**CHAPTER ONE**

1. **INTRODUCTION**

One of the main characteristics of a solar power panel is that the primary energy source (solar radiation) cannot be manipulated. Besides, the solar radiation intensity depends on daily and seasonal cycle variations, like clouds, atmospheric humidity, and air transparency. This justifies the relevance of solar power panel control. This study considers the Acurex distributed collector solar panel field, located at the Alhikmah University, Ilorin, Kwara State. In this solar power panel, the main control goal is to maintain constant outlet oil temperature, despite the operation conditions changes, by manipulating the field oil flow. To maintain constant outlet temperatures during the day while the solar conditions changes, significant flow variations are required. This produces considerable variations in the dynamics of the process. Hence, conventional control algorithms based on a simplified model of the process, for example the linear quadratic Gaussian (LQG) regulator, proves to be ineffective [1]. However LQG/linear transfer recovery (LTR) regulator gives better results even when the working conditions are far from the ones that LQG controller has been designed for [2]. Due to its nonlinear characteristics, the Acurex solar collector field has been used as an experimental platform for the application of many modern control algorithms [3].

**1.1 BACKGROUND TO THE STUDY**

In 1992, Camacho *et al.* [4] described a self-tuning proportional–integral (PI) controller for this solar panel, based on a pole assignment approach. In order to compensate the measured disturbances, a feed-forward controller is included. The self-tuning controller is capable to deal with changes in the operating conditions of the panel.

Solar power panel has become relevant as a source of electricity generation in power grids worldwide during the past two decades. In the last fifteen years, Solar energy reached a compound annual growth rate of circa 40% [1]. The installed capacity in OECD countries has already reached 60 GW. In some European countries, Solar energy production reaches 30% of overall power production during clear summer days. This scenario encourages the incorporation of solar power energy into electrical power grids that operate with other energy sources, such as fossil.

Solar power panel is a source of energy very sensitive to climatic variations. Weather conditions, such as cloud motion, can affect the production of energy. These characteristics highlight the importance of applying a forecasting method to a solar power system [2]. It is useful to distinguish forecasting techniques according to the temporal scales we are interested in. Solar power predictive system deals with time horizons from minutes to hours, from hours to a few days ahead, from months to months, and from years to years. This work focuses on a solar energy forecasting, investigating data collected from a station of a solar power panel system located in Alhikmah University, Ilorin, Kwara State, specifically in ICT department.

For instance, Yap and Yap [4] and Hernandez et al. [5] considered load or demand profiles associated with specific days of the year to divide the forecasting problem into smaller problems. Jain et al. [6] proposed a load forecasting method based on similar day approach in conjunction with fuzzy rule based logic. The next-day is obtained by using fuzzy logic to modify the load curves on selected similar days.

Solar power predictive system provides extremely useful information for tasks such as management of electricity grids and solar energy trading. In a solar energy forecasting context, it means that fast turnaround of results is also an important feature to the model, where the time for decision making(such as determining how many panels are required to power the whole Alhikmah University and the cost for the panels acquisition) is reduced and the amount of data to be processed is usually higher. Hence, in addition to good accuracy, good performance is a desirable goal for a solar power forecasting model.

This paper proposes and investigates the use of some methods based on Fuzzy Time Series (FTS) to perform solar power (irradiance) forecasting. FTS methods have been providing good results for hard forecasting problems such as long memory time series [7] or stock market forecasting [8]. Despite the reported success of FTS methods in many applications, there are no studies about its application and performance in solar energy forecasting, which is also a very hard forecasting problem, given the characteristics of solar irradiance. However, this paper also introduces the application of FTS in solar power forecasting, describing the data, and discussing preprocessing steps. Specifically, Chen’s first order and high-order FTS methods and the Weighted FTS method are compared with other forecasting models widely used to approach solar power (irradiance) forecasting. This paper evaluates the performance of FTS methods and different forecasting techniques to solve solar power forecasting problems. The results show that FTS methods are able to achieve significant improvements in forecasting accuracy and performance if compared to other forecasting methods.

**1.2 STATEMENT OF THE PROBLEM**

Weather conditions, such as cloud motion, atmospheric humidity, and air transparency affect the production of energy. Seasonality is a recurrent problem in load forecasting models. Different seasons present different patterns of weather variables, which directly affect the solar irradiance curves along the days. Some models deal with seasonality by designing tools responsible for organizing data and generating distinct and more accurate forecasting or predictive models. In a solar power forecasting context, it means that fast turnaround of results is also an important feature to the model, where the time for decision making (such as determining how many panels are required to power the whole Alhikmah University and the cost for the panels acquisition) is reduced and the amount of data to be processed is usually higher. Hence, the need for a computerized solar power forecasting model not only produces precise and accurate results, but also good performance is a desirable goal.

**1.3 AIM AND OBJECTIVES OF THE STUDY**

This project aimed at developing a computerized solar power predictive system using fuzzy time series (FTS) model. The specific objectives of this research are to:

1. design a computerized solar power predictive system model.
2. implement the design in (i) above.
3. evaluate the performance of the proposed model against the existing forecasting model.

**1.4 RESEARCH METHODOLOGY**

In order to achieve the aforementioned objectives, several tools, procedures and

methods will be used, which are:

1. an establishment of a theoretical foundation for the project work through a sound review of relevant literatures on computerized solar power predictive system.
2. the design of a model for a computerized solar power predictive system using fuzzy time series (FTS).
3. the implementation of fuzzy time series (FTS) model for a computerized solar power predictive system using python programming language.
4. evaluation of the performance of the newly developed software against the existing system (manual) using collection of test cases and sample data.

**1.5 SCOPE OF STUDY**

The project covers some of the processes require for carrying out effective and efficient fuzzy time series (FTS) model for a computerized solar power forecasting system in Al-Hikmah University, Ilorin, Kwara State. Among which are:

* Data acquisition.
* Data Preprocessing.
* Fuzzy Time Series (FTS) model.
* Training Data
* Testing Data
* Reporting.

**1.6 LIMITATION OF THE STUDY**

The limitation of this study includes:

Financial constraint: study of this kind is meant to be carried out in a wider scope but due to lack of funds, some functions and programs could not be applied.

Time constraint: the time given to carry out this research was short so much that only a few was covered.

**1.7 SIGNIFICANCE OF THE PROJECT**

The implementation of this work will

1. forecast precise and accurate solar power.
2. reduce prediction error.
3. improve solar power performance.
4. reduce time in decision making.
5. higher amount of processing data.

**1.8 DEFINITION OF TERMS**

**Solar power:**is the conversion of energy from sunlight into electricity, either directly using photovoltaics (PV), indirectly using concentrated solar power, or a combination (wikipedia.com).

**Fuzzy logic:** is an approach to computing based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean **logic** on which the modern computer is based (wikipedia.com).

**Forecasting:** is the process of making predictions of the future based on past and present data and most commonly by analysis of trends. A common place example might be estimation of some variable of interest at some specified future date. Prediction is a similar, but more general term (wikipedia.com).

T**ime series:** is a **series** of data points indexed (or listed or graphed) in **time** order. Most commonly, a **time series** is a sequence taken at successive equally spaced points in **time**. Thus it is a sequence of discrete-**time** data (wikipedia.com).

**1.9 PROJECT LAYOUT**

CHAPTER ONE: This consists of the introduction which is the general overview of the research work, background to the study, statement of the problem, aim and objectives of the study, scope and limitation of the study, significance of the study.

CHAPTER TWO: It comprises the literature review which gives a sound review of the theoretical foundation for the project work, and review of relevant past works on solar power forecasting system.

CHAPTER THREE: It contains the research methodology explaining and analyzing in full details how the design and implementation of the proposed system is achieved with respect to the tools, methods, procedures and technicalities that were applied.

CHAPTER FOUR: It consists of the presentation of the result and system evaluation.

CHAPTER FIVE: It comprises summary, conclusions and recommendations

**CHAPTER TWO**

**2.0 LITERATURE REVIEW**

Solar power is the [conversion of energy](https://en.wikipedia.org/wiki/Energy_transformation) from [sunlight](https://en.wikipedia.org/wiki/Sunlight) into [electricity](https://en.wikipedia.org/wiki/Electricity), either directly using [photovoltaics](https://en.wikipedia.org/wiki/Photovoltaics" \o "Photovoltaics) (PV), indirectly using [concentrated solar power](https://en.wikipedia.org/wiki/Concentrated_solar_power), or a combination. Concentrated solar power systems use [lenses](https://en.wikipedia.org/wiki/Lens_(optics)) or [mirrors](https://en.wikipedia.org/wiki/Mirrors) and [tracking systems](https://en.wikipedia.org/wiki/Solar_tracking) to focus a large area of sunlight into a small beam. Photovoltaic cells convert light into an [electric current](https://en.wikipedia.org/wiki/Electric_current) using the [photovoltaic effect](https://en.wikipedia.org/wiki/Photovoltaic_effect) (wikipedia.com).

Photovoltaics were initially solely used as a source of [electricity](https://en.wikipedia.org/wiki/Electricity) for small and medium-sized applications, from the [calculator](https://en.wikipedia.org/wiki/Calculator) powered by a single solar cell to remote homes powered by an [off-grid](https://en.wikipedia.org/wiki/Off-grid) rooftop PV system. Commercial concentrated solar power plants were first developed in the 1980s. The 392 MW [Ivanpah](https://en.wikipedia.org/wiki/Ivanpah_Solar_Power_Facility" \o "Ivanpah Solar Power Facility) installation is the largest concentrating solar power plant in the world, located in the [Mojave Desert](https://en.wikipedia.org/wiki/Mojave_Desert) of [California](https://en.wikipedia.org/wiki/California) (wikipedia.com).

As the cost of solar electricity has fallen, the number of grid-connected [solar PV systems](https://en.wikipedia.org/wiki/Solar_PV_systems) has [grown into the millions](https://en.wikipedia.org/wiki/Growth_of_photovoltaics) and utility-scale [photovoltaic power stations](https://en.wikipedia.org/wiki/Photovoltaic_power_station) with hundreds of megawatts are being built. Solar PV is rapidly becoming an inexpensive, low-carbon technology to harness [renewable energy](https://en.wikipedia.org/wiki/Renewable_energy) from the Sun. The current largest photovoltaic power station in the world is the 850 MW [Longyangxia Dam](https://en.wikipedia.org/wiki/Longyangxia_Dam" \o "Longyangxia Dam) Solar Park, in [Qinghai](https://en.wikipedia.org/wiki/Qinghai), [China](https://en.wikipedia.org/wiki/China) (wikipedia.com).

The [International Energy Agency](https://en.wikipedia.org/wiki/International_Energy_Agency) projected in 2014 that under its "high renewables" scenario, by 2050, solar photovoltaics and concentrated solar power would contribute about 16 and 11 percent, respectively, of the [worldwide electricity consumption](https://en.wikipedia.org/wiki/Worldwide_electricity_consumption), and solar would be the world's largest source of electricity. Most solar installations would be in [China](https://en.wikipedia.org/wiki/Solar_power_in_China) and [India](https://en.wikipedia.org/wiki/Solar_power_in_India).[[2]](https://en.wikipedia.org/wiki/Solar_power#cite_note-IEA-roadmap-PV-2014-2) In 2017, solar power provided 1.7% of total worldwide electricity production, growing at 35% per annum.[[3]](https://en.wikipedia.org/wiki/Solar_power#cite_note-bp2018-3) As of 2018, the unsubsidized [levelized cost of electricity](https://en.wikipedia.org/wiki/Levelised_cost_of_electricity" \o "Levelised cost of electricity) for utility scale solar power is around $43/MWh (wikipedia.com).

Power quality improvement has been given considerable attention due to the intensive use of nonlinear loads and the limitations required by international standards such as IEEE519-1992. Those limitations were set to limit the disturbances and avoid major problems in power system. Since linear and/or non-linear single-phase loads are rapidly increasing, zero sequence component and current harmonics are generated. This causes overheating of the associate distribution transformers that may lead to a system failure, especially in weak networks. Photovoltaic (PV) power supplied to the utility grid is gaining more and more visibility, while the world’s power demand is increasing. Global demand of electrical energy is growing by high rate due to the requirement of modern civilization. Recently, energy generated from clean, efficient and environmentally friendly sources has become one of the major challenges for engineers and scientists. Among them, PV application has received a great attention in research because it appears to be one of the most efficient and effective solutions to this environmental problem. There are two topologies used to connect the PV with the grid; two stages and single stage PV system. A two stage is the traditional type and consists of a CUK DC/DC converter direct coupled with PV array and a grid connected universal bridge inverter Carlos et al (2017).

In single stage PV system, the DC/AC inverter has more complex control goals; Maximum Power Point Tracking (MPPT) and output current control. Regardless its control complicity, single stage PV system is more efficient and cheaper than two stages system. For connecting the PV system to the grid, there are three widely used grid interactive PV systems; the centralized inverter system, the string inverter system and the AC modulator the Module Integrated Converter (MIC) system. Among these, the MIC system offers “plug and play” concept and greatly optimizes the energy yield, H. J. Sadaei, R. Enayatifar, A. H. Abdullah, and A. Gani(2004).With these advantages, the MIC concept has become the trend for the future PV system development but challenges remain in terms of cost, reliability and stability for the grid connection. Conventionally single phase shunt active power filter(APF) uses an inverter for harmonics elimination and reactive power compensation]. A grid connected PV system with active power filtering feature has been presented in. However, measuring the load current is mandatory. In this paper, an inverter is used as a single phase shunt active power in addition to interfacing a power of a photovoltaic (PV) as shown in Fig.1. Fuzzy Logic Control (FLC) is used as a robust controller for MPPT; this control technique can handle the model uncertainties in addition to easily handle the nonlinearity. The single-phase shunt active power filter (APF) uses a predictive control technique to mitigate of the grid current harmonics and improve the power factor. Carlos et al. (2017).

**2.1 SOLAR PANEL**

Photovoltaic solar panels absorb [sunlight](https://en.wikipedia.org/wiki/Sunlight) as a source of energy to generate [electricity](https://en.wikipedia.org/wiki/Electricity). A [photovoltaic](https://en.wikipedia.org/wiki/Photovoltaic) (PV) module is a packaged, connected assembly of typically 6x10 photovoltaic [solar cells](https://en.wikipedia.org/wiki/Solar_cell). Photovoltaic modules constitute the photovoltaic array of a [photovoltaic system](https://en.wikipedia.org/wiki/Photovoltaic_system) that generates and supplies [solar electricity](https://en.wikipedia.org/wiki/Solar_electricity) in commercial and residential applications (wikipedia.com).

The most common application of solar energy collection outside agriculture is [solar water heating](https://en.wikipedia.org/wiki/Solar_water_heating) systems (wikipedia.com).

In 1839, the ability of some materials to create an electrical charge from light exposure was first observed by [Alexandre-Edmond Becquerel](https://en.wikipedia.org/wiki/Alexandre-Edmond_Becquerel" \o "Alexandre-Edmond Becquerel). Though the premiere solar panels were too inefficient for even simple electric devices they were used as an instrument to measure light. The observation by Becquerel was not replicated again until 1873, when [Willoughby Smith](https://en.wikipedia.org/wiki/Willoughby_Smith) discovered that the charge could be caused by light hitting selenium. After this discovery, [William Grylls Adams](https://en.wikipedia.org/wiki/William_Grylls_Adams) and [Richard Evans Day](https://en.wikipedia.org/w/index.php?title=Richard_Evans_Day&action=edit&redlink=1) published "The action of light on selenium" in 1876, describing the experiment they used to replicate Smith's results.[[3]](https://en.wikipedia.org/wiki/Solar_panel#cite_note-:0-3)[[5]](https://en.wikipedia.org/wiki/Solar_panel#cite_note-5) In 1881, [Charles Fritts](https://en.wikipedia.org/wiki/Charles_Fritts) created the first commercial solar panel, which was reported by Fritts as "continuous, constant and of considerable force not only by exposure to sunlight but also to dim, diffused daylight."[[6]](https://en.wikipedia.org/wiki/Solar_panel#cite_note-6) However, these solar panels were very inefficient, especially compared to coal-fired power plants. In 1939, [Russell Ohl](https://en.wikipedia.org/wiki/Russell_Ohl) created the solar cell design that is used in many modern solar panels. He patented his design in 1941. In 1954, this design was first used by [Bell Labs](https://en.wikipedia.org/wiki/Bell_Labs) to create the first commercially viable silicon solar cell (wikipedia.com).

[Photovoltaic](https://en.wikipedia.org/wiki/Photovoltaic) modules use light energy ([photons](https://en.wikipedia.org/wiki/Photon)) from the Sun to generate electricity through the [photovoltaic effect](https://en.wikipedia.org/wiki/Photovoltaic_effect). The majority of modules use [wafer](https://en.wikipedia.org/wiki/Wafer_(electronics))-based [crystalline silicon](https://en.wikipedia.org/wiki/Crystalline_silicon) cells or [thin-film cells](https://en.wikipedia.org/wiki/Thin_film_solar_cell). The structural ([load carrying](https://en.wikipedia.org/wiki/Dead_and_live_loads)) member of a module can either be the top layer or the back layer. Cells must also be protected from mechanical damage and moisture. Most modules are rigid, but semi-flexible ones based on thin-film cells are also available. The cells must be connected electrically in series, one to another (wikipedia.com).

A PV [junction box](https://en.wikipedia.org/wiki/Junction_box) is attached to the back of the solar panel and it is its output interface. Externally, most of photovoltaic modules use [MC4 connectors](https://en.wikipedia.org/wiki/MC4_connector) type to facilitate easy weatherproof connections to the rest of the system. Also, USB power interface can be used.

Module electrical connections are made [in series](https://en.wikipedia.org/wiki/Series_circuits) to achieve a desired output voltage or [in parallel](https://en.wikipedia.org/wiki/Parallel_circuits) to provide a desired current capability (amperes). The conducting wires that take the current off the modules may contain silver, copper or other non-magnetic conductive transition metals. Bypass [diodes](https://en.wikipedia.org/wiki/Diode) may be incorporated or used externally, in case of partial module shading, to maximize the output of module sections still illuminated (wikipedia.com).

Some special solar PV modules include [concentrators](https://en.wikipedia.org/wiki/Solar_concentrator) in which light is focused by [lenses](https://en.wikipedia.org/wiki/Lens_(optics)) or mirrors onto smaller cells. This enables the use of cells with a high cost per unit area (such as [gallium arsenide](https://en.wikipedia.org/wiki/Gallium_arsenide)) in a cost-effective way (wikipedia.com).

Solar panels also use metal frames consisting of racking components, brackets, reflector shapes, and troughs to better support the panel structure (wikipedia.com).



Fig. 2.1. Solar Photovoltaics(PV) modules (source: www.wikipedia.com)



Fig. 2.2. Two Solar hot water panels mounted on rooftops (source: www.wikipedia.com)

**2.2 SOLAR IRRADIANCE FORECASTING**

Electrical load forecasting models suffer from similar needs of techniques with good capability of dealing with complex relations between input and output, which encourages the adoption of Soft Computing models Carlos et al(2017). Specifically in solar forecasting, Mellit and Pavan (2010) and Pedro and Coimbra (2012) applied Artificial Neural Networks (ANN) to solve this problem. Sfetsos and Coonick (2000) present a comparison of various forecasting methods to solve a solar energy problem. Among them, the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) is evaluated, whose performance was also evaluated when applied to wind speed time series (2000). Mart´ın et al. (2010) tested autoregressive, neural networks and fuzzy logic models and their results suggest that different methods can be more suitable to specific weather profiles. A comprehensive review of methods is presented by Inman et al. (2013). Several techniques are applied to address different forecast horizons located in PV systems around the world. Most of the cited publications come from temperate climates, such as United States, Europe and Japan, which reflects the current actual distribution of installed capacities.

Tropical regions usually present a high variability in cloud movements and irradiance patterns. This scenario may reduce the accuracy of a forecasting method. Yang et al. (2012) used a model which considers cloud cover index as an input. It was evaluated in a Singapore dataset, achieving normalized root mean square errors (nRMSE) of circa 20% for a 1h prediction horizon. Martins et al. (2012) applied ANNs for station located in the southern Brazil. Average nRMSE results for the datasets were around 26%. Dong et al. (2013) proposed a forecasting model using exponential smoothing state space (ESSS) method, applied to Singapore and U.S. datasets, obtaining average nRMSE of circa 25% and 17%, respectively, which represent slight improvement if compared to an ARIMA model. It is worth highlighting the higher level of nRMSE for the dataset located in a tropical region compared to other areas outside the tropics.

**2.3 RELATED WORKS**

Camacho *et al.* (2009) proposed a gain scheduling GPC, based on the fact that the controller’s parameters depend on the same variables that define the operating condition. In this case, the dynamics of the field are mainly conditioned to the oil flow, which can be used to change the controller’s parameters. The main advantage of this controller compared to the previous adaptive algorithms is that the controller parameters are fixed.

Later, several model based predictive control algorithms have been implemented and experimentally tested. For example, Camacho *et al.* (2009) presented an adaptive generalized predictive controller (GPC). The algorithm is based on reaction curve modeling that uses recursive least squares estimation. The proposed controller is successfully compared with a self-tuning PI controller [4].

Camacho and Berenguel (2014) described a GPC algorithm based on a nonlinear model. In this case, the nonlinear model is used to generate an estimation of the *free response* of the process, due to past control actions and disturbances. This term is combined with the *forced response*, which is calculated using a linear model. The nonlinear model allows the controller to deal with changes in the dynamics of the process. Camacho *et al.* [8] described an extension of the mentioned algorithm, in which the free response is based on a neural network obtaining a control scheme that shows very good performance.

In 1995, Rubio *et al.* (2010) presented a fuzzy logic controller for the solar panel. The fuzzy controller is based on rules obtained using expert knowledge of the process. Subsequently, Gordillo *et al.* (2012) proposed a genetic design of a fuzzy logic controller. The genetic algorithm is used to optimize the parameters of the fuzzy controller.

Cardoso *et al.* (2010) and Henriques *et al.* (2000) described a fuzzy switching supervisor PID control strategy for the solar plant. The fuzzy supervisor controller measures actual data available from the plant providing a way to switch between several fixed controllers. Additionally, the local PID controllers are offline tuned, with a dynamic recurrent neural network with pole placement.

In 1999, Henriques *et al.* (2010) proposed the same idea but the fuzzy switching is made using -means clustering. Distinctly, Juuso *et al.* (2013) presented a fuzzy PI controller applied to the solar plant. The results show that the fuzzy algorithm is very robust in various difficult operating conditions. Pickardt (2012) described an indirect adaptive controller LQG and GPC for the solar plant. The algorithm uses three or five linear auto regressive with moving average and exogenous inputs (ARMAX) models and contains an online identification procedure to determine and to update the corresponding model of the operating point. In this case, adaptive LQG and GPC are designed and compared, obtaining similar satisfactory results.

Johansen *et al.* (2013) proposed a gain-scheduled control for the solar plant. In this case, the algorithm uses high-order local linear auto regressive with exogenous inputs (ARX) models and the local linear controllers are designed based on pole placement. This author’s fore-coming work describes a distributed model based controller for the solar plant. Stability of the closed-loop is proven using Lyapunov conditions.

In order to compare fuzzy predictive control with classical predictive control, this paper considers a simple MBPC controller based on a linear model of the solar collector field. The system is kept around the operation point and no “hard” constraints are imposed to the process. A fuzzy predictive controller is designed using the same linear model, but applying fuzzy characterization to goals for the controlled variable error and constraints over the manipulated variable.

**CHAPTER THREE**

**3.0 RESEARCH METHODOLOGY**

**3.1 RESEARCH APPROACH**

The project was carried out using the following methods:

* 1. the design of a model for a computerized solar power predictive system using fuzzy time series (FTS).
  2. the implementation of fuzzy time series (FTS) model for a computerized solar power predictive system using python programming language.
  3. evaluation of the performance of the newly developed software against the existing system (manual) using collection of test cases and sample data.

**3.2 DATA ACQUISITION**

The data used in this work was obtained from [photovoltaic](https://en.wikipedia.org/wiki/Photovoltaic) (PV) solar panels installed and located in Al-Hikmah University, Ilorin, Kwara State. Photovoltaic solar panels absorb [sunlight](https://en.wikipedia.org/wiki/Sunlight) as a source of energy to generate [electricity](https://en.wikipedia.org/wiki/Electricity). A [photovoltaic](https://en.wikipedia.org/wiki/Photovoltaic) (PV) module is a packaged, connected assembly of typically 6x10 photovoltaic [solar cells](https://en.wikipedia.org/wiki/Solar_cell). Photovoltaic modules constitute the photovoltaic array of a [photovoltaic system](https://en.wikipedia.org/wiki/Photovoltaic_system) that generates and supplies [solar electricity](https://en.wikipedia.org/wiki/Solar_electricity).

All the monitoring systems record the solar irradiance values as one minute averages, with a sampling rate of 1 Hz. Similarly, the 30-min values used in this work correspond to averages of one minute groups. It is expected that, due to material specifications, loggers utilized in this work present errors in the order of +/-0.2%. Since the focus of this work is presenting the training and forecasting characteristics of this model only a central station was chosen.

**3.3 DATA PREPROCESSING**

As previously discussed, the observed solar irradiance values can be seen as time series with trend and seasonal components. In this case, better results in forecasting can be obtained if these components are eliminated or mitigated, specially when working with neural network models. De-trending and seasonal adjustment are common steps in order to improve time series analysis, Carlos, et al. (2017).

In this work, the applied de-trending method was smoothing the time series using the moving average filter. It means that, considering a time series y, its smoothed ˜y values are calculated with:

˜y(1) = y(1) (eq. 1)

˜y(2) = (y(1) + y(2) + y(3))/3

˜y(3) = (y(1) + y(2) + y(3) + y(4) + y(5))/5

˜y(4) = (y(2) + y(3) + y(4) + y(5) + y(6))/5

:::

˜y(n) = (y(n - 2) + y(n - 1) + y(n) + y(n + 1) + y(n + 2))/5

Figure 2 shows an example of smoothed values obtained from the application of a moving average filter with a span of 5 to a period of observations.

Thus, the de-trending process consists of removing the smoothed values It from the original time series I, leaving only the residual de-trended data Idt.

I = Idt + It (eq. 2)

Since preliminary results pointed that the de-trending process improved the average forecasting accuracy, all the evaluated methods in this work operate with the de-trended data Idt.

According to Carlos, et al. (2017), seasonal adjustment is a more complicated task for this kind of time series, since sky conditions are affected by different factors along the year, which provide different daily solar irradiance curves. This leads to a scenario where inferring a proper additive or multiplicative model for seasonality can be a complex task. Seasonal adjustment is not performed during the preprocessing step in a traditional way, but left for each forecasting method, if applied.

**3.3 THE PROPOSED SOLAR POWER PREDICTING MODEL**

This project proposes a well structured and standard model for the computerized solar power predicting system. The model is Fuzzy Time Series (FTS) which is driven by both Fuzzy Logic and Time Series Forecasting algorithms.

According to Carlos, et al. (2017), Fuzzy Time Series (FTS) provide a different representation of a time series. If a conventional time series are composed by observations represented by real numbers, fuzzy time series are composed by fuzzy sets. These fuzzy sets form the universe of discourse for the forecasting problem. The universe of discourse is obtained from the range of values observed in the conventional time series. For example, consider a time series Yt, where t belongs to Z, defined as a subset of R. The universe of discourse can be divided into sub intervals such as U = u1, u2, …, un. The fuzzy sets Ai are then defined over each sub interval with a corresponding membership function, mean value of Ai as E(Ai) : Ui 🡪 [0, 1].

Therefore, if F(t) consists of E(Ai) (t), then F(t) is considered a FTS on Yt, as stated in Carlos, et al. (2017).

***A. Fuzzy Logical Relationships***

Carlos, et al. (2017) describes Fuzzy Logical Relationships (FLR) as a representation of the causal relationship between the observations at time t and previous observations. Establishing the FLR is one of the main steps for a FTS algorithm. If there exists a fuzzy relationship R(t – p, t), such that

F(t) = F(t - p) \* R(t - p, t) (eq. 3)

where \* is an arithmetic operator, then F(t) is said to be caused by F(t - p). The relationship between F(t) and F(t - p) can be denoted by F(t - p) 🡪 F(t).

Consider F(t - 1) = Ai and F(t) = Aj. The first order FLR can be defined as Ai 🡪 Aj where Ai and Aj are called the left-hand side (LHS) and the right-hand side (RHS) of the FLR, respectively.

Suppose F(t - 1) = Ai1, F(t - 2) = Ai2, F(t - 3) = Ai3, … , F(t - p) = Aip and F(t) = Aj. The high order FLR can be defined as Ai1, Ai2, Ai3, … , Aip 🡪 Aj where Ai1, Ai2, Ai3, … , Aip is called the left-hand side (LHS) and Aj is called the right-hand side (RHS) of the FLR.

***B. High Order FTS***

The FLRs with the same LHS are gathered into groups called FLR Groups (FLRG). LHS of groups indicate input value (the point which prediction is performed) and RHS corresponds to the outputs that were experienced in the estimation period.

If F(t) is caused by F(t - 1), F(t - 2), F(t - 3), … , F(t - p), then the corresponding high order FLR proposed by Chen (2002) is

F(t - 1), F(t - 2), F(t - 3), … , F(t - p) 🡪 F(t) (eq. 4)

These FLR are the basis of the high-order FTS (with order p) proposed by Chen (2002). Thus, equation (4) can be interpreted as follows: the weight of each one of F(t - 1), F(t - 2), F(t - 3), … , F(t - p), for obtaining the fuzzy forecast at time t, i.e., F(t) is equal to one. However, The Algorithm below details the forecasting or predicting process.

***The Proposed FTS Algorithm:***

1. Define the universe of discourse U,
2. Partition U into subintervals i.e. U = u1, u2, …, un,
3. Define fuzzy sets Ai on U with the membership functions, mean value of Ai as E(Ai),
4. Establish high-order FLR as:

F(t - 1), F(t - 2), F(t - 3), … , F(t - p) 🡪 F(t)

1. Establish the FLRGs using above FLRs. FLRGs are determined by grouping those FLRs that have the same LHS:

For example, the following FLRs:

Ai1, Ai2, Ai3, … , Aip 🡪 Ak1

Ai1, Ai2, Ai3, … , Aip 🡪 Ak2

.

.

.

Ai1, Ai2, Ai3, … , Aip 🡪 Akm

produces the following FLRG:

Ai1, Ai2, Ai3, … , Aip 🡪 Ak1, Ak2, Ak3, …. Akm

**if** At time t RHS contains one or more fuzzy set in the sequence, i.e.,

Ai1, Ai2, Ai3, … , Aip 🡪 Ak1, Ak2, Ak3, …. Akm

**then** forecast at time t + 1 is

FVar = (Summation of Mij / k) – Mi1  (eq. 5)

Forecast(t + 1) = RV(t - 1) + FVar

where RV(t 􀀀 1) is the real value at time t - 1 and Mij is the midpoint of the interval related to the fuzzy set Aij, i.e. the de-fuzzified value of Aij.

**End if**