ESTIMATING DUST ACCUMULATION ON PHOTOVOLTAIC MODULES IN THE UAE

by

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Approval Signatures

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Dedication

To my mother: My strength and guidance

To my father: My support and motivation

Abstract

Among the challenges facing solar photovoltaic (PV) systems in the United Arab Emirates (UAE), dust is considered the most severe problem that faces the growth of solar power plants. Dust accumulation on solar PV panels results in a degradation in the output power. The UAE has a low intensity of rainfalls and wind velocity; thus, solar PV panels must be cleaned manually or using automated cleaning methods which are costly. Estimating dust accumulation on solar PV panels will increase the output power of solar PV power plants and reduce maintenance costs by initiating cleaning actions only when required. In this thesis, the effect of natural dust accumulation on solar PV panels is investigated using field measurements and regression modeling. Experimental data were collected under various weather conditions and controlled levels of dust. Solar PV output power, ambient temperature, solar irradiance, and dust were monitored in a period of two months to collect sufficient data for constructing a dust estimation model. Regression models were trained and tested to develop an accurate model for estimating the dust accumulated on solar PV panels in the UAE. The developed fine tree regression model provided accurate dust accumulation prediction with Root Mean Square Error (RMSE) of 0.0255 g/m^2. The model was tested on different case studies with a random amount of dust applied the solar PV panels to confirm the accuracy of the developed model.

Keywords: ***Solar Photovoltaic, Regression Models, Dust Accumulation, Renewable Energy, Dust Estimation.***

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Chapter 1. Introduction

In this chapter, we introduce the renewable energy topic and the challenges facing its growth. Thesis objectives will be summarized, followed by research contribution and research organization.

1.1. Overview

The need for integrating renewable energy into power grids has become a topic of interest worldwide due to many environmental impacts caused by conventional power generators. Thermal power plants have a great impact on global warming due to the release of smoke, which contains CO_2 into the atmosphere. In addition, running a thermal plant has economic drawbacks. The fossil fuel used to run such plants has an increasing cost throughout the year given that it is a nonrenewable resource and limited in nature.

Meanwhile, renewable energy is environmentally friendly and economically feasible. It has a low long term cost. Numerous renewable resources can be integrated into power grids, such as solar power, wind power, biomass, geothermal energy, fuel cells, and hydro energy. The use of renewable resources is considered efficient and reliable and has a positive health impact. Air pollution and actual plant waste caused by conventional power plants, such as coal or natural gas, can cause many health issues, from breathing problems to cancer, to the people living in the surrounding areas [1].

The integration of renewable energy into power girds is the main goal of many countries. The total installed hydropower capacity worldwide was 19 GW in 2017 [2]. While the total installed capacity of Geothermal is 1.4 GW in the same year. For solar power, the total global installed capacity of concentrated solar power (CSP) is 4.9 GW while the solar photovoltaic (PV) is 402 GW in 2017 [2]. This shows that the most advanced and economic renewable energy is solar photovoltaic. Figure 1 shows the increasing trend the world has witnessed in the area of installing a solar photovoltaic system from 2007 to 2017.

Renewable energy will decrease greenhouse gases since the Middle East produces a high amount of greenhouse gases [3]. Moreover, having renewable energy will help solve the region's environmental issues, since it's the second highest polluted region in the world [3]. Furthermore, renewable energy will reduce the use of oil and gas which are currently used in generating electricity which will increase grid security by diversifying the power resources and yielding an increase of gas and oil lifetime [3].

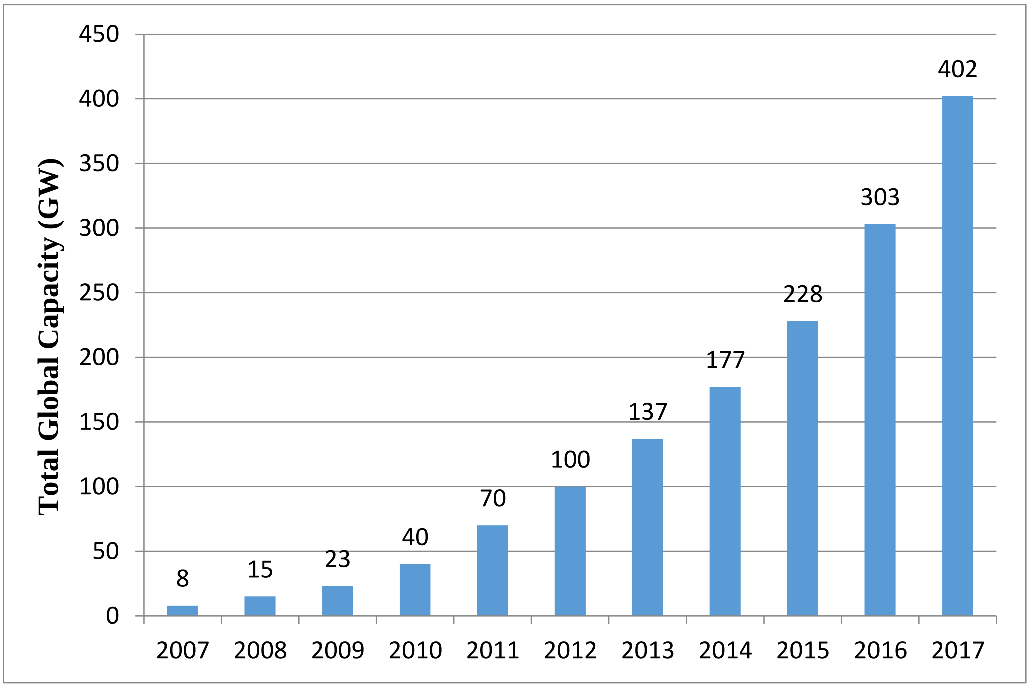

Figure 1: Solar PV Global Capacity [2].

In the Middle East, local demand for oil and gas has increased rapidly pushing the countries to look for other renewable sources to generate electricity. KSA has strategic plans to integrate 41 GW of renewables into the power grid by 2030 [4]. Moreover, Kuwait aims to produce 5% of the country's energy from renewable resources by 2020 [5]. Similarly, Jordan is moving towards the renewable energy field, it aims to produce 10% of the total electricity demand by 2020 [6]. By 2020, Morocco plans to produce 42% of the electric power by renewable resources [7]. The produced electric power is planned to be a mix of wind power, Concentrating Solar Power (CSP) and Photovoltaic (PV) technologies. However, the majority of power will be generated by PV technology.

The Middle East region has an appropriate climate and geographical location for producing the highest solar power output in the world [3]. This makes solar power the most commonly used renewable energy source in the region. Many governments are planning to integrate solar energy into the electrical power grid. Using solar energy technology is added to the energy strategy plan of many countries to produce clean sources.

Renewable energy and solar power technologies are currently considered a feasible alternative energy source in the Middle East and other countries around the world. The United Arab Emirates is also eager to integrate solar power and generate electrical energy from the sun. Currently, different solar projects have been tendered in both Dubai and Abu Dhabi with excepted growth of solar energy in the coming years. The United Arab Emirates (UAE) is positioned between 22°30´ and 26°10´ north latitude and 51° and 56°25´ east longitude. The location of the UAE gives it the advantage of having high sun exposure throughout the year. The average global solar irradiance ranges between 1900 kWh/m^2 and 2300 kWh/m^2 [8].

Solar Panels are manufactured using semi-conductors. The inherent properties of these materials affect the efficiency of photovoltaic systems. The design used to build power plant also affects the output power of photovoltaic panels, such as the orientation of the installed panels, the amount of sun exposure to the power plant and the sun tracking systems. Sun trackers are used to maximize the output power of a power plant but it increases the cost of the photovoltaic system. Furthermore, losses in wiring, inverters, transformers along with the dust accumulated on solar photovoltaic panels reduced the efficiency of the system further by 10-25% [9].

The yield of Photovoltaic panels depends on many factors. The output power of solar panel depends on the materials used in manufacturing the panel, the coatings on the glass for self-cleaning such as dust free coatings and many other factors. The solar irradiance affects the output power of the panel. The irradiance can vary depending on environmental conditions and PV panel installation design. Figure 2 shows the factors affecting the yield of solar photovoltaic panels.

There are many challenges facing the widespread of solar energy in the world and specifically in the middle-east, among which the dust effect is the most salient, which is the main focus of this thesis. Dust accumulation on photovoltaic panels causes a significant reduction in the output power. Research on the effect of dust accumulation on solar photovoltaic panels is location dependent. The behavior and response of the output power of solar photovoltaic panels differ with different locations, dust properties, and the environment. Therefore, studies done in one country cannot be generalized to other countries. Thus, detecting the amount of dust and initiating the necessary cleaning action when needed is vital to increase the yield of photovoltaic farms and to reduce maintenance cost.

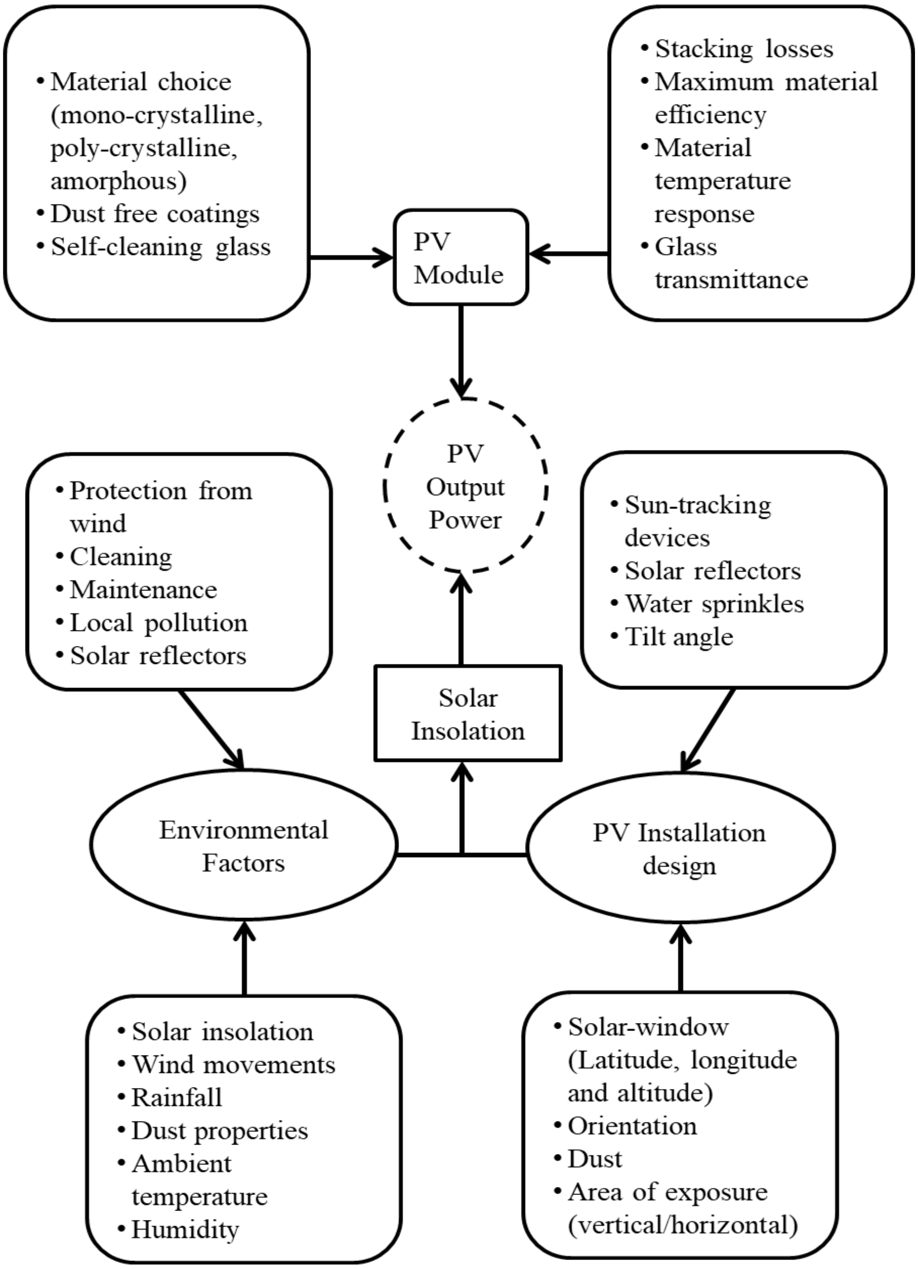

Figure 2: Factors affecting PV output power [9].

Dust estimation can be done using numerical methods, analyzing satellite images or machine learning methods. In this thesis, regression models will be used for dust accumulation estimation.

1.2. Thesis Objectives

The detailed objectives of this thesis can be summarized as follows:

- Conduct experiments to measure the output power at different dust accumulation, temperature, and solar irradiance.
- Design and train a dust estimation unit based on Regression Models.
- Validate the developed model by testing it on different case studies.

1.3. Research Contribution

The contribution of this thesis can be summarized as follows:

- Study the impact of dust accumulation on the output power of the solar photovoltaic panels experimentally under real environmental conditions.
- Develop a regression model that estimates the amount of dust accumulated on the solar photovoltaic panel based on input ambient temperature, solar irradiance, and solar PV output power.
- Test the developed regression model on pre-measured amounts of dust and random amounts of dust applied on solar PV panels.

1.4. Thesis Organization

This thesis is organized in five chapters. Chapter 2 provides a background insight to the topic followed by a literature review. Chapter 3 presents the proposed research including the methodology and the experimental setup. Chapter 4 discusses the results and the different case studies used to verify the developed work. Finally, chapter 5 concludes the work and presents recommendations for future works.

Chapter 2. Background and Literature Review

To have a clear view of the motivation for the work completed in the thesis, it is important to have a background about solar energy. Solar energy is a wide field that has different types, and each type has different technologies. In this section, an overview of solar energy will be introduced and more depth details about photovoltaic energy system. The challenges facing photovoltaic energy systems including the dust effect, which is the focus of this research, will be explained. Then the chapter ends with a literature review.

2.1. Solar Energy

There are multiple technologies used for solar energy generation such as Concentrating Solar Power (CSP), Photovoltaic (PV) and heating and cooling systems.

2.1.1. Concentrating solar power. Concentrating Solar Power systems reflect the direct solar irradiance from sunlight into a receiver using mirrors. There are many Concentrating Solar Power technologies such as Dish Engine and Compact Linear Fresnel Reflector (CLFR), however, the mostly used commercial technologies in the power systems are parabolic troughs and solar towers [10].

Concentrating Solar Power plants consist of mirrors that reflect sun rays and concentrate the direct sunlight (DNI) towards a receiver. Concentrating Solar Power plants work only with DNI that is in Sunbelt regions. Some Concentrating Solar Power plants have a storage system to store heat and produce electricity when DNI is unavailable. The fluid used for thermal storage in parabolic trough plants can be molten salt, steam or synthetic oil [11]. Usually, a steam turbine is used in Concentrating Solar Power technologies.

There are two main types of Concentrating Solar Power that are commercially used worldwide. The first type is parabolic trough Concentrating Solar Power, shown in Figure 3.

In parabolic trough technology, the mirrors concentrate the sunlight on a focal line. The maximum operating temperature of CSP parabolic trough is 300°C to 500°C [11]. A parabolic trough is considered the most famous and mature technology that is used widely and can result in a low levelized cost of electricity. Parabolic trough receivers, also known as collectors, are encapsulated in a glass to minimize losses due to convection heat. They are also coated with a special material to increase energy absorption from sun rays and reduce the infrared re-irradiation [11]. The fluid running through the collector tube removes solar heat and transfers it to a steam generator for steam production. The steam flows to move the turbine hence generate electricity. A parabolic trough collector consists of mirrors that reflects direct solar irradiance and concentrates it on a receiver tube [12]. The location of the tube is on the parabolic focal point. The focal concentration factor is around 30 to 100 of the DNI value. Sun rays get concentrated on the absorber tube by the mirrors. This results in heating up the fluid circulating inside the tube. In this stage, solar irradiance is transformed into thermal energy stored in the fluid.

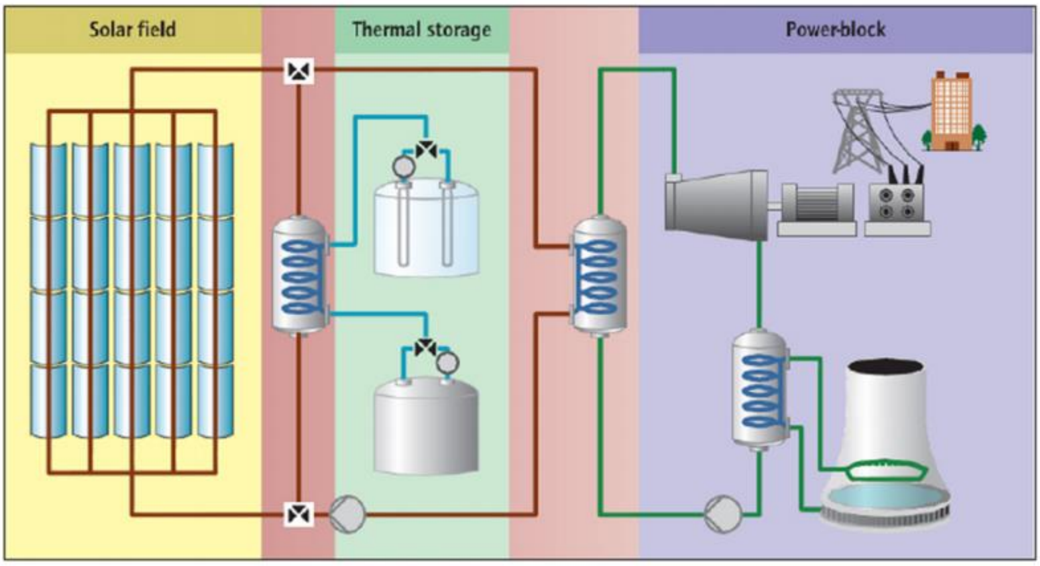

Figure 3: Parabolic Trough Concentrating Solar Power [10].

The second type of Concentrating Solar Power that is commercially used is Solar Tower, shown in Figure 4. Solar tower systems consist of heliostats which act as mirrors. Heliostats reflect the direct solar irradiance from sunlight into a receiver located on top of the tower. A steam cycle runs in the solar tower. The fluid used in the solar tower moves in the pipe. It gets heated up once it reaches the receiver as the sunrays hit the receiver. The heated fluid continues its cycle and heats up the steam which rotates the turbine to generate electricity. Parts of the heated fluid can be stored to be used at later times at time depending on the storage capacity.

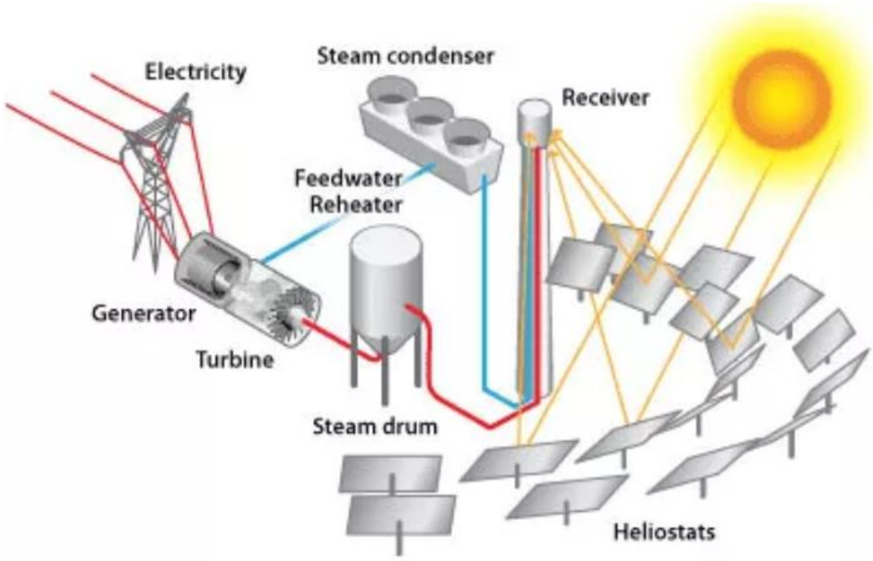

Figure 4: Solar Tower Concentrating Solar Power [13].

2.1.2. Photovoltaic energy system. Photovoltaic cells consist of semiconductors which convert the global irradiance of the sunlight into electricity in the solar cells. Photovoltaic cells are connected in series and parallel to form a photovoltaic module. Photovoltaic modules connected in series and in parallel to form a photovoltaic array. There are two types of photovoltaic cells that are mostly used in the market; crystalline silicon (c-Si) and Thin-film [14].

A typical photovoltaic system consists of solar photovoltaic modules that are connected in series and in parallel to provide a certain voltage and current value. The output of the solar photovoltaic modules is a direct current (DC). The modules are connected to an inverter to convert the current from direct current (DC) to alternating current (AC). The inverter is then connected to a transformer to step up the voltage to be connected into the power grid. Figure 5 shows a photovoltaic solar power system architecture. The architecture includes photovoltaic modules connected through an on-grid inverter and a step up transformer which connects the system to the power grid.

2.1.2.1. ***Types of photovoltaic.*** Crystalline silicon (c-Si) can be either Monocrystalline or Polycrystalline. The process of manufacturing these crystalline cells, which are wafer-based, requires high temperature to ensure the purity of the wafer. Monocrystalline is more homogeneous in color and has higher efficiency than polycrystalline, while polycrystalline cells have lower manufacturing costs.

Monocrystalline solar photovoltaic cells and polycrystalline photovoltaic cells are shown in Figure 6. Crystalline cells have a blue color finish since the cells contain silicon nitride antireflection layer.

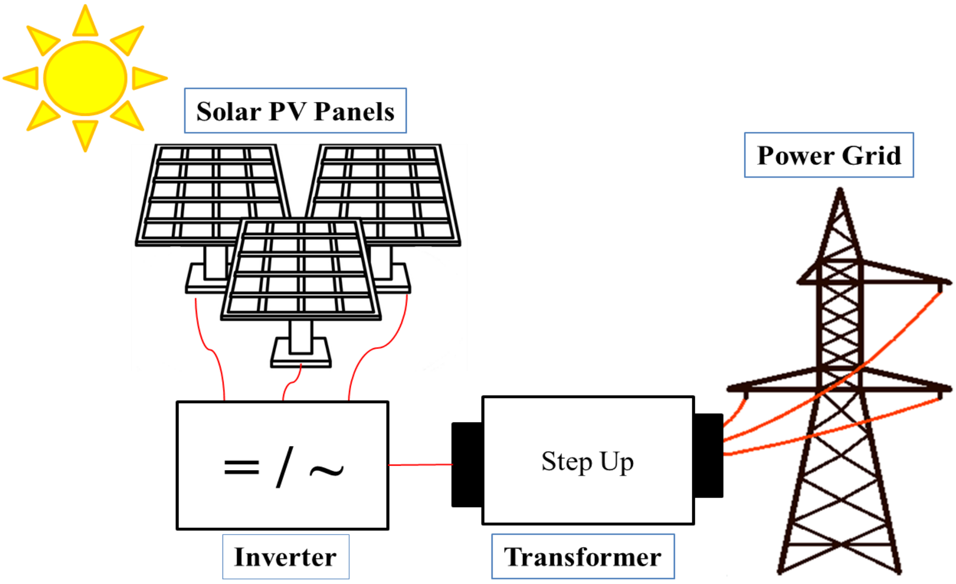

Figure 5: Photovoltaic Solar Power System Architecture.

Figure 6: Monocrystalline (left) and polycrystalline (right) PV cells [14].

Thin-Film PV cells require lower energy than c-Si since it requires a lower temperature to manufacture, and hence it has a lower cost. However, thin-film provides lower efficiencies. The most famous thin-film technologies are Copper indium gallium Sulfur selenide (CIGS), Cadmium Telluride (CdTe) and amorphous silicon (a-Si) [14]. The CdTe is the most commonly used type which provides a lower cost and a better performance in high temperatures than c-Si cells. It is the most commonly used technology in commercial.

2.1.2.2. ***Challenges in photovoltaic systems.*** The global PV installed capacity reached up to 139 GWs in 2013, compared to less than 4 GWs of CSP technology [15]. PV technology has many commercial projects with economically attractive prices reaching as low as 3 cents per kilowatt hour compared to CSP [16]. The UAE aims to generate 30% of the power demand from clean sources by 2030. Dubai aims to install 1000 MW of solar CSP technology and 4000 MW of PV technology by 2030 [17]. This shows that the most commonly used solar technology is the PV technology.

The energy produced by PV modules (E in kWh) directly depends on the area of the panel (A in m^2), solar panel efficiency (r), annual average solar radiation on tilted panels (H in kWh/m^2) and performance ratio (PR ranges between 0.5 and 0.9); according to the following equation [18]:

$$E = A \,.\, r \,.\, H \,.\, PR \tag{1}$$

However, it is not easy to calculate the performance ratio since it depends on inverter losses, DC and AC cables losses, diode and connection loss, mismatch loss, sun-tracking loss, shading losses and soiling losses due to dust or snow [19]. In addition, solar PV panels are affected by environmental conditions besides the irradiance such as temperature, dust, and shading.

Irradiance affects the solar photovoltaic panels' output power. Irradiance is defined as the amount of sunlight that hits the solar PV cell and is measured in (W/m^2). For a clear weather condition, the maximum irradiance is approximately 1000 W/m^2. As the irradiance reduces, the short circuit current decreases significantly while the voltage witnesses only a slight decrease. Hence the solar PV panel will experience a reduction in the output power. Figure 7 shows the I-V curve of the solar PV module while varying the irradiance under STC conditions.

The temperature also affects the output power of solar photovoltaic panels. Increasing the temperature reduces the open circuit voltage hence a drop in the output power of the PV panel. For most crystalline-silicon PV modules, a temperature increase of 1°C results in a decrease of the PV panel open circuit voltage by 0.3% to

0.5% and an increase of the PV panel short circuit current by 0.05% to 0.1% [20]. Figure 8 shows the I-V curve of the solar PV module while varying the temperature under STC conditions.

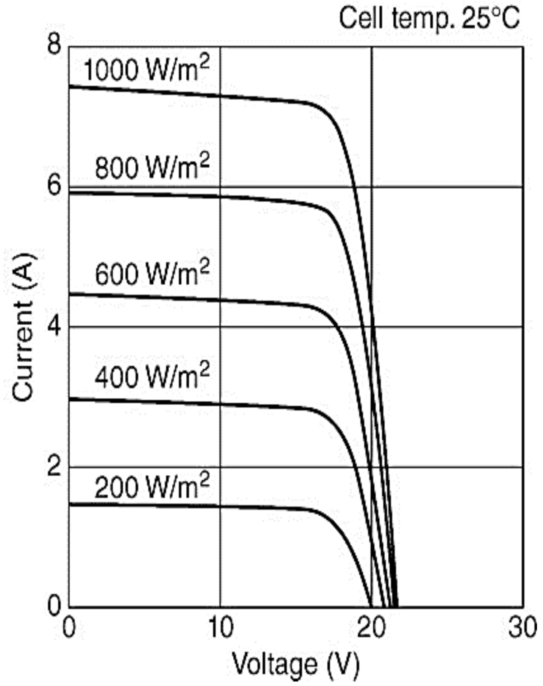

Figure 7: Irradiance effect on the I-V curve of the solar PV module [21].

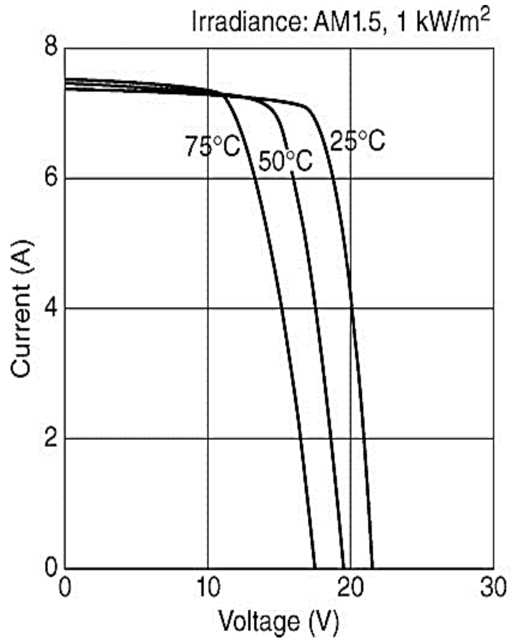

Figure 8: Temperature effect on the I-V curve of the solar PV module [21].

Buildings and clouds covering the solar panels result in shading losses. Figure 9 shows the shading effect on the I-V curve of the solar PV module. For a perfect weather with full sun, PV produces maximum power. However, as number of the shaded cells increases the output power of the solar PV reduces.

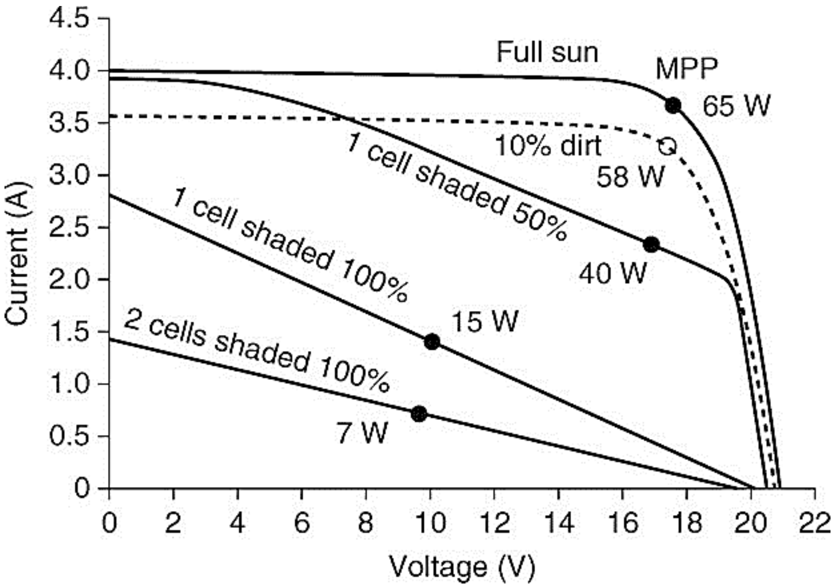

Figure 9: Shading effect on the I-V curve of the solar PV module [21].

The mathematical expression of the output power of PV modules depends on the fill factor (FF), panel voltage (V_{PV}) and panel current (I_{PV}); given in the following relations at MPPT:

$$P_{PV} = FF * V_{PV} * I_{PV} \tag{2}$$

$$T_{cell} = T_A + S_{IR} \times \left(\frac{NOCT-20}{0.8\ kW/m^2}\right) \tag{3}$$

$$I_{PV} = S_{IR} \times \left(I_{sc}\left(1 + K_i(T_{cell} - 25)\right)\right) \tag{4}$$

$$V_{PV} = V_{OC}\left(1 - K_v(T_{cell} - 25)\right) \tag{5}$$

$$FF = \frac{V_{MPP} \times I_{MPP}}{V_{OC} \times I_{SC}} \tag{6}$$

where T_{cell}, T_A, and $NOCT$ are the cells' ambient, and nominal operating cell temperature in ^{o}C, respectively; S_{IR} is the solar irradiance in kW/m^2; V_{PV} and I_{PV} are the module open circuit voltage and short circuit current at actual conditions; I_{sc} and V_{OC} are the module short-circuit current and open-circuit voltage at rated test conditions; FF is the fill factor; K_i and K_v are the current temperature coefficient and voltage temperature coefficient; P_{PV} is the output power of the module. Although the output power of solar PV panel changes with the solar irradiance, temperature, humidity, shading, and soiling. However, equations (2-6) do not include the effect of other environmental conditions such as dust and soiling.

2.2. Dust on Solar Panels

Soiling losses occur in the UAE due to its dusty weather climate. The dusty climate causes dust settlements on the PV panel. The dust particle size is normally less than 10 µm [19]. Dust accumulation is affecting by two factors; environmental conditions and dust properties [22]. Dust properties refer to the weight, shape, and size of the particle while environmental conditions include weather conditions and geographical location [22].

Research has revealed that the Middle East has the worst dust accumulation zones in the world [19]. Therefore, the dust effect on solar panels must be studied to ensure the optimal efficiency and estimate the right time to clean the panel when the dust accumulation increases.

2.2.1. Causes of dust. Dust accumulates on solar photovoltaic panels due to many factors. Dust properties such as dust type, weight, chemical properties, size, shape, and electrostatic properties affect the dust settlement. The wind is another factor that affects the settlement of dust. High-speed wind can help in removing the dust settled on the solar photovoltaic panels, while areas with low wind velocity experience the worst degradation in solar photovoltaic output power due to the high accumulation of dust. Furthermore, photovoltaic panels can be coated with a special glazing material that limits the dust accumulation.

The orientation of the built photovoltaic system and the tilt angle used in the installation affect dust settlement on the solar photovoltaic power; photovoltaic plants that are built with the optimal orientation considering the wind direction are high in efficiency. The ambient temperature and humidity also affect dust settlement. Areas with high temperature and humidity experience higher dust accumulation since the dust gets wet with high humidity and sticks to the glass of the photovoltaic panels, and hence reduces their efficiency. Another important factor is the site characteristics. Building power plants in areas with high air-pollution due to vehicular traffic or construction works increases the amount of dust in the air and hence results in more dust settlement on the photovoltaic panels [23]. Figure 10 summarizes the causes of dust accumulation. The causes for dust accumulation include environmental factors, dust properties factors, location and installation factors.

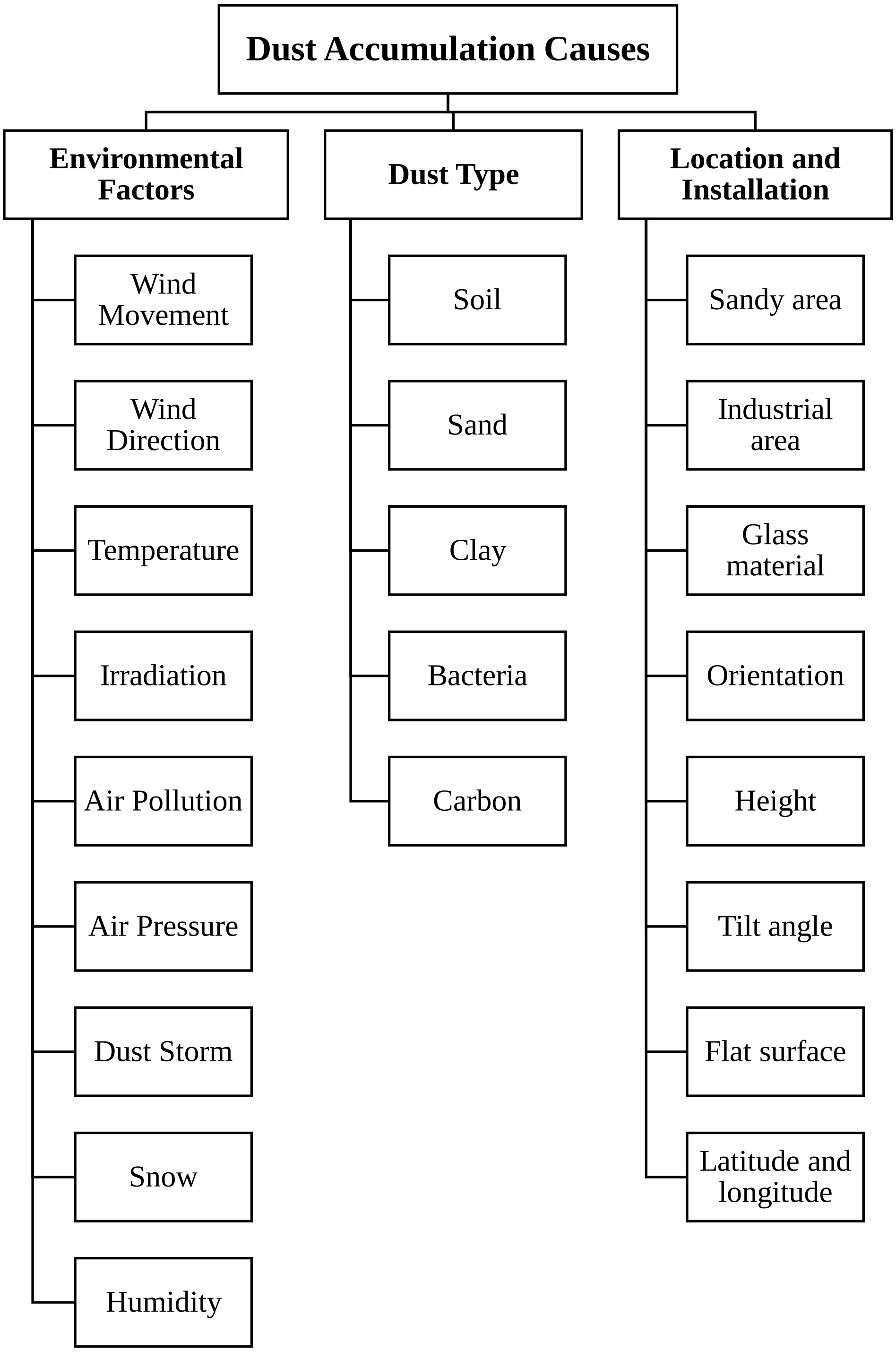

Figure 10: Causes of Dust Accumulation [23].

2.2.2. Dust effect on solar panels. Dust affects the output power of solar photovoltaic panels. Dust causes high degradation in the efficiency of the solar photovoltaic system. Regular cleaning of these panels is required to ensure continuous optimum output power of the power plant. Low amount of dust accumulated causes soft shading which results in the drop of the current, while a high amount of dust that blocks the sun which is hard shade reduces the voltage. Figure 11 shows the Voltage–current characteristics of a PV module for soft and hard shading [19]. Shading over an entire photovoltaic array causes a significant impact on the overall output power of the power plant. Dust storms cause a big drop in the output power of the solar photovoltaic power plant. Figure 12 shows the effect of shading on the output power and the difference between lightly shaded and heavily shaded photovoltaic modules due to dust.

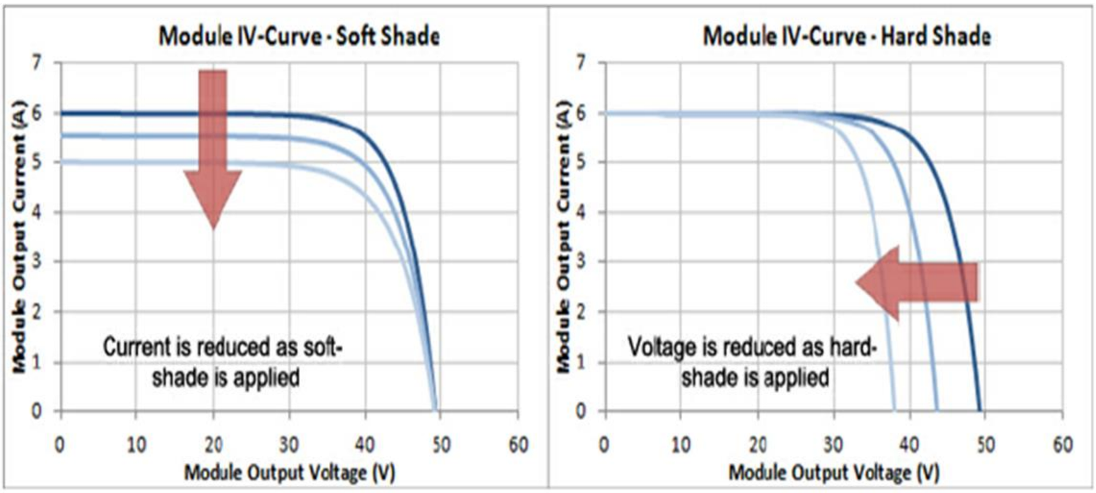

Figure 11: V–I characteristics of a PV module for soft and hard shading [19].

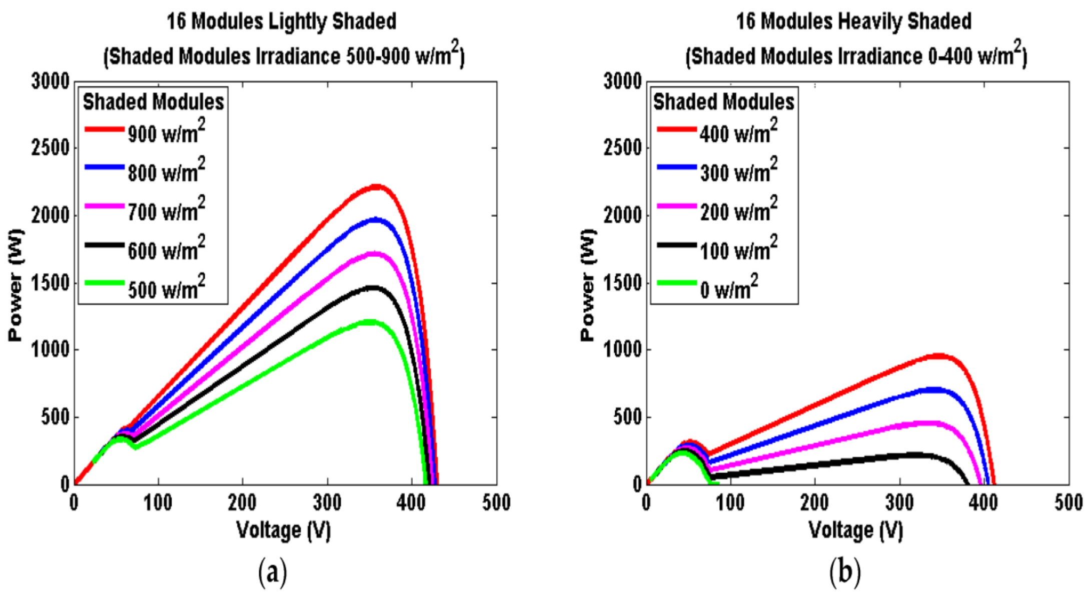

Figure 12: Characteristics of the PV array under partial shading condition [19].

2.2.3. **Dust removal.** Removing the dust on the PV surface by wind or rainfall can be enough in some regions. However, in other regions, high rainfall can result in high degradation in the yield of the solar panel. Cleaning photovoltaic panels can be summarized in four main methods. Rainfalls can clean photovoltaic panels; however, rain is seasonal and unreliable. Rainfalls must be with a certain amount to be suitable for cleaning the panels. Light rainfall might have a negative impact on the solar PV panel.

Wind with adequate velocity can help in removing the dust on solar photovoltaic modules; however, there are some regions in the world that experience very low wind velocity. Furthermore, the wind isn't enough to clean the solar photovoltaic panels to achieve optimum output power; photovoltaic cells must be cleaned by water.

Another way of cleaning the photovoltaic panel which is more reliable is manual cleaning or mobile cleaners. Manual cleaning is to clean the photovoltaic modules with sensitive brushes to avoid scratching the glass of the panel. Water is needed in manual cleaning to remove all the dust. Performing this method of cleaning can be tough for big modules since some parts are out of reach and ladders must be used [19]. It requires a large amount of manpower to perform the cleaning of a large photovoltaic power plant in one day.

On the other hand, mobile cleaners use advanced machinery technologies that include water to clean the panels. Usually washing the panels are done on a scheduled basis to be economically feasible. Cleaning the panels on a daily basis ensure high efficiency of output power however it's not economic and may result in a waste of resources if cleaning is not needed [19]. Therefore, developing a model that estimates the dust accumulated on the solar photovoltaic panels and setting a threshold value where a cleaning action must be taken is highly economical.

2.3. Literature Review

There are numerous researches in the literature that predict the output power of the solar photovoltaic panel due to different environmental conditions. Three different approaches are used in literature to study the impact of the environment on the output of solar photovoltaic panels. Researchers studied the issue either by conducting experiments or developing prediction models or as a review.

A significant body of review papers in research has studied the impact of the environment. Review papers covered the impact of dust on solar PV panels. A review study was conducted to survey the impact of dust, humidity and air velocity separately and as a group. The survey determined that the efficiency of solar panels drops significantly with fine particles compared to coarse particles [24]. Furthermore, less dust gets accumulated with a larger tilt angle, on the other hand, humidity results in more dust coagulation, while wind lifts the dust but might result in shading due to dust scattered in the air [24]. In another study, a review covered a summary of different experiments done on different weights of multiple pollutant types [23]. The experiments were carried out under the same environmental conditions of temperature, solar irradiance, and humidity. The variable in the experiments was the pollutant type and weight. The objective of the conducted experiments was to study the variation in the output power between a clean PV panel and an artificially polluted panel. For different types of pollutant, the output power changed significantly, this shows the importance of identifying the pollutant type.

Another way to study the effect of environmental conditions on the solar panel is conducting experiments. Artificial or natural dust can be used to conduct these experiments. In Doha, natural dusts accumulated on solar panels were collected for a period of 10 months. The experiment categorized the collected dust to study their effect on the output of the solar panel [25]. Dust was dusted off the solar panel using a rubber spatula and measured on a petri dish, which was used in the experiments to weigh the collected dust. Then, laser diffraction particle size analyzer was used to study the spread of the dust on the PV. The factors that were considered in the study were dust accumulation rate (DAR) measured in (mg m^{-2} day^{-1}), ambient dust concentration (PM10), wind speed (WS), wind direction (WD), and relative humidity (RH). The outcome of the experiment showed that dust accumulation rate and relative humidity were higher in winter compared to summer which experienced low wind speed. Moreover, the experiments showed that dust weight increased by time however the dust accumulation rate decreased. Other studies of the output energy of the photovoltaic were experimentally studied for clean and artificially polluted PV panel

[26-28]. In [26], the output power of the solar PV dropped by 30% and the efficiency reduced by 1.5% decrease in efficiency with different weights of ash applied on the panel. Another experiment was conducted where three different artificial pollutants were applied on the solar photovoltaic panel with different masses. The pollutants used in the experiments are red soil, limestone and carbonaceous fly-ash particles [27]. The results of the experiment showed that the highest reduction in solar output power was due to red soil. Limestone provided better output power then ash. Red soil caused a reduction of 19% in energy compared to a clean panel. Limestone and ash resulted in reduction in energy of 10% and 6%, respectively. A similar study was conducted on a three different artificial pollutants which are red soil, sand and ash [28]. The experiments measured the output power of three different PV panel technologies; mono-c, multi-c and a-Si while applying the pollutants on them. Figure 13 shows the decrease in voltage resulting from the applied three pollutants. The experiments results show that the best performance was provided by amorphous silicon technology.

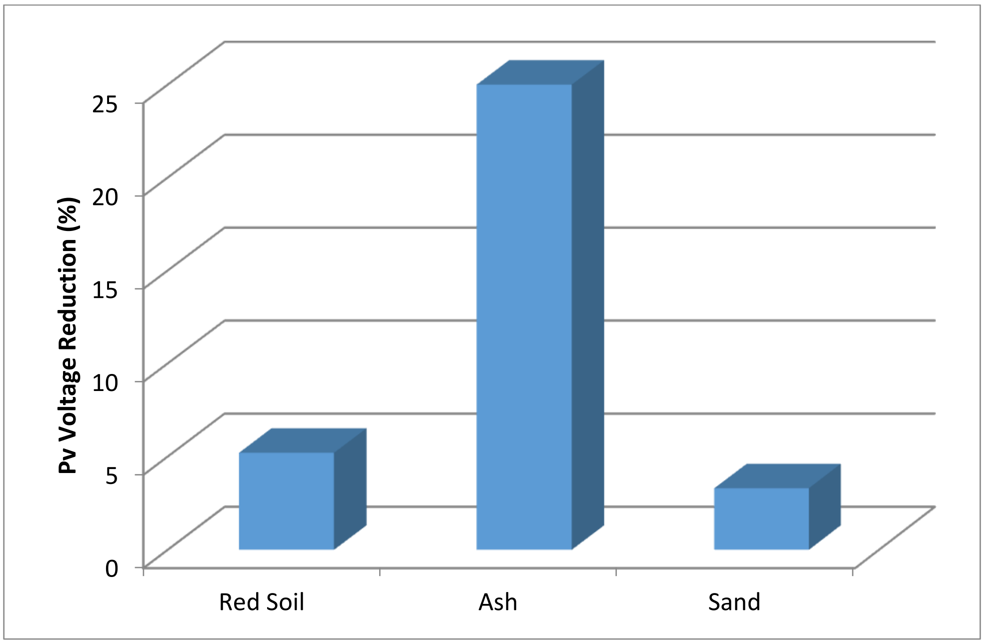

Figure 13: Voltage Reduction on tested PV panel [28].

In the UAE, different experiments were conducted to study the effect of dust on solar PV panels. A study was done for 23 days to show the effectiveness of self-cleaning coating material on solar panels [8]. It was concluded that panels covered with the self-cleaning coat and the panel without it performed the same. An experiment was also done in a different location in the UAE to study the effect of dust on solar PV panels which showed that 20% of output power reduced in the first month, followed by a reduction of 30% to 40% in the second month. The drop stops after a while since wind contributes to cleaning the panels.

Another study was conducted in the UAE to study dust effect on a solar photovoltaic panel with different tilt angles. Dust amounts of 0.0063 g/m^2 to 0.36 g/m^2 were distributed on 3 solar panel modules with tilt angles 0°, 25°, and 45°. The results show a linear relation between the dust weight and the drop in output photovoltaic power. Experiments showed a drop of 1.7% per g/m^2 [29]. The linear relation can be applied for a certain type of dust with dust chemical compositions and volume mentioned in the study.

Another experiment under real environmental conditions was conducted on a period of 5 months. Dust amount of 3 g/m^2, 5 g/m^2, and 8 g/m^2 were accumulated on the solar photovoltaic panel. Dust was naturally accumulated on site and measured. As the amount of dust increased, the output power of the solar PV reduced. Figure 14 shows a drop in short circuit current by 8.78% and a drop in open circuit voltage by 4.25% [29].

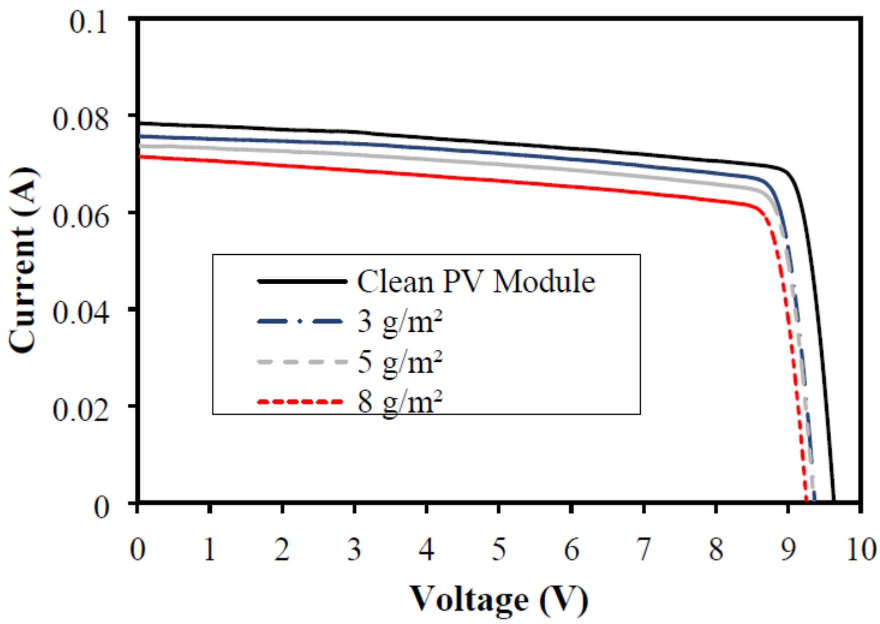

Figure 14: I-V Characteristics of clean and dusty panels [29].

Another approach used in research to study the impact of environmental conditions on the output power of PV panels is by developing models and simulations. Satellite images or machine learning methods can be used. A study used satellite images and a support vector machine (SVM) learning scheme for the prediction model and the results were compared with the conventional time-series model and artificial neural network [30]. However, the study was done to estimate the solar irradiance and cloud movement. The study did not cover estimating the output power of the PV panel. However, it was mentioned that it will be utilized for grid operations. The developed approach resulted in a more precise estimation of the solar irradiance and cloud movement compared to time series and artificial neural network.

A study done in the UAE studied the climate, geographical locations and economic conditions on the output power of the PV. Maps were generated from satellite images and weather data to study the difference between PV and CSP on a specified location. It was concluded that solar PV panels perform better in the UAE compared to CSP [31]. Furthermore, in Denmark, auto-regression was used to forecast the solar power output for up to 36 hours [32]. The experiments were conducted under real environmental conditions on rooftop installed solar PV.

Artificial Neural Networks tool is used to predict an output from a set of inputs. Weather station data or satellite images can be inputs to the model. There are many research papers that used an artificial neural network as a prediction tool for estimating the solar irradiance from the input weather data. ANN provided an error of less than 20% nRMSE using up to 900 inputs to predict the global solar irradiance [33]. Many research studied different review of forecasting methods for solar irradiance [34]. However, for the UAE's dusty environment, research is limited that use artificial neural networks or regression models to estimate the output power of the solar PV.

Another study was conducted to estimate the hourly diffuse solar irradiation under all weather conditions using new regressive models. This model is based on sigmoid function and examines the clearness index and relative optical mass as predictors. This model was compared to five regression models using radiations data. Results showed the new model showed better results and better estimates. The new model provides a relative mean bias error in the range -15% to 15% and relative root mean square error in the range 25-35%. Moreover, the results showed that the global fitting model provides better estimates and results than using locally fitted models with relative root mean square error ranging between 20-35%. The advantages of using this method are that the sigmoid models were able to provide physically reliable estimates for extreme values of the clearness index [35].

There are many methods to examine solar irradiance. For example, in Germany, a test was done to examine and derive a method of direct normal irradiance DNI from MSG data. In this experiment, the heliostat method was used to check the cloudiness from the satellite images. The cause of the fluctuation in the DNI is the clouds so a new model was derived to calculate the DNI [36].

A study was conducted in Turkey using Artificial Neural Networks. A 750 W PV panel was installed. The model was used to estimate the output power for different time horizons in different seasons [37]. The research specifies the obtained RMSE for each time and season. The results show that the month of August provides good output power estimation in time horizons of 3 to 40 minutes. While the month of April the best prediction falls between 5 and 35 minutes [37].

Another study was conducted in California where four different forecasting techniques were developed for output power estimation. The estimation was done for a 1 MW solar panel field to forecast for 1 hour and 2 hours ahead [38]. The developed four forecasting techniques were studied and the best-developed technique was offered by an artificial neural network model. The model offered a RMSE of 15% compared to the other models which provided an error of up to 20%. Input data to the developed models were collected for the periods of 2009 to 2011. The study was done to study the best forecasting method; however, the research didn’t consider the different environmental conditions affecting the output power of the system.

Many studies were done to use ANN to predict the output power of a PV panel; however, such studies did not account for all environmental conditions. In China, clouds movements, sunshine duration, and rain conditions were tackled but without tackling the dust issue [20].

Regular cleaning of photovoltaic modules is important. An experiment was conducted in Spain to study the impact of rainfalls in cleaning photovoltaic modules. The study showed that solar photovoltaic power plants experience a reduction in energy by 20% in periods without rain compared to only 4.4% energy reduction in rainy periods due to dust accumulation [39]. This shows the importance of rain in cleaning solar photovoltaic panels. For dry areas, it is important to investigate alternative economical methods for cleaning solar photovoltaic panels.

A study was done in Morocco to estimate dust accumulation by having a correlated input of output power of solar photovoltaic panel and rainfall. The study was done for over 4 months. The rainfall data were obtained from a meteorological data center. The experiment was done using glass by measuring the irradiance above and below the glass to measure the reduction in irradiance due to soil settlement. Four different kinds of soil were applied to the glass. Each soil type transmits the irradiance in a different rate shown in Figure 15 [40].

Studying the effect of dust on solar PV panels is location-dependent. It is not practical to study the dust effect in a certain location and develop a generalized model for all solar power generation. Studies of which addressed using Artificial Neural Networks or Regression Models to estimate the dust accumulation on solar PV under dust conditions in different seasons in the Middle East and particularly in the UAE are very limited. More studies are required to cover the UAE.

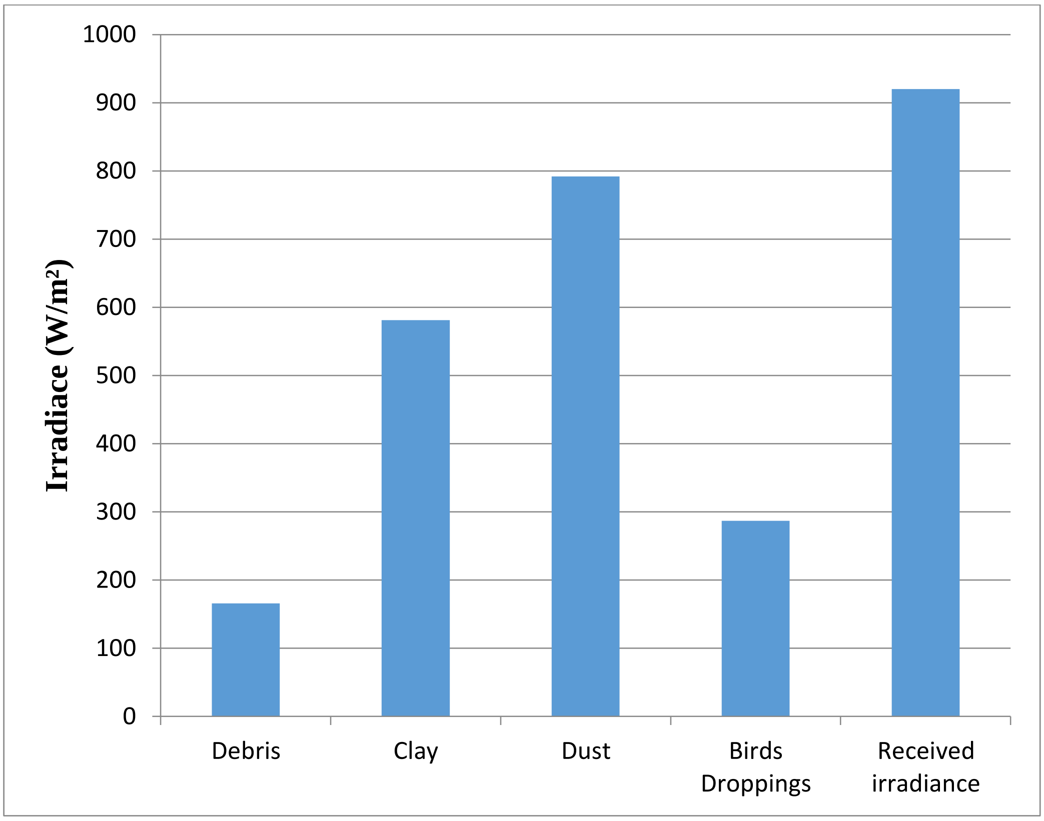

Figure 15: Effect of Different types of Soil on the Solar Irradiance [40].

2.4. Problem Statement

Renewable energy is being rapidly integrated into power grids worldwide. Replacing conventional power plants which use gas and oil to run generators by renewable power plants has contributed to reducing global warming since renewable sources do not produce carbon emissions. There are many types of renewable energy resources that can be used in the Middle East, however, the most common types are wind and solar power resources. In the UAE, the most suitable renewable energy resource that can be utilized is solar power. PV solar panels are used widely worldwide due to their low installation cost and renewable output power. PV panels consist of cells that convert direct irradiance into DC power which is then converted into an AC power by an inverter to be fed into the power grid. PV technology is widely used worldwide; however, PV panels are facing some challenges due to the environmental conditions that affect their output power and reduce their efficiency. Such challenges include temperature, irradiance, humidity, dust, and snow. This issue has been tackled and studied in many journals. However, different technologies like image processing and sky cameras were used in to quantifying the dust accumulated on the solar panel and studying its effect on solar panels in the UAE.

Accurate prediction of the dust accumulating on the solar PV is important. Variations in the output power of Solar PV have a negative impact on the transmission system and the spinning reserves; therefore identifying the cause of the drop in the solar output power results in reducing the cost of running unnecessary gas turbines to manage the reserves. These variations can be caused by climate variations and dust accumulations. Accurate prediction of the dust accumulated on the solar PV is important for investors and for grid operators. By measuring the irradiance and temperature on site, dust accumulation on the solar PV can be predicted and cleaning actions can be taken if the dust accumulation is high.

Chapter 3. Proposed Research

This chapter explains the research methodology used to solve the problem tackled in the thesis and proposes a solution.

3.1. Research Methodology

Based on the aforementioned, this thesis will focus on estimating the dust accumulated on the solar photovoltaic in the UAE from measured photovoltaic output power, solar irradiance, and temperature. The methodology used to estimate the dust accumulated on solar photovoltaic panels was done under real environmental conditions in two stages.

The first stage is the data collection stage. The effect of known quantities of dust on the solar photovoltaic output power with known ambient temperature and solar irradiance is studied. Experiments were conducted outdoors with real environmental conditions on a solar photovoltaic panel. The output power of the solar photovoltaic panel was measured with different levels of natural dust while recording the temperature and irradiance. The dust used in the experiments is natural dust collected from the same site at which the experiments were conducted. The steps of the experiments can be summarized as follows:

- The output power of solar photovoltaic panel, temperature, and solar irradiance were measured with 0 g/m^2 dust accumulated on the panel.
- An amount of 0.1 g/m^2 of dust was uniformly distributed on the panel.
- The output power of solar photovoltaic panel, temperature, and solar irradiance were measured again.
- An amount of 0.2 g/m^2 of dust was uniformly distributed on the solar photovoltaic panel.
- The output power of solar photovoltaic panel, temperature, and solar irradiance were measured again.
- The experiments continued with a dust amount of 0.3 g/m^2 to 0.9 g/m^2 with a step of 0.1 g/m^2.
- The output power of solar photovoltaic panel, temperature, and solar irradiance were measured with each dust accumulated.

Experiments were conducted at different times of the day and for multiple days to collect a wide range of data that has different solar irradiance and different temperature. A total of 4800 data points were collected.

The second stage was to divide the collected data into the training group and testing group. 4000 data points were used for developing the model. 800 data points were kept for testing the accuracy of the system which will be used in 4.2. Case Study 1. The collected 4000 data points were divided into two groups; a group for training and another for testing. Five Fold Cross-Validation Method was applied to the data. Five Fold Cross-Validation Method divided the data into four groups for training and one group for testing. The four groups of data were trained with a regression model. The fifth group was used for testing the model. This was done for five times with five different sets of groups.

The third stage was to choose the regression model suitable for the collected data points. The first step was to use a linear regression model to train the data. The collected data was trained with different linear regression models. Other nonlinear regression models were considered after proving the inaccuracy of the linear regression models. Different non-linear regression models were used such as tree, support vector machine and Gaussian process regression.

The final stage was to choose the best regression prediction model which provided the most accurate dust estimation with minimum root mean square error (RMSE). After choosing the best model that estimates the dust accumulated with the least error, the model can be tested on different case studies.

The flow chart of the stages used in this thesis for dust estimation on solar photovoltaic panels in the UAE is shown in Figure 16. It starts with data collection followed by data preparation, then data training and testing and finally model testing.

As mentioned in the second stage, for validations, cross-validation will be applied in this research. Cross-validation is a statistical method used in the applied machine to estimate the skills of machine learning methods. It is also used to compare and select the models because it is easy to use, easy to understand and implement and easy to get results [41]. Cross validation helps in dividing the database to different groups which deliver the least possible error.

Cross-validation is a method used to repeat the labels of the limited data samples. A single parameter called k that refers to the number of groups, for example, if k=5, then it's called five-fold cross-validation. It is also used to estimate the skills of unseen data. This method is very popular because it is simple to understand and the results received are less biased than other methods [41]. The procedure is to randomly divide the dataset into five groups. Then, one group will be kept as a test data and the remaining groups will be used for training. The model will be trained using the four groups and evaluated using the one test group. The evaluation score is saved and the procedure is repeated with different groups. The best score will be the best to be fitted by the model [41].

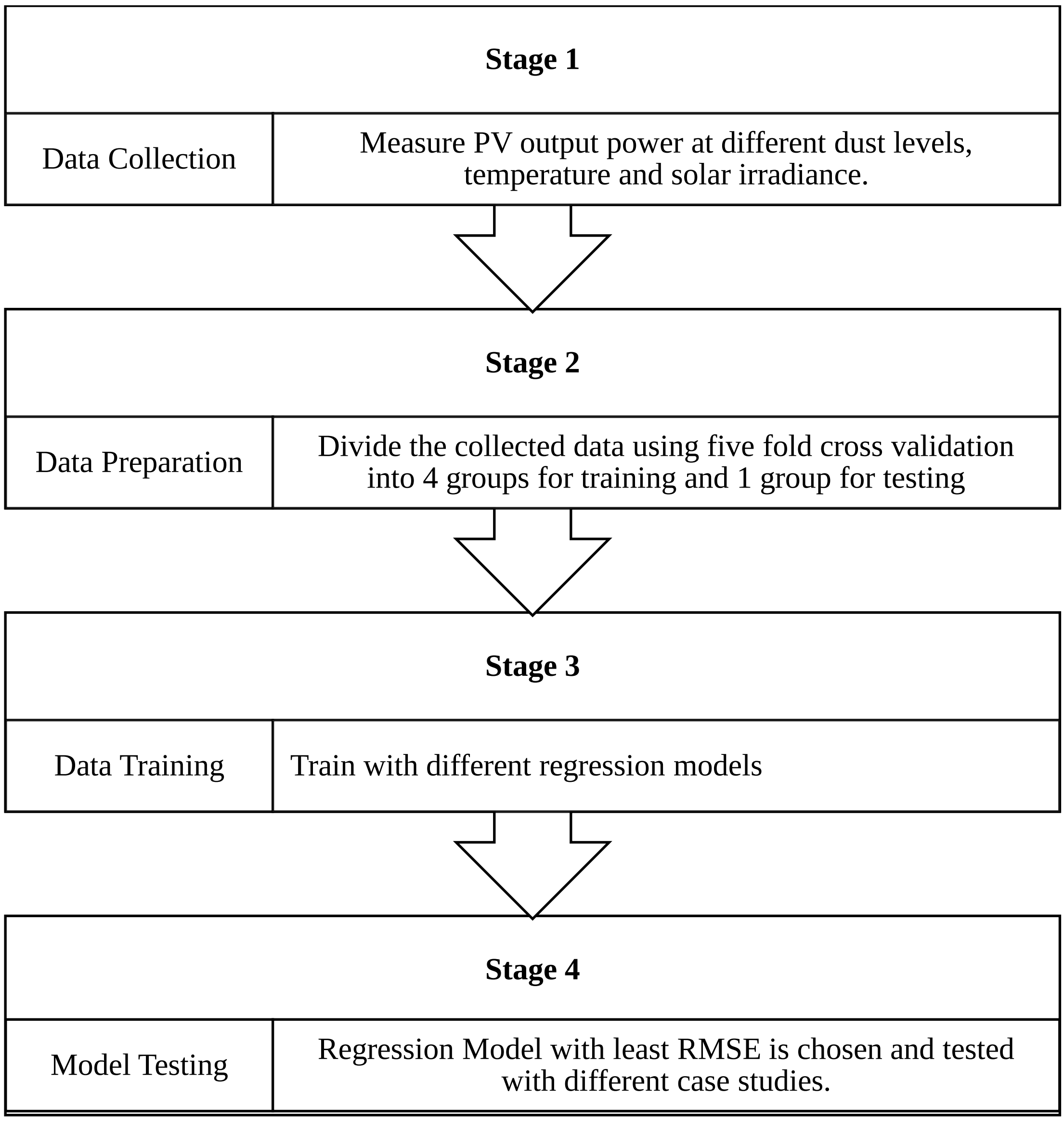

Figure 16: Proposed stages for accurate dust accumulation estimation.

3.2. Artificial Neural Network and Regression Learner

An artificial neural network is a problem-solving method. It is a computation technique that predicts unknown output data by discovering a relation between some known input data. The system is composed of different nodes and artificial neurons and consists of multiple layers, as shown in Figure 17 [42]. The artificial neural network has input data which is the input layer shown in Figure 17. The output layer is the expected result to be estimated by the artificial neural network model. Between the input and the output layers, there are hidden layers. The number of hidden layers is defined by the user. The hidden layers work to estimate the relation between the output and the input layers. The intermediate hidden layers can be interconnected if the inputs have correlated relation.

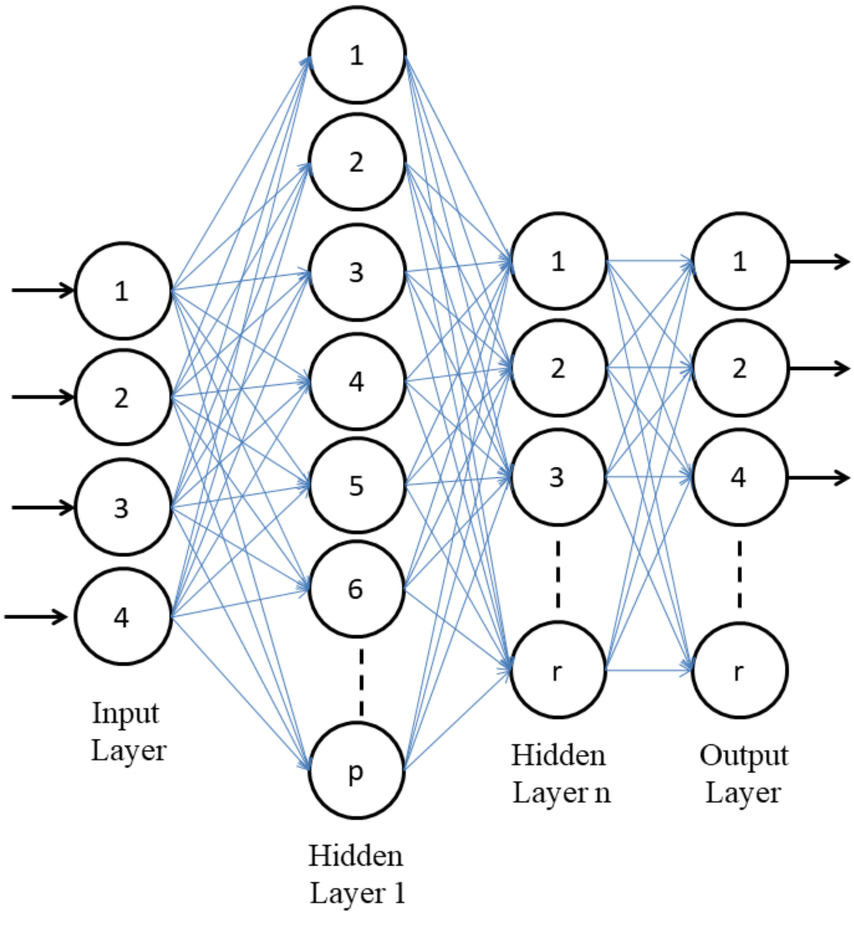

Figure 17: Artificial neural networks interconnected layers.

Artificial neural network systems learn by entering experimental data of multiple inputs and the resulting output to teach the system how to predict the output from the input. Artificial neural network act as a black box that tries to find a non-linear function that relates the inputs to the outputs using a set of experiments to learn. For accurate estimation of the relation between the outputs and the inputs, more experiments are needed. The input layer neurons are given weights, which increase or decrease with every training step according to the strength of the input neuron. Neural networks are used in problems that require clustering, classification or regression.

Continuous variables can be estimated using regression. One of the famous examples is the linear regressions, shown in Figure 18, which fits the input dataset by linear relations. Using linear regression is not suitable for non-linear relationships. Other methods such as support vector machine, regression trees, and deep learning are used with more complicated nonlinear problems [43]. Classification methods help in problems, where predicting the class of the input set is required. There are different methods used for classification such as deep learning, classification trees or logistic regression, which is shown in Figure 19 [43]. Finally, clustering is an unsupervised classification technique used for feature extraction and pattern recognition by identifying some inherent structures present in a set of objects based on a similarity measure [44].

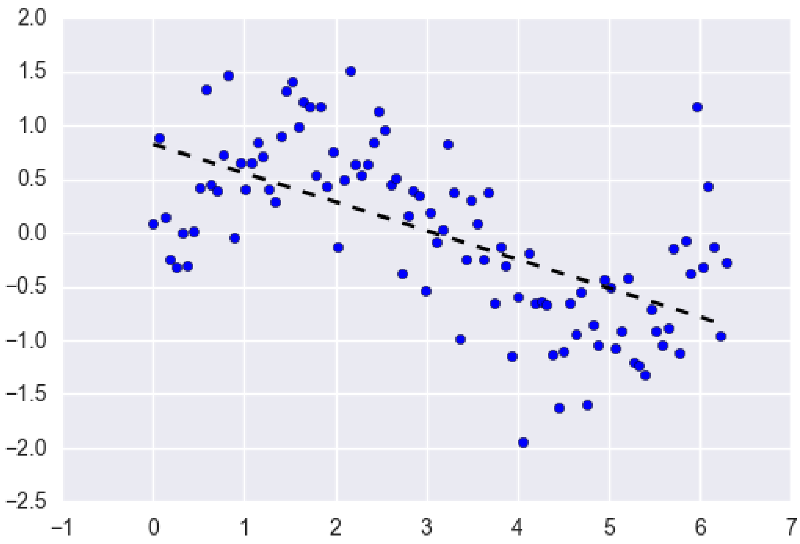

Figure 18: Linear Regression [43].

Steepest descent and quasi-newton are different algorithms used for Neural Network learning. The Neural Network Toolbox in MATLAB includes a Fitting Tool, which map the inputs entered to the tool with a set of outputs [45]. The collected data are divided into training, validation, and testing. The hidden layer structure can be modified according to the prediction results. After training, the results and output plots can be analyzed.

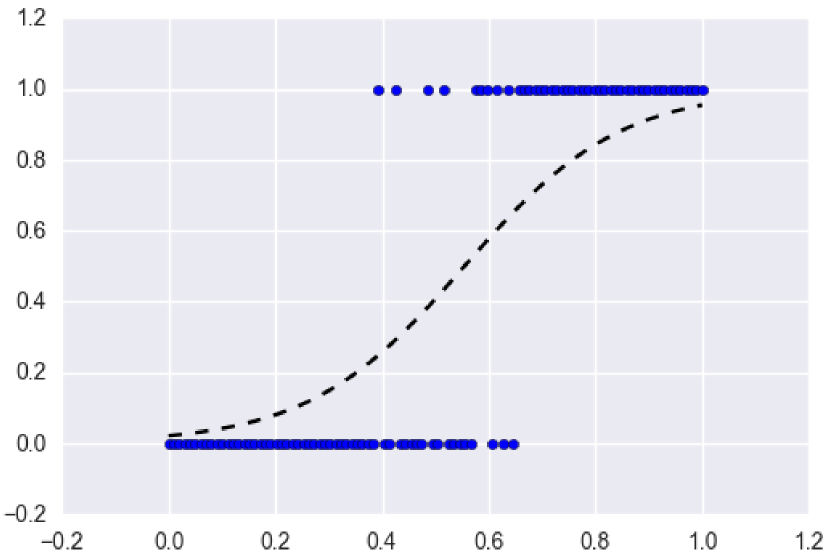

Figure 19: Logistic Classification [43].

Furthermore, there is a Regression Analysis which is a statistical approach that is used to predict the relationship between different variables. It is mainly used to estimate the relationship among independent variables and one or more dependent variable. Many different regression techniques can be used to study the response of a dependent variable when any one or multiple independent variables are changing. The field of Regression is part of machine learning; it is commonly used in forecasting and estimation problems [46].

Regression is suitable for predicting dust accumulation on solar PV panels. The independent variables are the temperature, solar irradiance, and solar PV output power, while the dependent variable is the dust accumulated. There are many regression techniques, such as linear regression, non-linear regression, Gaussian Process Regression, and many others [46].

Linear Regression is known as the ordinary least square and linear least square. This type of regression is the most common and very straightforward. It is used if there are continuous dependent variables. Also, linear regression is used to understand the mean change in a dependent variable given in one unit in each independent variable [47].

Linear Regression is based on six fundamental assumptions. The first assumption is that the independent variable is not random. The second is that the dependent and independent variables show a linear relationship between the slope and the intercept. For any linear relation between the inputs and the outputs, linear regression can be used for estimation and predictions. Also, the value of the residual (error) is zero or the value of the residual (error) is constant across all observations. Moreover, the value of the residual (error) should not be correlated across all observations. Finally, the residual (error) values follow the normal distribution [47].

Simple Linear Regression is a model that shows the relationship between dependent and independent variables. Also, there are some special options available for linear regression. For example, if you have one independent variable the best option is to use the fitted line plots. On the other hand, multiple linear regression is similar to the linear model with the exception that the multiple regression has multiple independent variables. Multiple linear regression has several independent variables so there is another mandatory condition for this model. The Non-collinearity is used when there are independent variables that show a minimum correlation with each other [47].

The below equation shows linear regression model where y expresses the dependent variable or the response variable, x is the input independent variable, β_o and β_1 are the parameters of the model and ϵ express the residual (error) [47]:

$$y_i = \beta_o + \beta_1 x_i + \varepsilon \tag{7}$$

ε represents the failure of the model to fit the data exactly.

The least square method can be used to solve the equation to calculate β_o and $\beta_1$as follows:

$$\varepsilon_i = \ y_i - \beta_o - \beta_1 x_i\, , i = 1,2, \dots , n \tag{8}$$

The sum of squares of these distances is re-written as:

$$S(\beta_o, \beta_1) = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} (\, y_i - \beta_o - \beta_1 x_i)^2 \tag{9}$$

To minimize $S(\beta_o, \beta_1)$, the values of $\hat{\beta}_o$ and $\hat{\beta}_1$ are calculated by:

$$\hat{\beta}_1 = \frac{\sum(y_i - \bar{y})(x_i - \bar{x})}{\sum(x_i - \bar{x})^2} \tag{10}$$

and

$$\hat{\beta}_o = \bar{y} - \hat{\beta}_1\, \bar{x} \tag{11}$$

For each data point from the data set equation (7) is computed.

Non-linear regression is used for more complicated data where the independent and dependent variables have a non-linear relation. Also, non-linear regression requires continuous dependent variable and it needs greater effort to fit the curves than linear regression. Non-linear approaches are more complex than the linear so it needs to choose the best model to use when non-linear methods are required [47].

There are many types of non-linear regression including regression trees, gauss process regression models, vector support vehicles and regression tree complexes. The models provide many results such as the error so we can choose the best model that suits the problem being solved. The model can be exported as a code to be used for other case studies.

3.3. Experimental Set up

Experiments were conducted to study the impact of natural dust accumulated on solar photovoltaic panels. Dust effect on the output power and performance of the solar photovoltaic panels was studied under real environmental conditions. The experimental setup consisted of a 100 Watt solar photovoltaic panel with an electrical load and it was carried out in Dubai (at latitude $25^o27'42.52''$ N and longitude $55^o40'44.06''$ E). Dust used in the experiment was collected from the same location used to conduct the experiment. Since different locations in the UAE have different dust physical properties, solar photovoltaic panels performance can change depending on the location. The location of Dubai city was chosen for the experiment because Dubai city has the largest single-site solar park in the world as mentioned earlier, so studying the dust effect in that location will help to manage the solar variations caused by dust.

The output power of the solar PV panel was measured at different times of the day to have various ranges of input environmental conditions related to solar irradiance, temperature, and dust. The irradiance was measured by using RS PRO Solar Power Meter ISM400. The best accuracy the meter can provide is +/- 5 W/m^2 with a resolution of 0.1 W/m^2 [48]. The maximum light level it can detect is 2000 W/m^2 [48]. The temperature data was collected from a weather station.

Dust was weighed using a high precision electronic scale with a precision of 50/0.001 g and an error range of +/-0.003 g. Then, it was distributed evenly on the solar PV panel using a thin brush.

A dust amount of 0.1 g/m^2 was distributed on the panel. Then, temperature, solar irradiance, and output power were measured. The same experiment was repeated for dust amounts of 0.2 g/m^2 up to 0.9 g/m^2 with 0.1 g/m^2 steps. Hence, for each instant of time, 10 data points were collected; 1 point with no dust and 9 points with dust with an increased amount of 0.1 g/m^2 to 0.9 g/m^2. The experiment was conducted at different times of the day for a period of 1 month. 4800 data points were collected to be fed to the regression model for training and testing.

After conducting the experiment, the data were divided randomly into 4000 data points and 800 data points. 4000 data points of the collected experimental data were divided using 5-Fold Cross Validation into 4 data groups for training and 1 data group for testing.

A total of 19 different Regression Models were trained using the collected data. Each model gives an estimation of dust with a different root mean square error (RMSE) value. Figure 20 shows a structure of the experimental setup and the processing of the data. The inputs that are measured during the experiment are the solar irradiance, ambient temperature, dust accumulation, and the solar photovoltaic panel output power. These experimental data are fed into 5 fold cross-validation to divide the collected data into four groups for training and one group for testing. Regression models are developed to estimate the dust accumulated on the solar photovoltaic panel. The best regression model which provides the least RMSE is chosen for dust estimation purposes.

The solar panel used in the experiment is from sun power manufacturer and the specifications are shown in Table 1.

Table 1: Solar Panel Manufacturer Specification

Specifications	Sun Power Manufacturer
Material	c-Si
Model	E20/435
Panel efficiency	20.1%
Rated Power (W)	435
Rated Voltage (V)	72.9
Rated Current (A)	5.97
Open-circuit voltage (V)	85.6
Short circuit Current (A)	6.43
NOCT (°C)	45
Temp. Coeff. of Pmax (%/K)	-0.38
Temp. Coeff. Voc (%/K)	-0.27
Temp. Coeff. Isc (%/K)	0.05

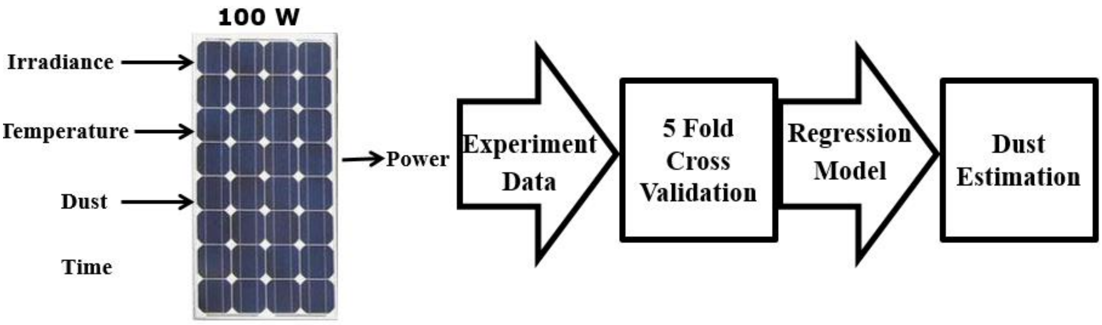

Figure 20: Structure of the Experimental Set up.

Chapter 4. Results and Case Studies

Experiments were conducted under real environmental conditions to collect enough data to be used to build and train different regression models for predicting dust accumulation on solar photovoltaic systems. The collected data was divided into two parts, one for testing and another for validation. The collected data used for testing was divided into groups using cross-validation method. Different regression models were built and tested, and the regression model which provided the smallest value of root mean squared error (RMSE) was chosen. The model was then tested with new data in two different case studies to test its accuracy.

4.1. Results

A sample of the experimental output results data collected under real environmental conditions is shown in Table 2. The experiments were done in different time periods and on different days to construct a database with various ranges on input environmental conditions. Experiments were done on a 2 months' time period. Experiments were conducted under real environmental conditions to obtain data that showcases the environment in the UAE.

The irradiance values ranged between 77.7 W/m^2 and 650.9 W/m^2, while the temperature ranged between 21.8°C and 45°C. The output power of the solar photovoltaic panel was measured with values of dust ranging between 0 g/m^2 to 0.9 g/m^2 with a step of 0.1 g/m^2. The dust applied on the solar photovoltaic panel was naturally collected on site and distributed evenly on the solar photovoltaic panel. The measured output power ranged between 2.6 W and 313 W with different masses of dust, different solar irradiance and ambient temperature.

The data collected from field experiments, including output PV power, solar irradiance and ambient temperature were considered input predictors. The accumulated dust was chosen to be the output response for the model. Regression models will be trained to predict the output response based on input predictors, and hence predict dust accumulation based on input temperature, solar irradiance, and output PV power. The 4000 data points collected from the field experiment were divided using Cross-Validation into four groups for training and one group for testing.

Table 2: Sample of Experimental Output Results

Solar Irradiance (W/m^2)	**Ambient Temperature (°C)**	**Output Power (W)**	**Dust (g/m2)**
650.9	33	309.278	0
310	32	118.059	0.1
341.8	34	148.518	0.1
77.7	33	25.993	0.2
507.1	30	176.707	0.2
424.5	35	133.023	0.3
536.9	33	158.910	0.3
295.2	28	65.214	0.4
310	30	94.433	0.4
411.5	34	91.411	0.5
341.8	34	80.961	0.5
501.6	30	98.573	0.6
564	31	125.775	0.6
375.8	34	34.331	0.7
295.2	34	26.301	0.7
507.4	34	86.900	0.8
457.7	35	62.919	0.8
341.8	34	16.809	0.9
25.5	33	10.201	0.9

All the 4000 collected data from the field experiment were rearranged based on the dust weight. Figure 21 shows the original data set. The x-axis shows the number of data points that were collected in the field experiment, which are 4000 points of input predictors. The y-axis shows the dust accumulation weight which ranges between 0 to 0.9 g/m^2, with a step of 0.1 g/m^2. The blue line represents the actual dust level for the 4000 data points. Data points 0 to 399 consist of different combinations of output PV power, temperature, and solar irradiance, however, all these points were measured with 0 dust accumulation. Similarly, data points from 400 to 799 consist of different combinations of solar irradiance, temperature and output power measured all with 0.1 g/m^2 dust accumulation.

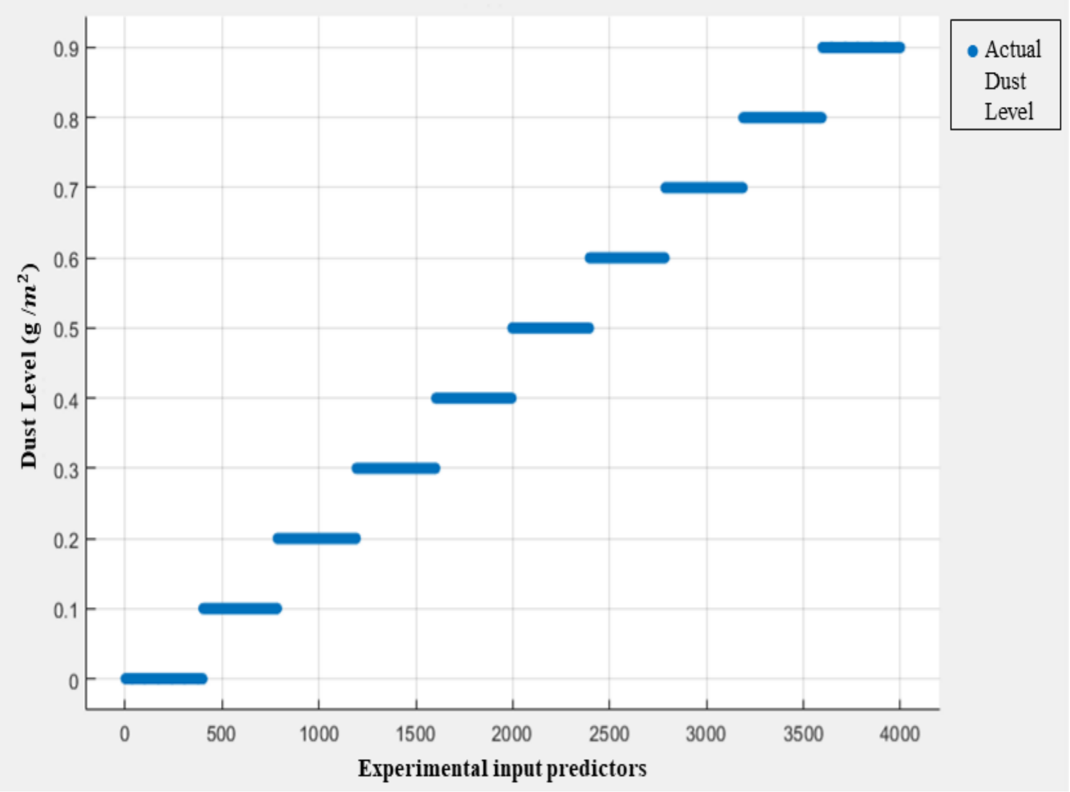

Figure 21: Original Data Set of Dust Accumulation.

The data was trained with 19 different regression models. Each model predicted the dust accumulation with a different root mean squared error (RMSE).

Linear Regression was used to train the collected experimental data since it is the most simple regression type. The data was trained with four different linear regression models; linear regression, interactions linear regression, robust linear regression, and stepwise linear regression. All four linear regression models resulted in high errors as shown in Table 4. The best linear regression model that resulted in the lowest RMSE compared to the other linear regression models is interactions linear shown in Figure 22. RMSE of interactions linear regression is 0.08419 g/m^2. Interactions linear regression improved the dust prediction by 13% compared to robust linear regressions, which is the worst linear regression model for dust estimation. Estimating the output power of the photovoltaic panel based on solar irradiance and temperature can be done using linear regression [49]. However, when the dust is included in the study of PV output power, the relation turns to be nonlinear. Therefore, non-linear regression models will be investigated to choose the best nonlinear model to estimate the dust accumulation on PV output power.

Non-linear regression models are used for inputs and outputs that have a non-linear relation. Different non-linear regression models were used to train the collected experimental data under real environmental conditions. Four different non-linear regression models categories were used with different types for each model category. The models used were tree regression, support vector machine regression, ensemble tree, and Gaussian process regression. Table 4 shows the different 19 regression models and the RMSE achieved.

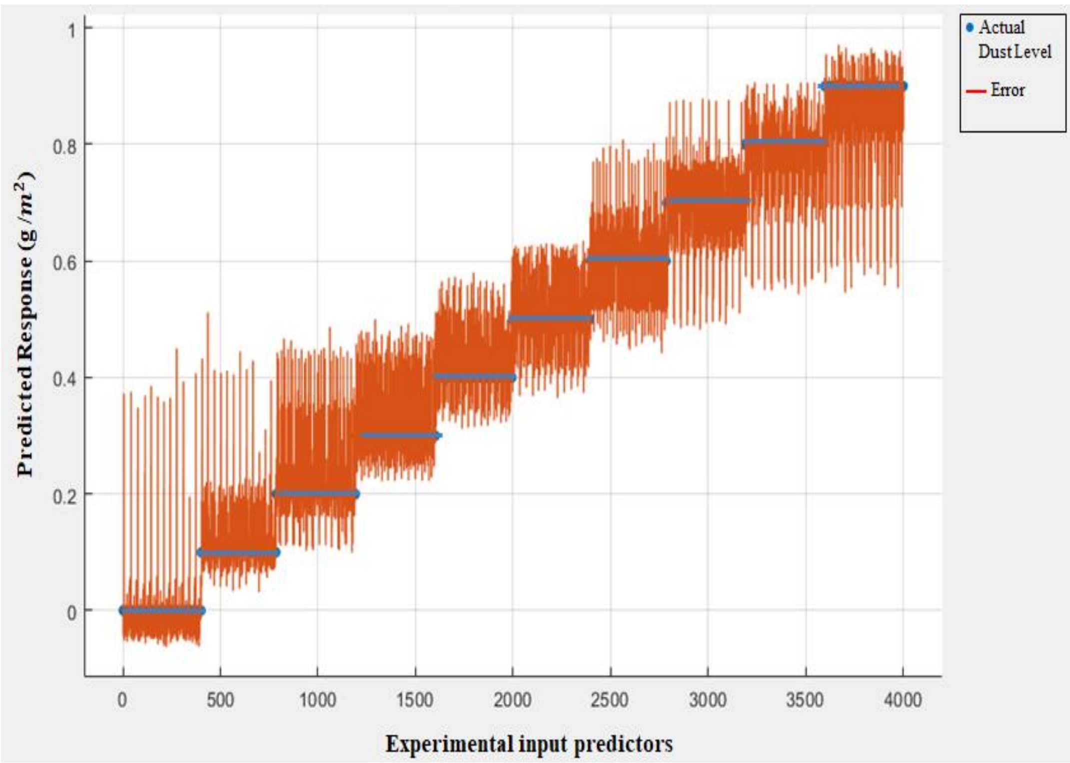

Figure 22: Error in Dust Accumulation Estimation using Interactions Linear.

Table 3: Regression Models for Dust Accumulation Estimation

Regression Model	**Model Type**	**RMSE (g/m^2)**
Linear Regression	Linear	0.093204
Linear Regression	Interactions Linear	0.08419
Linear Regression	Robust Linear	0.096736
Linear Regression	Stepwise Linear	0.084241
Tree	Fine Tree	0.026737
Tree	Medium Tree	0.045073
Tree	Coarse Tree	0.074296
Support Vector Machine	Linear SVM	0.094035
Support Vector Machine	Quadratic SVM	0.083166
Support Vector Machine	Cubic SVM	0.07658
Support Vector Machine	Fine Gaussian SVM	0.071962
Support Vector Machine	Medium Gaussian SVM	0.068671
Support Vector Machine	Coarse Gaussian SVM	0.080998
Ensemble	Boosted Trees	0.064575
Ensemble	Bagged Trees	0.067699
Gaussian Process Regression	Squared Exponential GPR	0.063416
Gaussian Process Regression	Matern 5/2 GPR	0.06141
Gaussian Process Regression	Exponential GPR	0.057048
Gaussian Process Regression	Rational Quadratic GPR	0.063026

RMSE ranged between 0.096736 g/m^2 and 0.026737 g/m^2 for the different models. The best RMSE achieved was obtained by using Fine Tree Model, which is 0.026737 g/m^2, the predicted data points are shown in Figure 23. The predicted dust level are scattered around the actual dust levels used in the experiments, which range from 0 g/m^2 to 0.9 g/m^2 with a step level of 0.1 g/m^2. Figure 24 shows the different regression models using for dust accumulation estimation in a bar chart. It is clear that linear regression provides the highest RMSE. The best regression models to be used are tree regression models. Figure 25 shows the errors in dust estimation using Fine Tree Model. Comparing to Figure 22, fine tree regression provided less error compared to interactions linear regression model.

For better visualization of the output predicted points versus the actual dust level, the model is plotted in a line plot response form. For a perfect dust accumulation prediction response, the predicted values will be exactly equal to the actual values of dust. All the points of the prediction will be located on the horizontal line which represents zero error. The error was calculated based on the difference between the actual dust levels of 0 g/m^2 to 0.9 g/m^2 with a step level of 0.1 g/m^2 and the predicted dust level by the model. A well-developed prediction model will provide prediction points located close to the horizontal line. Figure 26 shows the line response of fine tree regression model.

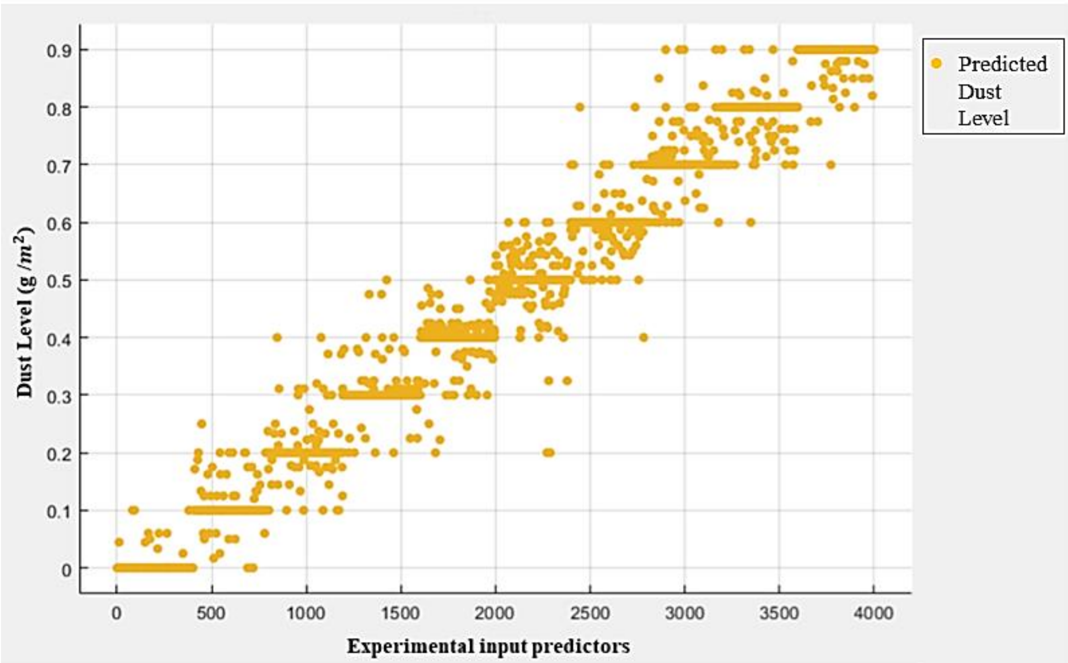

Figure 23: Fine Tree Model for Dust Accumulation Estimation.

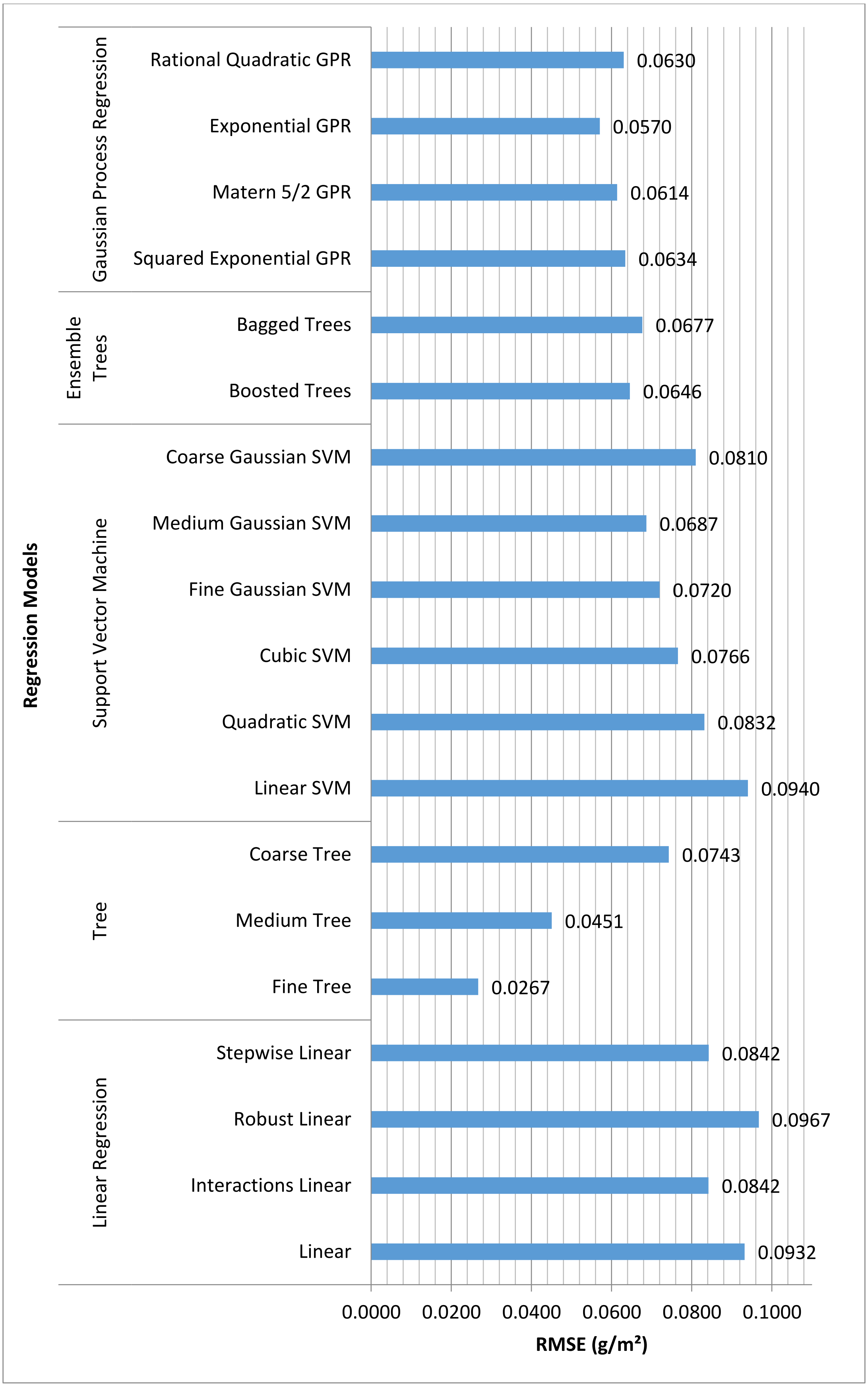

Figure 24: Different Regression Models using for Dust Accumulation Estimation.

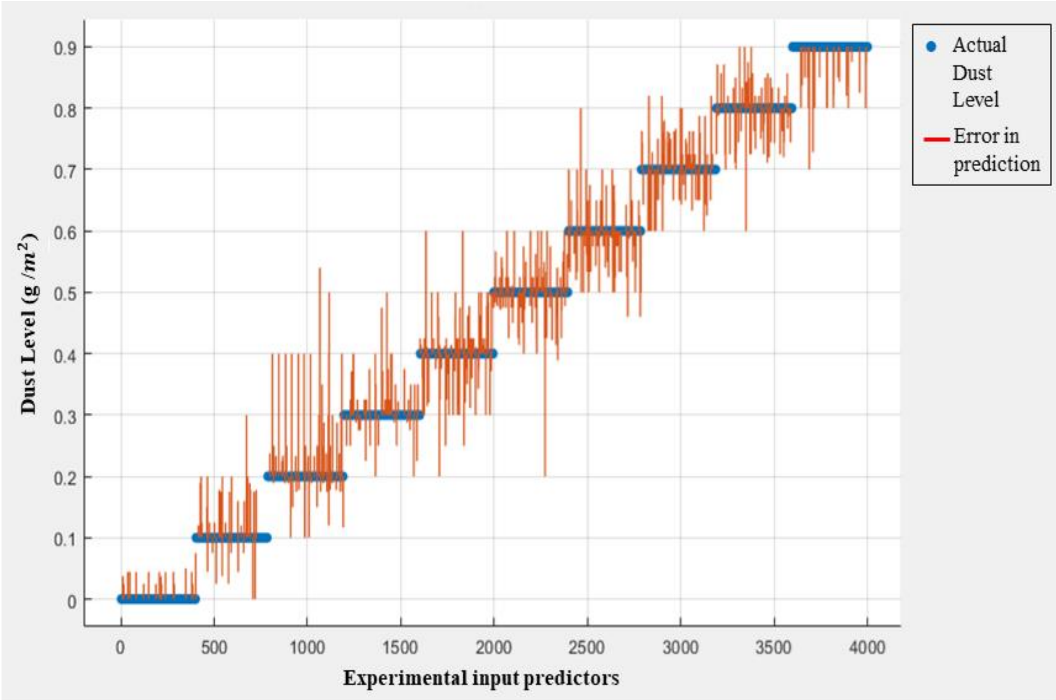

Figure 25: Error in Dust Accumulation Estimation using Fine Tree Model.

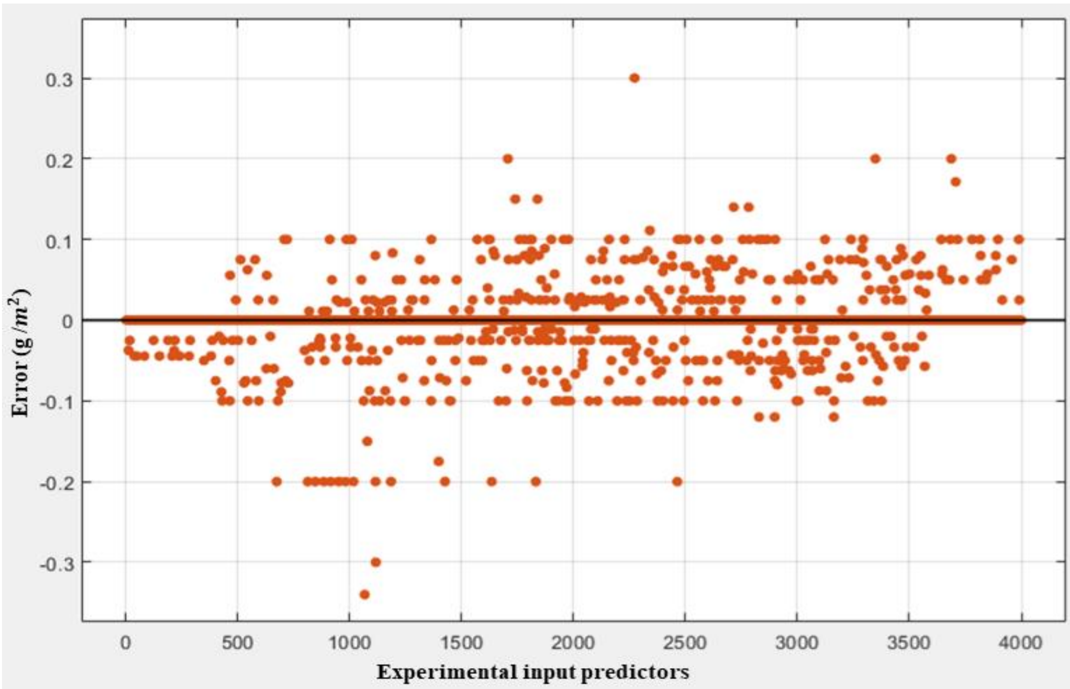

Figure 26: Fine Tree Model Line Response of dust accumulation.

The horizontal line represents a perfect prediction of dust level which results in zero error. The blue points are the predicted values of the dust accumulation using a fine tree model. The majority of predicted dust accumulation points by fine tree model are located around the horizontal line except for a few measured points, which shows a good estimation of dust accumulation level. Maximum error obtained for dust values less than 0.6 g/m^2 is 0.35 g/m^2. However, for high dust accumulation of more than 0.6 g/m^2, the maximum error in estimation is 0.2 g/m^2. Therefore, the model is reliable for estimating high dust accumulation which is more critical in solar photovoltaic power plants.

Compared to all linear and non-linear regression models that were used to estimate dust accumulation on the solar photovoltaic panel, the worst prediction model is Robust Linear Regression. Robust Linear predicted the dust accumulation with the highest value of RMSE compared to the other models, which is 0.096736 g/m^2. Figure 27 shows the errors in dust accumulation prediction using robust linear regression. Robust Linear Regression provided better estimation with less error in dust accumulation amounts smaller than 0.6 g/m^2. On the other hand, dust accumulation estimation for dust amounts greater than 0.6 g/m^2 has high errors. Predicting big amounts of dust accumulated on solar photovoltaic is more important that small amounts. Figure 28 shows the line response of robust linear regression model; where it is clear that the model couldn’t estimate the dust accumulation when the dust amount is high. The estimated dust accumulation points are scattered far away from the horizontal line, hence the prediction results in a high error.

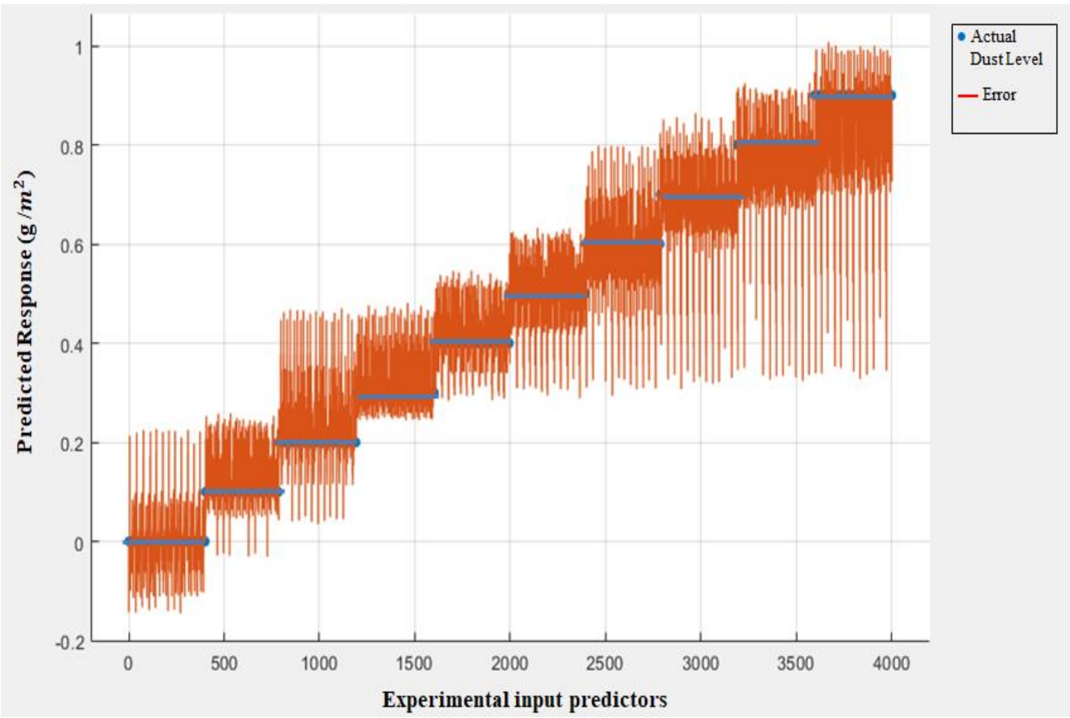

Figure 27: Error in Dust Estimation using Robust Linear Regression.

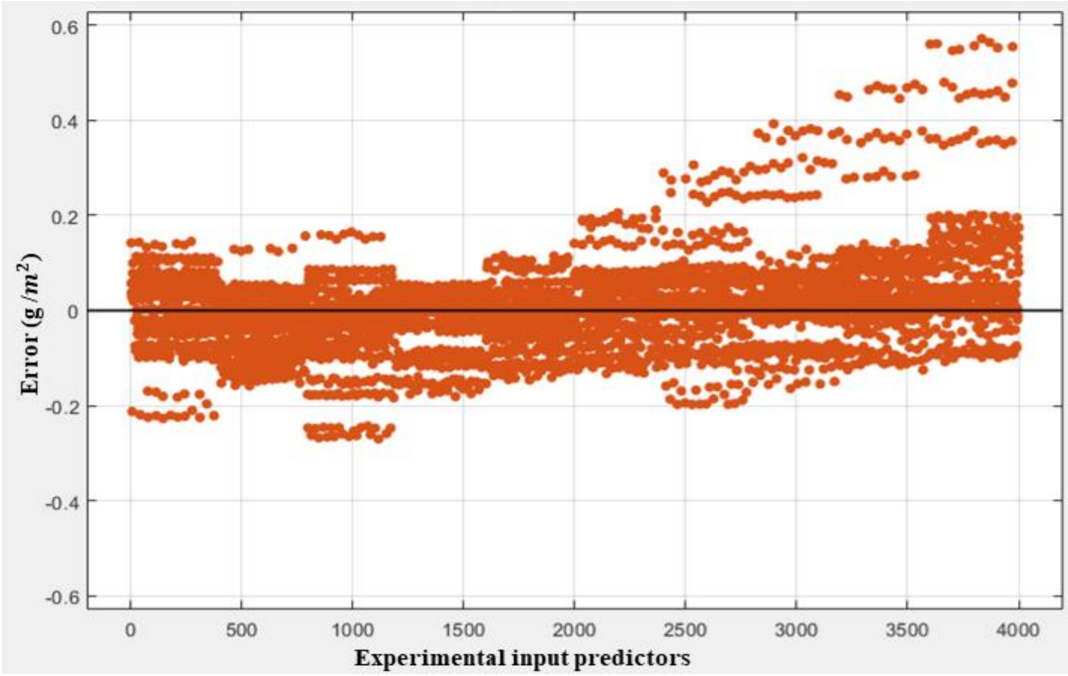

Figure 28: Robust Linear Regression Line Response of dust accumulation.

Fine Tree model provided dust accumulation estimation with a very small error. The model provided 72% more accurate prediction compared to Robust Linear Regression. Fine Tree model also estimated the dust with 41% better accuracy than Medium Tree Regression type; which is the second best-developed model for dust estimation which is shown in Figure 29.

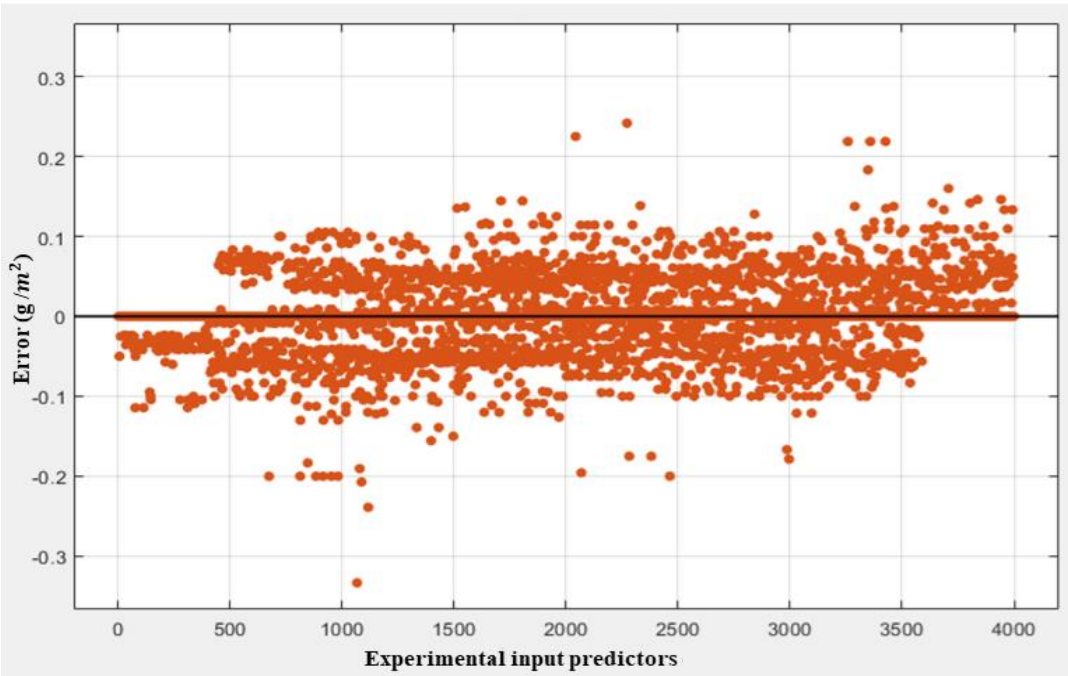

Figure 29: Error in Dust Accumulation Estimation using Medium Tree Regression.

4.2. Case Study 1

Two case studies were conducted to test the developed fine tree regression model. The first case study was conducted using pre-measured dust amount for 800 points. The amount of dust used in the first case study ranged between 0 g/m^2 to 0.9 g/m^2 with a step of 0.1 g/m^2. However, the second case study was conducted using random amounts of dust, where the weights were measured after the experiment. Since the model was trained with dust amounts of less than 0.9 g/m^2, the dust amounts used in the second case study were less than 1 g/m^2.

The first case study was done to test the performance of Fine Tree Model for the estimation of dust accumulation on the solar photovoltaic panel under different environmental conditions such as solar irradiance and ambient temperature. The original 4800 data points were divided into 4000 data points and 800 data points. 4000 data points were used to develop the model and the remaining 800 data points were used in this case study. The 800 data points were randomly selected from the original 4800 data points using a developed code which extracted randomly the required number of points from a larger data set points using a while loop.

The 800 data points, which included ambient temperature, solar irradiance, output solar photovoltaic power, and dust, were divided into two groups. The first group included ambient temperature, solar irradiance, and output solar photovoltaic power. The second group included dust accumulation masses. The first group was fed into the developed fine tree regression model as inputs. The model estimated the dust accumulated on the solar photovoltaic panel and the result was a matrix which contained 800 dust estimated values. These values were compared to the original dust masses from the experiment.

For a total of 800 collected data points, the highest error between the measured dust value and the estimated dust value was 0.2 g/m^2. Figure 30 shows the error of the collected 800 experimental data points with error ranging between -0.2 g/m^2 and 0.1 g/m^2. The errors for small dust amounts accumulated on solar panels are higher than the error for larger amounts of accumulated dust. However, RMSE was calculated and the resulted error was RMSE= 0.0255 g/m^2. Hence, the model provided accurate dust estimation.

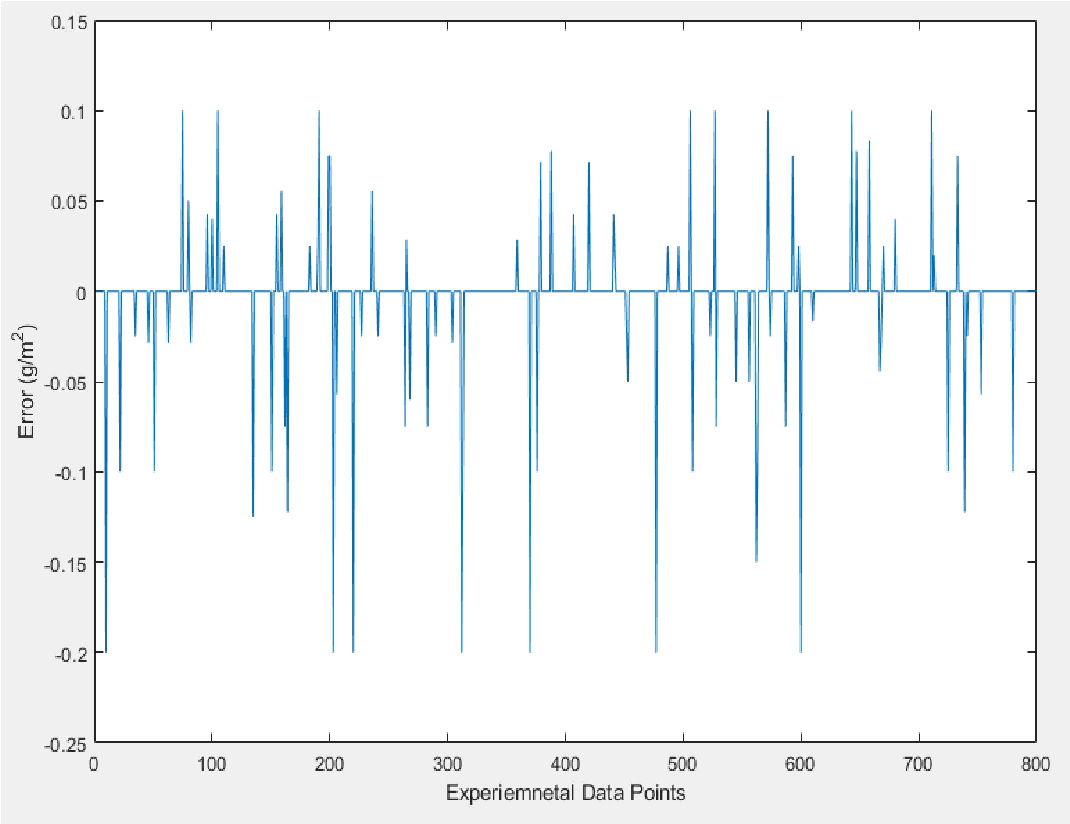

Figure 30: Error between measured and estimated dust values.

4.3. Case Study 2

Another case study was conducted to test the accuracy of the developed fine tree regression model for dust accumulation estimation. Experiments were performed to measure the output power of solar photovoltaic panels with different solar irradiance, ambient temperature, and dust accumulation amounts. Random dust amounts were spread uniformly on the solar photovoltaic panel. Dust amounts were measured to be less than 1 g/m^2. The output power of the solar photovoltaic panel, the solar irradiance, and the ambient temperature were measured at each instant.

A total of 35 different data points were measured. The experiments were conducted outdoors under real environmental conditions. Dust used in the experiments was natural dust collected from the same location at which the experiment was conducted. Different locations have different dust properties that affect the output power of the PV. A sample of the collected experimental data is shown in Table 4. The sample points ranged between 0.14 g/m^2 and 0.92 g/m^2. The experiments were done under real environmental conditions with temperature ranging between 31°C and 33°C, and solar irradiance between 606.36 W/m^2 and 505.18 W/m^2.

The collected experimental data was then fed into the developed fine tree regression model to estimate the accumulated dust on the solar photovoltaic panel. The inputs to the developed fine tree regression model are ambient temperature, solar irradiance, and output solar photovoltaic power. The developed regression model estimated the dust accumulated on the solar photovoltaic panel. The resulting dust accumulation estimation is shown in Figure 31.

As shown in Figure 31, for low dust accumulation amounts, the error is higher than for high dust accumulation. For example, the actual dust measured is 0.14 g/m^2 for sample no. 6 from the data points while the estimated dust level by the developed fine tree regression model is 0.2 g/m^2. The error is 0.06 g/m^2. However, the actual dust measured for sample no. 10 from the data points is 0.92 g/m^2 while the estimated dust level by the developed fine tree regression model is 0.9 g/m^2. The error is calculated to be 0.02 g/m^2. The results show that the error at high amounts of dust level is lower than the error at small amounts of dust level. The result is promising since estimating high amounts of dust is more important for its high effect on solar photovoltaic output power compared to low dust accumulation effect. However, the overall resulting RMSE of the estimation is low which is equal to 0.0259 g/m^2.

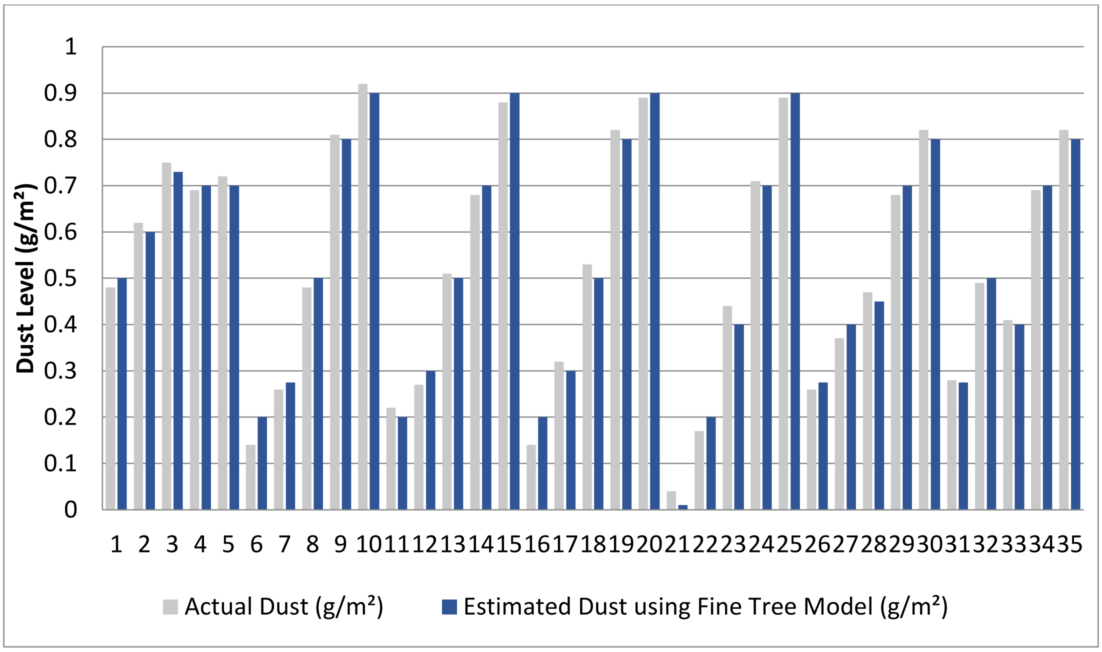

Figure 31: Case Study Dust Accumulation Estimation.

Table 4: Sample Experimental Output Results of Case Study 2

Solar Irradiance (W/m^2)	Ambient Temperature (°C)	Output Power (W)	Dust (g/m^2)
606.36	33	225.3067	0.14
506.18	31	198.9736	0.14
546.1	32	207.0312	0.22
546.1	32	179.52	0.27
606.36	33	198.6428	0.32
609.8	33	139.1534	0.48
609.8	33	95.16859	0.69
516.8	33	90.15419	0.71
516.8	33	45.35105	0.89
506.18	31	39.64586	0.92

4.4. Discussions

Dust accumulation rate in the UAE is high due to the geographic location of the country. High dust accumulation results in a misleading forecast of the output power of a solar photovoltaic power system. It also results in increased the cost related to cleaning photovoltaic modules. To solve the problem of dust accumulation on solar photovoltaic panels, a self-coating material is applied on the solar photovoltaic module or regular cleaning actions must be taken. The solution of applying self-coating material is proven to be insufficient with high dust accumulation rates in the UAE [8]. The other solution for dealing with high dust accumulation rate is cleaning the solar photovoltaic panels.

The results showed that the dust accumulated on the solar photovoltaic modules causes degradation in the output power of the solar photovoltaic modules. Accurate prediction of dust helps system operators to estimate the most optimal time to clean solar photovoltaic modules. This can be done by setting a threshold value for the dust weight (g/m^2). The dust threshold value can be chosen for the dust accumulation that results in big degradation of the output power of solar photovoltaic systems. Hence, cleaning actions can be taken once the threshold is reached.

Utilizing the most optimal time for cleaning solar photovoltaic modules reduces unnecessary costs of continuous cleaning of solar photovoltaic modules. Cleaning solar photovoltaic modules can be avoided if the dust accumulation rate in the area is low, or if it is not causing big degradation in the solar photovoltaic modules.

On the other hand, during days with a high dust accumulation rate, sending cleaning orders to the maintenance team to clean the solar photovoltaic modules can be economically feasible. Cleaning solar photovoltaic modules before the scheduled time reduces the cost of running gas turbines to manage the drop of solar output power caused by high dust accumulation rate.

In this research, different regression models were tested to reach a sound understanding of the best and the most reliable method of dust accumulation prediction. Experiments were conducted under real environmental conditions to collect enough data to train the models. Natural dust was distributed with different amounts on solar photovoltaic panels collected on site. The dust was weighed before applying it on the solar photovoltaic panel. Solar irradiance, ambient temperature and solar photovoltaic output power were measured at each instant of time.

According to [29], the relation between dust accumulation and solar photovoltaic output power in the UAE is linear. Therefore, the first regression model was used to estimate dust accumulation on the solar photovoltaic panel is linear regression. Four linear regression models were developed and used for dust estimation. Each linear regression model provided different RMSE. The resultant

RMSE of linear regression was quite high. The linear regression model is suitable for estimating dust with amounts less than 0.34 g/m^2 under controlled indoors environmental conditions [29]. However, for high amounts of dust accumulation under real environmental conditions, non-linear relation between the input predictors must be investigated. Non-linear regression models were developed to estimate dust accumulation on solar photovoltaic panels.

Among all used nonlinear regression model, Fine Tree Regression provided the best dust accumulation estimation. The developed fine tree regression model provided accurate dust predictions with RMSE= 0.0255 g/m^2. Fine Tree Regression Model provided the least RMSE compared to other tested regression models. Linear Regression methods provided the worst dust estimation with high RMSE. This is due to the non-linearity relation among the input data of solar photovoltaic output power, ambient temperature, and solar irradiance. The fine tree model proved to be the most suitable method as shown in this thesis.

In case study 1, a set of input data of solar irradiance, ambient temperature and solar photovoltaic was entered to the developed Fine Tree Regression Model. The model could estimate accumulated dust with RMSE= 0.0255 g/m^2. Testing the model was done in case study 2 using a random amount of natural dust accumulation. The model could predict the dust accumulation on a solar photovoltaic panel with RMSE= 0.0259 g/m^2. For high amounts of dust, the error ranged between 0.02 g/m^2 and 0.01 g/m^2. For low amounts of dust accumulation, the error was in the range of 0.06 g/m^2 and 0.01 g/m^2.

The results show that the developed Fine Tree Regression Model is suitable to predict the dust accumulated on solar photovoltaic panels in the UAE. Once the dust is predicted, cleaning actions can be initiated or avoided depending on the dust level and the level of dust degradation.

Chapter 5. Conclusions and Future Work

This chapter will provide a conclusion of the work done in this thesis along with a recommendation for future work in areas related to further investigating and providing solutions to the problem of dust accumulation predictions.

5.1. Conclusions

Renewable energy and mainly solar systems are currently considered a viable energy alternative source in the Middle East and other parts of the world. The United Arab Emirates is eager to harness the energy coming from the sun to generate electricity in a clean form. Solar photovoltaic power is the most advanced solar technology that is commercially available. Due to low rainfalls and low wind velocity in the UAE, photovoltaic panels experience high dust settlement.

Motivated by the importance of integrating solar power into the power grid, estimating dust accumulation on solar photovoltaic panels is crucial to guarantee maximum power output of the power plant.

In order to investigate the effect of dust accumulation on solar photovoltaic panels, experiments were conducted under real environmental conditions.

The main objectives of the thesis are as follows:

- Conduct experiments under real environmental condition to study the dust effect on the output power of the photovoltaic panel.
- Develop a regression model that estimates dust accumulation on the solar photovoltaic panel by getting to know the input solar irradiance, ambient temperature and output power of the solar photovoltaic panel.
- Validate the obtained model with different case studies.

The objectives were achieved by measuring solar irradiance, ambient temperature and output power of the solar photovoltaic panel while applying a pre-measured amount of dust. Enough data were collected to be used to develop a regression model. Different linear regression models were developed and tested, which provided high RMSE. Non-linear regression models were investigated and Fine

Tree Regression Model proved to be the most suitable regression model to be used for dust accumulation estimation.

This thesis used Fine Tree Regression Model to predict the amount of dust accumulated on a solar PV panel. The achieved best RMSE is 0.026737 g/m^2 which is better than any other developed model with at least 41%.

Case studies were performed to test the accuracy of the developed model. The model was tested by applying the model on two different case studies with pre-defined amounts of dust and random amounts of dust. Each case study provided a low RMSE. RMSE of case study 1 where pre-measured amounts of dust level were distributed on the solar photovoltaic panel was 0.0255 g/m^2. While in case study 2, RMSE was equal to 0.0259 $g/m^2$where random amounts of dust level were distributed. For random amounts of dust levels accumulated on solar photovoltaic panels, the error was in the range of 0.06 g/m^2 and 0.01 g/m^2 for low dust levels and in the range of 0.02 g/m^2 and 0.01 g/m^2 for high levels of dust. By knowing the output power of the solar PV panel and the input temperature and irradiance, the model can estimate if the reduction in the output power is caused by dust accumulation. Actions can be taken, such as cleaning the panel at the most optimal time, if the reason of the power reduction is the dust accumulation.

In conclusion, manufacturers can use the model to train their cleaning systems before installing PV farm.

5.2. Future Work

Future work is still needed to improve the accuracy of dust accumulation prediction. The developed dust prediction model can be improved to provide smaller RMSE by using real-time data. Using a bigger capacity of a solar photovoltaic system for training the model will enhance the accuracy of the developed model.

Collecting real experimental data for longer periods of time to cover winter, summer and the transitional months will also provide a bigger database of input data. Collecting experimental data that covers all four seasons will provide better dust accumulation estimation. Furthermore, including other environmental data as inputs to train the model will reduce errors. Cloud movement is correlated with solar irradiance and shading since it causes a partial drop in solar irradiance. Therefore, cloud movement can be investigated to see if it affects the dust accumulation. Another environmental condition input data can be investigated; which is humidity. Humidity affects the rate of dust accumulation. Long term field experiments are needed to get accurate data of humidity effect on dust which can be used to build a prediction model.

Moreover, based on the weight of dust and humidity, different cleaning actions can be considered. Different dust properties and dust weight affect cleaning scheduling and cleaning methods. There are many cleaning methods for solar photovoltaic systems, which reduce the cost and utilize resources. Choose the best method of cleaning is economically essential. Also, testing the model on different types of photovoltaic panels can be investigated.

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Vita

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