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EMPIRICAL ANALYSIS OF THE VIABILITY OF SOLAR PROJECTS: A CASE STUDY OF THE STRATHMORE UNIVERSITY SOLAR PHOTOVOLTAIC PROJECT

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DEDICATION

I dedicate this project to my loving parents Mrs Njore and Mr Njore (the late) and to my dear siblings Christine and Mary.

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ABSTRACT

This study evaluates the viability of investment in solar photovoltaic projects. The Autoregressive Moving Average (ARMA) technique was used to model the monthly solar radiation levels within Nairobi for the period between 1985 and 2013 whereas the net present value (NPV) and internal rate of return (IRR) methods were used to evaluate project viability. The solar radiation levels were obtained from the Kenya Meteorological Department and project specific information was obtained from the Strathmore Energy Research Centre. The behaviour of solar radiation levels in Nairobi was found to be ARMA (6, 2) and was high enough to generate sufficient electricity for large-scale use. Further, the forecast power of ARMA (6, 2) model was found to be high given the back testing procedures carried out. The project was found viable for cost of capital within a range of 4% - 6% and energy costs above USD 0.20. It was also noted that project viability is highly dependent on each project's specific details and that several other factors needed to be considered alongside the solar radiation levels before deeming a solar PV project economically viable.

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List of Abbreviations

ACF	Autocorrelation Function
ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
IRR	Internal Rate of Return
kW	Kilowatt
MA	Moving Average
MWp	Megawatt peak
NWP	Numerical Weather Prediction
NPV	Net Present Value
PACF	Partial Autocorrelation Function
PV	Photovoltaic
USD	United States Dollars

1 INTRODUCTION

1.1 Background of the study

Renewable energy is defined as that energy which is available in the long term and whose use does not result in environmental damage to the extent that nature cannot repair (Lynn, 2010) . It is obtained from sources such as solar, geothermal, wind, hydro, biofuels and biomass (Ondraczek, 2014). Non-renewable energy is derived from fossil fuels which include coal, oil and petroleum products, natural gas and nuclear energy from uranium. Over the last two decades, there has been increased adoption of renewable energy following declining fossil fuel reserves and the efforts to reduce carbon emissions that have caused increased global warming. The Kyoto agreement -first established in 1997- encouraged energy efficiency and encouraged developed countries to switch to sustainable and renewable sources of energy so as to minimize greenhouse emissions (Schermeier, 2012). In Kenya, the full capacity of renewable energy is yet to be fully achieved. The most utilized sources of renewable energy have been hydroelectric energy and geothermal energy (Ondraczek, 2014). Wind energy and solar energy exploitations have lagged behind (Theuri, 2008) .

For any institution wishing to invest in renewable energy, the choice is affected by a number of things. The initial feasibility study would look into how much energy is needed, how much energy could be obtained from the renewable energy chosen, how accessible is the renewable energy from where the institution is located, when is the renewable energy available and whether the renewable energy can penetrate the existing power grid. These considerations can be summarized into how much, where and when.

Solar energy has an advantage over geothermal, wind and hydroelectric energy sources due to its flexible nature; a solar system can be set up on rooftop. Investments in solar projects can be categorized into photovoltaic solar power that uses solar photovoltaic cells to convert solar energy into electricity; concentrating solar power that uses mirrors and lenses to convert solar energy into electricity; or solar thermal projects that convert solar energy into heat (Lynn, 2010). The preference for photovoltaic technology over concentrating solar power technology in electricity generation can be attributed to the wider research into photovoltaic cells.

These have seen improvements in cell and module efficiencies and a steady reduction in costs. In addition, the large scale production of the cells using highly automated facilities has contributed to driving down the costs (Lynn, 2010).

The high capital cost for investments in solar photovoltaic projects constitutes the greatest cash outflow for the project. For this reason, most investors do not consider the solar energy projects as economically feasible investments (Ondraczek, 2014). To ensure value for money, for projects that go through, the investors would require that the positive cash flows from the project during its lifetime be high enough to ensure a shorter payback period for the investment: the cash inflows are determined in terms of savings from the electricity bill that would otherwise have been paid and from the earnings of the excess electricity sold to the grid in the case of grid-connected systems.

Investors in grid-connected projects also face price risk resulting from volatile electricity prices. To curb this, feed-in-tariffs have been used that give fixed power rates for investors and which ensure they earn sufficient income even during periods with minimum sunshine. The tariffs also partly reduce the impact of volume risk resulting from the variation in solar radiation with respect to weather changes. Other risks that investors face and which could be mitigated through insurance or product warranties include damage from extreme weather, and faster degradation of the panels resulting in much shorter useful life than expected (Davison & Lu, 2013).

1.2 Solar energy in Kenya

Kenya lies along the equator and is among the 148 Sunbelt[1] countries in the world. As a result it enjoys abundant solar energy resource with an average daily solar insolation of 4-6 kWh/m^2 (Ondraczek, 2014) . An analysis of a sample of 66 Sunbelt countries accounting for about 5 billion inhabitants and 75% of the total population in the world, revealed that by 2009 Kenya ranked 14th in terms of the installed solar PV capacity (Hauff, Verdonck, Derveaux, Dumarest, Alberich, & Malherbe, 2011). The electrification rate in Kenya of 14% is however among the lowest in the world and is unable to sufficiently meet the energy demands from the quickly growing population (Ondraczek, 2014). The electricity sector which is dominated by

[1] Countries located between the latitudes of 35°N and 35°S of the equator

hydropower, geothermal power and thermal power plants would therefore greatly benefit from harnessing the solar energy which theoretically has been found to have the capacity to contribute to about 100 times the energy that Kenya consumes (Ondraczek, 2014).

1.3 Problem statement

The intermittent generation of non-renewable energy makes it difficult to predict the amount of electricity that could be generated from the renewable source in a given day. In the case of solar energy, cloud cover causes great changes in the radiation received during the day. Estimates of the average solar insolation in a day or for a given month are the key inputs used to estimate the amount of electricity that could be generated from a solar photovoltaic project. The variation in the amount of solar radiation depending on weather patterns or seasons results in uncertainties in the cost savings or net proceeds that could be obtained from a grid-connected solar systems. In the event that the solar radiation is over estimated when conducting a feasibility study for the project, it may result in the wrongful approval of a project that would actually not be financially viable. It is therefore vital that a reliable estimate of the daily solar radiation is made, or a reliable forecast is done, where necessary.

This research therefore sought to establish the month to month behaviour of solar radiation in Nairobi region. The information is critical in advising an investor within Nairobi about the amount of electricity that could be generated from their solar system and as a consequence, the amount of cost savings or revenue earned from the excess generated electricity that would be sold to Kenya Power in the case of a grid-tied systems.

1.4 Research Objectives

The aims of this research are:

1. To establish whether the electricity generated within Nairobi would be sufficient to make a solar PV viable

1.5 Research Questions

Through the research, the following questions were addressed:

1. Is the electricity output for a grid-connected solar photovoltaic system within Nairobi sufficient to make the project viable?

1.6 Justification of the Study

This research is important for investors in commercial or large scale institutional solar photovoltaic projects. It establishes how to accurately determine the amount of solar insolation for a given geographical region hence estimates the minimum amount of electricity that could be generated from the solar photovoltaic system. This will contribute to decision making with regards to approval of solar photovoltaic projects as the investor could estimate the cash flows likely to be received from the grid-connected solar systems.

2 LITERATURE REVIEW

2.1 Solar energy as an alternative source of energy

The inadequate and non-uniform distribution of fossil fuel reserves in the world resulted in energy insecurity in several countries not endowed with the fossil fuel resource (Shpil'rain, 1997). The oil price shocks in 1970s that affected most developed countries resulted in inflation and a slowdown of economic growth. Although most of the affected countries opted to exploit their own fossil fuel reserves, there was concern that the high dependence on fossil fuels would result in the exhaustion of the reserves and therefore creating the need for alternative sources of energy (Bhattacharyya, 2007). The increased damage to the environment as a result of the exploitation of fossil fuels provided the impetus that saw several countries shift focus towards renewable energy sources.

Recent studies have shown that although use of fossil fuels and nuclear energy are the main sources of global energy, the growth in the renewable energy market has been rapid in the past years with power production from renewable sources -other than hydro sources- increasing by about 22% between 2004 and 2009 (Davison & Lu, 2013). Globally, solar photovoltaic technology for power generation has grown faster than all other renewable energy technologies. A few factors have been attributed to this. Firstly, the solar energy needed for the solar photovoltaic power generation is available freely. Secondly, even though solar insolation levels vary depending on the weather patterns, when compared to wind energy, solar photovoltaic power is more stable and therefore easier to predict. Thirdly, in most developed counties the government support in terms of grants, tax credits, capital subsidies, use of favourable feed-in-tariffs for investors and other direct public financing have helped overcome the challenge of the high capital cost for a solar PV power investment (Davison & Lu, 2013). Increased research, improved technology and large scale production of solar panels were found to have also contributed to their declining costs, in return lowering the otherwise high upfront costs for such investments.

The ideal operating condition for a solar photovoltaic panel is a cell temperature of 25°C and at solar irradiance of 1000 Watts per square metre (W/m^2) (Davison & Lu, 2013). The energy output from solar photovoltaic panels is nonetheless affected by several factors including the quality of the components of the solar panel as per its manufacturing design; the cell technology, the amount of cloud cover and shading which affect the solar radiation received; location and inclination of the solar panels in relation to the sun; climate zone, season and time of the day; the ability of the panels to track the sun facilitated by its solar tracking capability; components that may pollute the modules such as dust that may settle on the panels blocking them from receiving maximum sunlight, among others (TUVRheinland, 2014). Research has revealed that of the different types of solar panels, the most efficient converts only about 23% of sunlight into electricity (Green, Emery, Hishikawa, & Warta, 2011). The inefficiencies contributing to the greatest energy losses occur at the point where solar panels convert solar radiation into solar power (Qu, Zhao, & Yu, 2008).

2.2 Significance of the level of solar radiation

For a solar panel to produce energy, the solar energy resource has to be utilized. This is undoubtedly the key input without which, the generation of solar power would be impossible. Solar radiation for a given region therefore indicates the region's potential of solar energy (Ettah, Nwabueze, & Njar, 2011). A study comparing the solar energy markets in Kenya and Tanzania revealed that the availability of abundant solar energy resource in the region- on average ranging from 1460 to 2430 kWh/m^2 annually- has been a key contributor to the development of the solar water heaters and the grid-connected solar photovoltaic systems market in both countries (Ondraczek, 2013). Further studies have also shown that for a good prediction of the amount of solar energy that could be produced, the solar radiation forecast should equally be good (Zhao, Antwi, & Yiranbon, 2014).

Solar radiation is regulated by the amount of cloud cover, and so varies from place to place depending on the local weather and climatic conditions. Cloud cover and other meteorological conditions are the greatest determinants of the availability of solar radiation (Ettah et al., 2011). An analysis of the performance of solar photovoltaic cells with the changing solar radiation and temperature revealed that whereas increases in temperature beyond a given favourable limit reduces the cell performance and electricity current generated, an increase in solar radiation increases the efficiency of the solar cells in generating electric current. Therefore, the solar panels perform best on cold but sunny days rather than during sunny yet hot weather (Arjyadhara, Ali, & Chitralekha, 2013).

Solar radiation received on a solar panel is broadly classified into direct radiation which is received on the earth directly from the sun and without any disturbances; and diffuse radiation which is scattered by clouds, dust and other gas molecules before reaching the earth. Often, solar radiation is measured as a total of both direct and diffuse radiation received on a horizontal surface and is termed global radiation (Sen, 2008). The equipment needed to measure and record solar radiations are costly to acquire and maintain and are often out of reach for many developing countries. Instead, other readily available meteorological data are used to estimate the radiation: sunshine duration, solar radiation levels, maximum and minimum temperatures, mean daily cloud cover, mean daily humidity, the average daily atmospheric pressure among others (Salmi, Chegaar, & Mialhe, 2011).

2.3 Estimating solar radiation

In order to estimate the cost savings that could be obtained from investing in a solar photovoltaic project, it was found important to determine the amount of solar radiation within the region in which the project is to be constructed. To do this it was found inevitable to first understand the behaviour of solar radiation.

2.3.1 Nature and behaviour of solar radiation

Solar radiation is naturally existent, hence renewable and inexhaustible. However it is non-continuous and intermittent as it varies severally within a given day due to changes in weather and cloud cover. Also, the solar radiation drops to zero after sunset and only picks up at sunrise. Since solar radiation is subject to daily, monthly, seasonal and annual changes, many years of observation are necessary to determine with fair accuracy its distribution (Yarhands, Gyamfi, & Appiah, 2013). As a result of the random and nonlinear nature of solar radiation forecasting in the short run is often complex. However, the annual global horizontal irradiance from one year to the next may not vary as much as the variation from one month to the next. However, this forecast was found to be of great importance for the power prediction of grid-connected solar photovoltaic systems.

2.3.2 Time series models and solar radiation forecasting

2.3.2.1 General overview of time series models

A time series is a sequence of observations X_t which are recorded over a given time period. A time series is called stationary if the mean level is constant with time. Each observation is recorded at a specific time t (Paoli, Voyant, Muselli, & Nivet, 2010). The amount of solar radiation observed over a year varies with the different times in the year and is thus an example of time series data. Studies have revealed that time series can be broken down into four main components- trend, seasonal component, cyclic component and a random component (Albright, Winston, & Zappe, 2004). These components are then used in forecasting the time series data.

The time series models are broadly classified as linear or non-linear. Examples of linear models include the moving averages models, exponential smoothing models, auto regressive models; autoregressive integrated moving average models among others. Linear models have the advantage of being simple to use and easy to comprehend. However, they are unable to simulate nonlinear processes. The development of non-linear time series analysis has been less compared to linear models with pioneer works on non-linear models being attributed to Volterra (Gooijer & Hyndman, 2006). Examples of nonlinear models include k-nearest neighbour models, bilinear models, self-exciting threshold auto regression models and neural network models among others.

Moving average methods employs the simplest technique in forecasting. It uses the average of the observations made in the past given periods as the forecast for the next period. The choice of the number of periods in the average is judgemental. It could be as small as just one time period or could be larger. The more the periods used, the smoother the forecast, as it tends more towards the average. On the contrary, the less the periods used the less the smoothing effect (Albright et al., 2004). The accuracy of this technique is however questionable as it assumes same weighting for each value in the moving average. For this reason we seek a better forecasting technique.

An N-period moving average model would be:

Equation 2.1

$$Y_{t+1} = (X_t + X_{t-1} + X_{t-2} + \cdots + X_{t-N-1})/N$$

Where $Y_{t+1}$is the forecast for period $t+1$, X_{t-1} is the observation at time $t-1$; N the number of periods in the moving average

Exponential smoothing is a time series forecasting technique that also bases its forecasts on a weighted average of past observations. It is an improvement from the moving average techniques, as it gives more weight on the recent period observations and lesser weighting on observations from older periods. Exponential smoothing has the disadvantage of being overly simplistic and inflexible and may thus not capture all the linear dependence in the data, making the model unreliable (Brooks, 2008). Different variations to the exponential smoothing technique include the Holt's linear method which is appropriate for series with trend and no seasonality effect; and the Holt Winters' method that has a seasonality component in addition to the trend component (Hyndman, Koehler, Ord, & Snyder, 2005).

Simple exponential smoothing model:

Equation 2.2

$$Y_{t+1} = \alpha X_t + (1-\alpha)Y_t$$

Where Y_t is the weighted average of all observations prior to t and X_t the last period's observation

Holt model splits the forecast into level (L) and trend (T) components:

Equation 2.3

$$L_t = \alpha X_t + (1-\alpha)(L_{t-1} + T_{t-1})$$

Equation 2.4

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

Where: $0 < \alpha < 1$ and $0 < \beta < 1$

Autoregressive Integrated Moving Average (ARIMA) models combine the concept of moving averages, trend and autoregression (where the explanatory variables are obtained as lagged values of the response variables). Box and Jenkins came up with a three-stage iterative procedure- Box-Jenkins methodology- for identifying the time series, approximating it and verifying it, which has had a great impact on modern time series analysis and forecasting (Gooijer & Hyndman, 2006).

The k-nearest neighbor's algorithm is a nonlinear time series method for classifying objects based on closest training examples in the feature space. It is considered a form of instance-based learning, in which the function is only estimated locally while all the computation is deferred until classification. This model however does not use a learning base. It looks into the history of the series for the case most resembling to the present case (Paoli et al., 2010).

Artificial neural networks are intelligent computing systems that are able to learn, memorize and build relationships among the data (Paoli, Voyant, Muselli, & Nivet, 2010). They are able to learn from the examples and generalize the knowledge which they apply to examples not seen before. Artificial neural networks are composed of interconnected processing units, the neurons, which are connected to each other using weighted links over which information can be passed from one neuron to the other and the acquired information can be stored (Paoli et al., 2010).

There are two main structures of neural networks as classified by how the neurons are interconnected to each other. In multi-layer feedforward networks, the neurons are categorized into layers- an input layer, a hidden or intermediate layer and an output layer. The neurons are linked from one layer to the other but are not linked within the same layer. Therefore signals flow in one direction only- from the input layer to the output layer. For recurrent networks, information can flow in any direction (Mihalakakou, Santamouris, & Asimakopoulos, 2000).

2.3.2.2 Models used to forecast solar radiation

Models adopted to forecast total solar radiation often depend on the forecast horizon. For every short-term predictions (five minutes to about six hours) time series models have been preferred. For forecasts for more than six hours numerical weather prediction (NWP) models that use satellite data have been found to be more accurate. However, in this study, a model that would only require inputs of solar radiation levels is preferred to ensure cheap and efficient computation (Dazhi, 2012).

Due to the nonlinear nature of solar radiation, the forecasting of solar radiation is often estimated using nonlinear time series models. In the recent years, the artificial neural network (ANN) technique has been preferred technique in predicting the total solar radiation time series (Mihalakakou et al., 2000).

When using a neural network, the time series prediction problem is handled in three steps. First, the neural network model is built by specifying the structure of the neurons in the different layers. Then the network is trained using the previously collected solar radiation data and finally a diagnostic check is conducted. The network is then used to make predictions (Mihalakakou et al., 2000).

Certain features of ANNs make them attractive for forecasting. First, they are data-driven methods and so minimize the need for a priori[2] assumptions. They simply learn from examples and experience. After learning from the data used to train them, ANNs are able to generalize and correctly forecast future behaviour. Thirdly, ANNs are more flexible than traditional statistical methods and are able to easily identify the underlying function linking the past values of the time series to the future values to be predicted (Zhang, Patuwo, & Hu, 1998).

It is however much more difficult to establish a parsimonious model for solving real problems when using ANNs as compared to other statistical methods and thus ANNs are more prone to overfitting problems. Building a neural network is also not easy as critical decisions regarding the structure of the network will need to be made and trial-and-error procedure followed to establish the best network. Interpreting the results is also difficult as it is difficult to explain how the outputs have been obtained from the inputs fed into the network. ANNs will also need more time and data to be trained (Zhang et al., 1998).

Autoregressive Moving Average (ARMA) models have been credited for their ability to extract and use important statistical properties in the data to forecast. They are also flexible as different orders can be used to come up with different types of time series that will be specific to the time series to be analysed. ARMA models require that the time series data is stationary. An Augmented Dickey-Fuller stationary test performed on solar radiation series revealed that the series was non-stationary (Diagne, Lauret,

[2] Assumptions that are considered true and thus there is no need to prove them

David, & Boland, 2014). To use ARMA model we would therefore need to carry out detrending to obtain a stationary series.

When choosing the solar radiation forecasting model (Dazhi, 2012) preferred the Autoregressive Integrated Moving Average (ARIMA) model over Autoregressive Moving Average (ARMA), Autoregressive (AR) models and Moving Average (MA) models since ARIMA could be used to forecast both stationary and non-stationary time series. This study therefore adopted ARIMA models in estimating the amount of solar radiation for each month of the year.

2.4 Project Viability Analysis

To assess whether a project is viable, several techniques can be employed namely the payback method, the return on investment method, the net present value technique and the internal rate of return method among others. Whereas each method has its advantages and disadvantages, some of the methods are deemed more superior than others.

2.4.1 Return on investment

This method is entails dividing the average profit by the average investment and is often expressed as a percentage. The project is accepted as viable if its return on investment is higher than a particular target rate. In the case of two mutually exclusive projects, the one with the highest return on investment is picked. This technique had been credited for being simple, for giving its value in percentage terms which is easier to understand and for taking into account all the cashflows arising in the project's lifetime. However, it relies on accounting profits (and not cash) which gives room for manipulation. Also, by using the average annual profits, the technique ignores the timing of profits (Watson & Head , 2010).

2.4.2 Payback method

The payback method assesses how long a project will take to recoup its initial investment from the net cashflows that the project generates. The project being assessed is considered viable if the payback period is less than the particular target rate (McLaney, 2006). Although this technique is straightforward, there may be difficulty in its interpretation especially when it results in more than one possible solution. The payback method gives equal weighting to the cashflows and so ignores the time value of money. Another disadvantage is that this technique does not consider the cashflows of the entire project. It ignores all the cashflows after the payback period (Watson & Head , 2010). Due to its numerous shortcomings, the payback method is not sufficient to determine the viability of a project.

2.4.3 Internal Rate of Return

This method identifies the rate of return which when used to discount the cashflows arising from a project, results in a net present value of zero. The IRR is often determined by interpolation. The project that returns an IRR greater than the cost of capital is considered viable (Watson & Head , 2010). This technique takes into account all the cashflows of the project and the time value of money. However, it is unsuitable when evaluating projects whose finance cost is expected to be changing in the course of the project's life. Also, for projects with unconventional cashflows, the technique may return multiple IRR's or none at all (McLaney, 2006).

2.4.4 Net Present Value Method

This method discounts the entire positive and the negative cashflows arising from the project to their present values at the cost of capital. The resulting net present value from the cash inflows and outflows is then determined to see if it will be positive or negative. A project is deemed viable if the net present value of the cashflows is positive at the project's cost of capital (Watson & Head , 2010). Difficulties are often encountered when estimating the future cash inflows and outflows from the project especially since it mostly involves forecasting the cashflows. The NPV method- unlike the payback method- takes into account the time value of money and incorporates the entire project's cashflows when estimating its viability. These advantages make the technique the most preferred method.

Overall, the NPV method is considered technically superior to the IRR method as it can cope with changes in discount rates. It is also more reliable as it gives clear results when dealing with mutually exclusive projects and with projects with unconventional cashflows. The NPV method also has comparatively more realistic reinvestment assumptions.

3 METHODOLOGY

3.1 Introduction

This study attempted to estimate the amount of energy output from a solar photovoltaic system and thus the cost savings likely to be made by self-consumption of the generated electricity as opposed to purchase of electricity from Kenya Power Company. To do this, the average amount of solar radiation that could be received for each month in a year was first estimated. This estimate was used to determine the amount of electricity that could be generated each month. The ARIMA time series model was adopted to forecast the amount of solar radiation in the next year for each given month (Dazhi, 2012).

The estimated power output was based on assumptions taken by the Strathmore University's 600kW rooftop solar photovoltaic project, including the cost of installation, cost of maintenance and other running costs. Since the university's solar PV system is connected to the grid, the excess energy generated by the system during sunny days were considered to be sold to the grid at the agreed feed-in-tariff (price) of USD 0.12 per kilowatt-hour. The electricity sold to the university from Kenya Power in the event the solar system does not generate enough power to meet the consumption was at USD 0.225 per kilowatt-hour. The two prices were essential in estimating the amount of cost savings and income from selling electricity to the grid (Da Silva, Ronoh, Ouma, & Jerono, 2014).

3.2 Research design

The study adopted had an exploratory research design as it described the behaviour of solar radiation, its distribution and forecasts its future pattern.

3.3 Sampling design

A purposive sampling design was adopted where the amount of data on solar radiation used in modelling and forecasting, was based on what I found appropriate for the study. The solar radiation data used is site specific. Thus, only the data relating to the Nairobi region was selected as the Strathmore solar photovoltaic system is within Nairobi. Measurements for the data were as per the Dagoretti

Corner Meteorological Department records. This form of sampling was in line with the definition of purposive sampling where the researcher purposefully chooses the particular units of the population that form the sample, on the basis that the small mass that they selected represented the whole population.

3.4 Data collection

Data used was secondary. The data for the past thirty years (1983 to 2013) on the average monthly solar radiation and on the monthly temperatures in Kenya- Nairobi region- was obtained from the Kenya Meteorological Department.

3.5 Data analysis

Based on the literature reviewed, the preferred class of models for forecasting was the ARIMA(p, d, q) models (Dazhi, 2012). This is a combination of an autoregressive model of order p, a moving average model of order q and an integration order d. The Box-Jenkins methodology was adopted to build the exact ARIMA model that would be simple enough yet accurate in giving a description of the behaviour of historical time series data (Brooks, 2008). The general ARIMA equation for non-stationary time series was given by

Equation 3.1

$$\varphi(B)\nabla^d X_t = \varphi_0 + \theta(B)a_t$$

Where:

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \varphi_3 B^3 - \cdots - \varphi_p B^p$$

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \theta_3 B^3 + \cdots + \theta_q B^q$$

And;

X_t : Time series observation at time t

t: Month of a given year

$\varphi(B)$: Is the autoregressive operator

$\theta(B)$: The moving average operator

a_t: The white noise process (errors) with mean zero and a constant variance

∇: The difference operator also denoted as $1 - B$

φ_0: The constant term

Equation 3.1 is rewritten as

Equation 3.2

$$Y_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \, a_{t-i} + a_t$$

Where $Y_t = \nabla^d X_t$

3.5.1 Pre-estimation tests

This study adopted a univariate time series as it involved observing a single variable over time. It was considered important to carry out some tests on the time series before using it in the ARIMA model chosen. A stationary test was first performed since this trait has a strong influence on the pattern and the behaviour of the series and using non-stationary data could have resulted in spurious regressions. A stationary series is defined as that which has a constant mean, variance and autocovariance (Brooks, 2008). A unit root test via the Augmented Dickey-Fuller (ADF) test was used to determine whether data was stationary.

Normally, if series is found to be non-stationary, it is differenced to make it stationary (Brooks, 2008). To obtain a stationary time series Y_t that follows an ARMA $(p\ , q)$ process, from a non-stationary time series X_t following an ARIMA $(p, 1, q)$ process, differencing is done as follows

Equation 3.3

$$Y_t = X_t - X_{t-1}$$

3.5.2 Building the ARIMA (p, d, q) model and forecasting

(Brooks, 2008) Following the three step Box-Jenkins procedure in developing the model, the order of the model was first identified by obtaining values of p, d and q parameters that characterize the model. The parameter d is the number of times the time series has to be differenced to make it stationary. I obtained the sample autocorrelation function r_k and concluded that the initial time series was stationary since r_k decreased rapidly to zero with increased lag$k$.

To obtain the parameters, the autocorrelation function (ACF) was observed from correlogram[3] and the parameter p was chosen to be the lag p at which the ACF cut off the axis, whereas, parameter q, was determined as the lag q at which the partial autocorrelation function (PACF) cut off the axis. The use of a correlogram was however rather subjective and difficult to interpret (Brooks, 2008). To overcome this subjectivity, a second approach was used – the Akaike Information Criterion method (AIC) -where the parameters determined using the first method were used as a benchmark for establishing the range of models to test under the AIC method. Under this method, the appropriate parameter for the autoregressive component of the model p and the moving average component of the model q were the ones that minimized the information criterion (Brooks, 2008). The Akaike Information Criterion was given by

Equation 3.4

$$AIC = \ln \hat{\sigma}^2 + \frac{2k}{T}$$

Where the information criteria is minimized subject to $p \leq \bar{p}, \; q \leq \bar{q}$

$\bar{p}$: The upper limit on the autoregressive term

$\bar{q}$: The upper limit of the moving averages

$\hat{\sigma}^2$: The residual variance

$k = p + q + 1$: The total number of parameters to be estimated.

T: The sample size

To estimate the parameters $\varphi_1, \varphi_2, \dots, \varphi_p$ and $\theta_1, \theta_2, \dots, \theta_q$ of the model, the method of Maximum Likelihood Estimators was employed. Diagnostic tests were then performed on the model to check whether it correctly approximated the underlying

[3] A plot of sample autocorrelations against the time lags

time series process (Brooks, 2008). This involved checking the residuals for any pattern or linear relationship as these would indicate that the model was inadequate. The Ljung-Box Statistic for the diagnostic checks was used where the null hypothesis was that all m autocorrelation coefficients are zero. According to (Tsay, 2006), the Ljung-Box test statistic applied to the residuals of an ARMA (p, q) is given by

Equation 3.5

$$\chi_m^2 = T(T+2)\sum_{j=1}^{m}\frac{\hat{\rho}_j^2(a_t^2)}{T-j}$$

Where χ_m^2 is the chi-squared random variable at $m-p-q$ degrees of freedom; T is the sample size; $\hat{\rho}_j^2(a_t^2)$ is the ACF of a_t^2 at lag-j; m is the number of autocorrelations used in the test; a_t is the residual series.

Once the model built passed the diagnostic test, it was then used to forecast the monthly solar radiation for the subsequent period. According to (Tsay, 2006), the general forecast function for s steps into the future, given all the observations up until time t is given by

Equation 3.6

$$Y_{t+s} = \varphi_0 + \sum_{i=1}^{p}\varphi_i Y_{t+s-i} + \sum_{i=1}^{q}\theta_i\, a_{t+s-i}$$

In general, if we consider a two-step ahead forecast for an ARIMA (1, 2, 1) process, then the forecast equation is written as

Equation 3.7

$$\hat{x}_t(2) = 2\,\hat{x}_t(1) - x_t + Y_{t+2}$$

The forecasting equation was obtained by using equation 3.2 to replace the value of Y_{t+2} into equation 3.7. The values of unknown parameters were then replaced into the resulting equation and the forecast value $\hat{x}_t(2)$ obtained. The model could be used to forecast values for each month in the next year. These forecasts were then used as inputs into a model that determined the amount of electricity that could be generated given the specific details of the solar PV system. An analysis of the possible cost savings per month as per the assumptions employed by the Strathmore University 600kW solar PV project were finally conducted.

3.5.3 Cash flow analysis

The net present value (NPV) of the project was used to evaluate its viability. The net present value method takes into account all cashflows of the project until termination and discounts these back to the present day at the cost of capital. A positive net present value is desired. The difficulty involved would be the selection of the appropriate risk discount rate at which to compute the net present value.

The internal rate of return (IRR) was also used to assess the viability of the project. Here, the interest rate that gives the project a net present value of zero is identified and compared with the cost of capital. If it is higher than the cost of capital, then the project is considered viable. However, if the interest rate does not satisfy the company criteria, it does not necessarily mean that the project is loss-making. Rather it could imply that it is not profitable enough to meet the investor's minimum requirements.

The internal rate of return method of project appraisal could however result in multiple solutions- especially where there are net negative cashflows at several stages of the project life. For this reason, the net present value method is considered more popular and reliable for project appraisal.

4 RESULTS AND DISCUSSION

4.1 Introduction

This section discusses the findings obtained when the solar radiation data within Nairobi was analysed to establish the ARIMA model it followed. A discussion of the possible month to month cost savings when an institution adopts a solar photovoltaic system follows. A line graph of the monthly solar radiation levels for the years ranging from 1983 to 2013 is as shown in figure 1 below.

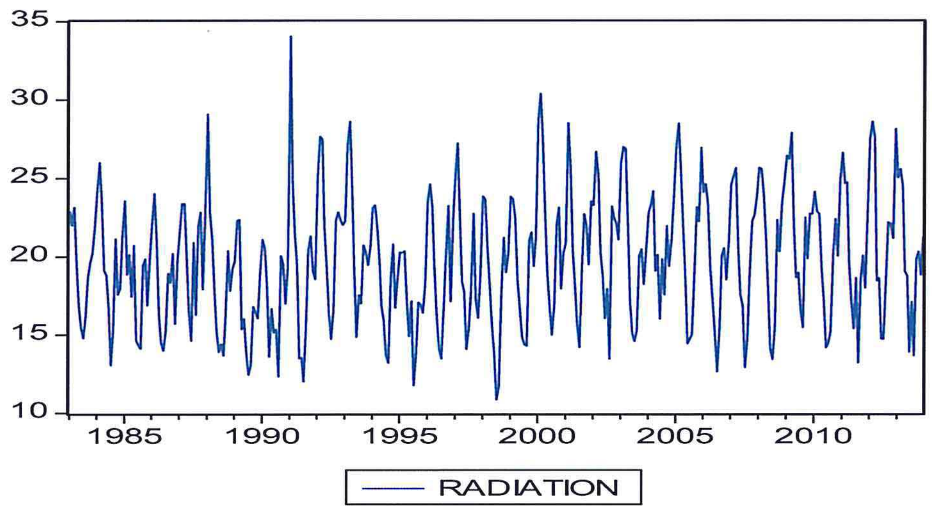

Figure 1: Solar radiation graph

From the graph, it can be seen that the data exhibits stationarity. There is no particular trend in the data. Differencing of the date would not be necessary.

4.2 Pre-estimation test

As outlined in the methodology, the Augmented Dickey Fuller test was used to determine whether the solar radiation data was stationary.

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-3.526377	0.0381*
Test critical values:	1% level	-3.983900	
	5% level	-3.422426	
	10% level	-3.134078	

Table 1: solar radiation Augmented Dickey Fuller Test

*The probability value from the test as seen in the table of 0.0381 is insignificant.

Thus testing at 5% significance level, we rejected the null hypothesis that the solar radiation data had a unit root, meaning the data was stationary. No differencing was needed to make the data stationary.

4.3 Model parameterization

To determine the autoregressive component of the model **p** and the moving average component **q** a correlogram was used. A given autocorrelation coefficient is considered significant if it exceeds the band shown by the dots. From the correlogram output as shown in appendix 2, the first two autocorrelation coefficients and the first seven partial autocorrelation coefficients were found to be significant under this rule, representing an ARIMA (7, 0, 2) model. This is because the identification of the autoregressive component is best done by the partial autocorrelation function while the identification of the moving average component is best done using the autocorrelation function. From the result, it was seen that a mixed ARIMA process was appropriate. However, it was hard to precisely determine from the graph the appropriate order given the results.

Several ARIMA models were investigated and the one which minimized the Akaike Information Criterion was selected. Parsimony was important when selecting the parameters for the appropriate model. The plausible models ranged from an ARIMA model of order (0, 0, 0) to (7, 0, 2). The table below shows the AIC values obtained

		Moving Average (q)		
		MA (0)	MA(1)	MA (2)
Autoregressive (p)	AR(0)	5.634	5.177	5.019
	AR(1)	5.051	5.022	5.005
	AR(2)	5.004	4.931	4.923
	AR(3)	4.971	4.929	4.925
	AR(4)	4.959	4.929	4.728
	AR(5)	4.919	4.914	4.668
	AR(6)	4.919	4.922	4.606*
	AR(7)	4.919	4.926	4.738

Table 2: Akaike Information Criterion values for ARMA (p,q) models

[*An ARIMA (6, 0, 2) also called ARMA (6, 2) minimized the information criterion as seen in the table. Thus, it was established to be the behaviour of solar radiation in Nairobi.]

4.4 Forecasting

The ARIMA (6,0,2) model was used to forecast solar radiation for the remaining project life (from 2015 to 2033). The project life was assumed to be 20 years starting 2013 when the loan was granted, to the year 2033. The forecast equation was adopted from the ARIMA equation shown below:

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \varphi_3 Y_{t-3} + \varphi_4 Y_{t-4} + \varphi_5 Y_{t-5} + \varphi_6 Y_{t-6} + \theta_1 a_{t-1} + \theta_2 a_{t-2} + a_t$$

Where the coefficients are as shown in the table below:

Variable	Notation	Coefficient	Std. Error	t-Statistic	Prob.
C		19.76382	0.247227	79.94209	0.0000
AR(1)	φ_1	2.177842	0.051560	42.23869	0.0000
AR(2)	φ_2	-1.859038	0.123805	-15.01585	0.0000
AR(3)	φ_3	0.557082	0.157743	3.531571	0.0005
AR(4)	φ_4	0.177095	0.158037	1.120595	0.2632*
AR(5)	φ_5	-0.379623	0.124902	-3.039364	0.0025
AR(6)	φ_6	0.196688	0.052284	3.761945	0.0002
MA(1)	θ_1	-1.737358	0.003298	-526.8101	0.0000
MA(2)	θ_2	0.994487	0.003462	287.2281	0.0000

[* the coefficient in asterisk is significant as it exceeds 5% whereas the others are not]

The forecast equation was:

Equation 4.1

$$Y_t = 2.177842\ Y_{t-1} - 1.859038. + 0.557082 Y_{t-3} + 0.177095 Y_{t-4} - 0.379623\ Y_{t-5} + 0.196688 Y_{t-6}$$

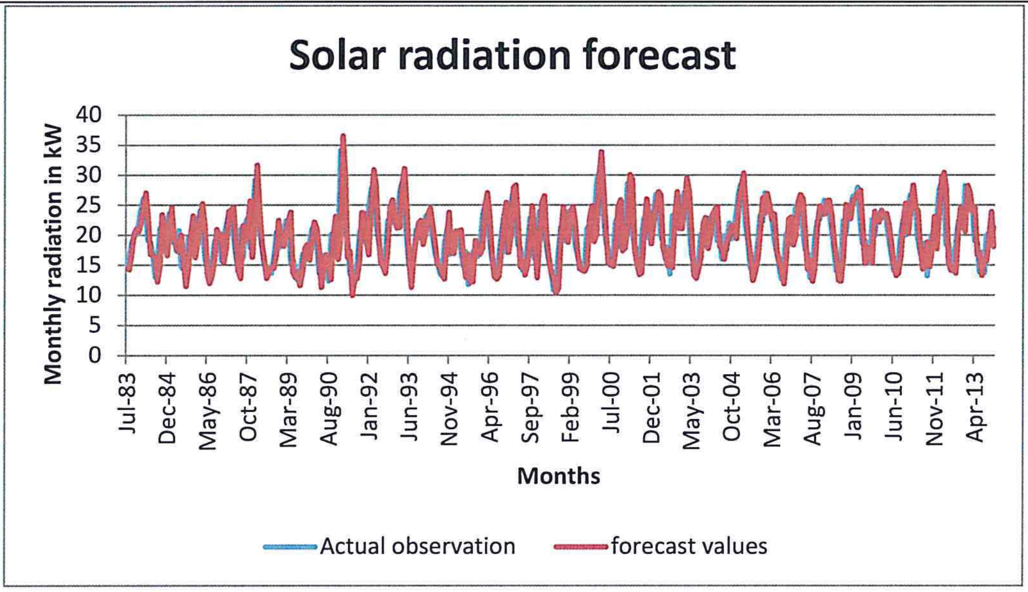

Figure 2: Solar radiation forecast

[Figure 2 above shows that the forecast equation adopted (equation 4.1) maps accurately onto the actual observation hence its credibility.]

4.5 Project Appraisal

The viability of the solar project was assessed based on the net present value method and the internal rate of return method. For a project to be viable the net present value (NPV) needed to be positive. The greater the NPV the greater the expected energy cost savings. The internal rate of return on the other hand needed to be greater than the cost of capital. This project appraisal was conducted based on the project specific assumptions discussed in this section.

4.5.1 Annual power output

The PV-Watts Calculator by the National Renewable Energy Laboratory (NREL) was used to calculate the amount of annual power output for the Strathmore solar PV project. First, the location was selected as Nairobi, and the Dagoretti weather data was chosen for use. The software uses an international file to obtain the required weather data.

The system information was then specified in order to compute the annual power output. The inputs selected were as shown in the table below:

Input	Value
DC System Size (kW)	600
Module type	Standard
Array type	Fixed (roof mount)
System losses %	14
Tilt (deg)	20
Azimuth (deg)	0

The DC system size shows the direct current power rating in kilowatts of the PV array under standard test conditions. The standard module type selected was the crystalline-silicon type with the approximate efficiency of 15%. This is normally the default setting in the PV calculator in case the module of the solar system is unknown. The array type distinguishes the different possible ways that the PV modules are arranged. It could be that they move to track the movement of the sun or that they are fixed like was the case for the Strathmore project. The system losses describe the possible performance losses of the solar panels due to soiling, wiring, connectivity issues or shading. A default value of 14% as suggested by the National Renewable Energy Research was adopted. Similarly default values were used for the tilt and azimuth[4] angle of the solar PV modules.

Other assumptions taken from the PV Calculator included:

Parameter	Value
DC to AC Size Ratio	1.1
Inverter Efficiency %	96
Ground coverage ratio	0

The DC to AC Size ratio represents the ratio at which the inverter converts 1 kW of direct current into 1 kW of alternating current. It is also assumed that the inverter performs at 96% efficiency level. The ground coverage ratio is relevant for arrays

[4] The angle which is clockwise from true north which shows what direction the arrays are facing.

with a tracking ability. We assume a zero value since the Strathmore array is fixed and mounted on the rooftop without any sun tracking ability.

The resulting annual estimate based on the above assumptions in the PV calculator was 823,512 kWh.

4.5.2 Other Project specifics

4.5.2.1 Project sizing

The size of the Strathmore project was 600kW. The choice was arrived at by considering the minimum project size for a project that could be eligible for the Feed-in-tariff regime which was a 500kW project. A financial model was then used to establish the optimum size of the project allowing for losses made from energy exported to the grid at a tariff that is normally much lower than the cost of purchasing electricity from Kenya Power.

4.5.2.2 Project funding

The project was funded through a loan amount of $1.3 million for a term of 10 years with a one year moratorium and at an interest rate of 4.1% per annum. This credit was accessible through a credit line by the French Development Agency in collaboration with the Cooperative Bank.

4.5.2.3 Own consumption assumptions

The yield degradation assumption taken (at 0.7%) was as per the Strathmore University solar PV project assumptions. It was assumed that there was 100% consumption of the electricity output from the solar project. This percentage was made flexible to cater for possibly different levels of consumption during different months of the year.

4.5.2.4 Cost of capital assumptions

Using the free cashflows to the firm, the net present value was determined by using a discount rate representing the cost of capital for the project. In the event that both debt and equity would have been used to finance the project, a weighted average would be used for the cost of debt and the cost of equity as shown below

$$WACC = \left[\frac{Market\ value\ of\ debt}{Market\ value\ of\ debt\ and\ equity} * Cost\ of\ debt\right] + \left[\frac{Market\ value\ of\ equity}{Market\ value\ of\ debt\ and\ equity} * Cost\ of\ equity\right]$$

Where WACC refers to Weighted Average Cost of Capital

However, the solar project was funded fully through debt. Hence the discount rate used was the cost of debt which was 4.1% per annum. The project viability was then assessed based on whether the net present value of the discounted cashflows was positive (viable) or negative (not viable).

4.5.2.5 Energy cost assumptions

As per the end of 2013, the energy costs were $0.225 per kilowatt hour whereas the feed-in-tariff was at $0.12 per kilowatt hour. The cost and grid inflation were set at 5% per annum to cater for the rising operating costs and the rising cost of electricity.

The direct costs assumed in the SU solar PV model was a one-off charge of $2.1 per watt generated. It consisted of the cost of purchasing the PV modules, the inverters and other necessary hardware and labour costs for their installation. This value was comparably lower than the average cost according to the National Renewable Energy Laboratory statistics which quoted that on average installation costs are $3.7 per Watt generated. The comparably fairly low installation charge was accredited to the efficiency of Quest Works which was in charge of the project delivery. The delivery time was one month ahead of the schedule which contributed to lower costs.

The operating costs which were incurred annually were assumed to be $0.022 per watt generated. This included the equipment replacement and maintenance costs once the system started generating electricity. The costs were subject to increase over the years due to inflation.

4.5.2.6 Tax assumptions

To arrive at the free cashflows to SU from the project, the income from the cost savings were adjusted by deducting the direct and operational costs. The loan principal and interest repayments were also deducted. Assuming a 30% tax rate, the net amount was considered as the free cash flow to the University from the project.

4.5.2.7 Summary of Annual cash flow projections

The table below shows a summary of cashflows for the useful life of the project and the resulting net present value based on the assumptions discussed. The cashflows are in USD.

The study found that the project returned a highly positive net present value and the internal rate of return for the project (7.82%) was higher than the cost of capital (4.1%). Both those findings revealed that the project was viable.

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
EBITDA	0	172090	179333	186880	194743	202936	211474	220369	229638	239296	249358	259843	270767	282149	294009	306365	319240	332654	346629	361191	376362
Fixed capital investment	(1260000)		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Working capital investment		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Principal repayment		(107777)	(112196)	(116796)	(121585)	(126570)	(131759)	(137161)	(142785)	(148639)	(154733)	0	0	0	0	0	0	0	0	0	0
Interest repayment	(53300)	(48881)	(44281)	(39492)	(34507)	(29318)	(23916)	(18292)	(12438)	(6344)	0	0	0	0	0	0	0	0	0	0	0
Tax		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FCF	**(1313300)**	**15432**	**22856**	**30591**	**38651**	**47049**	**55799**	**64916**	**74415**	**84313**	**94625**	**259843**	**270767**	**282149**	**294009**	**306365**	**319240**	**332654**	**346629**	**361191**	**376362**
NPV	**767,562**																				
	(1300000)	15432	22856	30591	38651	47049	55799	64916	74415	84313	94625	259843	270767	282149	294009	306365	319240	332654	346629	361191	376362
IRR	7.82%																				

5 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study set out to assess the viability of a solar photovoltaic project within Nairobi. The Strathmore university project was chosen as the sample. The assessment conducted on the solar radiation levels in Kenya exhibited ARMA (6, 2) behaviour and was sufficient to generate electricity. However, the project viability was seen to depend on other factors such as the nature and cost of project financing as well as direct and indirect costs of the project. Based on the project specifics and the assumptions made, the research concluded that the Strathmore University solar photovoltaic project was viable as it returned a positive net present value from the discounted cashflows.

5.2 Sensitivity Analysis

The key assumptions in the model were considered to be the energy costs and the cost of capital. These were varied and the viability of the project assessed under the different conditions.

5.2.1 Net Present Value

The table below show the net present value (in thousands) given different possible energy costs and different costs of capital.

		Energy costs					
		0.15	0.20	0.23	0.33	0.43	0.53
Cost of capital	0.04	(437)	366	768	2374	3980	5586
	0.06	(826)	(165)	166	1488	2809	4131
	0.08	(1129)	(577)	(301)	804	1909	3013
	0.10	(1371)	(903)	(669)	268	1204	2141
	0.12	(1567)	(1165)	(964)	(159)	645	1449
	0.14	(1729)	(1380)	(1205)	(505)	194	893
	0.16	(1866)	(1559)	(1405)	(790)	(175)	440
	0.18	(1983)	(1710)	(1574)	(1028)	(482)	64
	0.20	(2085)	(1841)	(1718)	(1229)	(740)	(251)

It was found that the project returned the highest net present value in the case where the energy costs were highest and the cost of capital lowest. This is because when the energy costs are higher, the investing institution will have benefited immensely from its solar project by cutting down on its electricity costs. These would be reflected as increase in savings from costs. When the cost of capital is lower, the charges that would need to be repaid to the owners of capital such as interest repayments or dividends are also lowered resulting in less negative cashflows for the project.

5.2.2 Internal rate of return

The table below shows the internal rate of return of the project given different possible energy costs and at different costs of capital.

		Energy costs					
		0.15	**0.20**	**0.23**	**0.33**	**0.43**	**0.53**
Cost of capital	**0.04**	0.02	0.06	0.08	0.15	0.21	0.27
	0.06	0.01	0.05	0.07	0.14	0.20	0.26
	0.08	0.01	0.05	0.07	0.13	0.19	0.25
	0.10	0.00	0.04	0.06	0.12	0.18	0.24
	0.12	0.00	0.04	0.05	0.12	0.18	0.23
	0.14	-0.01	0.03	0.05	0.11	0.17	0.22
	0.16	-0.01	0.02	0.04	0.10	0.16	0.22
	0.18	-0.02	0.02	0.04	0.10	0.15	0.21
	0.20	-0.03	0.01	0.03	0.09	0.14	0.20

In comparison to the results in the net present value scenario analysis, it was seen that the cost of capital per annum at which most solar PV projects were viable(for the range of energy cost tested) were 4% and 6%. The higher the cost of capital the fewer the viable projects based on the different energy cost levels. This implied that foreign or donor funding which are often at low rates of interest per annum (4% -6%) would be critical in ensuring solar PV project viability. Locally offered loans would be unsuitable as the interest rates often exceed 12% per annum.

5.3 Recommendations

The study could be improved by using a formula that would directly estimate the electricity output based on the behaviour of solar radiation within Nairobi without relying on the National Renewable Energy Laboratory PV Watts calculator.

Further studies should be conducted to assess the sensitivity of the project under other different conditions and to check whether the project would still be viable given those different scenarios.

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7 APPENDICES

Appendix 1: Solar radiation Augmented Dickey Fuller Test

Null Hypothesis: RADIATION has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic based on SIC, MAXLAG=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.526377	0.0381
Test critical values:	1% level	-3.983900	
	5% level	-3.422426	
	10% level	-3.134078	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RADIATION)
Method: Least Squares
Date: 12/01/14 Time: 15:45
Sample (adjusted): 1984M03 2013M12
Included observations: 358 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RADIATION(-1)	-0.399216	0.113208	-3.526377	0.0005
D(RADIATION(-1))	-0.150592	0.117128	-1.285704	0.1994
D(RADIATION(-2))	-0.111838	0.117004	-0.955847	0.3398
D(RADIATION(-3))	-0.171147	0.112801	-1.517251	0.1301
D(RADIATION(-4))	-0.127651	0.105395	-1.211160	0.2267
D(RADIATION(-5))	-0.245602	0.098541	-2.492377	0.0132
D(RADIATION(-6))	-0.245576	0.091751	-2.676537	0.0078
D(RADIATION(-7))	-0.248224	0.085731	-2.895387	0.0040
D(RADIATION(-8))	-0.318487	0.079742	-3.993953	0.0001
D(RADIATION(-9))	-0.304766	0.073699	-4.135289	0.0000
D(RADIATION(-10))	-0.360718	0.070040	-5.150155	0.0000
D(RADIATION(-11))	-0.200762	0.065726	-3.054505	0.0024
D(RADIATION(-12))	0.208770	0.060580	3.446167	0.0006
D(RADIATION(-13))	0.168583	0.054392	3.099400	0.0021
C	7.340751	2.100783	3.494292	0.0005
@TREND(1983M01)	0.002854	0.001425	2.003328	0.0459

R-squared	0.546976	Mean dependent var	-0.013156
Adjusted R-squared	0.527106	S.D. dependent var	3.340019
S.E. of regression	2.296840	Akaike info criterion	4.544608
Sum squared resid	1804.211	Schwarz criterion	4.718040
Log likelihood	-797.4849	F-statistic	27.52843
Durbin-Watson stat	2.031493	Prob(F-statistic)	0.000000

Appendix 2: Estimating the coefficients of the forecast equation

Dependent Variable: RADIATION
Method: Least Squares
Date: 01/12/15 Time: 14:30
Sample (adjusted): 1983M07 2013M12
Included observations: 366 after adjustments
Convergence achieved after 54 iterations
Backcast: 1983M05 1983M06

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	19.76382	0.247227	79.94209	0.0000
AR(1)	2.177842	0.051560	42.23869	0.0000
AR(2)	-1.859038	0.123805	-15.01585	0.0000
AR(3)	0.557082	0.157743	3.531571	0.0005
AR(4)	0.177095	0.158037	1.120595	0.2632
AR(5)	-0.379623	0.124902	-3.039364	0.0025
AR(6)	0.196688	0.052284	3.761945	0.0002
MA(1)	-1.737358	0.003298	-526.8101	0.0000
MA(2)	0.994487	0.003462	287.2281	0.0000

R-squared	0.660225	Mean dependent var	19.77079
Adjusted R-squared	0.652611	S.D. dependent var	4.057492
S.E. of regression	2.391475	Akaike info criterion	4.605981
Sum squared resid	2041.738	Schwarz criterion	4.701947
Log likelihood	-833.8945	F-statistic	86.71177
Durbin-Watson stat	2.067424	Prob(F-statistic)	0.000000

Inverted AR Roots	.87+.50i	.87-.50i	.74	.14+.67i
	.14-.67i	-.57		
	Estimated AR process is nonstationary			
Inverted MA Roots	.87+.49i	.87-.49i		

Appendix 3: Correlogram of Solar radiation data

Date: 12/01/14 Time: 15:50
Sample: 1983M01 2013M12
Included observations: 372

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|***** |	.|***** |	1	0.667	0.667	166.82	0.000
.|** |	**|. |	2	0.317	-0.231	204.50	0.000
.|. |	**|. |	3	0.001	-0.200	204.50	0.000
**|. |	*|. |	4	-0.219	-0.129	222.65	0.000
***|. |	**|. |	5	-0.384	-0.206	278.56	0.000
***|. |	*|. |	6	-0.422	-0.076	346.32	0.000
***|. |	*|. |	7	-0.367	-0.071	397.77	0.000
**|. |	.|. |	8	-0.229	-0.011	417.82	0.000
.|. |	.|* |	9	-0.019	0.099	417.96	0.000
.|** |	.|** |	10	0.244	0.203	440.79	0.000
.|**** |	.|*** |	11	0.541	0.378	553.44	0.000
.|***** |	.|** |	12	0.699	0.286	742.18	0.000
.|**** |	*|. |	13	0.542	-0.113	856.01	0.000
.|** |	*|. |	14	0.233	-0.143	877.05	0.000
.|. |	.|. |	15	-0.039	-0.008	877.64	0.000
**|. |	.|. |	16	-0.241	0.008	900.42	0.000
***|. |	.|. |	17	-0.388	-0.045	959.43	0.000
****|. |	*|. |	18	-0.452	-0.101	1039.6	0.000
***|. |	.|. |	19	-0.397	-0.037	1101.6	0.000
**|. |	.|. |	20	-0.256	-0.011	1127.5	0.000
*|. |	*|. |	21	-0.086	-0.104	1130.4	0.000
.|* |	.|* |	22	0.185	0.080	1144.0	0.000
.|*** |	.|* |	23	0.455	0.069	1226.6	0.000
.|***** |	.|* |	24	0.597	0.077	1369.2	0.000

Appendix 4: EBITDA workings

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Direct Revenue																				
Annual Radiation	3039	3028	3039	3050	3061	3072	3084	3095	3106	3118	3129	3141	3152	3164	3176	3187	3199	3211	3223	3235
Annual power output	823,512	817,747	812,023	806,339	800,695	795,090	789,524	783,997	778,510	773,060	767,649	762,275	756,939	751,640	746,379	741,154	735,966	730,815	725,699	720,619
Current energy price	0.23	0.24	0.25	0.26	0.27	0.29	0.30	0.32	0.33	0.35	0.37	0.38	0.40	0.42	0.45	0.47	0.49	0.52	0.54	0.57
Tariff	0.12	0.13	0.13	0.14	0.15	0.15	0.16	0.17	0.18	0.19	0.20	0.21	0.22	0.23	0.24	0.25	0.26	0.28	0.29	0.30
Indirect revenue																				
Grid electricity saved	185,290	193,193	201,433	210,024	218,981	228,321	238,059	248,212	258,798	269,836	281,344	293,344	305,855	318,899	332,500	346,681	361,467	376,884	392,958	409,718
Income selling to the grid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total revenue	**185,290**	**193,193**	**201,433**	**210,024**	**218,981**	**228,321**	**238,059**	**248,212**	**258,798**	**269,836**	**281,344**	**293,344**	**305,855**	**318,899**	**332,500**	**346,681**	**361,467**	**376,884**	**392,958**	**409,718**
COSTS																				
Direct	0.00																			

cost																				
Other costs	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total costs	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Gross profit	**185,290**	**193,193**	**201,433**	**210,024**	**218,981**	**228,321**	**238,059**	**248,212**	**258,798**	**269,836**	**281,344**	**293,344**	**305,855**	**318,899**	**332,500**	**346,681**	**361,467**	**376,884**	**392,958**	**409,718**
Operating cost OPEX ratio	13,200	13,860	14,553	15,281	16,045	16,847	17,689	18,574	19,502	20,478	21,501	22,576	23,705	24,891	26,135	27,442	28,814	30,255	31,767	33,356
EBITDA	**172,090**	**179,333**	**186,880**	**194,743**	**202,936**	**211,474**	**220,369**	**229,638**	**239,296**	**249,358**	**259,843**	**270,767**	**282,149**	**294,009**	**306,365**	**319,240**	**332,654**	**346,629**	**361,191**	**376,362**