing the significant area

B. Oil Production

Figs. 6-8 show the historical data curve, the ACF plot, and the partial correlation function (PCF) plot of the oil production factor, respectively. According to the behavior of the data, an ARIMA (1,1,0) model was constructed, which will lead to a normal distribution graph of the residuals with mean around zero and approximately 336 MSE value. Also, the crucial lags at the ACF and the PACF plots have been eliminated and the adjusted data points are now within the range with no pattern in higher-order lags. The forecasted value of the oil production in Egypt by 2035 using the constructed model is believed to be an average of 707 barrels per day.

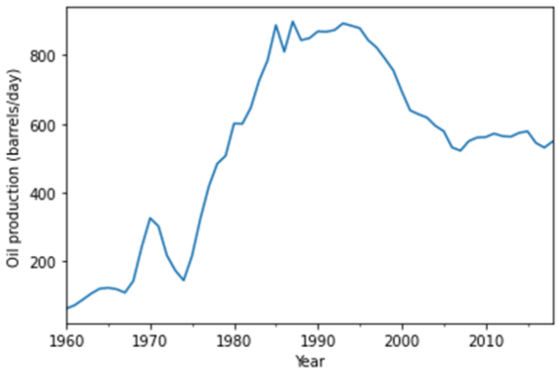

Fig. 6 Oil production curve (barrel/day) in Egypt vs year, in time frame from 1st Dec 1960 to 1st Dec 2018

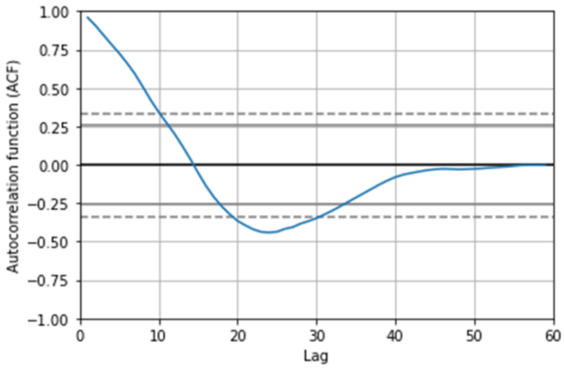

Fig. 7 Autocorrelation coefficient value of oil production vs lag, grey lines indicating the 95% confidence area & dashed lines indicating the 99% confidence area

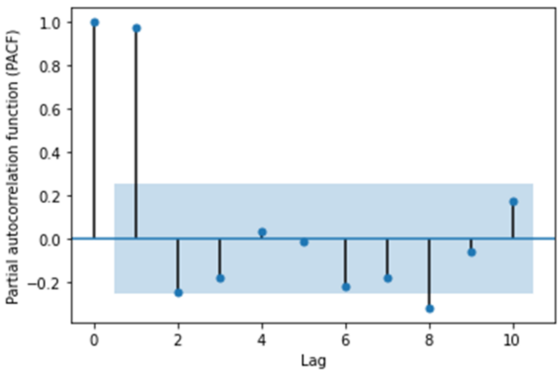

Fig. 8 Partial autocorrelation coefficient value of oil production vs lag, shaded part showing the significant area

C. Oil Price

Figs. 9-11 show the historical data curve, the ACF plot, and the PCF plot of the oil price factor, respectively. According to the behavior of the data, an ARIMA (1,1,0) model was constructed, which will lead to a normal distribution graph of the residuals with mean around zero and approximately 9.82e-06 MSE value. Also, the crucial lags at the ACF and the PACF plots have been eliminated and the adjusted data points are now within the range with no pattern in higher-order lags. The forecasted value of the oil price in Egypt by 2035 using the constructed model is believed to be an average of 1 dollar per liter.

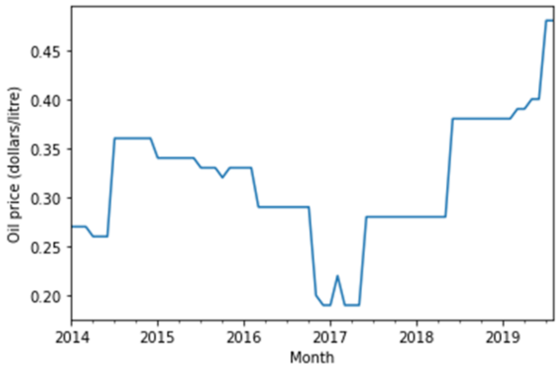

Fig. 9 Oil price (dollar/liter) in Egypt vs month, in time frame from 1st Jan 2014 to 1st Aug 2019

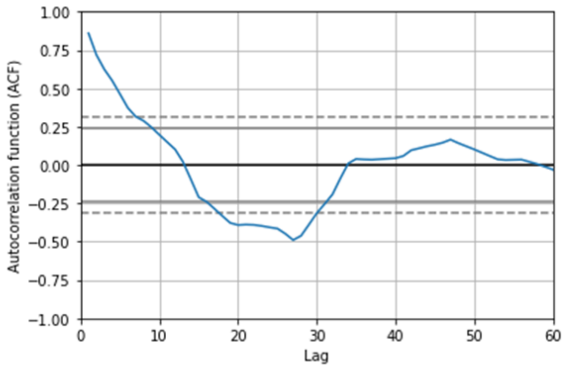

Fig. 10 Autocorrelation coefficient value of oil price vs lag, grey lines indicating the 95% confidence area & dashed lines indicating the 99% confidence area

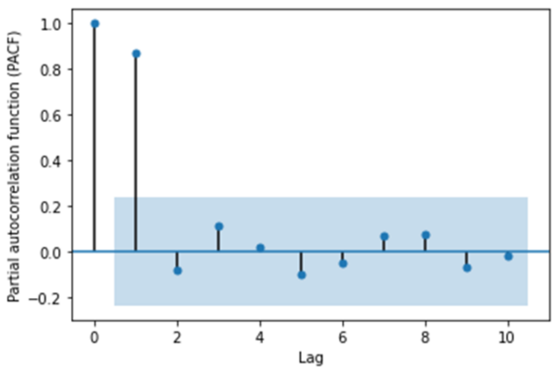

Fig. 11 Partial autocorrelation coefficient value of oil price vs lag, shaded part showing the significant area

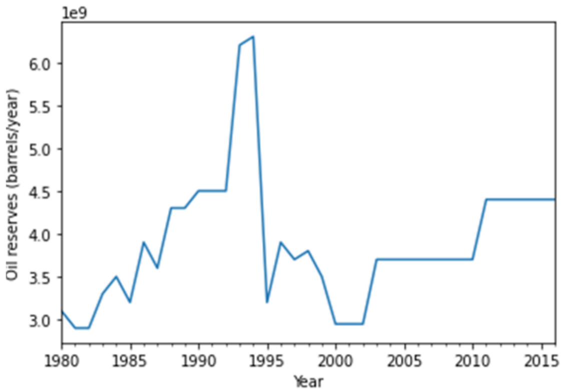

Fig. 12 Oil reserves (barrel/year) in Egypt vs year, in time frame from 1980 to 2016

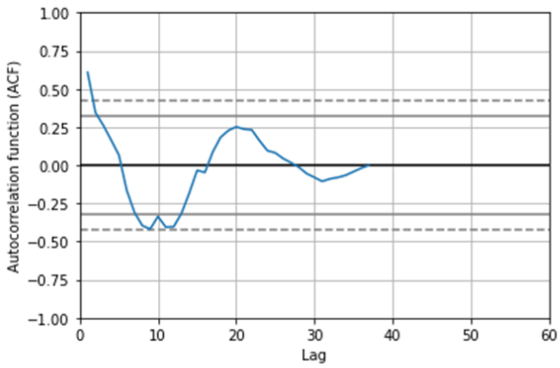

Fig. 13 Autocorrelation coefficient value of oil reserves vs lag, grey lines indicating the 95% confidence area & dashed lines indicating the 99% confidence area

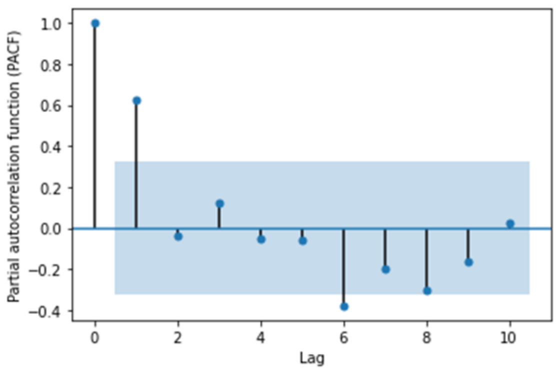

Fig. 14 Partial autocorrelation coefficient value of oil reserves vs lag, shaded part showing the significant area

D. Oil Reserves

Figs. 12-14 show the historical data curve, the ACF plot, and the PCF plot of the oil reserves factor, respectively. According to the behavior of the data, an ARIMA (1,1,0) model was constructed, which will lead to a normal distribution graph of the residuals with mean around zero and approximately 1.59e+16 MSE value. Also, the crucial lags at the ACF and the PACF plots have been eliminated and the adjusted data points are now within the range with no pattern in higher-order lags. The forecasted value of the oil reserves in Egypt by 2035 using the constructed model is believed to be an average of 5.091730e+09 barrels per year.

E. GDP per Capita

Figs. 15-17 show the historical data curve, the ACF plot, and the PCF plot of the GDP per capita factor, respectively. According to the behavior of the data, an ARIMA (1,1,1) model was constructed, which will lead to a normal distribution graph of the residuals with mean around zero and approximately 1976 MSE value. Also, the crucial lags at the ACF and the PACF plots have been eliminated and the adjusted data points are now within the range with no pattern in higher-order lags. The forecasted value of the GDP per capita in Egypt by 2035 using the constructed model is believed to be an average of 3670 dollars per year.

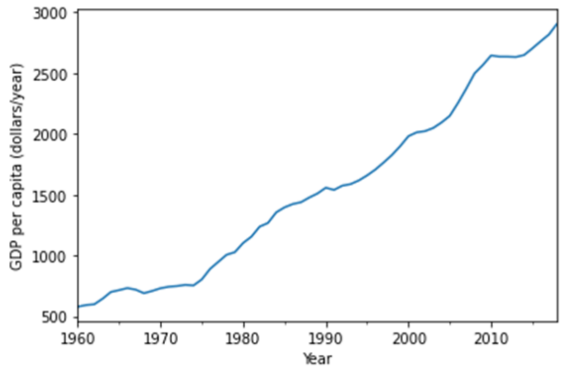

Fig. 15 GDP per capita (dollar/year) in Egypt vs year, in time frame from 1960 to 2018

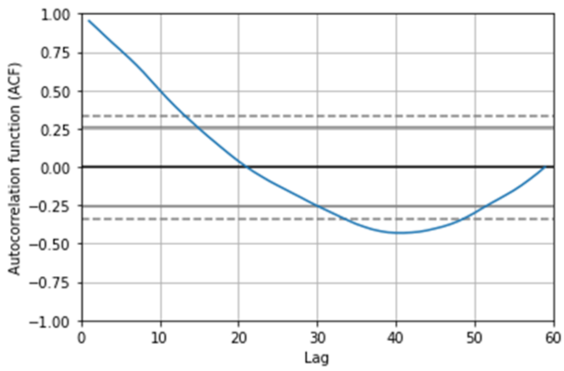

Fig. 16 Autocorrelation coefficient value of GDP per capita vs lag, grey lines indicating the 95% confidence area & dashed lines indicating the 99% confidence area

F. Personal Income Tax Rate

Figs. 18-20 show the historical data curve, the ACF plot, and the PCF plot of the personal income tax rate factor "topmarginal tax rate for individuals", respectively. According to the behavior of the data, an ARIMA (6,0,0) model was constructed, which will lead to a normal distribution graph of the residuals with mean around zero and approximately 12.45 MSE value. Also, the crucial lags at the ACF and the PACF plots have been eliminated and the adjusted data points are now within the range with no pattern in higher-order lags. The forecasted value of the personal income tax rate in Egypt by 2035 using the constructed model is believed to be an average of 24%.

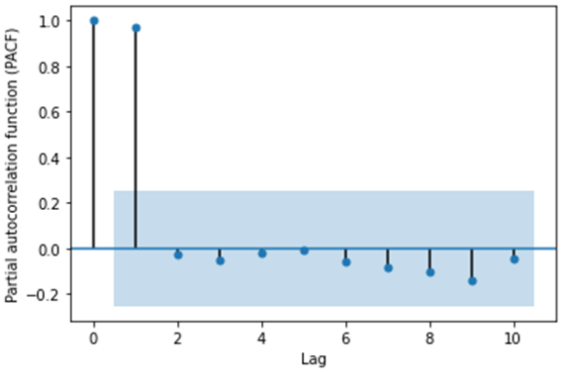

Fig. 17 Partial autocorrelation coefficient value of GDP per capita vs lag, shaded part showing the significant area

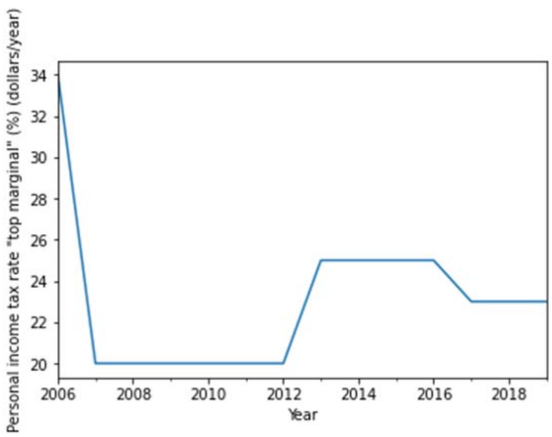

Fig. 18 Personal income tax rate (percentage/year) in Egypt vs year, in time frame from 2006 to 2019

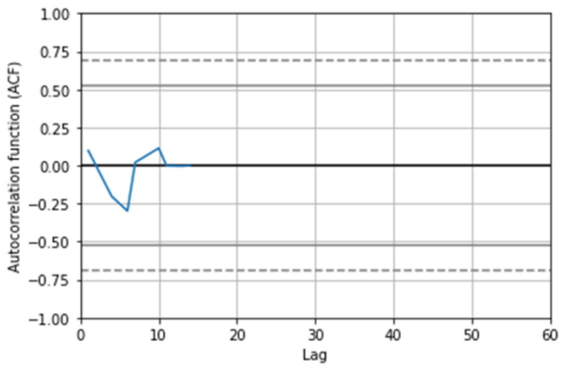

Fig. 19 Autocorrelation coefficient value of personal income tax rate vs lag, grey lines indicating the 95% confidence area & dashed lines indicating the 99% confidence area

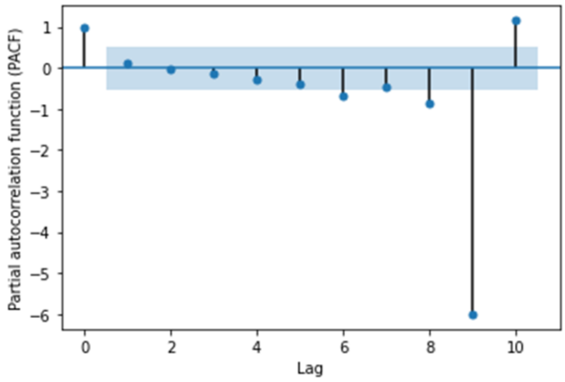

Fig. 20 Partial autocorrelation coefficient value of personal income tax rate vs lag, shaded part showing the significant area

G.Humidity

Figs. 21-23 show the historical data curve, the ACF plot, and the PCF plot of the humidity factor, respectively, after converting the data values from daily to weekly for a more compactable form. According to the behavior of the data, a SARIMA (1,1,1) (1,1,1) (52) model was constructed, which will lead to a normal distribution graph of the residuals with mean around zero and approximately 37.7 MSE value. Also, the crucial lags at the ACF and the PACF plots have been eliminated and the adjusted data points are now within the range with no pattern in higher-order lags. The forecasted value of the humidity in Egypt by 2035 using the constructed model is believed to be an average of 54%.

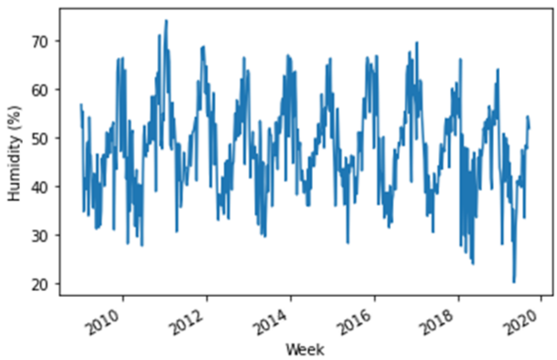

Fig. 21 Humidity (%) in Egypt vs weeks, in time frame from 1st Jan 2009 to 21st Sep 2019

As for the pollution & sand storms node, it will be represented using the historical data of two factors, which are; gust and wind.

H.Gust

Figs. 24-26 show the historical data curve, the ACF plot, and the PCF plot of the gust factor, respectively, after converting the data values from daily to weekly for a more compactable form. According to the behavior of the data, a SARIMA (1,1,1) (2,1,1) (52) model was constructed, which will lead to a normal distribution graph of the residuals with mean around zero and approximately 7.67 MSE value. Also, the crucial lags at the ACF and the PACF plots have been eliminated and the adjusted data points are now within the range with no pattern in higher-order lags. The forecasted value of the gust in Egypt by 2035 using the constructed model is believed to be an average of 23 km/hour.

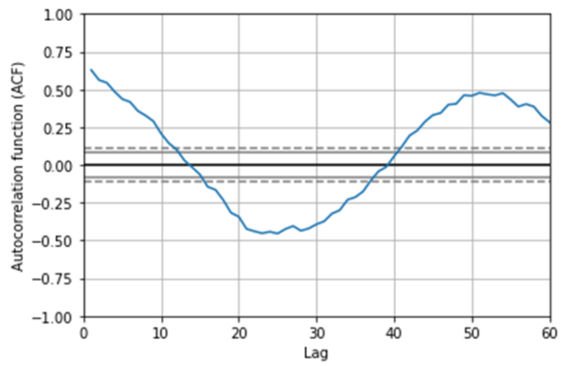

Fig. 22 Autocorrelation coefficient value of humidity vs lag, grey lines indicating the 95% confidence area & dashed lines indicating the 99% confidence area

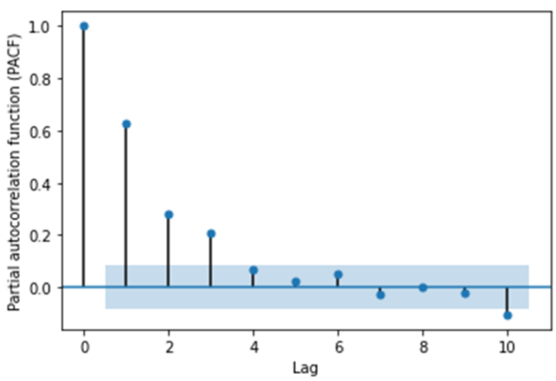

Fig. 23 Partial autocorrelation coefficient value of humidity vs lag, shaded part showing the significant area

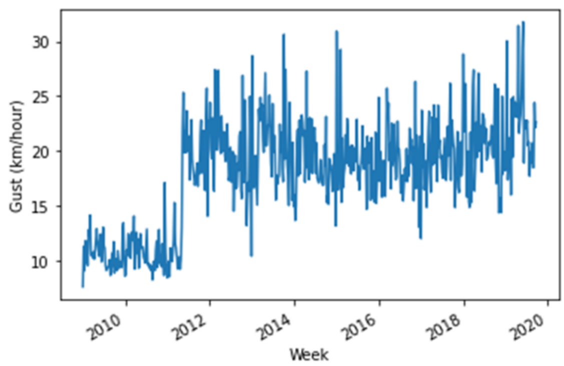

Fig. 24 Gust (km/hour) in Egypt vs week, in time frame from 1st Jan 2009 to 21st Sep 2019

I. Wind

Figs. 27-29 show the historical data curve, the ACF plot, and the PCF plot of the wind factor, respectively, after converting the data values from daily to weekly for a more compactable form. According to the behavior of the data, an SARIMA (1,1,1) (2,1,1) (52) model was constructed, which will lead to a normal distribution graph of the residuals with mean around zero and approximately 3.78 MSE value. Also, the crucial lags at the ACF and the PACF plots have been eliminated and the adjusted data points are now within the range with no pattern in higher-order lags. The forecasted value of the wind in Egypt by 2035 using the constructed model is believed to be an average of 18 km/hour.

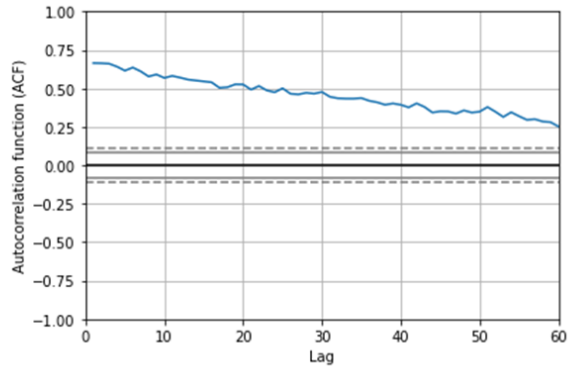

Fig. 25 Autocorrelation coefficient value of gust vs lag, grey lines indicating the 95% confidence area & dashed lines indicating the 99% confidence area

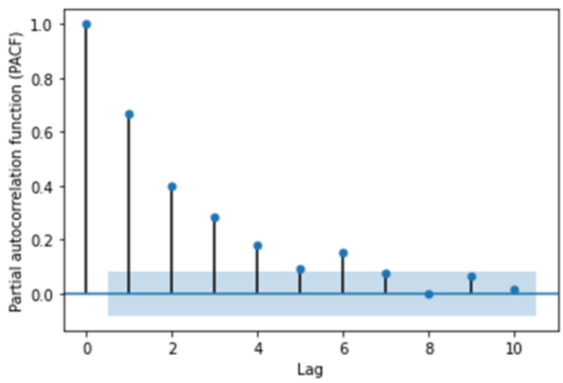

Fig. 26 Partial autocorrelation coefficient value of gust vs lag, shaded part showing the significant area

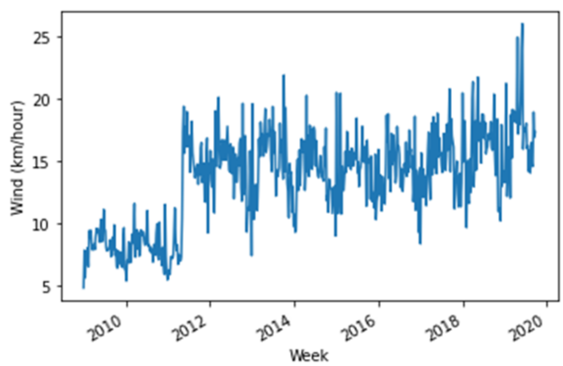

Fig. 27 Wind (km/hour) in Egypt vs week, in time frame from 1st Jan 2009 to 21st Sep 2019

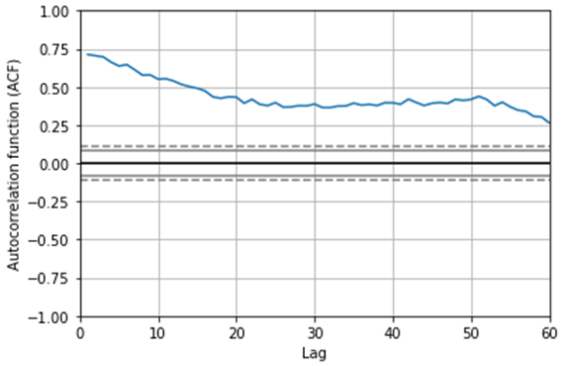

Fig. 28 Autocorrelation coefficient value of wind vs lag, grey lines indicating the 95% confidence area & dashed lines indicating the 99% confidence area

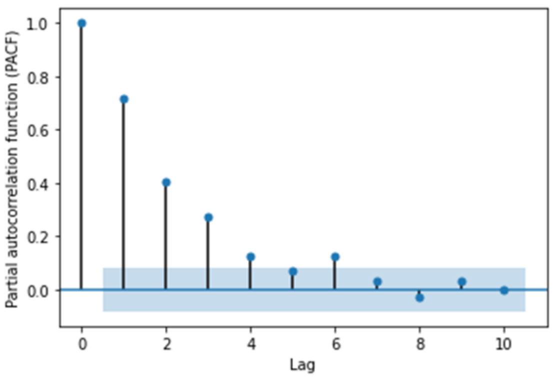

Fig. 29 Partial autocorrelation coefficient value of wind vs lag, shaded part showing the significant area

V. Results/Discussion

Results of this study, lead to detecting the most important factors that affect the market share of solar energy in Egypt and structuring their final states by 2035 in a Bayesian network, as follows; the states of energy consumption, oil production, oil price, oil reserves, GDP per capita, personal, income tax rate, global climate change, and pollution & sand storms were labelled using their numerical forecasted values resulted from the constructed ARIMA/SARIMA models before, as for the states of agriculture production, water saving, and the market share of the solar energy were determined based on experts' studies and estimates, whereas irradiance, total costs, and government regulations states were categorized qualitatively. The final states of the Bayesian network nodes are shown in Fig. 30.

VI. Conclusion/Future Work

In contrast with previous research [18], [47]-[50], this paper focused more on the analysis of data and forecasting the future states of the nodes, rather than collecting or manipulating them before constructing a Bayesian network as suggested by [51]. It is hoped that deriving the nodes and the states of the network using the machine learning techniques mentioned in the paper, would make the model more robust and accurate.

Future work concerns deriving the conditional probabilities of the states in the network, applying different scenarios, and building influence diagrams for decision analysis, in order to indicate the best and worst scenarios, related to the percentage of the solar energy's market share in Egypt by 2035 and its total costs.

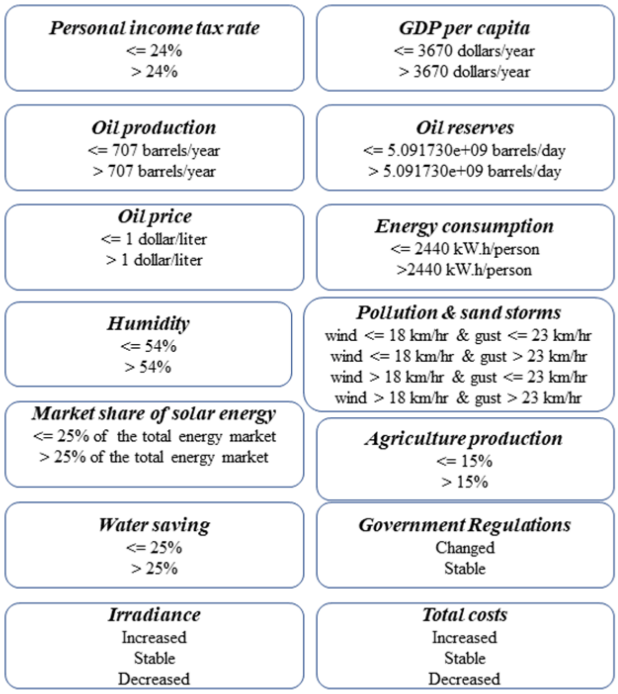

Fig. 30 Final states of the nodes in the Bayesian network

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