A NOVEL STOCHASTIC DYNAMIC MODELING FOR PV SYSTEMS CONSIDERING DUST AND CLEANING EFFECTS

by

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Declaration of Authorship

I declare that this thesis is my own work and, to the best of my knowledge and belief, it does not contain material published or written by a third party, except where permission has been obtained and/or appropriately cited through full and accurate referencing.

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Dedication

To my family…

Abstract

Stochastic photovoltaic (PV) modeling is essential for the long-term planning of renewable power generation. One of the most prevalent problems that PV systems face is the accumulation of dust on the PV panel surface that negatively impacts the output power. Wind speed along with other weather variables including relative humidity, temperature, and precipitation are some of the major factors that contribute to dust accumulation. Unlike the available models in the literature, this thesis presents a novel dynamic model of the PV output power profile considering the effect of dust accumulation using a Markov chain model. The proposed model is composed of three stages and it incorporates the seasonal variations in the weather conditions as well as the desired cleaning frequency, which affects the overall energy yield of the PV system. The first stage is the data acquisition and processing stage where the raw data is discretized and categorized. The second stage utilizes the outcome of the first stage in a Markovian Chain model, which is the core of the overall model. The third and final stage is the cumulative distribution function generation, which is generated using the probability mass function output of the Markov Chain simulation. The outcome of the model can be described as virtual scenarios, which can help the investors to decide on the optimal size of the PV system and the optimal cleaning frequency for each season subject to some constraints. The model outcome shows an error of less than 5% when compared to actual data collected from the field without cleaning. Various case studies are presented to show the effectiveness of the proposed model and its benefits.

Keywords: ***Stochastic modeling, weather effects on PV, Markov chain, photovoltaic, planning.***

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List of Abbreviations

BATS	Bayesian Autoregressive Time-Series
CDF	Cumulative Distribution Function
EP	Electrostatic Precipitator
FRP	Fixed Rate Precipitation
MC	Markov Chain
MCS	Monte Carlo Simulation
PM	Particulate Matter
PV	Photovoltaic
PDF	Probability Density Function
SSV	Static Settling Velocity
SSR	Stochastic Rate and Recovery

Chapter 1. Introduction

In this chapter, we provide a short introduction about the existing issues related to dust accumulation specifically in desert climates like in the Middle East where this problem has grown a lot over the past few years. Then, we present the way this issue is tackled as well as the research contribution. Finally, a general organization of the thesis is presented.

1.1. Overview

The recent growth in solar energy in the Middle East and specifically the United Arab Emirates (UAE) has led to numerous solar plants being installed in the region. This includes the Shams Solar Power Station and the Masdar 10MW Solar Photovoltaic Farm in Abu Dhabi, the Mohammed Bin Rashid Al Maktoum Solar Park in Dubai, and much more [1]. However, a common concern in almost every power plant within the region is the development of dust on the solar panel surface, especially during summer. Whether it is through a sandstorm or other climate-related variables, dust is known to negatively impact solar panel performance [2]. This is because the formation of dust on the surface of the solar panel prevents the device from absorbing the sunlight it needs to later convert to energy. Considering that some of the best commercial solar panels have an efficiency level close to 30%, even the slightest negative impact on a solar panel will greatly impact its output performance [3]. This is considering that the solar panel is continuously tracking the sun and, if not, the likelihood of the solar panel performing even poorer is much higher.

Consequently, there is a greater need for cleaning to mitigate the issue of dust on solar panels. Currently, there are numerous cleaning technologies that have been implemented not only within the UAE but also around the world. However, as water is a scarce resource and continuous cleaning will be costly from a labor and resource point of view, it is important to optimally manage the best way to clean solar panels while using minimal resources. Hence the need for a model for dust accumulation that can help determine the optimal cleaning frequency for solar panels depending on the season.

1.2. Thesis Objectives

Driven by the developing interest in renewable energy and specifically in solar energy in the United Arab Emirates, the need to tackle the issue of dust on solar panels has grown over the past few years. In desert climates like the Middle East, the likelihood of dust negatively impacting the behavior of solar panels is extremely high. As a result, there is a great need to consider the impact of dust on solar plants long term planning. Thus, the main objective of this thesis is to develop an accurate model that considers the stochastic nature of PV including dust accumulation. The model should also be able to consider the recommended cleaning action on a PV farm and the corresponding response on output power.

1.3. Research Contribution

The contributions of this research work can be summarized as follows:

- The development of a novel model for the stochastic nature of PV performance including the effect of dust accumulation using meteorological data.
- The development of a unique mechanism in the model that depicts dust accumulation levels at different cleaning frequencies in the PV system.

1.4. Thesis Organization

The rest of the thesis is organized as follows: Chapter 2 provides background about the factors affecting dust accumulation on solar panels and the effectiveness of the various cleaning techniques on solar panels. The employed methods and algorithms to develop the proposed model are discussed in Chapter 3. Chapter 4 presents a power profile generation mechanism that uses the results of the model proposed in Chapter 3. Chapter 5 discusses the results of the simulation, model validation, and the optimal planning of the model on a case study. Finally, Chapter 6 concludes the thesis and outlines future work.

Chapter 2. Background and Literature Review

In this chapter, we discuss the negative impact of dust on solar panels and the different cleaning methods that are currently being implemented in the region to tackle the situation. After that, the related work to PV modeling including dust is discussed.

2.1. Popularity of Solar Energy

With research associated with renewable energy growth over the last few decades, there is a growing level of the popularity associated with sustainable energy. This has partly been due to the realization that fossil fuels will no longer support the energy demand of people in the future and there is a need to limit or reduce the amount of fossil fuels that are currently being burned. Not just that, but the negative impact that fossil fuels have on the environment has been well documented to cause climate-related concerns and, most famously, global warming. Hence, there is a pushed need for the photovoltaic industry to grow with the recognition that solar energy, one of the easiest to implement forms of renewable energy, having the potential to form as one of the world's main forms of electrical energy production [4]. A reflection of this view can be seen in the actions of China who, in 2018, have installed close to 45 GW of solar power plants and has had its total solar energy capacity grow close to 176 GW [5]. When discussing solar panel technology itself, silicon crystalline PV modules are arguably the most common and most widely used solar panels in the world. At the same time, emerging solar panel technologies that use different materials, which are cheaper have also begun to emerge in the market including amorphous silicon, copper indium selenide, and cadmium telluride.

At the same time, with a steady increase in the prices associated with electricity around the world, solar panels could provide residential house owners and companies a cheaper alternative for acquiring energy. This is especially popular in regions where grid implementation of electrical energy is possible, which would therefore allow for residential owners to implement solar panels on their rooftops, which could supply power to the household during hours when the electricity price is high [6]. In such cases, the operation of a solar panel would also require a battery that could be used to store the energy the solar panel generates in the morning hours. This is already being implemented in countries like Germany where building-integrated photovoltaics

(BIPV) and rooftop installations of solar panels have been growing in popularity. For the residents of Germany, there has been a major reduction in their energy bills due to this change [7]. While the optimal generation of solar panels is dependent upon several factors including the location of the sun, weather variables, intensity of the solar irradiance, and load demand, the general consensus is that solar energy helps reduce the overall cost of energy especially when paired with a storage system. However, it is important to note that the uncertainty related to PV performance models in terms of how much specific external technologies impact solar panels is far too high even today. Existing research related to solar panels has largely centered on the performance of the solar module and not necessarily the performance of the overall system [8].

2.2. Factors Affecting the Dust Accumulation on Solar Panels

When discussing dust and its impact on solar panels, there is no doubt that the performance drop of solar panels with the existence of dust on its surface is large. When dust forms on the surface of solar panels, the solar panels ability to produce electricity is hindered by the trouble it has absorbing and receiving the sunlight being shone on top of it. When this occurs, there is a drop in current output and that will inevitably lead to a drop in power output. The major downside to this when ignoring the performance of the solar panel is the economic loss that photovoltaic power plants can suffer from after investing a lot of money in installing the solar panels. Even the smallest of particles sizes, categorized as less than 500 μm, is labeled as enough dust to negatively impact solar panel performance [9]. The size and frequency of dust accumulation is largely dependent upon the region where the solar panel is located. For example, in Colorado, a dust accumulation rate of 150 mg·m^2 was measured after only after a few days in summer [9] while in Egypt it was close to 150–300 mg·m^2 [10]. The evident difference in the results for the two countries was clear and it is mainly dependent upon the weather conditions of the two areas. Egypt, when compared to Colorado, is much drier and surrounded by a desert environment, which makes it far more prone to dust than Colorado. In fact, in 2018, an experimental study on the performance of solar panels after 70 days of not cleaning it [11]. Results from his findings showed that the dust surface density had increased dramatically and the reduction in overall output power was close to 25%.

One of the most common concerns related to dust accumulation is how strongly it is dependent on weather variables as well as the size of the particle [12-13]. This indicates that the rate of dust accumulation will only be much higher if the source of the dust particles is closer to the solar panel and, with further distance, the rate of dust accumulation will correspondingly decrease [14]. Dust deposition on the surface of a solar panel can occur in various weather conditions as well with the first of them being dry conditions. In drier conditions, airborne particles locate themselves on the surface of the PV when there is a clear absence of water. In such conditions, dust atoms adhere to the solar panel surface mainly due to adhesive forces. However, in wet conditions, the dust particles stick to the surface of the solar panel due in the presence of fog, rain, and snow, which can make their contamination even more problematic for solar panels. During clear weather conditions, solar panel performance is ideal and only with dust will its performance begin to degrade assuming that the panel is tracking the sun at all times. However, with adverse weather conditions, the performance drop off of solar panels is inevitable and, combined with dust accumulation that might contain sticky dust particles that are hard to remove from the surface of the panel, dust accumulation is a major source of this. There are times when the atmospheric dust is pushed onto the surface of the solar panel simply because of the existence of fog or through water droplets, which contaminate the surface of the solar panel. Additionally, a study was done on the effect of dust on the output of a PV and it showed that PV output energy can also be dependent upon the number of pollutants in the air with greater number of pollutants leading to an increased likelihood of poorer PV performance [15]. Overall, dust accumulation or soiling is generally an unavoidable factor that will continue to negatively impact solar power performance. Only with an optimal cleaning method and schedule can solar panels continue to operate at their optimum level.

At the same time, it is important to consider that dust accumulation on solar panels might be based on the size of the dust itself and the tilt angle of the solar panel [16-17]. With a more favorable angle for dust to land and remain on the surface, more dust could form on top of a solar panel, which would therefore require more cleaning and higher costs. For particles in Colorado, the maximum rate of disposition was close to 150 µm dust particles when it was tilted close to 155° the deposition rate is 9.78%.

2.2.1. Dust characteristics. The rate of dust accumulation varies depending upon the characteristics of dust that is being deposited on the surface of the solar panel. If the dust particle that is being deposited is less than 1 μm, categorized as fine dust particles, they will tend to stay and accumulate on the surface of a solar panel much faster than dust particles that are 5 μm in size, which are considered coarse dust particles [18]. At the same time, the different particles that are larger in diameter get effected much easier by other impacts like inertia and gravity, which could either increase or decrease the rate of dust accumulation. Often, this also involves multiple forces including van der Waals forces, cohesive forces and electrostatic forces. Furthermore, dust particles that have any sort of charted electrostatic property accumulate much faster than dust particles that have neutral electrostatic properties [19]. In addition, research has also been done on the impact of dust on different PV devices, specifically the polycrystalline, monocrystalline and amorphous silicon types, while taking into consideration the different types of dust as an influencing factor [20]. The study concluded that dust samples that are larger in size allow more light to pass and dust with a more diagonal shape and are more angular than others have better optical properties than those with spheroid or elliptical shapes. At the same time, other studies considered the impact of bird droppings on PV performance as well when taking into account the various tilt angles in correlation with the likelihood of the bird dropping pattern [21]. The study indicated that at an angle of 40^o, there is a very low chance of bird dropping to form on the surface of the solar panel with an angle of 0^o associated with the highest rate of disposition. When they studied the relationship between tilt angle and dust accumulation, it was revealed that there is a decrease of dust accumulation with an increase in tilt angle with 37.63%, 14.11%, and 10.95% with respect to 0^o, 25^o, and 45^o tilt angles.

2.2.2. Wind. Wind is one of the most fundamental aspects of influencing dust accumulation. Through wind, dust particles can transport themselves hundreds of kilometers and reach a surface to land upon. Wind influences dust accumulation negatively and positively by removing and depositing dust. The dust properties and wind velocity determine the influence of wind over dust accumulation and that changes depending upon the location [22]. The rate of dust accumulation is reduced on a PV module because of the wind blowing when the module is put at a particular orientation and tilt angle [23]. Moreover, other research states that wind has a negative impact on soiling as it promotes the spread of dust particles in the atmosphere, which leads to increased surface deposition [24]. Additionally, studies on the effect of wind velocity and solar panel surface orientation in relation to dust accumulation show that dust accumulation increases with an increase in wind speed [25]. Furthermore, dust also affects the transmittance levels of PV, which can be measured by noting on glass the amount of dust on the surface of a solar panel [26]. In fact, in a study done in Egypt for over a year, the results showed that degradation was dependent on the tilt angle where the maximum degradation was observed at a horizontal position and minimum at the vertical position

2.2.3. Temperature and relative humidity. Temperature and relative humidity are weather variables that can significantly influence dust accumulation on a solar panel. The relative humidity is considered to become higher at night as there is an increase in the content of water vapor in the air. As a result, when there is any sort of contact with a surface at lower temperatures, there will be condensation, which will result in water droplets that will help dust particles stick to the solar panels due to capillary forces [27-28]. Additionally, approximately 40%–80% relative humidity increases adhesion between the water droplets and dust particles close to 80% [29]. This indicates that relative humidity increases the likelihood of dust particles gathering on to the surface of solar panels. As a result, the only way to solve such an issue would be through continuous cleaning of a module over time [30]. Research on the effect of dust on solar panel performance when considering both temperature and relative humidity was performed in Qatar for two years. Results showed that there was close to a 50% degradation of power because of an eight-month exposure of the solar panel to the open environment without any cleaning [31-32]. In fact, research on the seasonal effect of dust deposition on PV performance in the UAE showed that the glass transmittance reduction is higher during summer and approximately 10% and 6% during the winter [33]. In addition to that, 70% of the efficiency degradation was recorded when the module was not cleaned for over a year [33].

2.3. Cleaning Methods

The current existing technologies around the world vary in their method of cleaning solar panels and, with it, the cost associated with its overall operation and maintenance. The benefits and drawbacks of each type of cleaning method as well asan overview of some of the most common cleaning techniques are discussed in this section.

2.3.1. Manual cleaning method. This method requires a human to manually clean the surface of a solar panel using either a mop or using wipers with or without any sort of support. In this cleaning technique, the quality of the cleaning surface depends highly upon the visual judgment of an individual. The likelihood of all the dust particles being removed from the surface of the solar panel depends on the person cleaning to notice if the panel is dust-free or not. In this case, the cleaning process is generally categorized as being extremely challenging and tedious especially in solar plants where the solar panels are installed at a certain height. Consequently, manual cleaning is labeled as not only being tough to operate but also extremely time-consuming due to the need for a worker to go to every single solar panel and clean every part of it. At the same time, given that certain solar panels might be installed at heights, there is also the risk of laborers hurting themselves during the cleaning process in the case of climbing up or down a structure [34]. When specifically discussing the cleaning method, the person cleaning the solar panel simply uses a cleaning fluid, often a gel-like substance that is rubbed on the surface of the solar panel along with water. However, the drawback of continuously rubbing the surface of the solar panel is the damage that can be caused by continuous cleaning over an extended period of time and the likelihood of the surface transparency to reduce if the cleaning process is not optimal. Consequently, there is also the risk of physical damage occurring on the solar panel [35].

2.3.2. Vacuum suction cleaning method. Another common cleaning process is the vacuum suction cleaning process where a device is used to create a small vacuum that can suck dirt and dust. The general purpose of this device was to clean floors, window panes, and related equipment and so its introduction in the field of cleaning solar panels has reaped many benefits. Firstly, there is no use of water, which makes this cleaning technique extremely attractive from a resource point of view as water is a resource that is generally not desired to use unless necessary for cleaning. Also, when discussing the cleaning device itself, the vacuum cleaning motor operates off of a battery and a motor, which helps create the suction pressure required to remove dust and dirt off of the surface of a solar panel [36]. However, a downside of this cleaning process is the fact that while dust can be eliminated from the general surface of the solar panel, the accumulated dust in the sides and corners of the solar panel is extremely difficult to get rid of. With continuous dust accumulating at the corners or sides of a solar panel, this could prove to be problematic as it could cause more dust to accumulate, hence cleaning occurring more often, and a higher cost for labor to clean the solar panels. Therefore, there is a need to properly use the device and to tilt it in ways to get as much dust off of the surface of the solar panel as possible. Another downside to this cleaning process is the possibility of causing scratches on the surface of the solar panel as large scratches can impact the effectiveness of the absorption of solar energy in a solar panel as the panel itself could be damaged [36].

2.3.3. Automatic wiper based cleaning method. The automatic wiper-based cleaning method is another popular cleaning technology that has been implemented in some places around the world. This simply consists of the use of a rubber wiper and water, along with a spray for the water, so that cleaning can be performed. The overall cleaning process resembles the cleaning method for the front glass in a vehicle where an automatic mechanism is used to operate the task. However, in this case, the wipers are connecting not at the bottom but on one side of the solar panel and they simply glide and clean the solar panel while brushing off and cleaning off the air [37]. While this method is also battery powered like the vacuum cleaning method, it has a drawback where the use of water puts this technology at a disadvantage. While the wipers are generally going to be placed on either end of a row of solar panels connected together in a solar plant, the overall cleaning process might become tedious if there are several solar panels spread out or not necessarily attached together. As a result, the cleaning wipers would have to be attached and detached from the sides of the solar panel every time there would be a need for cleaning. In addition, when using water, there is always the risk of creating mud or small deposits of mud that, if not cleaned properly, would be more problematic than small dust particles on the surface of a solar panel [37].

2.3.4. Electrostatic precipitator cleaning method. One of the most upcoming and effective cleaning methods is the electrostatic precipitator (EP) cleaning method. Considering that the previously mentioned cleaning methods have the likelihood of causing a solar panel mechanical damage, scratches on its surface, possible mud formation, and even possible dust deposits on the sides of the solar panel from the cleaning, this method is completely non-contact. Based primarily off of electrostatic charges, this cleaning method is unique in the sense that there is no contact being made with the surface of the solar panel. Essentially, the EP cleaning method is able to effectively clean and protect the surface of a solar panel while protecting it from any physical damage that other cleaning methods are at risk of causing. Overall, this cleaning process is a device that pushes off the dust particles available on the surface of the solar panel through a force that is induced from an electrostatic charge. Small transparent electrodes that are placed on the solar panels obtain a signal generally from an Arduino controlled signal once the microcontroller obtains information regarding a change in weight of the solar panel itself [38]. As accumulated dust can be identified through the weight it causes a solar panel to increase by, the Arduino sends a signal to the electrostatic precipitators to induce a negative charge on the dust particles that are on the surface of the solar panel. After that, the dust particles are gathered at the positive electrode after they are attracted to it and they are then pushed away and off the surface of the solar panel. Consequently, without using any water or contact in any way, the EP cleaning method is one of the most effective and harmless methods of cleaning a solar panel for optimal cleaning results [38].

2.4. Related Work

When it comes to related work, the modeling of PV and dust accumulation has been carried out through numerous techniques depending on the complexity of the model and the assumptions made. When it comes to modeling PV energy production alone, it has often been performed by clustering daily values of solar irradiance together or by using monthly-hourly data to guarantee greater precision [39]. In most research cases, solar irradiance is generally modeled statistically as a beta distribution [40]. At the same time, other research has modeled global solar irradiance through exponential, Weibull, gamma, normal, log normal, beta, or geometric distributions [41-42].

Some models have taken into consideration the importance of temperature and how it impacts temperature where mean temperature data is used. Those models are based on Monte Carlo simulations (MCS) and they take into consideration the random behavior of solar irradiance with historical mean temperature data [43-44]. However, there is a lack of modeling temperature from a probabilistic perspective, which makes this approach less accurate. Other models have used solar irradiance and air temperature data for short-term forecasting using a power probability density function (PDF) that is based on a Bayesian autoregressive time-series (BATS) model [45]. Such a model relies on predicting the clearness index and an MCS for the power distribution function when it came to the random sampling associated with the clearness index [46]. The downfall to this approach is that the likelihood of error due to representing power through the nonlinear relationship between the clearness index and power is high.

However, an accurate model of PVs cannot be done without taking into consideration the numerous weather factors that impact it and, specifically, dust accumulation. A common way of modeling dust accumulation levels, as seen in [47], is by directly looking at the PV output and, using historical data, predicting the level of dust that accumulates on the surface of the panel based on losses. Other models rely on MCS for stochastically generating possible soiling profiles on a daily basis for a specific length of time [48]. In addition, some research recommends the use of a fixed rate precipitation estimate to calculate dust accumulation as it depends on soiling rate, cleaning threshold, and refractory periods of time [49]. Dust accumulation modeling has also been performed using particulate matter concentration values like in [50-51] where a specific particulate matter could help predict future precipitation patterns using historical data. Particulate matter and the period in, which the climate is dry have been seen as two variables most affecting soiling rates [52-53]. In such studies, the correlation of particulate matter concentration and soiling desperation rates often exists but not in other climate conditions.

PV yield can also be used to model dust accumulation and PV soiling loss as in [54] using the stochastic rate and recovery (SSR) method, which is based on a Monte Carlo simulation. However, this method lacks the use of historical precipitation data, which makes this method less reliable when considering the behavior of dust in reality. Dust accumulation rates along with soiling rates have also been modeling in [55] as the slope of the daily soiling ratio using the Theil-Sen estimator assuming a dry period of at least 14 days. While this model is more accurate than using a least-squared regression model, it fails to take precipitation into account. Another model discussed in [56] that models PV and dust accumulation based on soiling rates is the Fixed Rate Precipitation (FRP) model where it extracts a daily soiling profile from a PV assuming that the soiling rate is fixed between rainfall events. However, the rate of dust accumulation is never fixed as the weather variables surrounding the PV at any time can either increase or decrease the rate of dust accumulation that occurs.

Overall, while the modeling of dust as a constant factor may fit certain research criteria, a more realistic approach would be to model dust as a variable that changes in terms of time when considering PV loss. In models like [57] and [58], dust is considered as a constant that does not vary with time. However, a more accurate model of dust and its impact on PV performance would be to vary dust based on time. Models of dust behavior in [59] suggest that dust accumulation increases and eventually after reaching a certain dust level, the accumulation rate decreases. Only through cleaning a solar panel manually, automatically, or through weather factors such as rain can a panel's dust level on its surface decrease. While certain models like [60] relied upon particulate matter (PM) concentrations, namely PM10 and PM2.5, there are far more weather factors like rain, wind speed, relative humidity, and much more that must be taken into consideration. Other models in [61] relied more on the static settling velocity (SSV) of dust particles along with the angle of inclination of the PV panel to model dust accumulation. While both of those factors are significant in modeling dust, those models have not been tried in drier climates where rain, which is a major influencing factor for the SSV, is less frequent. Moreover, dust particle sizes vary depending upon the geographical location of the PV and more test locations would have to be tried out to further verify the accuracy of these models [62].

Consequently, there is a lack of literature on the modeling of dust accumulation and its corresponding losses on PV performance as a function of time. Dust accumulation cannot accurately be modeled as a static carriable as its value increases or decreases with time depending mainly upon numerous weather variables. The absence of such an approach facilitates the need to model dust in terms of time, preferably per hour to get more accurate results so that soiling loss can more accurately be modeled.

Chapter 3. Proposed Model

In this chapter, we will discuss the proposed model shown in Figure 3.1 that has three stages and uses historical data related to the behavior of solar irradiance, temperature, and rate of dust accumulation. The first stage is the data acquisition and processing stage where the raw data is discretized and categorized in a unique way. This would allow it to be inputted into the second stage, which is where the Markov chain model is used. The third and final stage is the cumulative distribution function generation, which is generated using the probability mass function output of the Markov Chain simulation. The proposed model is then used to generate virtual scenarios.

3.1. Historical Input Data

The primary inputs to the proposed model shown in Figure 3.1 are the PV power measurements and climate data for N_y years of hourly historical data. This includes data regarding ambient temperature (T_{ambient}), solar irradiance (SI), dust accumulation (D_{acc}), and rate of dust accumulation (RDA). Sample dataset values for SI, T_{ambient}, D_{acc}, can be seen in Appendix A. While other factors including wind speed, relative humidity, and precipitation are also valid weather variables to include, the data for dust accumulation would account for any changes in the previously mentioned three weather variables. Furthermore, RDA was calculated using the dust accumulation data by noting the change in dust levels at any given hour to the one succeeding it. Additionally, as the panels were initially clean, dust levels began at zero. At this point, we have four data sets, which include T_{ambient}, SI, D_{acc}, and RDA.

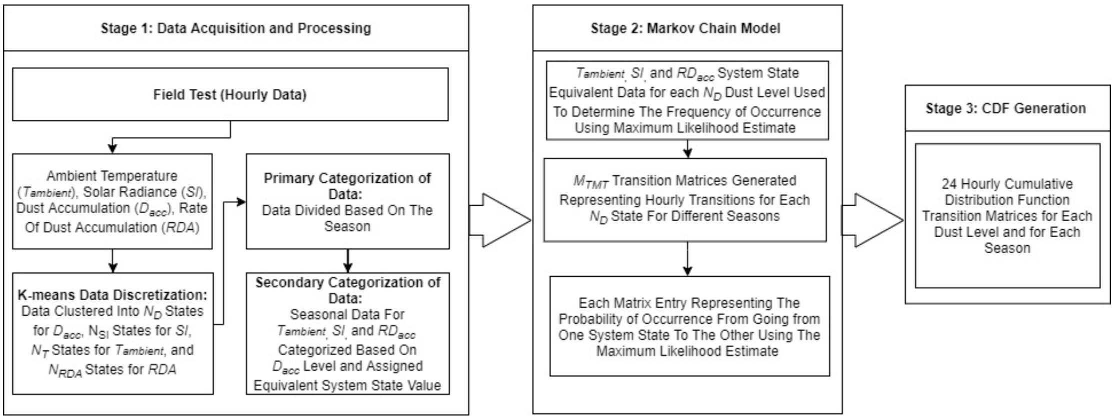

Figure 3.1: Overall System Model Flowchart

3.2. Stage 1: Data Acquisition and Processing

To analyze and use the hourly data for a set number of years, N_y, the discretization of each datapoint was necessary so that it could then be used in the Markov chain model. Consequently, the most efficient way to discretize the data and cluster them based on the centroids was using the k-means clustering algorithm, which is based on the squared error function in (1).

$$\underset{S}{\arg\min} = \sum_{i=1}^{k} \sum_{x \in S_i} || x - \mu_i ||^2 \tag{1}$$

Assuming there is a set of data from $x_1, x_2, \ldots x_n$, then the k-means clustering partitions the *n* observations into k sets $S = \{S_1, S_2, \ldots, S_k\}$ where μ_i is the mean of points in S_i. To model the weather variables accurately, the data was discretized and clustered into N_D different states, which is the number of dust accumulation states. Each of the weather variables used in the Markov chain have a varying number of states into which they are clustered to make the simulation more realistic. In this model, N_{RDA} is the number of states for the rate of dust accumulation, N_{SI} is the number of states for solar irradiance, and N_T is the number of states for temperature. By increasing the number of states that the data is clustered into, the level of complexity of the simulation increases and it becomes more realistic. The four data sets of T_{ambient}, SI, D_{acc}, and RDA were then discretized and after that the primary and secondary categorization is performed as follows

3.2.1. Primary categorization. The four data sets are then categorized according to the season such that the model could account for seasonal differences in weather variables. Each data set is categorized as follows. The T_{ambient} data set is organized in matrix $T = [\,T_{i,h}]$, the SI data set in matrix $SI = [\,SI_{i,h}]$, the D_{acc} data set in matrix $D = \left[\,D_{i,h}\right]$, and the RDA data set in matrix $RDA = [\,RDA_{i,h}]$. The element of each of the matrices is based on $i \in \mathcal{I}$, where i is the days in the original data and $\mathcal{I}$ is the original data set, and h, which is the hour of the day that ranges from 1 to 24. When categorizing these data sets further according to the four seasons, the T_{ambient} seasonal data is organized in matrix $T^s = [\,T^s_{i,h}]$, the SI data set in matrix $SI^s = [\,SI^s_{i,h}]$, the D_{acc} data set in matrix $D^s = \left[\,D^s_{i,h}\right]$, and the RDA data set in matrix $RDA^s = [\,RDA^s_{i,h}]$. In this case, sample $i \in \mathcal{I}_s \subset \mathcal{I}$, where $\mathcal{I}_s$ is the seasonal data and is

$90 \times N_y$ and s represents the seasons ranging from 1 to 4. At this point, there are a total of 16×24 data sets in total and 4×24 data sets for each season.

3.2.2. Secondary categorization. The seasonal data sets T_{ambient}, SI, and RDA are then categorized further to N_{D} groups, as shown in Figure 3.2, based on the dust level in the first hour of the day assuming that the dust level would not change for the rest of the day. By doing this, the T_{ambient} seasonal data would then be represented in matrix $T^{s,d} = [\, T_{i,h}^{s,d}]$, the SI data set in matrix $SI^{s,d} = [\, SI_{i,h}^{s,d}]$, and the RDA data set in matrix $RDA^{s,d} = [\, RDA_{i,h}^{s,d}]$. As previously mentioned, sample $i \in \mathcal{I}_s \subset \mathcal{I}$ and would represent the number of days, h would represent the number of hours from 1 till 24, s would represent the seasons from 1 till 4 and d would represent the dust level from 1 till N_D. At this point, there are $12 \times N_D$ data sets and $3 \times N_D$ data sets per season.

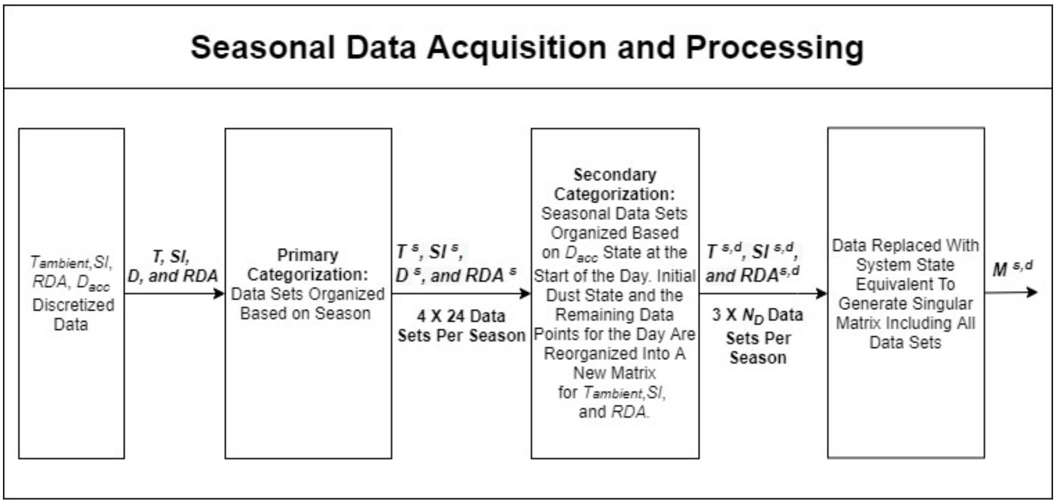

Figure 3.2: Seasonal Data Organization

In other words, for any day i in season s, the T_{ambient}, SI, and RDA are categorized together if the dust level in the first hour of day i for that season matches the dust level in the D^s matrix. If so, the data elements of the first hour and the following 24 data point from matrices T^s, SI^s, and RDA^s are categorized together to form matrices $T^{s,d}$, $SI^{s,d}$, and $RDA^{s,d}$, respectively. In total, 25 data points were taken with the first 24 data points representing the day in focus and the first hour of the following day is the 25th data point that will be used in the next stage.

To analyze all the data together and not separately as three different matrices, it was important to put all the data under a single matrix. Hence to generate an overall multi-state model, the three variables affecting the PV are combined into one matrix $M^{s,d} = [M_{i,h}^{s,d}]$. Each element of matrix $M^{s,d}$ is composed of an element from each of the matrices $T^{s,d}$, $SI^{s,d}$, and $RDA^{s,d}$. The three matrix elements are then replaced with an equivalent system state value and stored in a single element in $M^{s,d}$. The total number of system states that describe all possible conditions should be

$$N_{\mathrm{SYS}} = N_{\mathrm{SI}} \times N_{\mathrm{T}} \times N_{\mathrm{RDA}} \tag{2}$$

Each data point would hold a value from $1, \dots, N_{\mathrm{SYS}}$ that would correspond to a specific state for N_{SI}, N_{T}, and N_{RDA}. By doing so, the N_{v} different weather variables, in this case four, could later be analyzed inside a single matrix. We assume there is no correlation between these random variables occurring at a certain hour of a certain season at the same dust level.

3.3. Stage 2: Markov Chain Model

While there are numerous stochastic modeling techniques used in research for PV modeling forecasting, one of the most common is the Markov chain model. While every forecasting model has its own advantages in solving complex real-world problems, the Markov process is commonly used when modeling dynamic stochastic systems and the state transitions that exist in complex stochastic systems. A Markov chain model is a discrete-time stochastic process that models how a random variable change at discrete points of time. The Markov chain model has therefore been employed in this thesis to model the behavior of numerous weather factors and their impact on dust accumulation to analyze the performance of a PV.

The discrete-time Markov chain $M(t)$ is a discrete time stochastic process based on the idea that each time step t is occupied by one state E_{μ} in a series of states defined as $E_1, \ldots, E_N$. Each of those states is defined stochastically on the basis of only the previous state and this satisfies the *Markov property.* In other words, the probability distribution of any state at any time step of $t + 1$ is dependent on the state t and not dependent upon the previous states that lead to the state at time t. More importantly, the state transition that occurs between time step t and $t + 1$ is independent of time. The time steps involved in the entire process can be defined from $t = 1, \dots, T$ with $\mu = 1, \dots, N$ representing the index of which state the Markov chain is in. After that, the transition matrices must be generated. As the Markov process moves from time step t

to the next time step at $t + 1$, the state of the process at time $t + 1$ can be determined from the state at time step t using the transition probabilities given as

$$P_{\mu v}(t) \equiv Prob\ (X_{t+1} = E_v\ |X_t = E_\mu) \tag{3}$$

It is important to note that (3) satisfies the Markov property that the state at any time instant $t + 1$ is only dependent on the state at time t. Using this, the transition matrices P, which are square matrices, can be generated with dimension $N \times N$. For each N_D for dust accumulation, there are 24 different Markov transition matrices with each matrix representing the transition from a specific hour of the day to the following hour. As there are now 24 transition matrices for each dust level for each season, the total number of Markov transition matrices, M_{TMT}, can be calculated from the following

$$M_{TMT} = 24 \times 4 \times N_D \tag{4}$$

The transition matrices each have dimensions $N_{SYS} \times N_{SYS}$, with the columns and rows representing the different system map values. Each element with the transition matrix P represents the probability of state v occurring at time slot $t + 1$ given that the previous state at time slot t is considered as μ. The way the probabilities for each matrix value were calculated using the maximum likelihood M_L can be expanded to reach

$$M_L = \frac{n_{\mu v}}{\sum_p n_{\mu p}} \tag{5}$$

where $n_{\mu v}$ is the number of transitions from state μ at the time instance t till time instance $t + 1$. The maximum likelihood estimate is used to calculate the probability that is the frequency of occurrences divided by the total number of possible occurrences. To guarantee that each transition matrix was calculated accurately, the sum of each row for the transition matrices had be equal to 1 as it is an important characteristic of the Markov model.

3.4. Stage 3: Cumulative Distribution Function Generation

Using the transition probability matrices, the cumulative distribution function (CDF) could be created that would later be used for generating virtual scenarios. The CDF of a random variable X, when plotted, would form a staircase plot with the CDF of any random variable flat between x_k and x_{k+1}. The probability mass function (PMF), which is the data from the Markov transition matrices, is used to develop the CDF F_X as follows: Using (6), the CDF of the Markov transition matrices can be determined.

$$F_X(x) = \sum_{x_k \leq x} P_X(x_k) \tag{6}$$

3.5. Virtual Scenarios Generation

With the transition matrix CDF’s created, the next step was to create virtual scenarios to accurately understand the behavior of dust accumulation as seen in Figure 3.3. Assuming there are $N_{scenarios}$ that are to be modeled, the dimensions of the virtual scenarios matrix will be 8760 × $N_{scenarios}$ with the columns representing each hour of the day for a complete year. It is important to note that the first column of the virtual scenarios matrix will be calculated differently than the rest of the columns as it is not based on any previous information from any hour before that first day. Therefore, for the first hour of the first day for each row of the virtual scenario matrix, the initial data was converted into a transition matrix without any separation based on correlating it with any level of dust accumulation. After that is done, it is also converted into the system map that is then systematically placed as the first column of the virtual scenario matrix.

With the first column of the virtual scenario calculated, the remaining parts of the virtual scenarios were calculated with the information from the transition matrix CDF’s and the first column of the virtual scenario matrix. Depending upon the value of the first number in the first column of the virtual scenario matrix, the corresponding row for the transition matrix CDF for hour 1 to hour 2 would be focused on. After that, a uniformly distributed random number between 0 and 1 was generated and depending upon that value, the corresponding two numbers around that uniformly distributed random number is selected. For every uniformly distributed random number, there will be a number less than and greater than it in the transition matrix CDF. Between the two numbers, the number that is greater than it is chosen and selected as the second row value in the second column of the virtual scenario matrix. This is because the values in the second column represent the transition from hour one to hour two of the first day that is virtually generated. A similar process is followed for the remaining hours of the day and for every hour of each day for the year. An important aspect of the virtual scenario design is also the implementation of a cleaning pattern within the virtual scenarios. Given the solar panels are cleaned every N_{clean} days throughout the year, the first column after the N_{clean} day uses information for the first, or otherwise, clean dust level that will correspond to the first dust state. As the dust accumulation, which is monitored as increasing throughout the virtual scenarios is studied, the corresponding transition matrix with a different dust level is chosen. After each hour of the virtual generation, the dust level is measured, using information from the rate of dust accumulation, to determine if the dust level has entered another category of dust states. If this occurs, a different hourly transition for a different dust state transition matrix is used to continue.

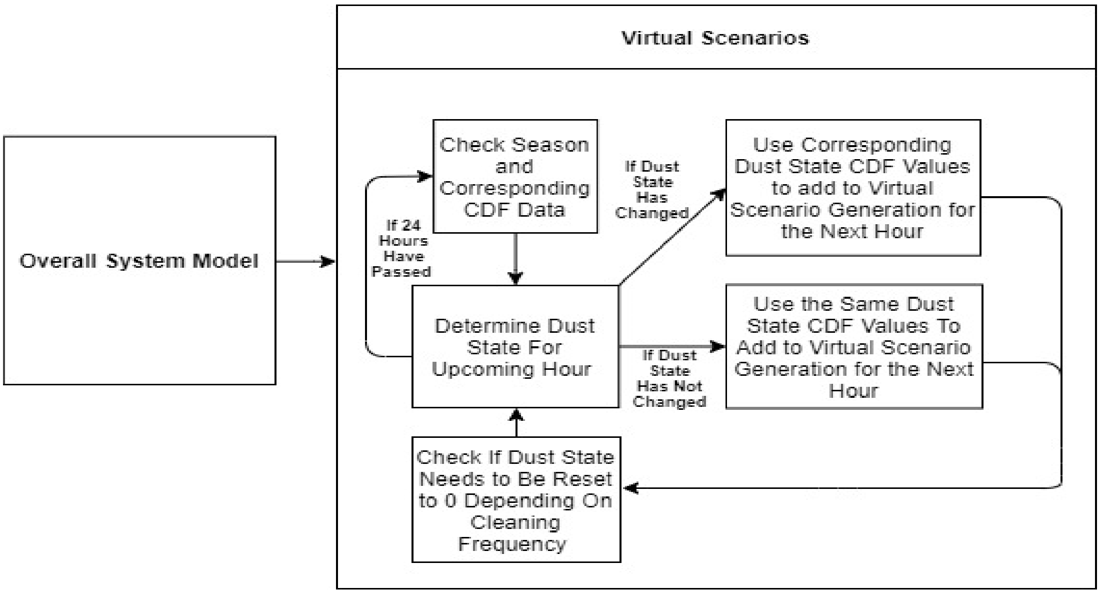

Figure 3.3: Output of Overall System Model: Virtual Scenarios.

Chapter 4. Power Profile Generation Mechanism

In this chapter, the model proposed in Chapter 3 is used to develop the power profile of a PV. To perform this, a relationship between dust accumulation and the power output was developed that was then applied to the virtual scenarios as seen in Figure 4.1.

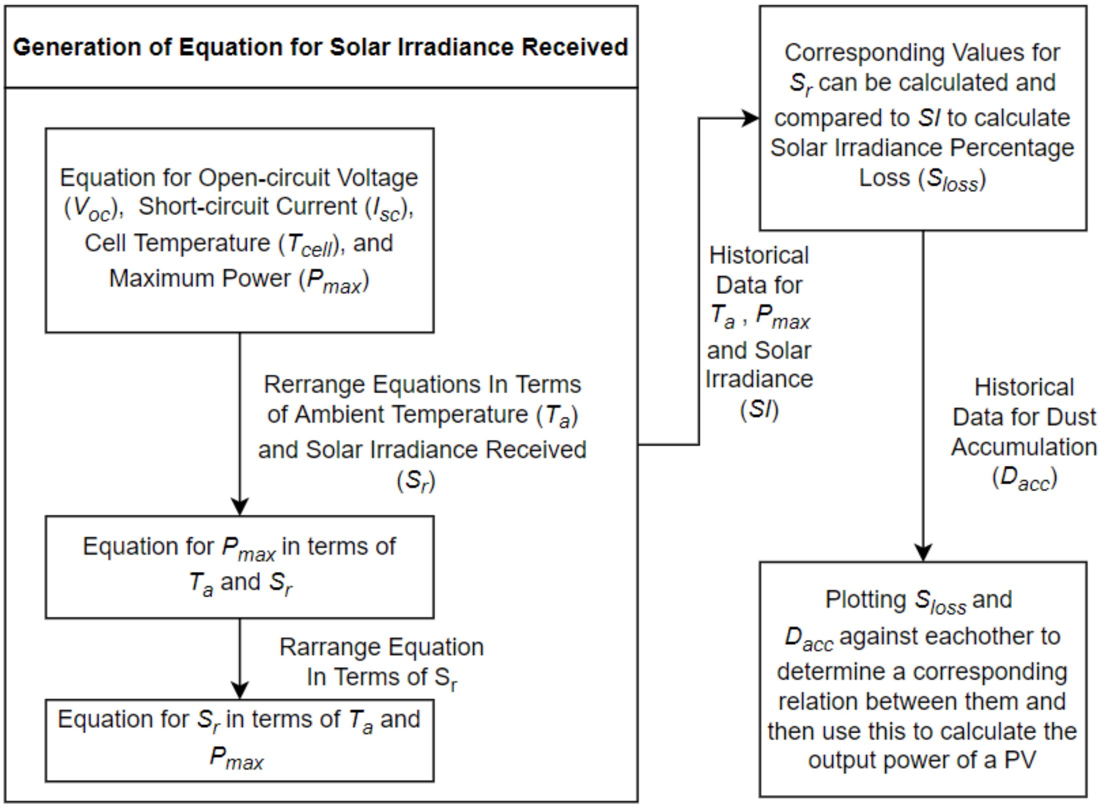

Figure 4.1: Relationship Between Dust Accumulation and Solar Irradiance Received Flowchart.

4.1. Proposed Mechanism

The virtual scenarios generate dust accumulation values that can be converted to the output power of a PV. To perform this, a relationship must be developed between dust accumulation and power output. Existing relations for the module short-circuit current (I_{sc}), module open-circuit voltage (V_{oc}), and the PV maximum power output ($P_{maximum}$) in [45] were modified and can be seen below.

$$I_{sc} = I_{sc_{stc}} \times \left(1 + K_{isc} \times (T_{cell} - T_{stc})\right) \times \frac{S_R}{S_{stc}} \tag{7}$$

$$V_{oc} = V_{oc_{stc}} \times \left(1 + K_{voc} \times (T_{cell} - T_{stc})\right) \tag{8}$$

$$T_{cell} = T_A + S_R \times (\frac{NOCT - T_{NOCT}}{S_{NOCT}}) \tag{9}$$

$$P_{max} = FF \times I_{sc} \times V_{oc} \times N_{PVModules} \tag{10}$$

where $I_{sc_{stc}}$ represents the short-circuit current at standard test conditions, K_{isc} the temperature coefficient for of I_{sc}, T_{cell} the temperature of the cell, T_{stc} the temperature at standard test conditions, S_R the solar irradiance received, S_{stc} the solar irradiance at standard test conditions, $V_{oc_{stc}}$ the open-circuit voltage at standard test conditions, K_v the temperature coefficient for V_{oc}, $NOCT$ the nominal operating cell temperature, T_{NOCT} the temperature at the nominal operating cell temperature, S_{NOCT} the solar irradiance at that specific nominal operating cell temperature, FF the fill factor, and $N_{PVModules}$ the number of PV modules. The temperature relation in (7) is integrated in (8) and (9) so that I_{sc} and V_{oc} would only be in terms of T_A and S_R. Then, the I_{sc} and for V_{oc} relations are substituted into (10), where the FF and $N_{PVModules}$ are also fixed variables, to determine P_{max} as seen below with C representing a constant that is generated during the re-arranging process.

$$P_{max} = {T_A}^2 \times S_R \times C \tag{11}$$

At this point, there is a single equation to calculate P_{max} that is only in terms of T_A and S_R. Therefore, (11) can now be rewritten to solve for S_R with T_A and P_{max} being required for it as seen below.

$$S_R = \frac{P_{max}}{{T_A}^2 \times C} \tag{12}$$

Using (12) and data from N_y years of historical data regarding T_A and P_{max}, S_R can be calculated. In this case, P_{max} would represent the power that the solar panel is generating over the course of N_y years of historical data. The reason this information is relevant is because solar panels generally have built-in methods to determine the ideal solar irradiance available at a certain time of the day. However, when considering the existence of dust, the solar irradiance absorbed by the solar panel is not what the reference cell on the solar panel would suggest as it would be less. Therefore, given

P_{max} generated by a solar panel and the corresponding T_A for N_y years of historical data, the actual S_R that is unknown can be determined. After determining what S_R is, it can be compared to S_{ideal}, the optimal solar irradiance assuming no dust from a reference cell, to determine solar irradiance percentage loss S_{loss}. S_{loss} can then be plotted versus dust accumulation for N_y years of historical data to determine a relationship between the two and can be seen in Figure 4.2.

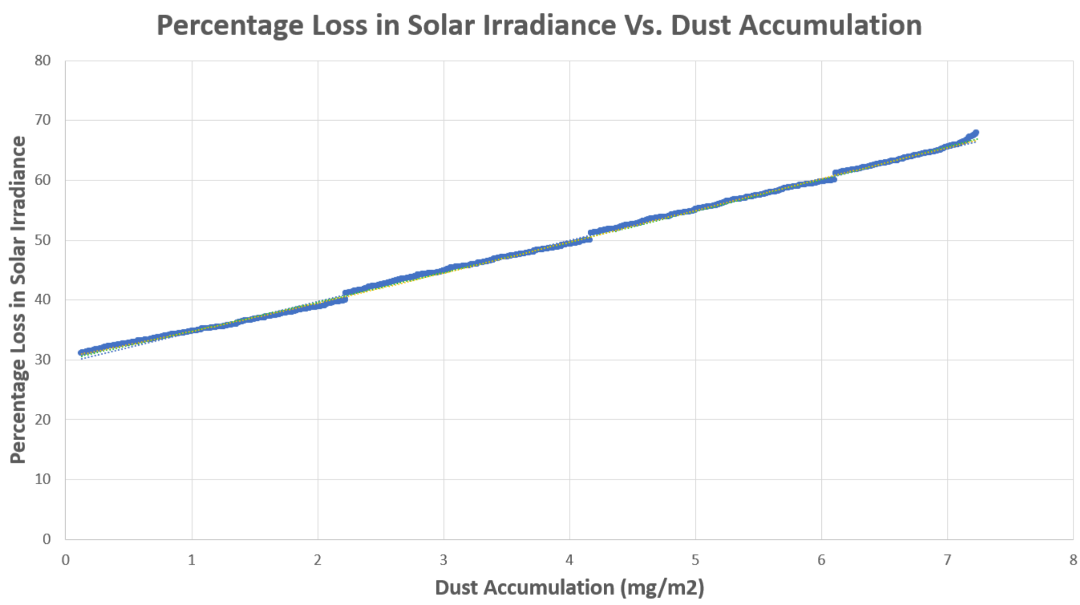

Figure 4.2: Percentage Loss in Solar Irradiance Versus Dust Accumulation.

As seen in Figure 4.2, as dust accumulation increases, the percentage loss in solar irradiance S_{loss} also increases. After determining the best fit curve to represent the relationship between S_{loss} and dust accumulation, which is through a quadratic equation, an overall relationship connecting dust accumulation and power output can be established. The implementation of this can be seen in Figure 4.3, Figure 4.4, Figure 4.5, and Figure 4.6 where the power output of a PV for N_y years of historical data across a year can be seen and is represented by P_{actual}. It is important to note that in this specific case, there is no cleaning done and dust is expected to accumulate naturally on the panel over time for the entire year. P_{ideal} represents solar panel power output assuming that it receives maximum solar irradiance with no dust, which is recorded by the reference cell on the panel and calculated using (7-10). Across the entire year, the average percentage difference is as high as 62.7% between P_{actual} and P_{ideal}.

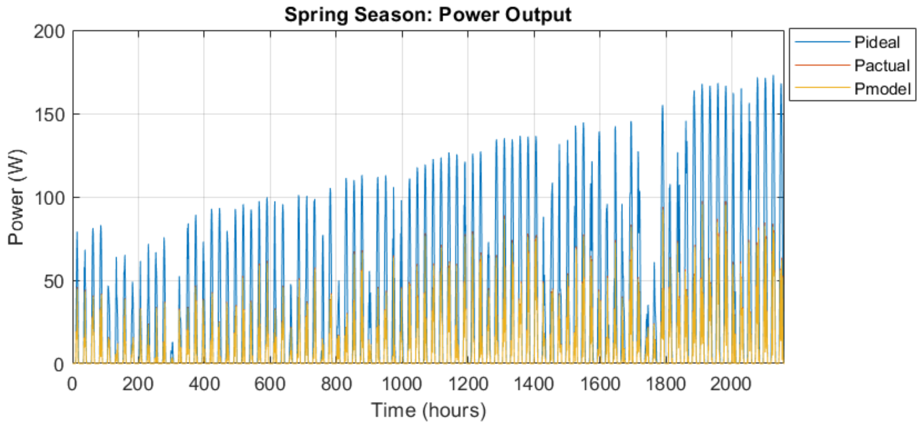

Figure 4.3: Power Output of Solar Panel Under Ideal, Actual, and Model Conditions During the Spring Season.

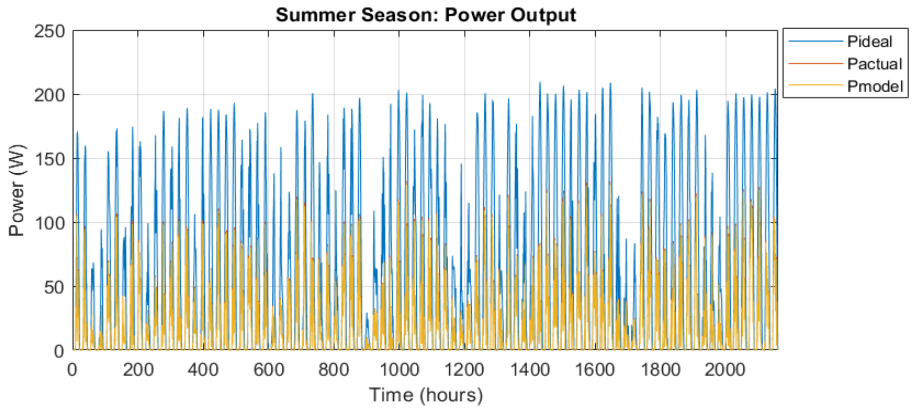

Figure 4.4: Power Output of Solar Panel Under Ideal, Actual, and Model Conditions During the Summer Season.

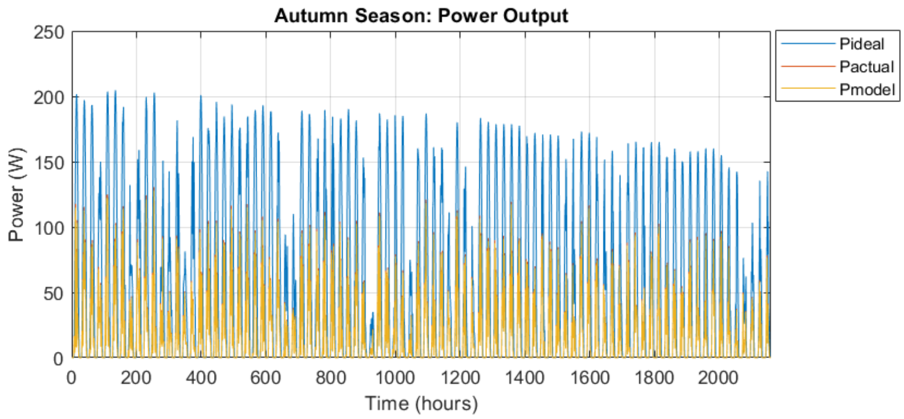

Figure 4.5: Power Output of Solar Panel Under Ideal, Actual, and Model Conditions During the Autumn Season.

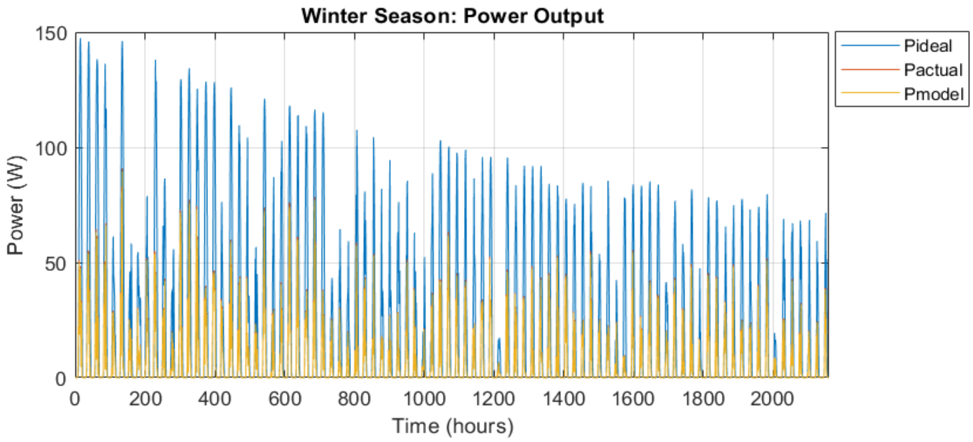

Figure 4.6: Power Output of Solar Panel Under Ideal, Actual, and Model Conditions During the Winter Season.

As expected, there is a huge difference between the actual power output of the panel and the ideal power output of the panel assuming no dust and no hindrance to overall solar irradiance. Now, using the relationship determined earlier between S_{loss} and dust accumulation, existing data for dust accumulation and maximum solar irradiance from the reference cell for the same panel can be used to determine S_{loss} for any data set. Using the calculated S_{loss}, S_R can be determined. Using S_R with T_A, P_{max} can then be calculated and is represented by P_{model} in the figure above. Across the entire year, the difference between P_{model} and P_{actual} is 2.08% and that highlights the accuracy of the relationships determined earlier between dust accumulation and S_{loss}. This also supports that overall relationship determined between dust accumulation and power output of a solar panel is also accurate.

Chapter 5. Results and Analysis

In this chapter, the simulation results achieved for the virtual scenarios generated is presented. An entire year with two different cleaning scenarios is studied and the dust accumulation for different seasons in the year is analyzed.

5.1. Simulation Results

The carried out investigated two seasons, summer and winter, while varying the cleaning frequencies. The reason summer and winter were chosen, as opposed to including spring and autumn, is that the weather variables in both of those seasons are close to completely opposite. Hence, a clear difference in the behavior of weather and, consequently, a difference in dust accumulation is hypothesized. The virtual scenarios that were generated were focused over a 90 day period that is close to a 3 month period that would account for a complete season. More specifically, the winter season was specified from 90 days after December 1 and the summer season would begin from 90 days after June 1. The five cleaning frequencies would range from cleaning every one week to cleaning every five weeks. With the summer season in focus, each of the five different cleaning frequencies spread over a 2160-hour time period, or 90 days, can be seen in Figure 5.1, Figure 5.2, Figure 5.3, Figure 5.4, and Figure 5.5. With PV panel cleaning occurring every week, the maximum the dust level reached was 6.0785 mg with an average dust accumulation of 1.9240 mg overall. For cleaning every two weeks, the maximum the dust level reached was 6.4206 mg with an average dust accumulation of 2.5347 mg. With cleaning every three weeks, the maximum dust level was 6.7535 mg and the average dust accumulation level was 2.5704 mg. Increasing the cleaning frequency to be every four weeks pushed the maximum dust level to be 7.0889 mg and the average dust level to be 2.7221 mg. Lastly, with a cleaning frequency of every five weeks, the maximum dust level was 7.9116 mg and the average dust accumulation level was 3.6672 mg.

Similarly, the results for simulating the winter season can be seen in Figure 5.6, Figure 5.7, Figure 5.8, Figure 5.9, and Figure 5.10. Once again, the cleaning frequency is varied while the maximum and average dust level is studied. With a cleaning frequency of every week, the maximum dust level reached was 2.7246 mg with an average dust accumulation level of 0.7839 mg.

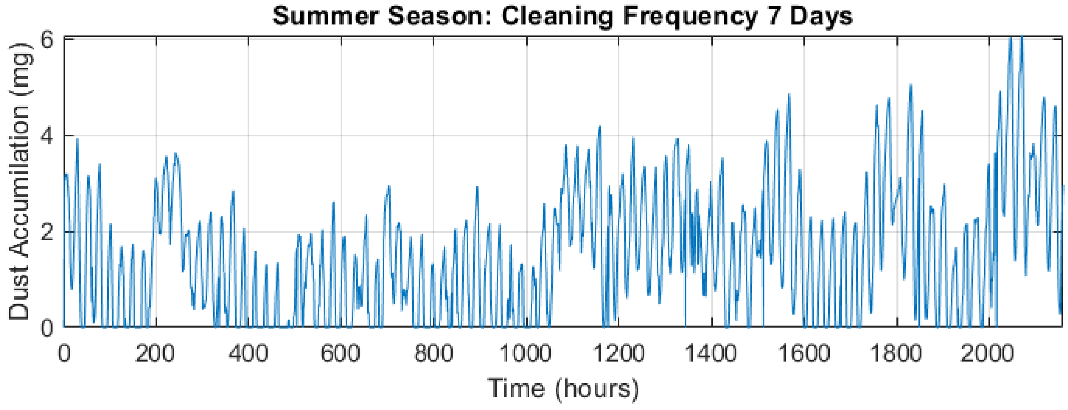

Figure 5.1: Virtually Generated Dust Accumulation on Solar Panels During the Summer Season with Cleaning Every 7 Days.

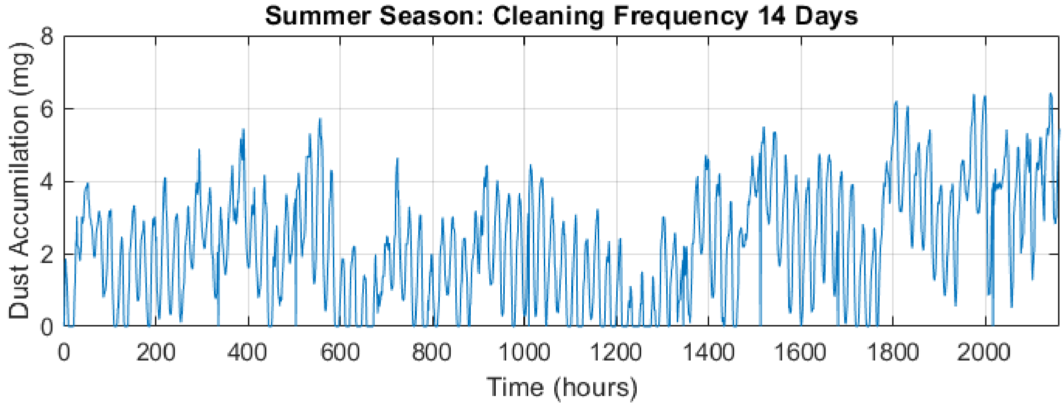

Figure 5.2: Virtually Generated Dust Accumulation on Solar Panels During the Summer Season with Cleaning Every 14 Days.

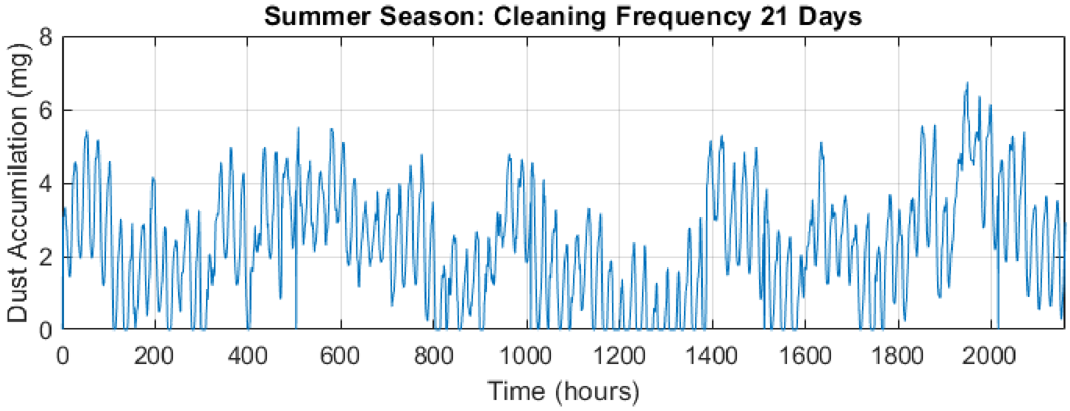

Figure 5.3: Virtually Generated Dust Accumulation on Solar Panels During the Summer Season with Cleaning Every 21 Days.

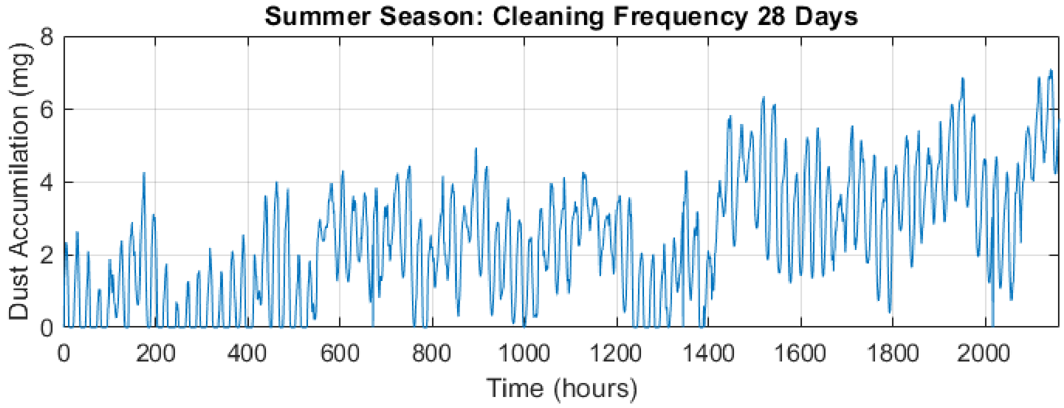

Figure 5.4: Virtually Generated Dust Accumulation on Solar Panels During the Summer Season with Cleaning Every 28 Days.

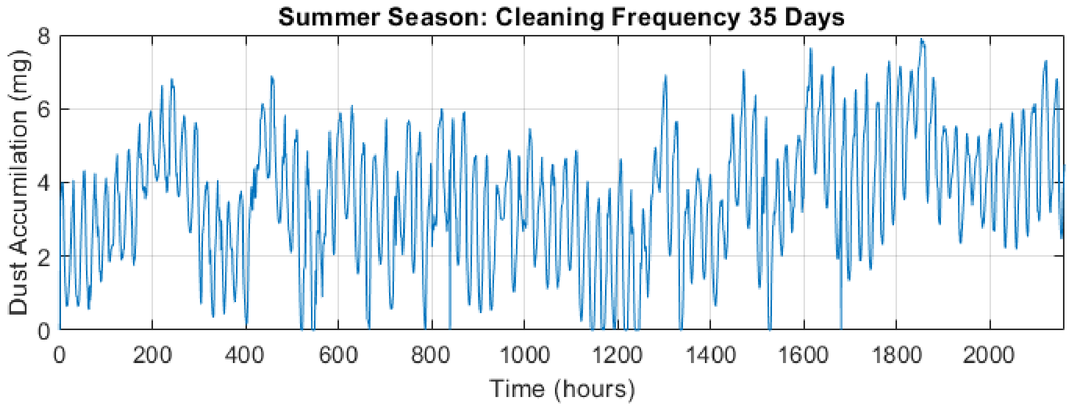

Figure 5.5: Virtually Generated Dust Accumulation on Solar Panels During the Summer Season with Cleaning Every 35 Days.

For cleaning occurring every two weeks, the maximum dust level reached was 3.2258 mg with an average dust accumulation level of 0.8267 mg. With a cleaning frequency of every three weeks, the maximum dust level increased to 4.1370 mg and the average dust accumulation level also increased to 1.2431 mg. Increasing the cleaning frequency by another week resulted in the dust level to remain fairly the same at 4.0536 mg with the average dust level also not changing significantly at 1.4115 mg. With cleaning every five weeks, the maximum dust level increased to 4.5734 mg and the average dust accumulation level increased slightly to 1.4792 mg.

A summary of the results for both the maximum and average dust levels across the summer and winter seasons for five different cleaning frequencies can be seen in Table 5.1 and Table 5.2 where the cleaning frequencies are compared.

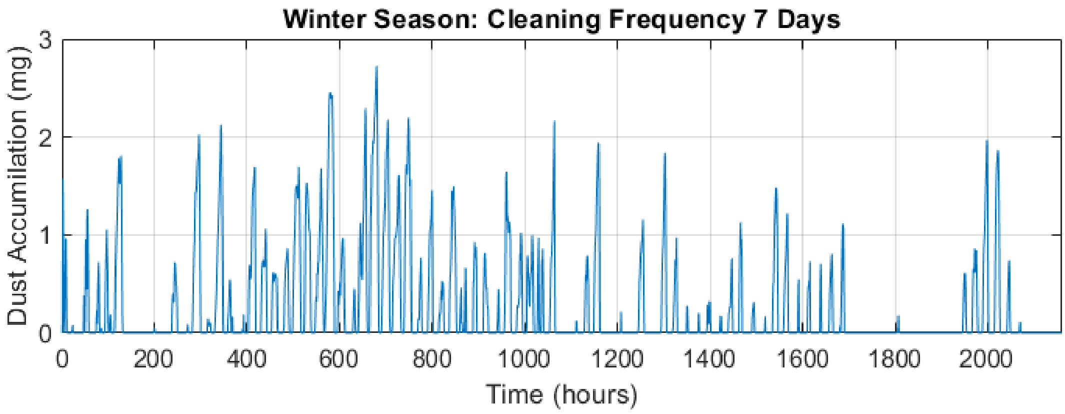

Figure 5.6: Virtually Generated Dust Accumulation on Solar Panels During the Winter Season with Cleaning Every 7 Days.

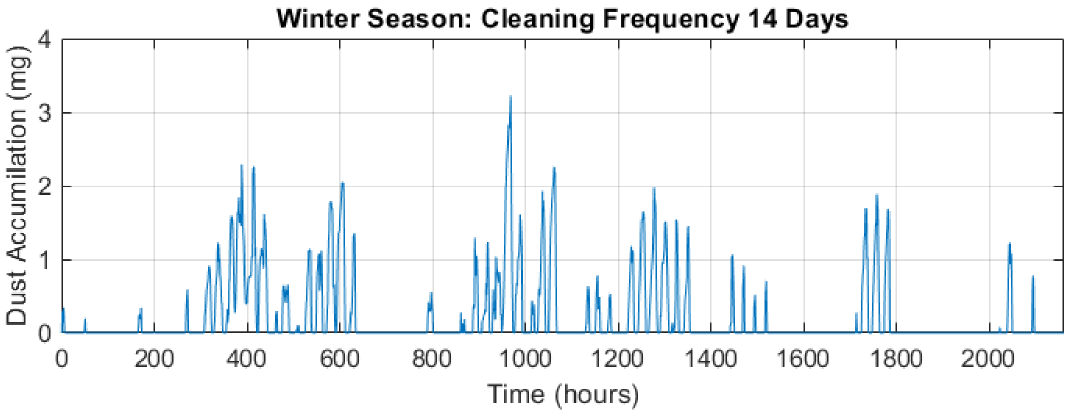

Figure 5.7: Virtually Generated Dust Accumulation on Solar Panels During the Winter Season with Cleaning Every 14 Days.

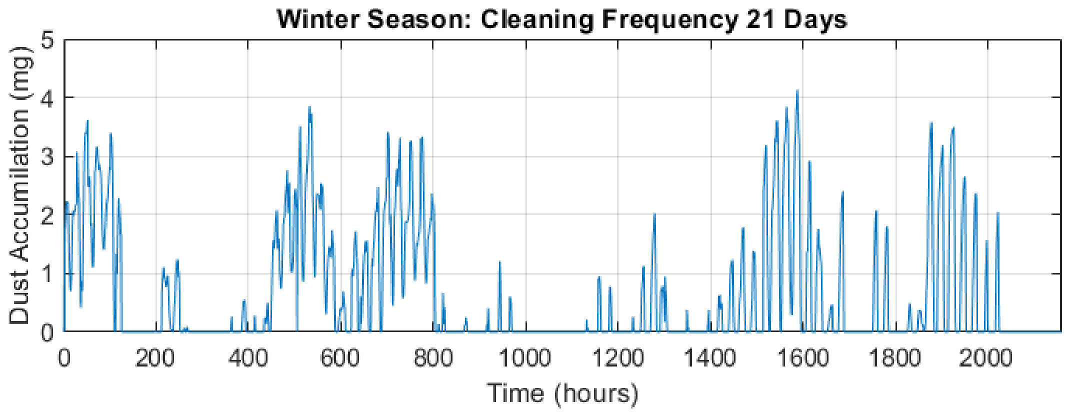

Figure 5.8: Virtually Generated Dust Accumulation on Solar Panels During the Winter Season with Cleaning Every 21 Days.

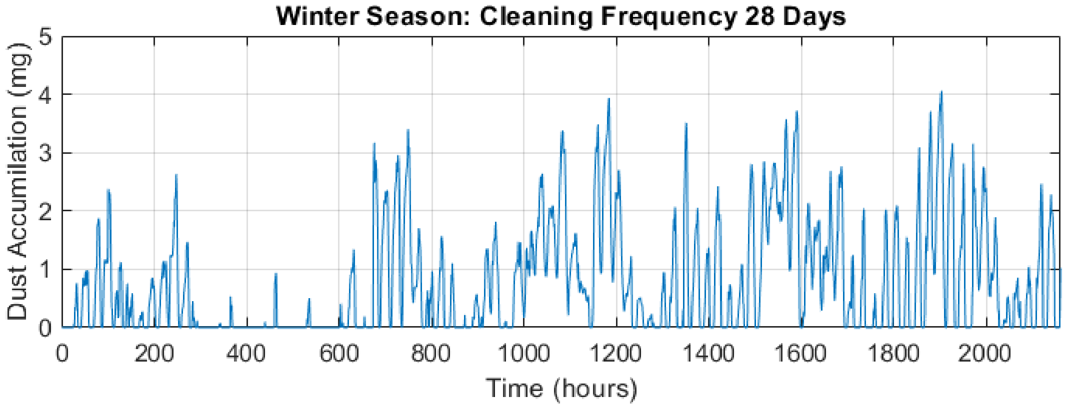

Figure 5.9: Virtually Generated Dust Accumulation on Solar Panels During the Winter Season with Cleaning Every 28 Days.

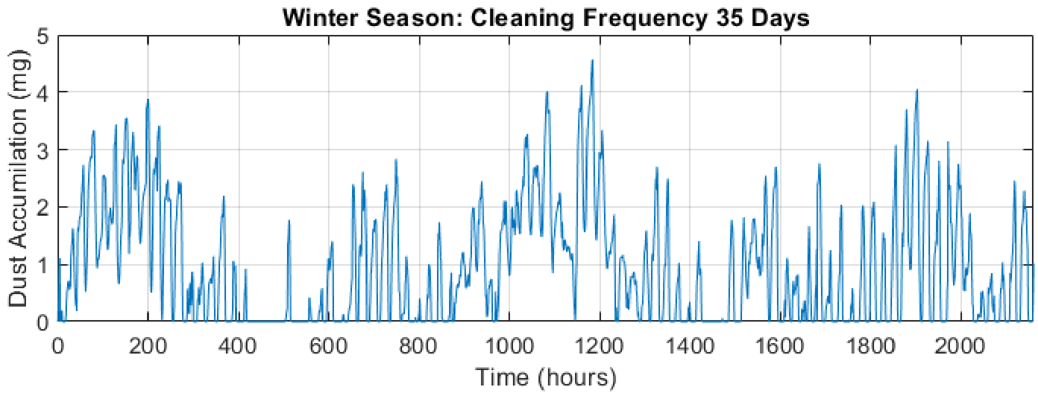

Figure 5.10: Virtually Generated Dust Accumulation on Solar Panels During the Winter Season with Cleaning Every 35 Days.

As seen when comparing the cleaning frequency of the summer season with the winter season, the need to clean in the summer season is far greater with dust levels reaching over 4 mg more than in winter seasons. With cleaning every 5 weeks, the levels of dust during the summer reached a peak level of 7.9116 mg where, during the winter months, cleaning ever 5 weeks reaches a maximum of 4.5734 mg. This indicates that the need for cleaning is far greater in the summer season as the rate of dust accumulation is very close to double during the warmest season of the year. When comparing the average dust levels for both seasons, similar results can also be seen. The summer season has an average dust level close to 3.6672 when cleaning occurs every five weeks while the winter season has an average level of 1.4115. Evidently, the average dust level is over double during the summer season than it is in the winter season, which indicates a far greater dust accumulation rate and a greater need for cleaning. When analyzing this further, it would take cleaning to occur every one week for the average dust level to drop close to the dust levels when cleaning occurs every five weeks in the winter season. If cleaning occurs every week in the summer, dust levels can drop significantly and the power losses that PVs face will be far less. In fact, the difference in the average dust level during the summer season for every week and every five weeks is 1.7432 mg. When comparing this to the winter season, the difference between the two extremes of cleaning frequency is less than half at 0.6276 mg. Evidently, there is a far greater benefit of cleaning every week in the summer than there is in the winter as dust accumulation levels would decrease by close to 2 mg on average and that will make a huge difference to overall PV performance. Consequently, cleaning does not have to occur anywhere near as frequently during the winter season as the difference in average dust levels is far less.

Table 5.1: Maximum Dust Levels Across the Summer and Winter Season for Five Different Cleaning Frequencies.

Cleaning Frequency	Summer	Winter
Every 7 Days	6.0785 mg	2.7246 mg
Every 14 Days	6.4206 mg	3.2258 mg
Every 21 Days	6.7535 mg	4.1370 mg
Every 28 Days	7.0889 mg	4.0536 mg
Every 35 Days	7.9116 mg	4.5734 mg

Table 5.2: Average Dust Levels Across the Summer and Winter Season for Five Different Cleaning Frequencies.

Cleaning Frequency	Summer	Winter
Every 7 Days	1.9240 mg	0.7839 mg
Every 14 Days	2.5347 mg	0.8267 mg
Every 21 Days	2.5704 mg	1.2431 mg
Every 28 Days	2.7221 mg	1.4115 mg
Every 35 Days	3.6672 mg	1.4792 mg

5.2. Model Validation

The virtual scenarios generated depict results for dust accumulation throughout the year that must be validated. To carry out the process of validating dust accumulation levels, the mean value of dust accumulation for each hour of each season was gathered from the virtual scenarios and the N_y years of historical data. It is important to note that the virtual scenarios generated were done assuming no cleaning was done throughout the year. This is because the existing N_y years of historical data is of dust accumulation with no cleaning. The mean values were then plotted together for an entire year and can be seen in Figure 5.11, Figure 5.12, Figure 5.13, and Figure 5.14 where there is a seasonal variance between the mean values of the levels of dust accumulation. An important observation is the large increase in dust accumulation levels between the seasons as is visible from the spring season to the summer season and other seasons.

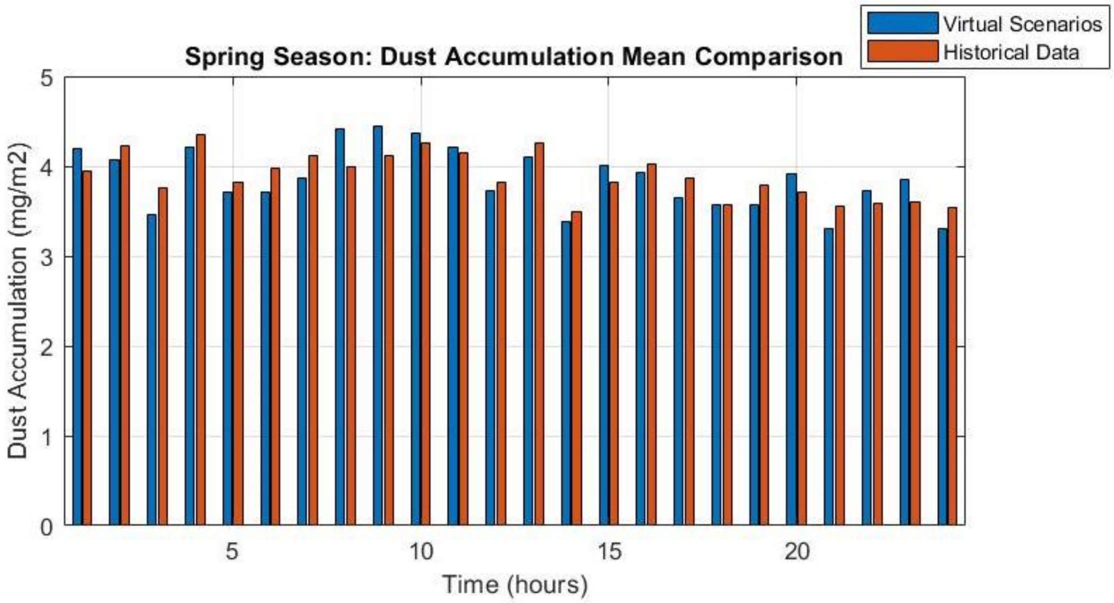

Figure 5.11: Dust Accumulation Mean Comparison for Spring Season

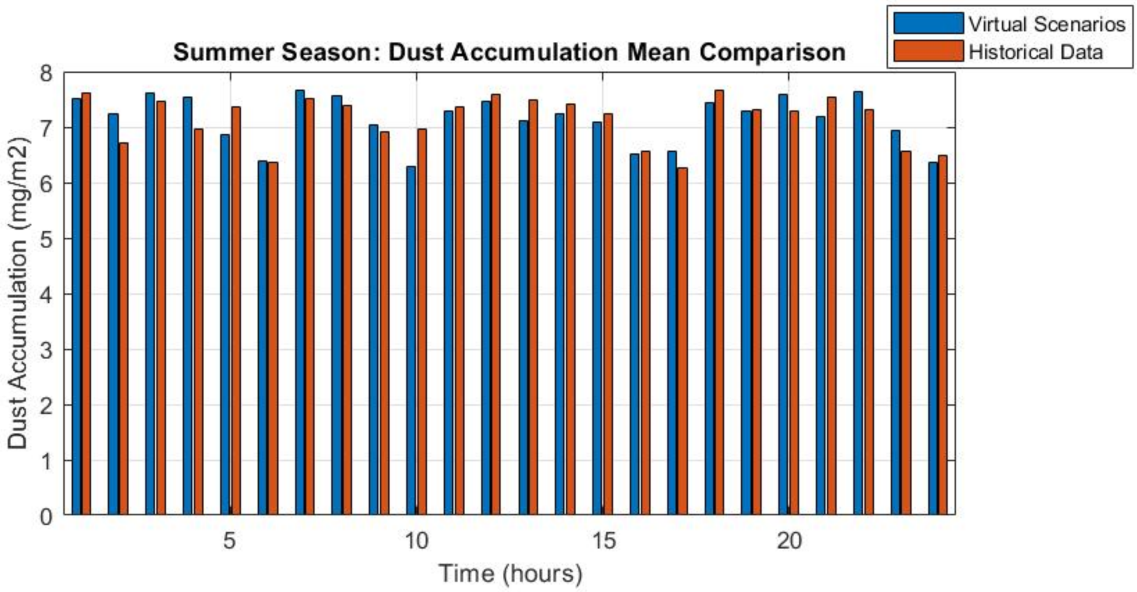

Figure 5.12: Dust Accumulation Mean Comparison for Summer Season

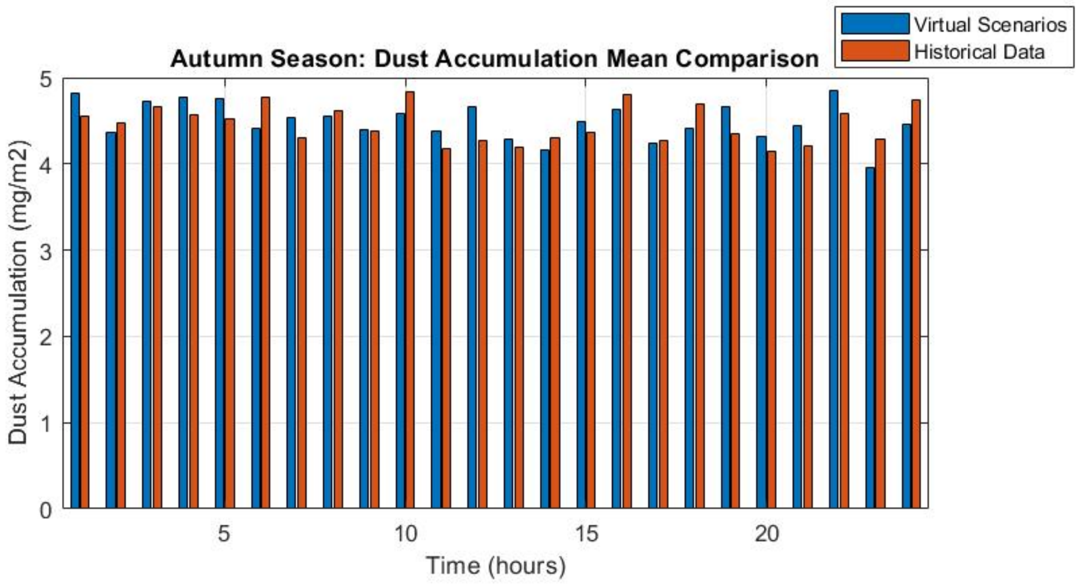

Figure 5.13: Dust Accumulation Mean Comparison for Autumn Season

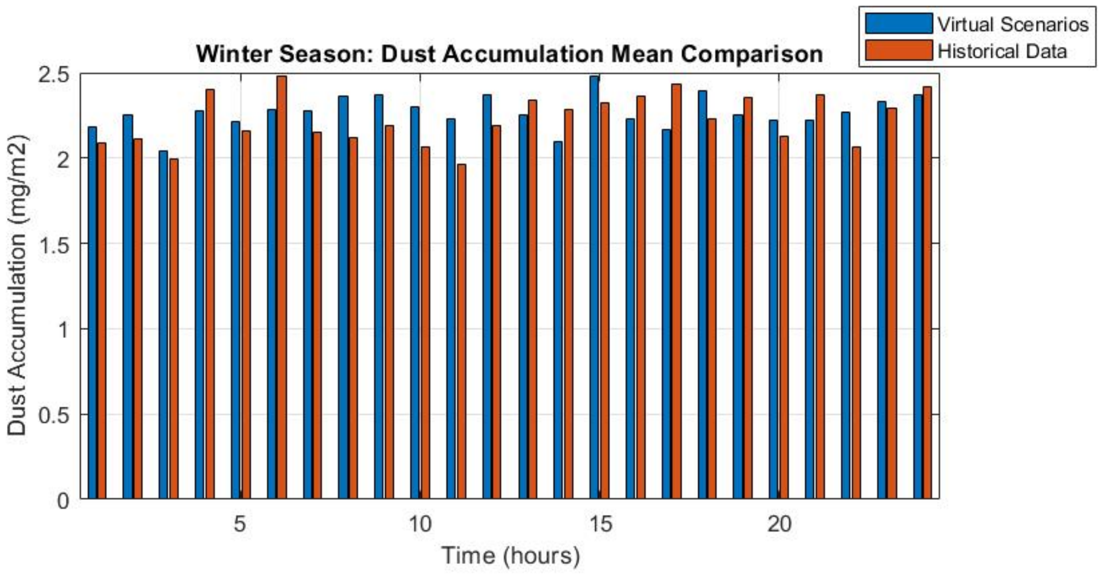

Figure 5.14: Dust Accumulation Mean Comparison for Winter Season

The reason behind this large increase is because the first hour of summer represents the mean value of dust accumulation for every first hour of the day over the entire season. In order to interpret the results of the mean values of dust accumulation for the virtual scenarios and the N_y years of historical data, the error percentage between the mean values was calculated for the entire year. Over the course of the year, the average error percentage was 4.57% and the maximum error percentage was 9.78% and that highlights the acceptable accuracy of the model.

5.3. Optimal Planning of Model

The proposed model can be implemented into a PV power plant of different sizes after which the financial benefits of using the model can be seen. To highlight these benefits, a case study was developed for a 100 MW PV power plant. The objective of this case study is to implement the model to understand what the recommended cleaning frequency would be in different seasons. As the virtual scenarios can be used to model what dust levels would be in different seasons and the corresponding output, the model was used to depict the output power of a 100MW PV plant under five different cleaning frequencies. Table 5.3 summarizes the parameters of the case study that were used to get a cost estimate.

Table 5.3: Parameters for Cleaning a 100 MW PV Power Plant.

Parameter	Value
Power Plant Size (MW)	100
Power Plant Area (m^2)	717,949
Module efficiency	14%
Cost of Water ($/liter)	0.0024
Water Consumption (liter/m^2)	0.5
Time to Clean 1 Panel (min)	0.5
Labor Rate ($/hr)	4.45
Cost of Other Materials ($/$m^2$)	0.0053
Capital Equipment ($)	90,000
Consumable & Maintenance Cost ($/hr)	7
Allocated Capital Cost ($/hr)	3.12
Automated Cleaning Rate (m^2/hr)	4460

5.3.1. Cleaning cost per cycle for different cleaning methods. The first step to calculating the cost estimate of cleaning was to determine the overall cost of a single cleaning cycle for the entire PV power plant based on the different cleaning methods. There were five different cleaning frequencies that included daily, weekly, biweekly, monthly, and no cleaning. The parameters that were varied in this case study was the cleaning frequency and the method of cleaning. In terms of the method of cleaning, there was automated and manual cleaning. All costs related to cleaning were acquired from an existing case study in [46]

Starting with manual cleaning, the cost of water, labor, and other materials was calculated to reach a total sum of $17,921 per cleaning cycle. It is important to note that in this calculation, there is no inclusion of any capital cost as this is not automated cleaning. For automated cleaning, costs were divided into either running or capital costs. With the running costs calculated first, the total automated running costs when including water, labor, and other materials is $2,344 while the automated total capital cost is $57,620

5.3.2. Levelized cleaning costs. To calculate the yearly cleaning cost depending on the different frequencies, the levelized cleaning cost of the different cleaning frequencies must first be calculated. To do that, the levelizing factor (LF) was first calculated using

$$LF = \left(\frac{(1+d')^{n_{loan}} - 1}{d'(1+d')^{n_{loan}}}\right) \times \left(\frac{d(1+d)^{n_{loan}}}{(1+d)^{n_{loan}} - 1}\right) \tag{13}$$

$$d' = \frac{d-e}{1+e} \tag{14}$$

where d represents the nominal discount rate without escalation which is 5%, e the escalation rate which is 1%, and n_{loan} the loan term which is 20 years. The LF can now be multiplied with the total cleaning cost per cycle for both cleaning types and with the cleaning frequency as well. The results of the levelized cleaning cost based on cleaning frequency for a year can be seen in Table 5.4 where the variance of cleaning frequency is observed for both the automated and the manual cleaning method that was analyzed earlier.

Table 5.4: Levelized Cleaning Cost Based on Cleaning Frequency.

Cleaning Frequency	Manual Cleaning	Automated Cleaning
Daily	$7,158,522	$994,074
Weekly	$1,019,844	$191,033
Biweekly	$509,922	$124,327
Monthly	$235,349	$88,408

As see in Table 5.4, the cost for using automated cleaning is far cheaper no matter what the cleaning frequency is. Consequently, only the automated cleaning option will be used in further calculations.

5.3.3. Cost analysis. The proposed model can now be implemented by varying the cleaning frequency while calculating the average energy as seen in Table 5.5.

Table 5.5: Average Energy in MWH for Different Seasons Depending on Cleaning Frequency.

Cleaning Frequency	Spring	Summer	Autumn	Winter
Daily	18,232	35,683	34,451	13,138
Weekly	16,562	32,193	30,943	11,860
Biweekly	15,419	30,642	29,276	11,203
Monthly	14,336	28,500	26,867	10,351
None	12,815	24,742	23,845	8,946

With the cost of electricity assumed set at $60 per MWh, the levelized annual per season can be calculated without any cleaning cost and can be seen in Table 5.6.

Table 5.6: Levelized Annual Per Season in US Dollars.

Cleaning Frequency	Spring	Summer	Autumn	Winter	Total
Daily	1,197,187	2,343,047	2,262,175	862,665	6,665,076
Weekly	1,087,494	2,113,939	2,031,824	778,766	6,012,025
Biweekly	1,012,487	2,012,075	1,922,365	735,654	5,682,583
Monthly	941,383	1,871,421	1,764,197	679,668	5,256,670
None	841,509	1,624,618	1,565,752	587,424	4,619,305

Using the levelized cleaning costs based on cleaning frequency calculated earlier, the total net profit including cleaning costs can be seen in Table 5.7.

Table 5.7: Total Net Profit in US Dollars.

Cleaning Frequency	Spring	Summer	Autumn	Winter	Total
Daily	948,669	**2,094,528**	**2,013,657**	614,147	5,671,002
Weekly	**1,039,736**	2,066,181	1,984,066	**731,007**	5,829,992
Biweekly	981,406	1,980,994	1,891,284	704,572	5,558,256
Monthly	919,281	1,849,319	1,742,095	657,566	5,168,262
None	841,509	1,624,618	1,565,752	587,424	4,619,305
Maximum	**1,039,736**	**2,094,528**	**2,013,657**	**731,007**	**5,878,930**

As seen in Table 5.7, depending upon the season, certain cleaning frequencies would be more profitable. In this specific case with the cost of electricity set at $60 per MWh, weekly cleaning would be the ideal cleaning frequency in spring, daily cleaning in the summer and autumn season, and weekly cleaning again in the winter season. If the same cleaning frequency was followed for every season, profits would not be maximized. The final row of Table 5.7 indicates the maximum values for each of the seasons to get the highest net total profit. The percentage difference between the highest net total profit by choosing the optimal cleaning frequency in different seasons and by keeping the same cleaning frequency for the entire year is 3.53%, 0.98%, 5.45%, 12.08%, and 21.42% for daily, weekly, biweekly, monthly, and no cleaning respectively. For the case of no cleaning, which has the highest percentage difference, that is a loss of $1,259,625. Even by keeping monthly cleaning for the entire year, the loss amount is as large as $710,667. Hence, there is a need to optimally choose the ideal cleaning frequency depending upon the season and not the same cleaning frequency for the entire year. Overall, the maximum total net profit is an acceptable and realistic amount for a 100 MW PV power plant. In addition, depending upon the Feed-in tariff (FIT), the recommended cleaning frequency depending upon the season would change to maximize profit. To understand this further, a summary of the result of varying FIT can be seen in Table 5.8.

Table 5.8: Recommended Cleaning Frequency for Different Seasons for Varying FIT.

FIT ($/MWh)	Recommended Cleaning Frequency to Maximize Profit			
	Spring	Summer	Autumn	Winter
40	Weekly	Weekly	Weekly	Weekly
60	Weekly	Daily	Daily	Weekly
80	Weekly	Daily	Daily	Weekly
100	Weekly	Daily	Daily	Weekly
120	Daily	Daily	Daily	Weekly
140	Daily	Daily	Daily	Weekly
160	Daily	Daily	Daily	Daily

As seen in Table 5.8, the recommended cleaning frequency when the price of electricity was $40 was weekly cleaning for all seasons throughout the year for maximum profit. As the price of electricity increased, the recommended cleaning frequencies for the summer and autumn season became daily. This pattern remained the same until the cost of electricity was $120 where the spring recommended cleaning frequency became daily. Finally, at an electricity cost of $160, the cleaning frequency for all seasons became daily.

In terms of a comparison, Table 5.7 indicates how the 100 MW PV plant would have varying degrees of financial benefit depending on the cleaning frequency they use over an entire year. As the objective of the case study was to vary the cleaning frequencies in a 100MV PV plant, the benefits of implementing the proposed model can be seen from a financial point of view. If the 100MW PV farm was to maintain the same cleaning frequency with electricity costing $60 per MWh for an entire year, it would not maximize its net profit. With a weekly cleaning frequency, the 100 MW PV farm would make $5,829,992 total net profit. Similarly, with a daily, bi-weekly, monthly, or no cleaning, the PV farm would make $5,671,002, $5,558,256, $5,168,262, and $4,619,305 respectively. However, after implementing the model, Table 5.7 indicates that by varying the cleaning frequency in different seasons, a higher total net profit can be made. In this case, if the spring season is cleaned on a weekly basis, the summer and autumn seasons cleaned daily, and the winter season cleaned on a weekly basis, a higher total net profit of $5,878,930 can be achieved. A further comparison can be made after interpreting the results of varying the cleaning cost as seen in Table 5.8. If the cost of electricity was cheaper at $40 per MWh, all four seasons of the year would have to be cleaned on a weekly basis to maximize the total net profit. However, if the cost of electricity was to increase till $80 or $100 per MWh, the spring and winter season would have to be cleaned on a weekly basis while the summer and autumn season would have to be cleaned on a daily basis. When increasing the cost of electricity to $120 or $140 per MWh, the spring, summer, and autumn season would have to be cleaned on a daily basis while the winter season would have to be cleaned on a weekly basis to maximize net profit. Lastly, by increasing the cost of electricity to $160 per MWh, all four seasons in the year would have to be cleaned on a daily basis to maximize net profit. Consequently, the benefit of the proposed model can be seen in the net profit gains that a PV farm can make. Without the proposed model, a fixed cleaning frequency over an entire year would not maximize the net profit gains of a PV farm. However, with the model, the projected output power of a PV farm under different cleaning frequencies can be calculated. Using this information, the optimal cleaning frequency for different seasons for varying rates of electricity can be selected to maximize the total net profit of a PV farm. Overall, the benefits of the proposed model can be seen in the financial profit that PV farms can make by varying the cleaning frequency depending upon the season rather than maintaining a fixed cleaning frequency or having no cleaning at all.

Chapter 6. Conclusion and Future Work

There has been a need for modeling dust accumulation as a function of time and not a fixed variable in order to model dust accumulation more accurately. By introducing the impact of solar irradiance, temperature, relative humidity, precipitation, and wind speed, the proposed model was able to better mimic the realistic behavior of dust accumulation in different seasons in a year. As a result, the thesis was able to address what was lacking in literature today by modeling dust as a function of time. In addition, the virtual scenarios generated were able to show that dust accumulation would increase and at certain times decrease as well depending upon weather variables depending upon the season of the year. As the Markov chain model was based off a finite number of states based on the amount of data, increasing the number of states would make the virtual scenarios more accurate. At the same time, by including more historical data to base the Markov chain model off, more accurate results would be possible as the transition probability matrices would have more data points to generate individual probabilities. More importantly, by analyzing the behavior of dust accumulation and how it increases or decreases based on the season of the year, it is clear that the drier and warmer climates of the year require more frequent cleaning. The average dust level and peak dust accumulation levels that were achieved during the summer season were almost double when compared to the winter season. Consequently, there is a far greater difference in dust accumulation levels when cleaning every one week to cleaning every five weeks during the summer season when further highlights the greater need for clean PV panels more often during the summer. Furthermore, the thesis also developed an accurate relationship between the output power of a PV and dust accumulation. Using information from dust accumulation that the proposed model can generate, accurate power levels for a PV can be determined. Additionally, after implementing the proposed model in a case study for a 100 MW PV power plant, results showed that depending upon the cost of electricity, the need for cleaning at different frequencies could profit PV power plants more or less. By allocated all resources towards automated cleaning, as it was shown to be more economical than manual cleaning, a PV power plant could maximize profit by determining which frequency they would want to clean in a specific season. If there was no cleaning, the PV power plant would lose as much as $1,259,625 assuming the cost of electricity was \$60 per MWh. If cleaning was implemented and it was monthly cleaning for the entire year, the PV power plant would still lose as much as \$710,667. Consequently, there is a need to choose the optimum cleaning frequency, which the proposed model is able to do, depending upon the season to maximize net profit.

In terms of recommendations for future work, it is important to note that the proposed model only included data for solar irradiance, ambient temperature, dust accumulation, and rate of dust accumulation. While other factors including relative humidity, wind speed, and precipitation are also important for dust accumulation, their data was assumed to be imbedded within the data for dust accumulation as noted in Section 3.1. Consequently, including separate data for relative humidity, wind speed, and precipitation along with dust accumulation would further improve the accuracy of the model. In addition, other factors including dust particle size, PV tilt angle, and pollutants in the environment can also be taken into consideration as they also dictate the behavior of dust accumulation. Therefore, by including the aforementioned factors affecting the behavior of dust, the proposed model would more accurately depict dust accumulation on a PV. The resulting output of the improved model would decide better when to optimally clean large PV systems that suffer greatly from dust like in the Middle East depending on the season.

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Appendix A

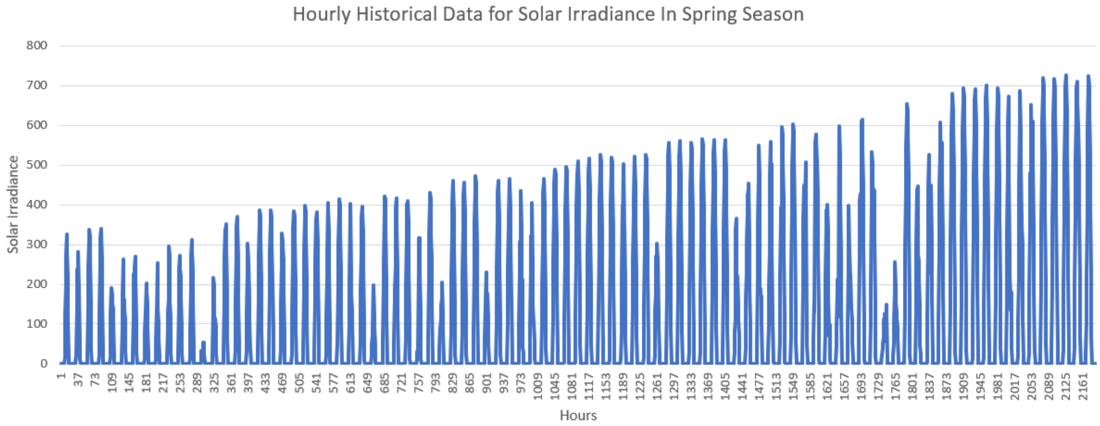

Figure 3.4: Historical Hourly Data for Solar Irradiance in Spring Season for One Year.

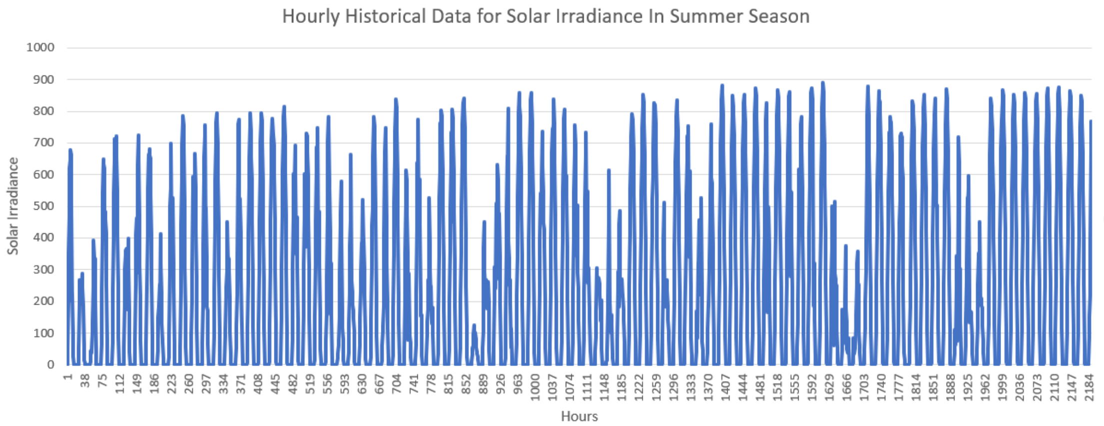

Figure 3.5: Historical Hourly Data for Solar Irradiance in Summer Season for One Year.

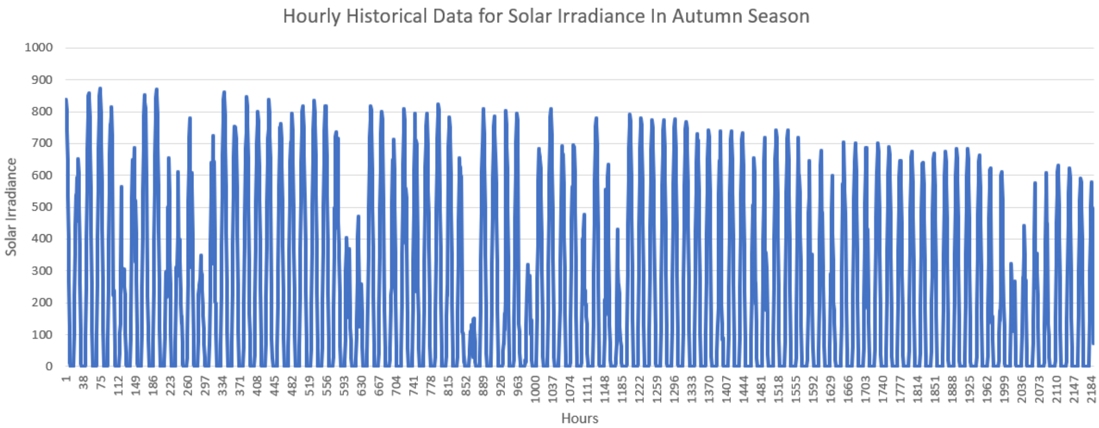

Figure 3.6: Historical Hourly Data for Solar Irradiance in Autumn Season for One Year.

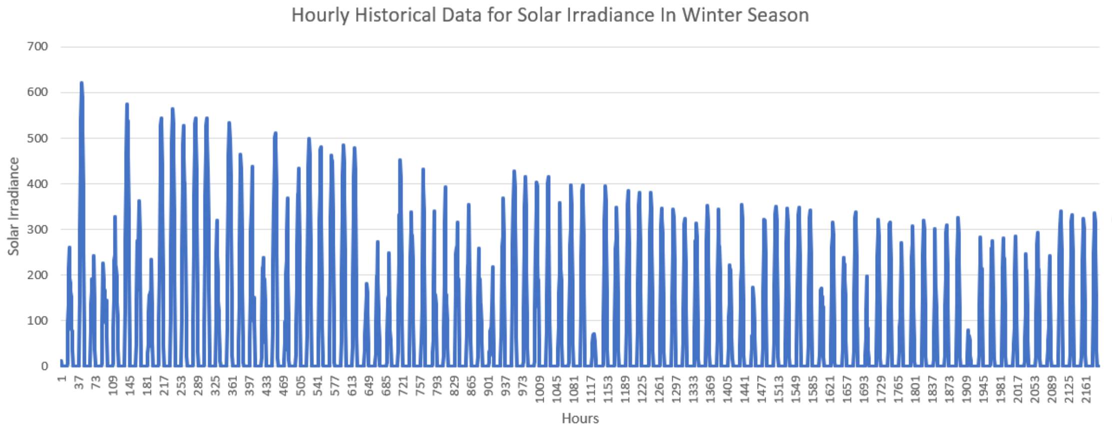

Figure 3.7: Historical Hourly Data for Solar Irradiance in Winter Season for One Year.

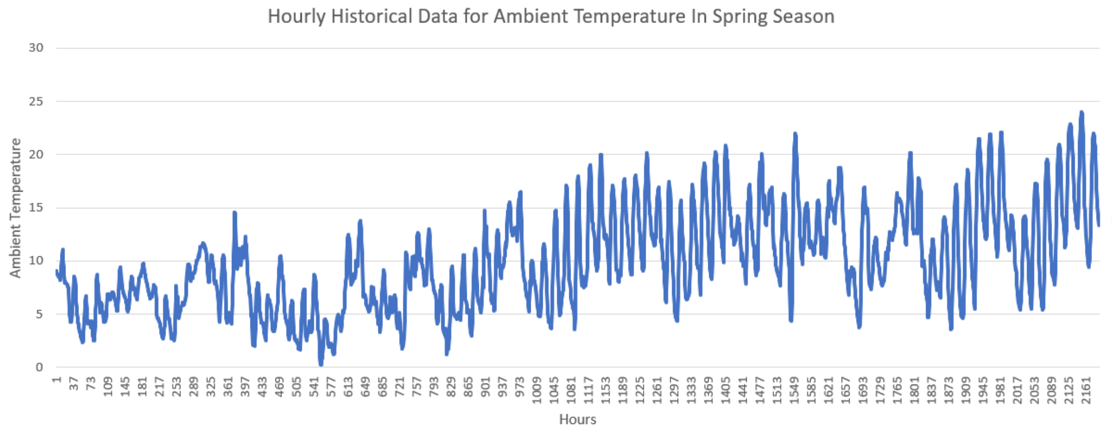

Figure 3.8: Historical Hourly Data for Ambient Temperature in Spring Season for One Year.

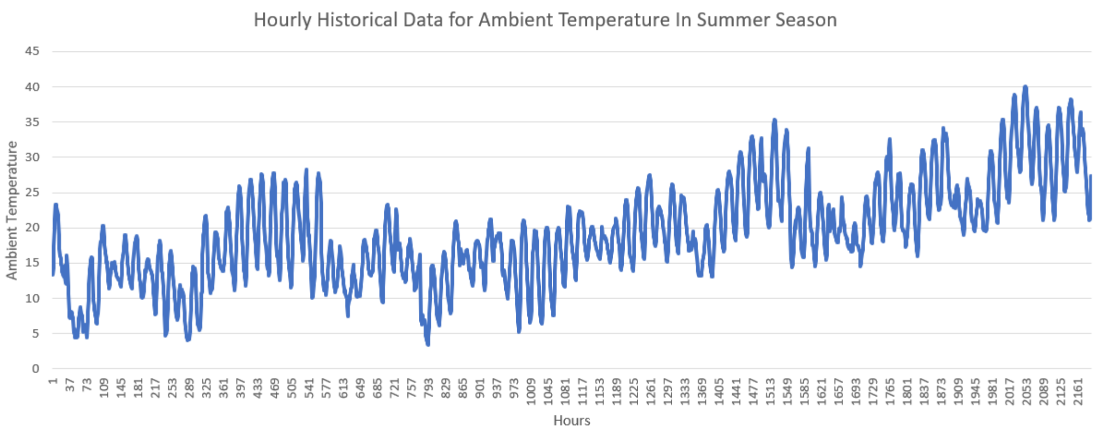

Figure 3.9: Historical Hourly Data for Ambient Temperature in Summer Season for One Year.

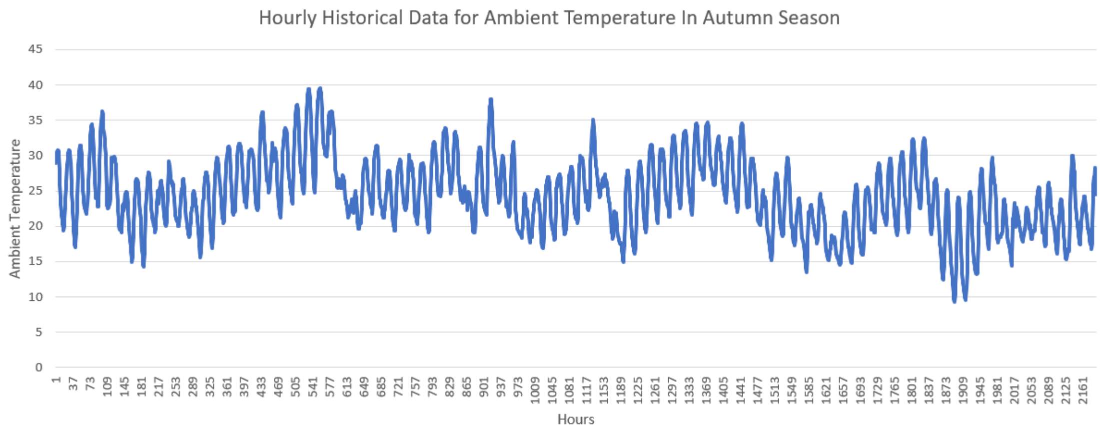

Figure 3.10: Historical Hourly Data for Ambient Temperature in Autumn Season for One Year.

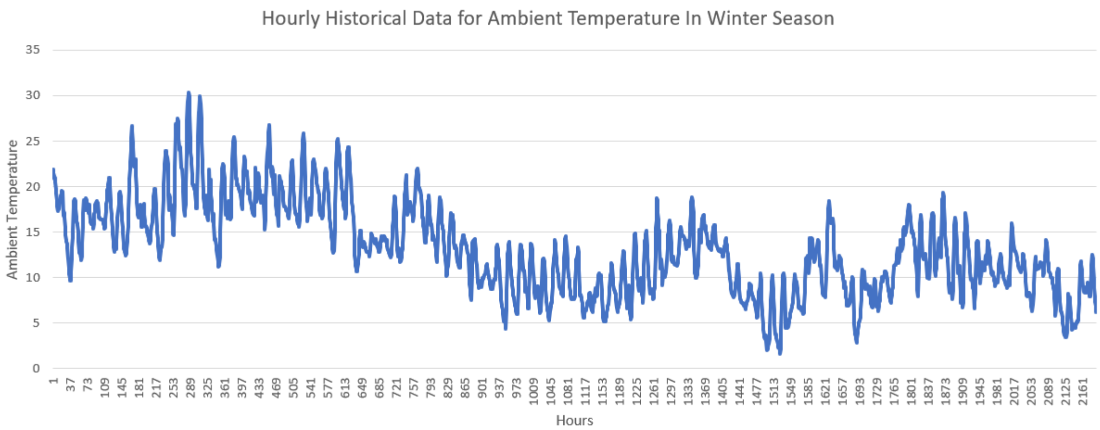

Figure 3.11: Historical Hourly Data for Ambient Temperature in Winter Season for One Year.

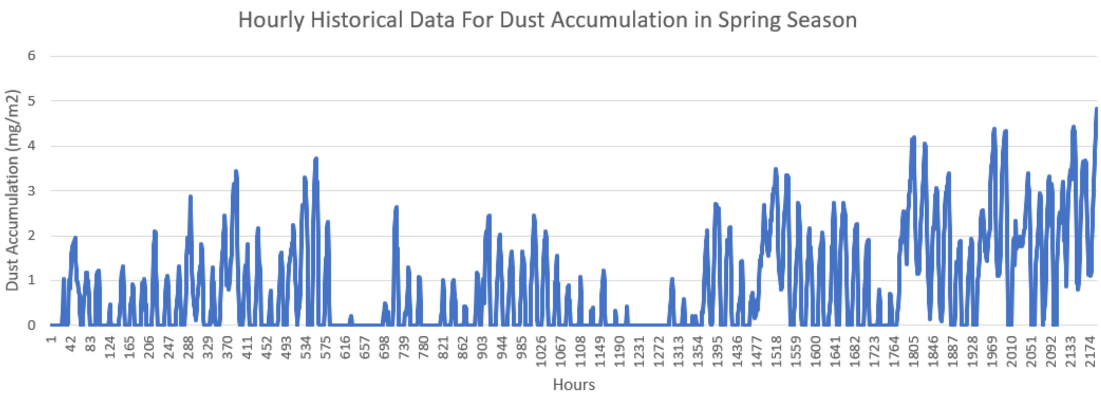

Figure 3.12: Historical Hourly Data for Dust Accumulation in Spring Season for One Year.

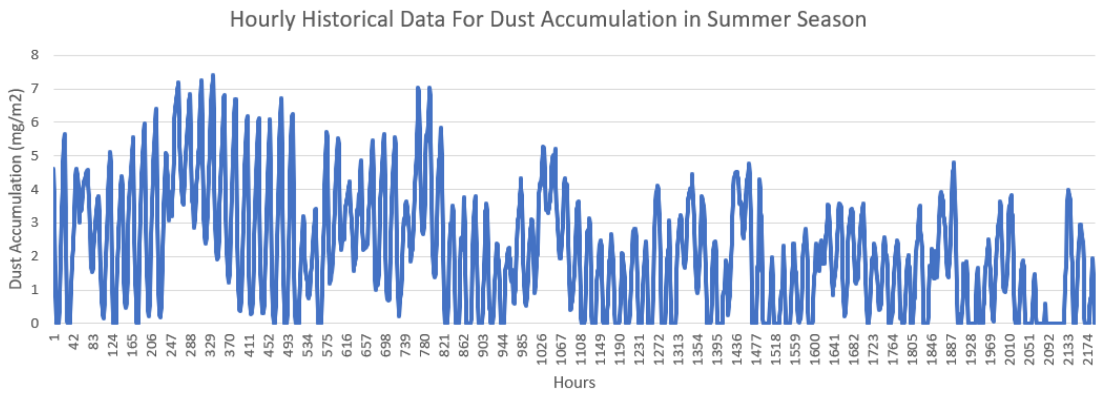

Figure 3.13: Historical Hourly Data for Dust Accumulation in Summer Season for One Year.

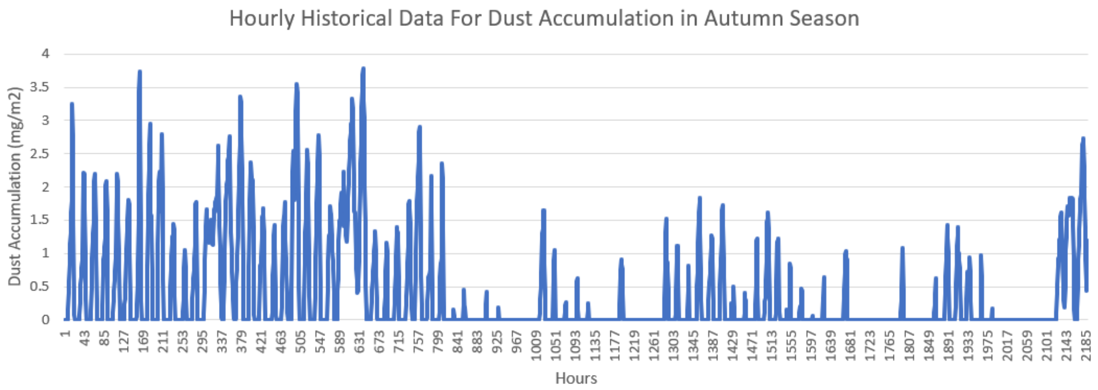

Figure 3.14: Historical Hourly Data for Dust Accumulation in Autumn Season for One Year.

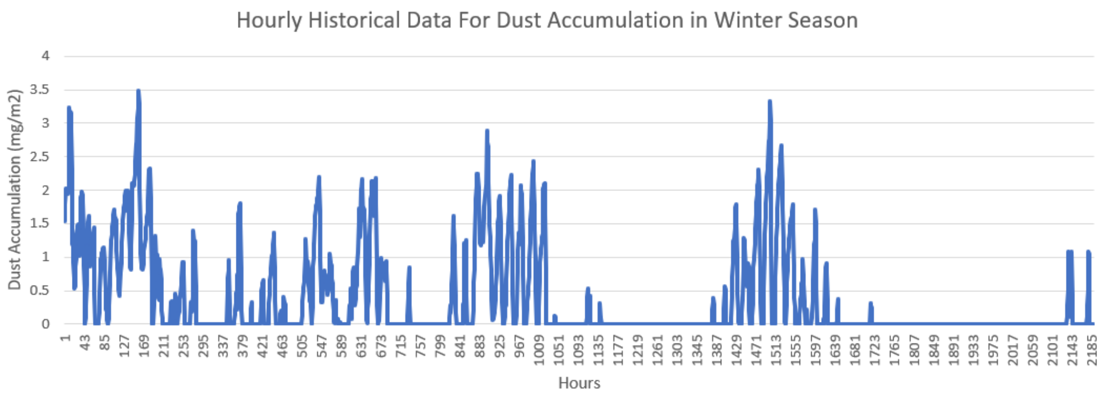

Figure 3.15: Historical Hourly Data for Dust Accumulation in Winter Season for One Year.

Vita

Armaghan Ali Cheema was born in 1996 in Australia. He received his primary and secondary education in Saudi Arabia and graduated from Dhahran High School. He received his B.Sc. degree in Electrical Engineering from the American University of Sharjah, from which he earned a Chancellor's List Scholarship, and graduated in 2018.

In January 2019, Mr. Cheema joined the Electrical Engineering master's program at the American University of Sharjah as a graduate teaching assistant. His research interests are in power generation and renewable energy. He is a member of the Engineering Honor's Society at the American University of Sharjah, the Institute of Electrical and Electronics Engineers and the Solid State Circuits Society.