MODELING A DRIP IRRIGATION SYSTEM POWERED BY A RENEWABLE ENERGY SOURCE

DISSERTATION
Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

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Food production is a problem in many of the regains in the world. Today, the process of producing food is very dependent on energy. The dependency on fossil fuels causes the cost of producing crops to increase as the prices of fuel increases. Using a renewable energy sources to power an irrigation system is a mean of decreasing the dependency of food products on the prices of fuel and minimize the impact of the irrigation system on the environment.

A model was developed to simulate and predict the performance of an irrigation system powered by a renewable energy source. Both solar energy and wind energy were considered for the modeling of the system.

The solar energy was simulated using the difference between the maximum and the minimum daily temperatures as an indicator of the amount of clouds in the atmosphere. The model is a modification of earlier models and has the advantage of not needing to be calibrated for each new site. Results showed that a model that calibrates it self for the upper and the lower expected values of the solar radiation can be developed using metrological data such as the location of the site, the daily temperatures, and the minimum relative humidity.
The wind energy was predicted using the power coefficient of the turbine and statistical representation of the daily wind speeds. The average hourly values of the wind speed were used for finding the distribution constants for the Weibull distribution and Rayleigh distribution. The results showed that the Weibull distribution is more accurate in predicting the expected power output of the turbine when the daily wind speed coefficient of variation (Cv) was less than 0.5. When the Cv is greater than 0.5 the Rayleigh distribution gives better results.

A computer model was developed using Visual Basic to model the system and the resulting model was tested and used in comparing the economics of a traditional irrigation system and an irrigation system powered by solar panels. The system powered by the solar panel had a greater total annual cost than the traditional system but the sensitivity analysis performed showed that if the trends in energy prices continue and the prices of the solar panels continue to decrease, the cost for operating the traditional systems will be close to the cost of operating the systems powered by the solar panels in less than a 10 years.
Dedicated to my family
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CHAPTER 1

INTRODUCTION

Food production is one of the fastest growing global problems today. As the world population grows to 8,300 million in the next 30 years (as estimated by the United Nations), water demand for non-agricultural uses will increase. On the other hand, energy supply is currently a growing concern for both researchers and governments. The growing energy use all over the world and the increase in energy cost results in an increase in the prices of energy-dependent products, such as crops, meat, etc. Environmental pollution caused by the use of traditional energy sources, such as fossil fuel, makes it necessary to find new solutions for this problem.

Pimentel et al. (1994) suggested that a new strategy for economical growth should be adapted by the developed countries. They stated that development strategies based on the economic theory of continuous growth imply a heavy reliance on stock depletion (e.g., coal, oil, minerals) and the option of imports from the international market. These strategies have worked well for the western world until now. However, in the last few decades several points suggest the need to seriously reconsider these strategies. Some of the natural resources listed that would have serious shortages and need evaluation of its use are described below.
Land: Pimentel et al. (1994) reported that the availability of arable land at the world level is less than 0.27 ha per capita, lower than it has ever been in history. Lal (1989) suggested a minimum of 0.5 ha per capita is required for a diverse diet of animal and plant food products.

Water supply: Pimentel et al. reported that humans are totally dependent on the functional activities of the biosphere for maintaining the productive conditions of ecosystems. Technology can do little to recharge underground reservoirs, whereas agricultural production requires more fresh water than any other human activity. Worldwide about 69% of the fresh water withdrawn is for the agricultural sector (WRI, 1994). Presently, 40% of the world's people live in regions that compete for short water supplies (Postel, 1989).

Energy sources: Sources of fossil fuel are being rapidly depleted and energy consumption is increasing at an exponential rate. The International Energy Outlook 2006 (IEO, 2006) projects strong growth for worldwide energy demand over the period from 2003 to 2030. The total world consumption of marketed energy expands from 421 quadrillion British thermal units (Btu) in 2003 to 563 quadrillion Btu in 2015; and then to 722 quadrillion Btu in 2030, or a 71% increase over the 2003 to 2030 period (Figure 1.1).
Pimentel et al. (1994) indicated that the food supply worldwide is increasingly dependent on stocks of fossil energy, in the form of fertilizers, pesticides, irrigation and machinery. They reported that 400 gallons of oil equivalents are expended annually to feed each American (as of data provided in 1994). Irrigation accounts for 13% of the agricultural energy consumption. There have been some attempts to power irrigation systems with renewable energies, but most of the resulting systems where designed for large farms and the cost for such systems is usually high. Designing successful irrigation systems powered with renewable energies for small farms depends on many factors, such as climate, crop, crop water needs, and type of irrigation system, and the kind of the crop. More accurately, it depends on the balance between the energy demand and supply.
Due to the large number of factors involved in the design process of such a system, it is not easy to conduct experiments to evaluate the effect of each factor so modeling the whole process enables investigation of the effect of each factor without conducting expensive and labor intensive field experiments.

1.1 Wind energy

Ackermann and Soder (2002) states that although the use of wind energy started three thousand years ago, major developments in this field started in the 1970s. At the start of modern industrialization, it was more economical to use stable energy produced by fossil fuel than the fluctuating energy supply provided by wind energy systems. Until 1970 the use of wind energy was limited to providing mechanical energy (which is very difficult to store) for water pumping and grain grinding. After that when oil prices started to rise, wind energy systems were used to generate electrical energy which is less expensive to store than mechanical energy. In the 1990’s the capacity of wind energy was doubling every three years, and the cost of wind power generated electricity dropped to one sixth of what it was in 1980.

Wind-powered energy systems are one of two types (depending on the use of the system):

1) Grid connected generation systems: usually large capacity systems connected to the electric grid to provide electric power. This type of systems needs major investments and strategic planning.

2) Stand-alone generation systems: used in remote places to provide power for electricity, telecommunications, and some farm needs. Stand-alone wind turbine systems are also
used in some places in Africa and India to provide mechanical power for pumping drinking and irrigation water. The wind turbines used for these applications can vary between a few watts and 300 kW.

The theoretical wind power for a wind turbine with a rotor disk area of A can be calculated using the continuity equation:

\[
\frac{dm}{dt} = \rho AU
\]  

(1.1)

Where:

\[ \frac{dm}{dt} \] is the mass flow rate of air (kg/sec);
\[ \rho \] is the air density (kg/m\(^3\));
\[ A \] is the rotor area (m\(^2\)); and
\[ U \] is the air velocity (m/sec);

Then the maximum available power P is:

\[
P = \frac{1}{2} \frac{dm}{dt} U^2 = \frac{1}{2} \rho AU^3
\]  

(1.2)

Betz (1926) found that it is practically impossible to capture all the energy available from a wind turbine. Betz then introduced a constant to give the maximum amount of energy that can be captured by a wind turbine:

\[
\left( \frac{P}{A} \right)_{\text{Betz}} = \frac{1}{2} C_p \rho U^3
\]  

(1.3)

Where: \( C_p \) is the turbine power coefficient.

The maximum value of \( C_p \) is 0.59 for an ideal wind turbine, but other factors, such as the blade shape and the ratio between the blades tip velocity and the wind velocity, may decrease the value of \( C_p \) furthermore.
From Equation 1.3 it is clear that the main factor affecting the power output from a wind turbine is wind speed. Representing the wind speed distribution over a period of time as a probability density function, and integrating over the entire period using Equation 1.3 gives the average expected wind power through this period of time. There is more than one distribution to express the probability distribution of wind speed depending on the available data and the desired degree of accuracy.

The Raleigh distribution is the simplest way to express a wind speed probability distribution. The only data needed for this representation are mean wind velocity. The probability density function of such a distribution is in the form:

\[
p(u) = \frac{\pi}{2} \left( \frac{U}{\bar{U}} \right) \exp \left[ -\frac{\pi}{4} \left( \frac{U}{\bar{U}} \right)^2 \right]
\]  

(1.4)

A more general representation is the Weibull distribution, which defines the curve by means of a shape factor, k, and a scale factor, c. Both k and c depend on the mean wind speed velocity \( \bar{U} \) and \( \sigma \), the standard deviation of the data. A probability density function for the Weibull distribution is in the form:

\[
p(u) = \frac{k}{c} \left( \frac{u}{c} \right)^{k-1} \exp \left[ -\left( \frac{u}{c} \right)^k \right]
\]  

(1.5)

Kestens and Teugels (2001) reported some of the problems associated with the use of statistical techniques to characterize wind. They concluded that it is not statistically correct to always assume that the wind distribution will follow the Rayleigh distribution. Although the use of the wind speed distribution to predict the average power for periods ranging from several years to one year can give a good estimate of the expected power generated by a tribune system, it does not give any indication about the
variability of the energy supply. For an accurate estimation of the wind energy available for a system with different seasonal energy needs (such as an irrigation system), the use of a statistical representation of the wind speed distribution for shorter time periods, such as a day or a week, is needed. There is a lack of research on whether the wind distribution in such short periods of time can be described using a statistical distribution, as well as which distribution would give the best fit, and the accuracy of the predicted results.

1.2 Solar energy

Solar energy is the source of all other energy types on earth. The rate of energy emission from the sun is $3.8 \times 10^{23}$ kW. The terrestrial radiation is approximately one third of the extraterrestrial radiation during a given year, and most of this energy falls on the oceans and seas. The amount usable of the remaining $1.5 \times 10^{17}$ kW intercepted by land is limited by physical socioeconomic constrains.

The solar constant as measured by NASA is 1,353 W/m$^2$. Predicting the terrestrial solar radiation is a complex problem that involves accounting for solar rays reflected back into space, absorbed by water and CO$_2$ in the atmosphere, scattered by impurities in the atmosphere, and diffused. Several different models have been developed to predict daily solar radiation on any given day.

Hargreaves and Samani (1982) used the difference between the maximum and minimum daily temperature to predict the solar radiation at the ground surface from the extraterrestrial radiation as:

$$ R_s = K_s (T_{max} - T_{min})^{0.5} R_e $$

(1.6)
where:

\[ R_s: \text{is the solar radiation at ground surface (W/m}^2\text{)}; \]

\[ T_{\text{max}} \text{ and } T_{\text{min}}: \text{are the mean maximum and minimum daily air temperatures for a month (°C)}; \]

\[ R_e: \text{is the extraterrestrial solar radiation (W/m}^2\text{)}; \text{and} \]

\[ K_r: \text{is an empirical coefficient.} \]

This model uses the maximum and minimum daily temperature as an indicator of cloudiness. The value of the empirical coefficient is 0.16 for interior regions and 0.19 for coastal regions. Although a lot of other factors affect the maximum and minimum daily temperature, such as wind speed, elevation, precipitation, and air vapor content, the models still gives good results when used to predict the solar radiation for monthly periods.

Allen (1995) used an adjustment to account for the change in the volumetric heat capacity of the atmosphere with the change in elevation. Allen (1997) proposed a self-calibrating method to estimate the solar radiation from air temperature. The method depends on the fact that the Hargreaves and Samani (1982) model tends to underestimate the solar radiation for a completely clear day. The value of an empirical coefficient \( K_r \) is changed until the maximum estimated value of solar radiation reaches the value solar radiation on a completely clear day. Allen reported that the largest variation between the model and the measured actual values was in Gainesville, Florida, and North Baltimore, Ohio.
1.3 Trickle irrigation system

It is sensible to think that a trickle irrigation system would be a good application to use wind or solar power. This irrigation system needs a continuous low energy supply, it is usually found in rural areas where there is no electricity and the irrigation demand is seasonal. The design and operation of an irrigation system for a given energy supply depends on the purposes of irrigation, climatic conditions, and available energy sources.

A trickle irrigation system is a way of giving water to plants in small amounts over a period of time. The different types of trickle irrigation systems are:

Drip irrigation: it is the supply of irrigation water in a slow nearly continuous rate from a single point or a line source.

Subsurface irrigation: the use of line source emitters to apply water under the surface of the soil.

Bubbler irrigation: is the application of water to the soil surface as a small stream.

Spray irrigation: the application of water over the land surface as a spray or mist from small sprinklers-like devices called microsprinklers.

The design of a trickle system depends on determining the total flow and the energy losses of each of the laterals, the mains, and the submains, all of which distribute irrigation water. The choosing of the most suitable diameter for pipelines is an economical process that depends on the cost of pipes and energy supply. The larger the pipeline, the less energy cost will be needed during the operation of the system, but that also means an increase in the initial capital cost of the system. Using renewable energy to
power the drip irrigation system will add to the initial capital cost but will minimize the operating cost.

The final system design will vary from one case to another depending on the purposes of irrigation, climactic conditions, and the available energy sources. English et al. (2002) emphasized the fact that there is a shift in the way irrigation design is conducted regarding the water regime used in operating the system. The old way of designing the irrigation system to give the maximum yield is now replaced by designing to achieve the maximization of net benefits. This may be because of the limitation of natural resources, and concerns about the environmental effect of irrigation. According to English et al., the maximization of net benefits could be per unit of water or land or cost depending on the surrounding circumstances and the objective of the system. Each different goal will require a different method of analyzing the system and will produce a different final design. Deciding the goal to be achieved by the design will depend on the limiting factor in the design. For example in arid areas the main concern will be water availability and the design should be aimed at maximizing the net benefit of water unit, but in areas where energy is expensive the design should minimize the energy consumption.

1.4 Aim

A renewable energy powered irrigation system would be a way of minimizing the irrigation impact on the environment, and decreasing the dependency of food production on traditional energy sources. Several renewable energy systems have been used for irrigation and water pumping, such as the 25 kW University of Nebraska photovoltaic
solar irrigation system, which was used in pumping water for corn irrigation from 1981 to 1984. Economical analysis of some wind powered irrigation systems in Texas was conducted by Vick et al. (2000). They analyzed the economics of a wind powered irrigation system connected to the utility grad using a new wind turbine and a used one from California. Different factors should be investigated to assure that an irrigation system powered by a renewable energy sources could be successful. Soil type, climate, grown crop, farm size, availability of energy resources, capital and operational costs, and environmental effects are some of the factors that can affect the performance and the output of such systems. Identifying the conditions when such systems perform properly and are economically feasible requires studying the effects of each of the factors on the system performance and the system economics.

The focus of this research is:

1) To investigate the possibility of using metrological data available from weather station in estimating and simulating the performance of a wind and solar energy system, and evaluating the reliability of such an estimate.

2) Model a renewable energy powered irrigation system using statistical and probabilistic methods to assure the proper functioning of the system then evaluate the model performance.

3) Investigate the possible changes in the economical design of the irrigation system when such a system is powered by a renewable energy sources.
1.5 Overview of the next chapters

The next four chapters discuss the modeling process, the validation of the model, and an elementary comparison between the economics of an irrigation system powered by a renewable energy and a traditional irrigation system. Chapter two deals with the prediction of the total daily solar radiation using the day of the year, the latitude, the longitude, the altitude, the daily minimum relative humidity and the daily maximum and the minimum temperatures. The development of a suggested model from the original Hargreaves and Samani (1982) model, testing of the model, developing a comparison between the model and the original model, and an error analysis of the upper and lower limits of the total daily solar radiation predicted by the model are discussed in the chapter.

Statistical methods of representing the daily wind speed distribution and the use of such methods for predicting the power output from a wind turbine are presented in Chapter 3. The statistical distribution that best fits the daily wind speed distribution, whether use only one distribution or use different distribution based on the conditions on any day, ways of identifying the best distribution in each case, and the integrity of the estimates wind parameters made using the average hourly values of the wind speed are discussed in the chapter.

Chapter 4 describes the process of modeling the irrigation system and determining the energy need of the system based on the water requirement needed for the plants, the prediction of the potential renewable energy available for the system using the methods tested in Chapter 2 and 3, the process of designing and choosing the renewable energy
system to satisfy the energy needs of the irrigation system, and the testing and validation of the model outputs.

Chapter 5 is an economical analysis comparing the process of choosing the most economical pipe diameter for an irrigation system powered by solar panels to the same process of a traditional system for a high value crop (tomato). The chapter also has the result of the sensitivity analysis performed to investigate the effect of the annual rate of energy escalation and the prices of the solar panels on the economical diameter of both the traditional irrigation system and the system powered by the solar panels.

Chapter 6 is the summary and conclusions of all the chapters and the recommendation for further research.

1.6 REFERENCES


CHAPTER 2

MODELING DAILY SOLAR RADIATION USING AVAILABLE METROLOGICAL DATA IN OHIO FOR APPLICATIONS WITH ALTERNATIVE ENERGY SOURCES FOR MICRO-IRRIGATION

2.1 INTRODUCTION

Solar energy is the source of all other energy types on earth. The rate of energy emission from the sun is $3.8 \times 10^{23}$ kW, but the amount intercepted by earth is only $1.7 \times 10^{14}$ kW. Thirty percent of the intercepted energy is reflected back into space, 47 percent is converted to low-temperature heat and goes back to space in the form of radiation, 23 percent is used in the evaporation-precipitation cycle and less than 0.5 percent is converted into kinetic energy in wind and waves, or stored in plant in the photosynthesis processes. Terrestrial radiation is one third of the extraterrestrial radiation during a given year, with most of this energy falling on the oceans and seas. The amount usable of the remaining $1.5 \times 10^{17}$ kWh intercepted by land is limited by physical and socioeconomic constrains.

The solar constant (average amount of solar radiation falling on a surface normal to the ray of the sun outside the atmosphere) as measured by NASA is 1353 W/m$^2$. However, the amount of extraterrestrial depends on the change in the distance between the sun and the earth during the year.
Terrestrial solar radiation is not as easy to predict as extraterrestrial radiation as the interaction between the atmosphere and solar rays results in a decrease in the amount of energy received on the earth’s surface compared to the energy received by the outer atmosphere. Some of the solar rays entering the atmosphere can be reflected back into space, absorbed by water or CO$_2$ in the atmosphere, scattered by impurities in the atmosphere, and diffused. The remaining part of the rays with nearly no change in direction is called direct or beam radiation.

Because solar radiation measurements for most locations are not available, several different models have been used to predict terrestrial solar radiation at the ground surface. Most of the models use meteorological factors that are commonly reported by weather stations and can be related to solar radiation.

Different approaches are used for the estimation of the amount of the solar radiation that reaches a horizontal surface through the atmosphere. Regression relation spatial representation and general methods were used. The successful use of either a site-specific model, or a general predictive model, for solar radiation prediction on a given day depends on the site and the availability of historical records. The basic idea in all approaches is to calculate the amount of extraterrestrial radiation as a function of the latitude and the day of the year (Duffie and Beckman 1980; 1991), then predict the solar radiation of a clear day according to the method used by Allen (1997). When the clear day radiation is calculated we can use available meteorological parameters to predict the amount of radiation under any cloud condition.
Several attempts were made to predict the amount of solar radiation on any given day. Annandale et al. (2002), Richardson (1985), Supitand and van Kappel (1998), and others reported that the solar radiation on any given day depends on cloudiness, daily sunshine hours, and the amount of water vapor in the atmosphere.

Bristow and Campbell (1984) used a total transmittance term $T_t$ to estimate terrestrial solar radiation. Total transmittance is the ratio of daily measured irradiance to daily extraterrestrial radiation, and can be calculated using the following equation:

$$T_t = A(1 - \exp(-BT_c^c))$$  \hspace{1cm} (2.1)

Where:

$$B = 0.036 \exp(-0.154\Delta T)$$  \hspace{1cm} (2.2)

$\Delta T$ is the monthly mean daily temperature range, and the coefficient $A$ can be calculated as a function of the elevation as:

$$A = A_{msl} + A_{lapse} \times \text{elevation}$$  \hspace{1cm} (2.3)

The parameters $A_{msl}$, $A_{lapse}$, and $C$ are constants.

The accuracy of the models described above depends on values of the constants, which are generally site specific. When used at a new location, the model needs to be calibrated to determine site-specific values of model constants. This is a problem when using the models on sites that have no historical solar records.
Thornton and Running (1999) modified the Bristow and Campbell (1984) algorithm as:

\[ T_r = A \left( 1 - 0.9 \cdot \exp \left( -B \Delta T^c \right) \right) \]  

(2.4)

They also expanded the original model to include the effects of pressure, solar zenith angle, and vapor pressure on the clear-sky transmittance (A), as:

\[ A = f \left( \left( \tau_{0,\text{nodir, dry}} \right) \left( \frac{P}{P_0} \right)^{\rho_e} + \alpha e \right) \]  

(2.5)

Where:

- \( \tau_{0,\text{nodir, dry}} \) is the instantaneous transmittance at the reference elevation for a dry atmosphere at solar noon;
- \( m_0 \) is the optical air mass for a given zenith angle;
- \( P \) is the surface air pressure;
- \( e \) is the vapor pressure;
- \( \alpha \) is a slope parameter, and \( B \) is:

\[ B = b_0 + b_1 \cdot \exp \left( -b_2 \cdot \Delta T^s \right) \]  

(2.6)

Where: \( b_0, b_1, \) and \( b_2 \) are constants.

Although constants in this model form do not depend on the geographical location of the site, the model still performs better in predicting the extreme values of solar radiation (clear day radiation or completely cloudy day radiation) than predicting the radiation for partially cloudy days. Another problem of this model is the need for dew point values, which are not available in many climatic records.
Berliner and Droppelmann (2003) evaluated the Thornton–Running (1999), model performance in predicting the daily global radiation for a coastal desert of the eastern Mediterranean. They found that the predicted values of maximum daily total atmospheric transmittance possible on days with clear skies were very close to the measured values, but not accurate for the realized proportion of this maximum daily total atmospheric transmittance possible on a clear day in a partially cloudy day. Although they could establish a good correlation between predicted and measured values, they reported a noticeable underprediction of global radiation and a systematic underestimation of daily Penman's potential evapotranspiration during the dry summer period. This result was especially true if the saturated vapor pressure at minimum daily temperature was used in the calculation instead of the actual measured average daily saturated vapor pressure. The result presented by Berliner and Droppelmann (need date) shows that the model needs a set of measured values in order to find the correlation between the actual values and the values the model predicts, especially in humid areas.

Hargreaves and Samani (1982) used the difference between the maximum and minimum daily temperature to predict the solar radiation at the ground surface from the extraterrestrial radiation as:

\[ R_s = K_r \left( T_{\text{max}} - T_{\text{min}} \right)^{0.5} R_e \]  

(2.7)

where: \( R_s \) is the solar radiation at ground surface (W/m\(^2\)); \( T_{\text{max}} \) and \( T_{\text{min}} \) are mean maximum and minimum daily air temperature for a month (°C); \( R_e \) is the extraterrestrial solar radiation (W/m\(^2\)); and \( K_r \) is an empirical coefficient.
This model uses the maximum and minimum daily temperature as an indicator for cloudiness. The value of the empirical coefficient in the model is 0.16 for interior regions and 0.19 for coastal regions. Although a lot of other factors affect the maximum and minimum daily temperature, such as wind speed, elevation, precipitation, and air vapor content, the model provides reasonable results when used to predict the solar radiation for monthly periods. An added advantage of such a model is the availability of the required data and the simplicity of the calculations.

Allen (1995) used an adjustment to account for the change in the volumetric heat capacity of the atmosphere with the change in elevation. However, with this approach the accuracy of the model still depends on the site and the values of the empirical coefficient.

Allen (1997) proposed a self-calibrating method to estimate the solar radiation from air temperature. The method depends on the fact that the Hargreaves and Samani (1982) model tends to underestimate the solar radiation for a completely clear day, therefore the value of the empirical coefficient \( K_r \) can be changed until the maximum estimated value of solar radiation reaches the solar radiation value on a completely clear day. Allen reported the largest variation between the model predicted and measured values were in Gainesville, FL, and North Baltimore, OH. The fact that those sites were the only semi-humid sites in this study suggests that the model poorly predicts solar radiation in humid climates.

In humid areas, the variation in the solar radiation from one day to another appears to be larger than the same values for arid areas. Thus the Hargreaves and Samani (1982) model tends to perform better in predicting over all average values of solar radiation than in predicting the day-to-day values of the expected radiation.
Ball et al. (2004) evaluated different models to predict solar radiation including site specific models developed using multiple regression, the modified version of Hargreaves and Samani (1982) model, a site specific coefficient for modified Hargreaves and Samani model, the modified version of Bristow and Campbell (1984) model developed by Weiss et al. (2001), and the Thornton-Running (1999) model. The evaluation of all of these models was based on the regression between the observed and the predicted values, the root mean square error, the model bias, and the mean absolute error. The results showed that the Thornton-Running model performed better over all of the 20 locations tested, but the performance of the model can vary from one location to another, and the best model for each site can vary depending on the site.

There is need to evaluate the performance of simple models that predict solar radiation from simple metrological records available from most any climatic station or agricultural weather station. Evaluating the model based on the mean absolute error or the root mean square error provides an idea of model performance over the total period tested, but gives no information about the model performance from one year to another, or between seasons within the same year. A complete picture of model performance would be better expressed if we can evaluate model performance in an average year, and in extreme conditions, such as drought and humid years.

2.2 AIM

The aim of this work is to evaluate the performance of simple solar radiation models that do not require site calibration, such as the Hargreaves and Samani (1982) model or the Allen (1997) self-calibrating model. Analysis will focus on model performance over a period of time with different levels of precipitation, and between
seasons within the same year; model performance for different modified versions of these models; the possibility of using such models to generate solar radiation data for sites where there are no solar data, and the reliability of a prediction made based on such generated data; and evaluation of model performance in simulating solar radiation in short time periods.

2.3 MATERIAL AND METHODS

The data were obtained from the Ohio Agricultural Research and Development Center (OARDC) in Wayne County. The weather station is located 1.61 km (1 mi) south of Wooster, Ohio, with latitude and longitude of 40° 47’ N and 81° 55’ W, respectively, and an elevation of 310.98 m (1020 ft) above sea level. The records contained daily data for maximum and minimum temperature, maximum and minimum relative humidity, wind speed, precipitation, and solar radiation. The 23-yr record from 1982 to 2004 had some years with a few missing records. The year 1984 had the maximum number of missing records with eight days missing, but distributed throughout the year. Correlation analysis between solar radiation, wind speed, relative humidity, and the difference between the maximum and minimum daily temperature were performed in order to identify the factors correlated with solar radiation.

The model forms evaluated were: a typical Hargreaves and Samani (1982) model with coefficient $K_r$ values of 0.16 or 0.19; an Allen (1997) self-calibrating model; a model with $K_r$ values as a function of the minimum relative humidity; and a modified form of the Hargreaves and Samani model constructed by choosing the value of $K_r$ based on the value of the difference between the maximum and the minimum daily temperature. The difference between the predicted and observed values were determined for each day
beginning with the 15th of April to the beginning of October, and the average for the rest of the year. The root mean square error (RMSE) for each model was determined for three different years of available data. The three years were chosen to show each model’s performance in a year with average precipitation, a dry (drought) year, and a wet (humid) year. To evaluate the simulation performance of each model, the daily error in prediction as a ratio to the actual predicted value of that day was determined for each day for the three chosen years as follows:

\[ E = \frac{A - P}{A} \]  

Where:

E is the error in prediction; A is the actual measured solar radiation value kWh/m²; and P is the predicted value of solar radiation kWh/m². The values of the error of each model were plotted for each month in the three chosen years.

For long-term prediction of the limits of solar radiation, the data were fitted to log-normal, Weibull, Weibull 3 parameters, exponential, and 2-parameter exponential models to determine the most suitable statistical distribution for the available data. For each day, the average, standard deviation, and the values of solar radiation at probability levels of 0.1, 0.9, 0.05, 0.95, 0.01, 0.99 were determined for the measured and predicted data for each prediction model.
2.4 RESULTS AND DISCUSSION

2.4.1 Regression analysis

Analysis showed that the strongest correlation was between the solar radiation and minimum relative humidity, and solar radiation with the difference between max and min daily temperature, as shown in figures 2.1 and 2.2, respectively. The correlation coefficient was -0.655 for the min relative humidity relationship, and 0.64 for the temperature difference relationship. The correlation between solar radiation and wind speed, max relative humidity, and precipitation is shown in figures 2.3, 2.4, and 2.5, respectively. The correlation coefficient for wind speed, maximum relative humidity, and precipitation with solar radiation was -0.286, -0.061, and -0.235, respectively.

The average values of solar radiation are greater in the period between April 15th and the beginning of October (day 105 to 270) than for the rest of the year, as shown in figure 2.6. Although the overall average values of radiation seems to have good correlation with the day of the year (correlation coefficient =0.56), in a single year the values of solar radiation can change sharply from one day to another. Figure 2.7 illustrates the solar radiation values for a single year and the average for the 23 years.
Figure 2.1: Correlation between the solar radiation and the daily minimum relative humidity.
Figure 2.2: Correlation between the solar radiation and the difference between the maximum and the minimum daily temperatures.
Figure 2.3: Correlation between the solar radiation and the average daily wind speed.
Figure 2.4: Correlation between the solar radiation and the daily maximum relative humidity.
Figure 2.5: Correlation between the solar radiation and the total daily precipitation.
Figure 2.6: Change in solar radiation with the day of the year.
Figure 2.7: Variation in daily solar radiation values in a typical year compared to the average values of the 23 years.
2.4.2 Determining the wet (humid) and dry (drought) years

The average annual precipitation over the 23-year records was 85.43 cm. The year closest to the average was 2000, and it was used for evaluation of model performance in an average year. The year with the largest precipitation was 2004, with a total precipitation of 119.05 cm. The year with the smallest precipitation was 1991, with 61.3 cm. The annual total precipitation for each year is shown in figure 2.8. An alternative method of identifying a drought year is to use the Palmer Drought Index (Palmer, 1965), from which the years 1988, 1991, 1993, 1999, 2001, and 2002 were found to be dry (drought) years, and the years 1990, 1992, 1996, 2004 were wet (humid) years.

![Figure 2.8: Average, annual, growing season, and growing season average precipitation for Wooster, OH, from 1982 to 2004.](image_url)
2.4.3 Model evaluation and modification

Predicted values of solar radiation using the Hargreaves and Samani (1982) model with a coefficient value $K_r$ of 0.16 or 0.19 were plotted on the same graph with the measured values of solar radiation and the average values for the 23 years. The model with $K_r = 0.16$ performed better in predicting solar radiation in the humid years than in the dry years. The RMSE (root mean square error) was 1.321 kWh/m$^2$ for the year 1991, 1.183 kWh/m$^2$ for the year 2000, and 1.086 kWh/m$^2$ for the year 2004. For the growing season the RMSE was 1.578 kWh/m$^2$ for the year 1991, 1.396 kWh/m$^2$ for 2000, and 1.242 kWh/m$^2$ for 2004. For the part of the year other than the growing season, the RMSE was 1.059 kWh/m$^2$ for 1991, 0.971 kWh/m$^2$ for 2000, and 0.937 kWh/m$^2$ for 2004. These results indicate that the model produces less prediction error in a humid year such as 2004 and this holds for the total year, the growing season, and the part of the year other than the growing season.

The same trend was observed from the model with $K_r = 0.19$. For the total year the RMSE was 1.067 kWh/m$^2$ for the year 1991, 1.041 kWh/m$^2$ for 2000, and 1.038 kWh/m$^2$ for 2004. For the growing season, the RMSE was 1.169 kWh/m$^2$ for 1991, 1.196 kWh/m$^2$ for 2000, and 1.185 kWh/m$^2$ for 2004. For the part of the year other than the growing season, the RMSE was 0.973 kWh/m$^2$ for 1991, 0.893 kWh/m$^2$ for 2000, and 0.899 kWh/m$^2$ for 2004. The measured and predicted values of solar radiation are shown in figures 2.9-2.14. The trend suggests that the value of the RMSE has a correlation with the solar radiation value therefore, RMSE value is not sufficient alone to evaluate the model performance.
Figure 2.9: Measured and predicted solar radiation using the Hargreaves and Samani model for inner region for the year 1991.
Figure 2.10: Measured and predicted solar radiation using the Hargreaves and Samani model for coastal region for the year 1991.
Figure 2.11: Measured and predicted solar radiation using the Hargreaves and Samani model for inner region for the year 2000.
Figure 2.12: Measured and predicted solar radiation using the Hargreaves and Samani model for coastal region for the year 2000.
Figure 2.13: Measured and predicted solar radiation using the Hargreaves and Samani model for inner region for the year 2004.
Figure 2.14: Measured and predicted solar radiation using the Hargreaves and Samani model for coastal region for the year 2004.
Figures 2.9-2.14 show that the value of $K_r = 0.16$ is more successful in predicting values of solar radiation when its value is less than the long-term average daily value, and the $K_r = 0.19$ is better when the value of solar radiation is greater than this average. For these three years the values of the RMSE with $K_r = 0.19$ were smaller than with $K_r = 0.16$, which contradicts the results found by Ball et al. (2004). They found the $K_r = 0.19$ had the largest error and bias even with the coastal stations used in their studies. This can be explained by the small number of years Ball et al. used in their study, and the correlation between the RMSE value and the number of dry and wet years. In the 7-year period of the data Ball et al. used, if dry conditions were the dominant conditions at one of the stations, the value of RMSE was greater than at the other stations. This indicates that the number of years used and the dominant conditions through those years can affect the value of RMSE. One way of avoiding this problem is to determine the RMSE for a single year at a time, as well for the average year, the extremely dry years and the extremely wet years.

A proposed modification for the model is as follows. The value of $K_r$ can be chosen based on the values of the difference between the max and min daily temperature with $K_r = 0.16$, when this difference is less than the average value, and $K_r = 0.19$ is used otherwise. This model will be referred to as a selective $K_r$ model in the rest of this paper. Performance of the selective $K_r$ model is illustrated in figures 2.15-2.17 for the years 1991, 2000, and 2004.
Figure 2.15: Measured and predicted solar radiation using selective K_r model for the year 1991.
Figure 2.16: Measured and predicted solar radiation using selective $K_r$ model for the year 2000.
Figure 2.17: Measured and predicted solar radiation using selective $K_r$ model for the year 2004.
When comparing the figures above with figures 2.9-2.14, the selective $K_r$ model is more representative of the solar data than the model with the $K_r = 0.16$ or $K_r = 0.19$.

Since relative humidity had a strong correlation with solar radiation from an earlier analysis, regression was used to construct a relative humidity based model. Correlation analysis was used to evaluate the possibility of using daily values of $\text{RH}_{\text{max}} - \text{RH}_{\text{min}}$ instead of values of $T_{\text{max}} - T_{\text{min}}$ to predict solar radiation. The correlation between values of $R_e(\text{RH}_{\text{max}} - \text{RH}_{\text{min}})^{0.5}$ and values of $R_e(T_{\text{max}} - T_{\text{min}})^{0.5}$ was 0.928, significant at $p = 0.0001$. This result indicates that both of these difference parameters indicate the same behavior. Therefore, determining new coefficients for a model using the relative humidity instead of the temperature was not conducted. Min relative humidity can still be used in evaluating the lower limit of the expected solar radiation on any given day; the data indicate that the min expected value of 25% of the clear days overestimates the min value of solar radiation on cloudy days. The value of $K_r$ can be predicted from the daily min relative humidity as:

$$K_r = 0.282 - 0.00183 \times RH_{\text{min}} \quad (2.9)$$

The Allen (1997) self-calibrating model (hereafter referred to as the Allen model) showed better performance in predicting the higher values of solar radiation but not in predicting the lower values. Figures 2.18-2.20 illustrate the measured and predicted values using this model. For all three years, 1991, 2000, and 2004, the model successfully predicted values of solar radiation larger than the average, but overpredicts the value of solar radiation when it is smaller than the average. This suggests that the model will tend to overestimate values of solar radiation, especially in wet years, such as 2004.
Figure 2.18: Measured and predicted solar radiation using Allen model for the year 1991.
Figure 2.19: Measured and predicted solar radiation using Allen model for the year 2000.
Figure 2.20: Measured and predicted solar radiation using Allen model for the year 2004.
Different selective models were constructed using different combination of the models discussed above to predict solar radiation. Table 2.1 provides a summary of the models used, description of each model, and values of the RMSE for the total year, and the seasons within the year for the 1991, 2000, and 2004.

Sorting the values of solar radiation in ascending order and plotting against the corresponding error for each model illustrates a trend of increasing error with increasing solar radiation. This trend changes from one model to another, and from year to year. Figure 2.21 illustrates the relation between the prediction error value and the measured solar radiation for the 23-years for the Hargreaves and Samani (1982) model for coastal regions. It is clear from figure 2.21 that the prediction error increases as the value of the solar radiation increases. The correlation between the error and the solar value indicate that parameters like the mean absolute error (MAE) and the RMSE are not good parameters to evaluate the performance of the different models and a relative error parameter such as the relative mean error is more suitable for evaluating the models.

An analysis of variance of the error values of each model was preformed with the year being wet or dry as one of the ANOVA factors. For all the models, there were significant differences between the amounts of error in dry years and wet years.

A ratio of the error to the measured value for which cases were all plotted. Representative results are provided below for discussion purposes. The positive values of error indicate an underprediction of solar radiation, and the negative values indicate an overprediction. The absolute value of the error is larger in the case of under-prediction than in the case of over-prediction. However, in proportion to the measured values, the percent error is larger in the case of over-prediction than for under-prediction.
<table>
<thead>
<tr>
<th>Model</th>
<th>Model description</th>
<th>Season</th>
<th>1991</th>
<th>2000</th>
<th>2004</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_r = 0.19$</td>
<td>Hargreaves and Samani, coastal regions</td>
<td>Total year</td>
<td>1.067</td>
<td>1.041</td>
<td>1.038</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Growing season</td>
<td>1.169</td>
<td>1.196</td>
<td>1.185</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Rest of year</td>
<td>0.973</td>
<td>0.893</td>
<td>0.899</td>
</tr>
<tr>
<td>$k_r = 0.16$</td>
<td>Hargreaves and Samani for interior regions</td>
<td>Total year</td>
<td>1.321</td>
<td>1.183</td>
<td>1.086</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Growing season</td>
<td>1.579</td>
<td>1.396</td>
<td>1.242</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Rest of year</td>
<td>1.059</td>
<td>0.971</td>
<td>0.937</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td>$k_r = 0.19$ when $(T_{\text{max}} - T_{\text{min}})$ greater than or equal to the overall $(T_{\text{max}} - T_{\text{min}})$ average, $k_r = 0.16$ otherwise</td>
<td>Total year</td>
<td>1.127</td>
<td>1.068</td>
<td>1.000</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td></td>
<td>Growing season</td>
<td>1.283</td>
<td>1.255</td>
<td>1.133</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td></td>
<td>Rest of year</td>
<td>0.977</td>
<td>0.883</td>
<td>0.875</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td>Allen self-calibrating model when $(T_{\text{max}} - T_{\text{min}})$ greater than or equal to the overall $(T_{\text{max}} - T_{\text{min}})$ average, $k_r = 0.16$ otherwise</td>
<td>Total year</td>
<td>1.132</td>
<td>1.268</td>
<td>1.380</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td></td>
<td>Growing season</td>
<td>1.146</td>
<td>1.540</td>
<td>1.672</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td></td>
<td>Rest of year</td>
<td>1.070</td>
<td>0.987</td>
<td>1.078</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td>Allen self-calibrating model when $(T_{\text{max}} - T_{\text{min}})$ greater than or equal to the overall $(T_{\text{max}} - T_{\text{min}})$ average, self-calibrating using min relative humidity otherwise</td>
<td>Total year</td>
<td>1.132</td>
<td>1.268</td>
<td>1.380</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td></td>
<td>Growing season</td>
<td>1.202</td>
<td>1.540</td>
<td>1.162</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td></td>
<td>Rest of year</td>
<td>1.070</td>
<td>0.987</td>
<td>1.078</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td>$k_r = 0.19$ when $(T_{\text{max}} - T_{\text{min}})$ greater than or equal to the overall $(T_{\text{max}} - T_{\text{min}})$ average, self-calibrating using min relative humidity otherwise</td>
<td>Total year</td>
<td>1.867</td>
<td>1.922</td>
<td>1.772</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td></td>
<td>Growing season</td>
<td>2.368</td>
<td>2.544</td>
<td>2.276</td>
</tr>
<tr>
<td>Selective $k_r$</td>
<td></td>
<td>Rest of year</td>
<td>1.308</td>
<td>1.179</td>
<td>1.200</td>
</tr>
</tbody>
</table>

Table 2.1: Summary of the models evaluated, description of each model, and values of the root mean square error (kWh/m²) for the total year, and for the seasons within 1991, 2000, and 2004, representing a dry year, an average year, and a wet year, respectively.
Figure 2.21: Ascending sorted measured daily solar radiation and corresponding prediction error for the period 1982-2004.
The performance of each model varies depending on the season and the value of the difference between max and min daily temperature. Models that depend on the Allen self-calibrating approach tend to reduce under-prediction errors, while producing larger over-prediction errors. Self-calibration models that use the relative humidity equation for the calibration of the lower limit of solar radiation had the smallest errors in the case of under-prediction and the largest errors in the case of over-prediction.

The Hargreaves and Samani (1982) model for coastal regions had smaller errors in the case of under-estimation than most of the other models, and that was true for the years 1991, 2000, and 2004. However, this model produced larger errors in over-estimation than all the other models. The Hargreaves and Samani (1982) model for inner regions preformed better in the over-prediction case than in the under-prediction case. Figure 2.22 is an example of the relative error graphs. The error in prediction shown in figure 2.22 is for the period form day 213 to day 244 (August) of the year 1991. The selective $k_r$ model produced better results than both Hargreaves and Samani models, for coastal or inner regions, most of the time. In most cases, the selective $k_r$ model had the error of the inner regions model when it over-predicted the solar radiation such as days 215 and 231 as seen in figure 2.22. In most case of under-prediction, the selective $k_r$ model had the same error as the costal regions model such as in days 213,219, and 222. Therefore the selective $k_r$ model overall error of prediction was better then the overall error of prediction of either of the Hargreaves and Samani models
Figure 2.22: Relative error in predicting solar radiation for day 213 to day 244 (August) 1991.
The best fit distribution for the data from the 23-yr record was the log-normal distribution. The average and standard deviation of the natural logarithm for the 23 values available for each day were determined using the measured data and values obtained from each of the prediction models. The error in prediction of each limit, lower and upper, were plotted. Figures 2.23 and 2.24 show the prediction error in predicting the lower (probability =0.1) and the upper (probability=0.9) limits of solar radiation for each model during the growing season as a ratio to the corresponding limit of solar radiation predicted using the measured data.

The smallest error in predicting the min value of solar radiation on a given day was with the Hargreaves and Samani (1982) model for inner regions, and with the selective $k_r$ model, but those models over-estimated solar radiation often. Because the purpose of predicting the lower limit of solar radiation is to find a limit that, the solar radiation will be larger than or equal to most of the time. It is better to use a model that under-estimates the value of the limit than a model that over-estimates it. The selective $k_{r3}$ model had the smallest error of all the models without over-estimating the value of solar radiation lower limit. This was true at the 0.1, 0.05, 0.001 probability levels.

For the upper limit value of solar radiation, the smallest estimation error was with the selective $k_{r4}$ model and the second best model was the selective $k_{r3}$ model. At a probability level of 0.9, the selective $k_{r4}$ model under-estimated solar radiation for almost half of the days, therefore it would be more conservative, or less risky to use the selective $k_{r3}$ model. At the 0.95 and 0.99 probability levels, the selective $k_{r4}$ model was the best estimator of solar radiation upper limits, and it had the smallest error in prediction without under-estimating solar radiation.
Figure 2.23: Error in predicting the lower limit of solar radiation at a probability $P=0.1$ during the growing season as a ratio to the lower limit of solar radiation predicted using the measured data.
Figure 2.24: Error in predicting the upper limit of solar radiation at a probability $P=0.9$ during the growing season as a ratio to the lower limit of solar radiation predicted using the measured data.
2.5 SUMMARY AND CONCLUSIONS

The solar radiation data are not available in a lot of sites. Several models have been developed to predict the solar radiation based on the metrological data. Hargreaves and Samani (1982) models predict the solar radiation using the location of the site, the elevation, and the maximum and minimum daily temperatures. The models are simple in calculation and are not site specific and don’t need calibration for the model constants. Allen (1997) proposed a self-calibrating model to modify the constant in the original Hargreaves and Samani models. Allen models modify the Hargreaves and Samani model’s constant based on the comparison between the models prediction and the solar radiation for a completely clear day. Solar radiation in humid areas can fluctuate widely from one day to another. Allen 1997 reported the largest error in the prediction of the solar radiation by the self-calibrating model in Gainesville, FL, and North Baltimore, OH.

The use of either of the Hargreaves and Samani models (inner and coastal region) does not adequately cover the range of fluctuations in the day to day solar radiation values. A regression analysis was performed to investigate the possibility of using other metrological parameters to predict the total daily solar radiation. The strongest correlation was between the solar radiation and the minimum relative humidity, and between the solar radiation and the deference between the daily maximum and minimum temperatures. The solar radiation correlation with the wind speed, the precipitation, and the maximum relative humidity was insignificant. Several models were developed as a modification of the original Hargreaves and Samani. The selective models chose the values of the constant to use in the Hargreaves and Samani based on the value of the difference between the max and min temperature. The models tested in this work are Hargreaves and Samani coastal regions ($k_r = 0.19$), Hargreaves and Samani for interior regions ($k_r = 0.16$), Selective $k_r$ ($k_r = 0.19$ when $(T_{max} - T_{min})$ greater than or equal to the overall $(T_{max} - T_{min})$ average.
$k_r = 0.16$ otherwise), Selective $k_{r2}$ (Allen self-calibrating model when $(T_{\text{max}} - T_{\text{min}})$ is greater than or equal to the overall $(T_{\text{max}} - T_{\text{min}})$ average, $k_r = 0.16$ otherwise), Selective $k_{r3}$ (Allen self-calibrating model when $(T_{\text{max}} - T_{\text{min}})$ is greater than or equal to the overall $(T_{\text{max}} - T_{\text{min}})$ average, self-calibrating using min relative humidity otherwise, and Selective $k_{r4}$ ($k_r = 0.19$ when $(T_{\text{max}} - T_{\text{min}})$ greater than or equal to the overall $(T_{\text{max}} - T_{\text{min}})$ average, self-calibrating using min relative humidity otherwise). Three years were chosen to evaluate the models performance in all conditions. The years was identified as dry year, average year, and wet (humid) year passed on the total annual precipitation and Palmer Drought Index.

Use of model where the value of the constant $k_r$ is chosen based on the difference between max and min daily temperature can enhance the prediction capability of the model. The value of the RMSE was found to be correlated to the value of the solar radiation and can change from dry years to wet years and from one season to the other in the same year. The higher the average value of the solar radiation the higher the value of the RMSE will be. The RMSE can be used as an indicator of the total amount of error of the model for the data period, but it is not a good indicator of model prediction performance for short periods, instead the model performance should be evaluated using a relative error term. For long-term predictions of the limits of solar radiation, the chosen model should depend on the application intended for the predicted limit. Because it seems impossible to find a model that will predict the exact upper and lower limits, use a model that tends to under-estimate solar radiation with the smallest error, such as the selective $k_{r3}$ model. For the upper limit, use a model that tends to over-estimate solar radiation with the smallest lowest error, such as the selective $k_{r4}$ model.
2.6 REFERENCES


CHAPTER 3

PREDICTING THE AVERAGE DAILY POWER FOR A WIND TURBINE USING
STATISTICAL REPRESENTATION OF HOURLY AVERAGES WIND SPEED

3.1 REVIEW OF LUTRTTURE

Ackermann and Soder (2002) in their review of wind energy emphasized the fact
that although the use of wind energy started 3000 years ago, major developments in this
field started in the 1970s. At the start of modern industrialization it was more economical
to use the stable energy produced by fossil fuel engines than the fluctuating energy
supply provided by wind energy systems. In the 1990’s the capacity of wind energy was
doubling every three years, and the cost of wind power generated electricity dropped to
one sixth of what it was in 1980.

Wind-powered energy systems are one of two types, depending on the use of the
system. Grid connected generation systems: usually large capacity systems connected to
an electric grid to provide electric power. This type of systems needs major investments
and strategic planning and is usually funded by governments. Another type called stand-
alone generation systems are used in remote places to provide electricity for
telecommunications and some farm needs. Stand-alone wind turbine systems are also
used world wide to provide mechanical power for pumping drinking and irrigation water.
Power from wind turbines used for these applications can vary between a few watts and
50 kW.
For the wind system to function properly and provide reliable energy supplies, design factors such as location, wind speed, wind direction, engineering design of the turbine, should be considered separately for each case.

3.1.1 General characteristics of wind resource

Global winds are generated because of atmospheric pressure difference across the earth’s surface. This pressure difference results from the heating of some surface areas more than others. The amount of heat (from solar radiation) is less at the poles than at the equator, and this causes air circulation with heated air rising at the equator and cooler air moving downward at the poles. Air circulation is also affected by other factors, such as variation in earth rotational speed between the poles and the equator, Variation in heat transferred from earth to the atmosphere causing regional high and low pressure cells, etc. In addition to global wind trends, there are smaller wind circulations that can be divided into the following categories:

- Secondary circulations, such as hurricanes, monsoon circulation, and extra tropical cyclone; and
- Tertiary circulation or local circulations, such as land and sea breezes, valley and mountain winds, tornados and thunderstorms (Cherry et al. 1981).

Wind speed and direction varies with time at four different scales

- Inter-annual variations: it is the variation in wind speed for a time scale larger than one year. From the meteorological data and experience, this variation takes place in a 30-year period (Cherry et al. 1981). Because of the complex nonlinear nature of long-term wind speed variation and the dependency on a lot of uncontrolled factor there are no accurate models to predict the variation in long-term mean wind speed.
• Annual variation: Seasonal variations in wind speed are common all over the world. These variations depend on the location and the elevation above sea level, and can affect the power generated from a wind turbine. Prediction of the annual variation in wind speed can be accomplished using several years wind data. Aspliden et al. (1986) said that from a statistical point of view, one-year data is generally sufficient to predict seasonal mean wind speed to a confidence level of 90%.

• Diurnal variation: Variation in earth heating during the day causes variations in wind speed. Generally, wind speed increases through the day, and the lowest wind speed is between midnight and sunrise.

• Short-term variation: Short-term variation in wind speed is represented by gusts and turbulent with a time interval of 10 minutes or less. The evaluation of such variation is important for a turbine system connected to the grid in order to determine the maximum load, the power quality, the mechanical and structural design of the turbine, and its tower (Manwell 2002).

3.1.2 Wind power estimation

The theoretical wind power for a wind turbine with a rotor disk area of $A$ can be calculated using the continuity equation:

$$\frac{dm}{dt} = \rho AU$$  \hspace{1cm} (3.1)

Where:

$\frac{dm}{dt}$ is the mass flow rate of air (kg sec$^{-1}$), $\rho$ is the air density (kg m$^{-3}$), $A$ is the rotor area (m$^2$), $U$ is the wind speed (m sec$^{-1}$).
Then the maximum available power $P$ at any given wind speed is

$$P = \frac{1}{2} \frac{dm}{dt} U^2 = \frac{1}{2} \rho A U^3$$  \hspace{1cm} (3.2)

Betz (1926) found that it is impossible to capture all the energy available from a wind turbine, and then introduced a constant to give the maximum amount of energy that can be captured by an ideal wind turbine as:

$$\left( \frac{P}{A} \right)_{Betz} = \frac{1}{2} C_p \rho U^3$$  \hspace{1cm} (3.3)

The maximum possible value of $C_p$ (power coefficient) is 0.59, but in an actual wind turbine the value $C_p$ decreases even more by the effect of factors such as drag forces and turbulence.

The power coefficient of a wind turbine is a function of the wind speed and the rotational speed of the turbine rotor. In other words, it is a function of the tip speed ratio for the turbine. The value of the power coefficient increases with the increase of the tip speed until a maximum value, then decreases. The tip speed ratio is not always available for all turbines, especially commercially produced turbines. A simpler way of showing the relation between the generated power and the wind speed is the turbine power curve, where the power generated is plotted against the wind speed. The power curve is usually provided by the manufacturer of the turbine and the relation between the wind speed and the power coefficient can be predicted using this curve.

3.1.3 Statistical representation of wind speeds

There is more than one distribution to express the probability distribution of wind speed depending on the available data and the desired degree of accuracy. If only considering the magnitude of the wind velocity and not the direction then wind speed
values will always be greater than zero. Thus log-normal, Rayleigh, or Weibull distribution can be used for the representation of the wind speed. Several researchers such as Stewart & Essenwanger 1978, Takle & brown 1978, and Van der Auwera et al. 1980 used the Weibull distribution to represent the wind speed distribution. Tuller & Brett 1984 reported that the Weibull distribution gives an approximate but generally good fit of the wind distribution. They attributed the selection of the Weibull distribution for representing the wind speed distribution to the distribution flexibility. Most of the other statistical distribution can be derived from the Weibull distribution by changing the shape factor of the distribution.

The general form of Weibull distribution is the three-parameter Weibull distribution. The distribution PDF is defined as follow:

\[
f(x,k,c,\gamma) = \frac{k}{c} \left( \frac{x - \gamma}{c} \right)^{k-1} \exp \left( -\frac{x - \gamma}{c} \right)^k
\]

Where: \( k \) is the shape factor; \( c \) is the scale factor; and \( \gamma \) is the location parameter (the threshold). The PDF curve of the Weibull distribution takes different shapes based on the value of the shape factor \( k \). For \( k = 3 \), the Weibull distribution is similar to the normal distribution, and for a \( k=1 \), the Weibull distribution is reduced to the exponential distribution. The scale factor controls the stretching of the curve, i.e., a larger value of the scale factor stretches the curve to the right and decreases its height. The threshold parameter shifts the curve to the right or the lift depending on its value as positive or negative. A special case of the three-parameter Weibull is the two-parameter Weibull, which is generated when the value of the threshold in the PDF is set to zero (Stacy 1962). While the three-parameter Weibull is likely to give better statistical fit, it is physically
impossible to explain the threshold values especially when these values are negative.

Using a log-log transformation of the wind speed $U$ and the corresponding cumulative distribution value $F(U)$, the slope of the resulting line is the shape factor. The scale factor value is located at the intersection between the X axis and a horizontal line passing through $F(U) = 0.632$. The resulting PDF of the two-parameter Weibull distribution is in the form:

$$p(U) = \frac{k}{c} \left( \frac{U}{c} \right)^{k-1} \exp \left[ - \left( \frac{U}{c} \right)^{k} \right]$$

(3.5)

Another special case of the Weibull distribution is Rayleigh distribution with a value of the shape factor $k = 2$ (Justus et al. 1978). The Rayleigh distribution is the simplest way to express wind speed probability distribution, and is used to represent the absolute value of a two-dimensional vector when its two orthogonal components are independent from each other and both are normally distributed.

The probability density function (PDF) of the Rayleigh distribution is of the form:

$$f(x, \sigma) = \frac{x \exp\left(-\frac{x^2}{2\sigma^2}\right)}{\sigma^2}$$

(3.6)

Where: $x$ is the value at which the density function is calculated; and $\sigma$ is the distribution parameter.

The maximum likelihood of $\sigma$ is calculated as

$$\sigma \approx \sqrt{\frac{1}{2N} \sum_{i=0}^{N} x_i^2}$$

(3.7)

Where: $N$ is the number of data values.
The mean can be calculated from the distribution parameter as:

\[ M = \sigma \sqrt{\frac{\pi}{2}} \]  

(3.8)

If the value of the mean is known, then the distribution parameter and the corresponding PDF can be determined. A larger value of the mean results in a larger value of the parameter \( \sigma \), and a larger maximum value of the \( x \) as shown in figure 3.1. The only data needed for this representation are the mean wind velocity.

![PDF for a Rayleigh distribution for different wind speed mean values.](https://example.com/pdf.png)

Figure 3.1: PDF for a Rayleigh distribution for different wind speed mean values.
(Source: Wind power explained 2002)

Kestens and Teugels (2001) reported some of the problem associated with the use of statistical technique to characterize wind. They said that although most studies show that overall the Weibull distribution provides the best fit to wind speed data. It is not statistically correct to assume that the wind speed will always follow the Rayleigh distribution.
3.2 AIM

The focus of most of the previous studies was on the yearly wind speed distribution but if the wind turbine is to be used for application with a large variation in energy needed from time to time in the year a way of predicting the average power produced by the turbine in shorter intervals than the year is needed. The aim of this work is to determine the possibility of representing the wind speed in short time intervals (1 day) using a statistical distribution and determine the accuracy of such representation if used to predict the energy output of a wind turbine. Using a stand-alone wind turbine to power a drip irrigation system for a small-scale farm requires the prediction of the amount of energy that would be available using the turbine in short interval such as 3-6 days. The continuous and varying energy demand by the irrigation system requires not only the average seasonal energy supply by the turbine but also the distribution of the energy supply throughout the season.

3.3 METHODS

The wind turbine used in this experiment where a 20 kW rated Jacob wind turbine with a maximum rated speed of 11.62 ms\(^{-1}\) (26 mph) and a cut in speed of 3.58 ms\(^{-1}\) (8 mph). The wind turbine shutdown speed is 13.86 ms\(^{-1}\) (31 mph). The turbine is installed at Lake Farmpark, an agricultural education facility owned and operated by Lake County Metroparks. The facility is located in Kirtland, a rural area about twenty-five miles east of Cleveland. The wind monitoring project is operated by the GEO Wind Committee. The wind speeds were recorded in 1-minute intervals for 250 days through the whole year. The temperatures were also recorded in order to adjust the air density. The hourly and
daily averages of the wind speed were also calculated. The correlation between the power and the wind speed were determent based on the manufacture provided power curve. Figure 3.2 shows the power curve of the used wind turbine.

![Power Curve](image)

Figure 3.2: Manufacture power curve for the 20 kW Jacob wind turbine.

Three different statistical representations were tested to describe the daily wind speeds at the turbine location

1- Assuming the wind distribution each day can be represented using the Rayleigh distribution, the average daily value of the wind speed and equation 3.8 can be used to estimate the parameter $\sigma$ and the PDF. For a wind distribution with an average wind speed of $\bar{U}$, and substituting in equation 3.6 the values of $\sigma$ with mean values from equation 3.8, the PDF at any wind speed $U$ can be calculated as follows:
\[ p(U) = \frac{\pi}{2} \left( \frac{U}{U^2} \right) \exp \left[ -\frac{\pi}{4} \left( \frac{U}{U} \right)^2 \right] \]  

(3.9)

The power generated will be:

\[ P = \int_{u_{crit}}^{u_{max}} p_w(U) p(U) dU \]  

(3.10)

or

\[ P = \int_{u_{crit}}^{u_{max}} p_w(U) dF(U) \]  

(3.11)

Where: \( P \) is the expected average power from the wind turbine; \( p_w(U) \) is the power generated at each wind speed; \( p(U) \) is the probability density function; \( F(U) \) the cumulative distribution function; \( u_{max} \) is the max wind speed (less than or equal to the shut down speed of the turbine) recorded at this day; and \( u_{crit} \) the cut-in speed of the wind turbine. The total energy generated can be calculated by multiplying the average power by time.

2- Assuming the wind distribution each hour of the day can be represented using the Rayleigh distribution and using equation 3.11 on hourly basis. The generated daily energy will be:

\[ E = \int_{h=1}^{h=24} P_w(h)dh \]  

(3.12)

3- Assuming that the daily values of wind speed follow Weibull distribution, use statistical software to predict the shape factor k and the scale factor c from the average hourly values for each day. The PDF of wind speed can be predicted using equation 3.5 and the average power can be predicted using equation 3.11.
For each of the previous representations of the wind speeds, the resulting cumulative distribution function and the cumulative distribution function of the observed data were plotted on the same graph to compare the predicted distribution with the distribution of the observed data. The average wind power was calculated using the distribution values and compared to the observed power values for each day. The year was divided into two different parts, the growing season and the rest of the year. A residual plot and the plot of the predicted verses observed were produced for each of the two periods to evaluate the accuracy of the power prediction using each of the statistical representation.

3.4 RESULT AND DISCUSSION

3.4.1 Wind speed distributions

The predictions using the Rayleigh hourly basis representation were always higher than the observed values. For the Weibull and the Rayleigh daily basis representations the results showed three different trends depending on the average wind speed and the Standard deviation on any certain day. The days were divided into three groups according to the performance of the statistical representation. The first group was days that the Weibull representation resulted in a distribution closer to the observed data distribution than the Rayleigh representation such as day 256. Figure 3.3 illustrates the CDF for the observed and the predicted values for day 256 of the year. The values predicted using the Weibull distribution are more representative of the observed values in the middle of the curve than in its beginning and end. This was the case for almost all the days of the year with no differences noticed between the growing season the rest of the year.
Rayleigh on an hourly basis tends to produce a sharply sloped CDF curve (Figure 3.4). This representation tends to result in greater percentage of larger wind speeds than the actual data. The Rayleigh representation using the daily average produces a curve that is closer to the actual data than the Rayleigh representation on hourly basis. This result may be because the daily average wind speed used in the daily representation is based on more data values than the hourly wind speed averages used in the hourly representation. Figure 3.5 shows the CDF curve for day 256 of the year. This figure illustrates that the Rayleigh daily CDF is closer to the observed data than the Rayleigh hourly representation, but does not represent the data as close as the Weibull representation.

The second group was days when the Rayleigh representation on daily basis resulted in a distribution closer to the observed data distribution than the Weibull representation such as day 221. Figures 3.6 and 3.7 show the CDF for day 221 of the year using the Weibull and the daily Rayleigh. It is clear from the figures that the Weibull representation is predicting a much larger max wind speed than what the observed data indicate, while the daily Rayleigh representation CDF is much closer to the observed data CDF.

The third group was days when both the Weibull and the daily Rayleigh representations resulted in a distribution that is close to the observed data distribution such as day 245 (figure 3.8 and 3.9).
Figure 3.3: The CDF for the observed data and predicted (Weibull distribution) daily wind speed.
Figure 3.4: CDF curve for day 256 for the observed data and predicted using Rayleigh distribution on an hourly basis.
Figure 3.5: CDF curve for day 256 for the observed data and predicted using Rayleigh distribution on a daily basis.
Figure 3.6: CDF curve for day 221 for the observed data and predicted using Weibull distribution.
Figure 3.7: CDF curve for day 221 for the observed data and predicted using Rayleigh distribution on a daily basis.
Figure 3.8: CDF curve for day 245 for the observed data and predicted using Weibull distribution.
Figure 3.9: CDF curve for day 245 for the actual data and predicted using Rayleigh distribution on a daily basis.
The average daily wind speed in day 256 was 2.73m$^{-1}$ (6.11 mph) with a standard deviation 0.78; for day 221 the average daily wind speed was 1.78m$^{-1}$ (3.98 mph) with a standard deviation 1.06; and for day 245 the average daily wind speed was 3.71m$^{-1}$ (8.31 mph) with a standard deviation 2.13. From these values of the averages and the standard deviations of the three days it can be seen that what determines which distribution will be closer to the observed data is not the value of the average or the standard deviation, but the ratio between the two values or the coefficient of variation Cv. With smaller values of Cv, the Weibull representation better represents the wind speed distribution (day 256, Cv =0.287). The larger the Cv (day 221, Cv =0.6), the daily Rayleigh representation tend to perform better. The observed trend was found to be true for the growing season and the rest of the year. Table 3.1 shows the average and the standard deviation values for the three days calculated using the observed 1-minute reading and the average hourly value.

<table>
<thead>
<tr>
<th>Day of the year</th>
<th>Value bases</th>
<th>Average(m$^{-1}$)</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>256</td>
<td>1 reading per minute</td>
<td>2.73</td>
<td>1.75</td>
</tr>
<tr>
<td></td>
<td>hourly averages</td>
<td>2.73</td>
<td>1.27</td>
</tr>
<tr>
<td>245</td>
<td>1 reading per minute</td>
<td>3.71</td>
<td>4.77</td>
</tr>
<tr>
<td></td>
<td>hourly averages</td>
<td>3.71</td>
<td>4.40</td>
</tr>
<tr>
<td>221</td>
<td>1 reading per minute</td>
<td>1.78</td>
<td>2.40</td>
</tr>
<tr>
<td></td>
<td>hourly averages</td>
<td>1.78</td>
<td>1.76</td>
</tr>
</tbody>
</table>

Table 3.1 The daily average wind speed and the corresponding standard deviation calculated based on one reading /minute or the average hourly wind speeds
3.4.2 Expected wind power form turbine

The amount of error that will occur in the prediction of the power generated by the turbine will depend on the error in predicting the percentage of the greater wind speeds more than the error in the predicting smaller wind speeds. This is because the wind speed in the power equation is raised to the third power so the amount in error in the power prediction is greater with the larger wind speeds than with the smaller wind speeds. The average power predicted for the day 256 of the year using the Weibull representation was 0.085kW; using daily Rayleigh representation was 0.29kW; and using the hourly Rayleigh representation, was 0.57kW. The observed value of the average power for day 256 of the year was 0.12kW. The results show that the Weibull representation underestimates the average power, while both of the Rayleigh representations overestimate average power. This is because on day 256, the Weibull representation slightly overestimates the probability of the smaller wind speeds and underestimates the probabilities of the greater wind speeds. On the other hand, the Rayleigh representations underestimate the probabilities of the smaller wind speeds and overestimate the larger wind speeds. From the previous result it can be concluded that the use of the hourly basis Rayleigh is not needed because it will always produce more error than Weibull and the daily Rayleigh representations. On day 221 the average power using the Weibull representation was 0.995kW, and using daily Rayleigh representation it was 0.03kW. The observed value of the average power for day 221 of the year was 0.025kW. In this case the power estimated using daily Rayleigh representation is closer to the observed average power value, and although the representation under estimates the probabilities of the wind speed most of the time in the middle part of the curve, the total estimate is still
slightly larger than the observed value because of the overestimation at the upper end of the curve. On day 245 the average power using Weibull representation was 0.81kW, and was 0.97kW using daily Rayleigh representation. The observed value of the average power for day 245 was 1.25kW. The average daily power estimation and the observed daily power average are shown in figure 3.10 for the lowest period of wind speed recorded in the growing season.

The predicted values based on the Weibull distribution are larger than the observed average daily power values when the daily average wind speed is small. This can be seen in the predicted values of days 217, 221, 228, 232, 234, and 247. The daily average wind speed on these days ranges from 2.99ms\(^{-1}\) (6.69mph) for day 217 to 1.73ms\(^{-1}\) (3.87mph) for day 228. The standard deviation for those days ranges from 1.06 for day 221 to 1.74 for day 228. The Cv values for these days ranged from 1 for day 228 to 0.51 for day 217. From the numbers above we can conclude that the Cv is the factor that indicates the success of the Weibull representation. All of the days above have a Cv value of 0.5 or larger.

Figure 3.11 illustrates the average daily power as a moving average for a 6 days interval it can be seen in figure 3.11 that the Rayleigh representation produces an average that is closer to or underestimating the observed average daily power. This is a desirable feature when using the prediction for choosing a wind turbine to satisfy the application energy needs. In the part of the year other than the growing season, the Weibull distribution was more successful overall in predicting the average daily power. This may be because of the larger daily average and the more steady wind in this period of the year. The observed, Weibull predicted, daily Rayleigh predicted average daily power for day 2
to 102 of the year is shown in figure 3.12. In this figure, it can be seen that the power predicted based on the Weibull representation is closer to the observed daily average power than is the daily Rayleigh. Also, the Cv values for this part of the year were found to be smaller than the growing season values and most of the time under the value of 0.5. Figure 3.13 shows the values of the daily average power calculated as a moving average for a 6 days interval. From the figure we can see that the power predicted using the Weibull representation is closer to the actual observed values most of the time and, while the power predicted using the daily Rayleigh representation overestimates the values of the power in some cases, the Weibull representation predicted power was less than or equal to the observed values throughout the entire period.

It is also clear that the average daily power value for this period is larger than the daily average power during the growing season. This can also be seen in figures 3.14 and 3.15 illustrating the residuals for the growing season and the rest of the year, respectively. Although the values of the residuals in the part of the year other than the growing season is larger than the residuals for the growing season relative to the observed average daily power, the error in the prediction of the power value in the growing season is larger.

The difference in the performance of the two representations from one part of the year to the other is illustrated in a plot of the predicted versus the observed values. Figure 3.16 and 3.17 show the predicted versus the observed for the Weibull and the daily Rayleigh representations for the growing season.
Figure 3.10: The observed, predicted Weibull, and predicted Rayleigh average daily power for lowest wind speed average during the growing season.
Figure 3.11: The observed, predicted Weibull, and predicted Rayleigh average daily power calculated as moving average for a 6 days interval for lowest wind speed average during the growing season.
Figure 3.12: The observed, predicted Weibull, and predicted Rayleigh average daily power for the part of the year other than the growing season.
Figure 3.13: The observed, predicted Weibull, and predicted Rayleigh average daily power calculated as moving average for a 6 days interval for the part of the year other than the growing season.
Figure 3.14: the residuals for the predicted average daily power for the lowest average wind speed during the growing season.
Figure 3.15: the residuals for the predicted average daily power for the part of the year other than the growing season.
Figure 3.16: the predicted versus the observed values of the daily average power predicted using the Weibull representation of the wind speed for the lowest wind speed average during the growing season.
Figure 3.17: the predicted versus the observed values of the daily average power predicted using the Rayleigh representation of the wind speed for the lowest wind speed average during the growing season.
The prediction using the Weibull representation appears not to accurately predict the smaller values of the power, but as the observed value increases the Weibull prediction performs better. On the other hand the prediction using the Rayleigh representation seems to perform consistently during this value range. For the part of the year other than the growing season, predictions using the Weibull representation are more consistent throughout the entire range of the values with a slight tendency to underestimate the power values especially in the larger end of the range, as seen in figure 3.18. When using the Rayleigh representation, predicted values are close to the observed values in the beginning, then the values are overestimated in the middle section of the curve, and then underestimated afterwards. The amount of underestimation continues to increase as the observed values increase (figure 3.19).

From the previous results, it can be concluded that the Weibull representation will be more successful in predicting the average daily power with more steady wind and larger wind speed averages. When the daily wind speed average is small and the wind speeds vary a lot with a standard deviation close to the half the value of the average daily wind speed or more, the error using the Rayleigh representation is likely to be less.
Figure 3.18: the predicted versus the observed values of the daily average power predicted using the Weibull representation of the wind speed for the part of the year other than the growing season.
Figure 3.19: the predicted versus the observed values of the daily average power predicted using the Rayleigh representation of the wind speed for the part of the year other than the growing season.
3.4.3 Integrity of wind estimates

The average daily wind speed and the Cv values can be used as indicators to decide which representation to choose. Because 1-min readings of wind speeds are not commonly available, the more available data would be the average hourly values. It is important to determine the integrity of the average and the standard deviation values obtained using average hourly values and how do they relate to average and the standard deviation values calculated using the 1-min readings. Figure 3.20 shows the daily average wind speed calculated using the hourly averages and the 1-minute data for a period of the growing season. The average values obtained using the average hourly values of the wind speeds are almost identical to the values obtained using the 1-min data. For the standard deviation, the values calculated using the hourly averages were always less than the values calculated using the 1-min data, as shown in figure 3.21. Strong correlation was found between the standard deviation values calculated using the two sets of data with a coefficient of Determination $R^2=0.988$. For the part of the year other than the growing season, the values obtained for the daily wind speed average using the hourly averages were also identical to the values obtained using the 1-min data (figure 3.22). The standard deviation values calculated using the hourly average values for this part of the year were also smaller than values calculated using the 1-min data.

The correlation between the values calculated using the two sets of data were also strongly correlated, but with a slightly lower correlation coefficient, $R^2=0.93$. Figure 3.23 shows standard deviation values calculated using the two data sets for the part of the year other than the growing season.
Figure 3.20: The daily average wind speed calculated using the 1-min data and the average hourly data for part of the growing season.
Figure 3.21: The Standard deviation of the wind data calculated using the 1-min data and the hourly averages for part of the growing season.
Figure 3.22: The daily average wind speed calculated using the 1-min data and the average hourly data for the part of the year other than the growing season.
Figure 3.23: The Standard deviation of the wind data calculated using the 1-min data and the hourly averages for the part of the year other than the growing season.
From this we can see that a good estimate for the values of the daily average wind speed can be obtained using the hourly average values, and if data available for both the 1-min and the hourly averages, the correlation between the standard deviation for both sets of data can be found and the values calculated using the hourly averages can be adjusted to the actual values.

3.5 SUMMARY and CONCLUSION

Stewart & Essenwanger 1978, Takle & Brown 1978, and Van der Auwera et al. 1980 used the Weibull distribution to represent the wind speed distribution. Tuller & Brett 1984 reported that the Weibull distribution gives an approximate but generally good fit of the wind distribution. Weibull distribution could take the form of other distribution depending on the values of the shape factor. Rayleigh distribution is a special case of Weibull distribution with a value of the shape factor $k=2$ (Justus et al. 1978). Rayleigh distribution is the simplest way to express wind speed probability distribution. The focus of this work was to determine the possibility of representing the wind speed in short time intervals (1day) using a statistical distribution and determine the accuracy of such representation if used to predict the energy output of a wind turbine. The wind turbine used in the experiment where a 20 kW rated Jacob wind turbine with a maximum rated speed of 11.62ms$^{-1}$ (26mph) and a cut in speed of 3.58ms$^{-1}$ (8mph). The turbine is installed in a rural area about twenty-five miles east of Cleveland Ohio. The wind speeds were recorded in 1-minute intervals for 250 days through the year. The results showed that the Weibull representation is more accurate in simulating the observed distribution when the Cv of the daily wind speeds is 0.5 or smaller. When the Cv of the daily wind
speeds is larger than 0.5 the daily Rayleigh representation is closer to the observed data distribution. The prediction using the Weibull representation appears not to accurately predict the smaller values of the power, but as the observed value increases the Weibull prediction performs better. The power of a wind turbine can be predicted for short intervals such as a day using a statistical representation of the daily wind speeds. The Weibull distribution is the best distribution to represent the daily wind speed distribution. Some times the Weibull distribution over predicts the average daily power expected from the turbine when the Cv of the wind speeds is larger than 0.5. In such cases, the Rayleigh distribution performs better in predicting the average daily power. The Cv of the daily wind speeds can be used to choose which distribution is better for predicting the expected average daily turbine power.

3.6 REFERENCES


CHAPTER 4

MODELING A DRIP IRRIGATION SYSTEM POWERED BY A RENEWABLE ENERGY SOURCE

4.1 INTRODUCTION

The need to produce more food for an expanding population is very important. The continued increase of the world population and the increasing demand for land use other than agricultural uses is making it a necessity to increase the food output of each unit area of land used for agricultural purposes. One of the major challenges facing agricultural expansion is finding a steady dependable clean supply of water. The water problem is becoming more serious taking into account that water uses other than agriculture are increasing rapidly. This shows that water availability will be a big factor in agricultural production in the next few years. Most of the productivity increases in land output in the last few years were from irrigated land. Although some places have enough rain to sustain a successful crop production operation, the water supply is random in those areas and can change considerably from one year to another. Irrigation systems, such as drip and sprinkler, have been used to provide uniform water distribution throughout the whole field and to help maximize water use efficiency. Irrigation systems can deliver the water uniformly and very close to the plant, and with a controlled amount in certain times. However, it has two problems that affect the spread of such systems, especially in developing countries.
One is the cost of such a system and the other problem is the need for an energy supply. There have been some improvements in the cost problem, and it is less expensive now to install an irrigation system than it was ten years ago.

The energy problem was solved using electricity when it is available and a generator when it is not. The problem with such approach is it makes the production process dependable on fossil fuels, especially in the case of a stand-alone system where there is no nearby source of electricity and it increases the negative impact of the system on the surrounding environment.

An irrigation system powered by renewable energy seems to be the solution of this problem. But there are several factors preventing the spread of such systems. The fact that the renewable energy systems are not as dependable as the traditional energy sources, the cost of gathering data for such systems, the fact that the data are site specific, the lack of knowledge of such systems, and the lack of knowledge about the effect of different factors on the design and performance of such systems.

There were some attempts to investigate the possibility of using an irrigation system powered by renewable energy in the last few years. The University of Nebraska had a 25-kW solar systems to pump water to a gated pipe system to irrigate corn. In Texas, a researcher irrigated fruit trees using wind power for pumping water (Vick et al., 2000). The Nebraska system was used successfully for a number of years but the main focus was not analyzing the system and the different factors affecting system design.
4.2 AIM

In order to decrease the cost of renewable energy systems, the systems have to be more reliable and produced commercially on a larger scale. To achieve such a goal we have to use these systems in an application that matches system capabilities and reliabilities and produces enough financial outcome to be profitable. This can only be done if the factor affecting system design and outcomes are studied and we have enough knowledge about what causes the system to be reliable or unreliable. One of the problems facing such a study is the high cost and the long time required for collecting and analyzing data, and the lack of such systems for study. One solution is to develop a simulation model that can predict the performance of the system with the minimum amount of site specific data needs.

Therefore it is the aim of this research to develop a computer simulation model that can be used to predict the performance of an irrigation system powered by renewable energy (solar and wind power is the focus of this paper). The approach depends on available simple metrological data that can be gathered using any agricultural weather station while minimizing the use of site specific data by using statistical methods, modeling the expected reliability of the system using the weather records and the statistical distribution techniques.

4.3 REVIEW OF LITERATURE

4.3.1 Modeling solar energy

Alzoheiry et al. (2006) evaluated solar energy for Wooster, OH (semi-humid area) using four basic models: the Hargreaves and Samani (1982) model with $K_r = 0.16$ or
0.19; the Allen (1997) self-calibrating model; a model with the value of $K_r$ as a function of the min relative humidity; and a modified form of the Hargreaves and Samani model using $K_r$ based on the difference between max and min daily temperature. [Details are described above in Chapter 2.] The evaluation included testing model ability to predict day-to-day radiation and the reliability of the upper and the lower limits of solar radiation predicted using data generated from the models. The best day-to-day prediction model was a form of the Hargreaves and Samani model using $K_r$ based on the difference between max and min daily temperature. Hargreaves and Samani reported that the self-calibrating models for both the upper and the lower limits of solar radiation was the most reliable for long term prediction of the upper and lower limits of solar radiation.

The amount of electrical power generated at a certain level of radiation depends on the type of the PV array and weather conditions in which the array will operate. ASTM E-1036 (ASTM, 1996) is the standard used for the testing of the performance of the PV arrays. The method is based on the assumption that the current output of the array depends on the solar irradiance and the voltage of the array depends on the array temperature. The array temperature is a function of the irradiance, the ambient temperature and the wind speed. A simple regression equation is developed using the previous parameters to predict the array power output (Whitaker et al., 1997).

King and Eckert (1996) introduced a new model for rating the performance of a PV array, and reported that the ASTM methods are not versatile or accurate enough to meet current system requirement and that it is suitable in testing systems under only one operating condition. King and Eckert characterized the performance of a 25-kW PV array in Arizona based on the outdoor test method developed at the Sandia National
Laboratories. Whitaker et al. (1997) tested the SANDIA array performance model and compared it to the ASTM method. Whitaker et al. reported that both methods were labor intensive, both provided acceptable rating of the array, both methods had an uncertainty of roughly 4-5%, and the regression ASTM method was significantly simpler than the SANDIA method. The SANDIA method provides characterization of the array while the ASTM method characterizes the combination of the PV and the inverter. Databases have been developed for both methods but neither has been developed to the “commercial product.” Whitaker et al. also indicated that the correct method to use depends on the purpose of the testing.

4.3.2 Modeling wind energy

Wind powered energy systems are one of two types (depending on the use of the system). Grid connected generation systems are usually large capacity systems connected to the electric grid to provide electric power. This type of system needs major investments and strategic planning, and is usually funded by governments. Stand-alone generation systems are often used in remote places to provide power for electricity, telecommunications and some farm needs. Stand-alone wind turbine systems are also used world wide to provide mechanical power for pumping drinking and irrigation water. The wind turbines used for these applications can vary between a few watts to 50 kW. For the wind system to function properly and provide reliable energy supplies, design factors such as location, wind speed, wind direction, engineering design of the turbine, should be considered separately for each case.
Using metrological data and data available at a desired site we can predict the long-term wind speed at the desired site using the Measure-Correlate-Predict approach described by Joensen et al. (1999). The data are binned based on the wind direction (usually 12 directions with 30 degrees each). A straight line is fitted within each bin using the least square method resulting in a relation in the form:

\[ Y = aX + b \]  
\[ \theta - \alpha = c \]

where:

- \( Y \) is the wind speed at the desired site;
- \( X \) is the wind speed at the reference site;
- \( \theta \) is the wind direction at the desired site;
- \( \alpha \) is the wind direction at the reference site;
- and \( a, b, c \) are functions of \( \alpha \) at the mid point of each direction.

For predicting the actual power output of a wind turbine, the electrical and mechanical engineering aspects of the system have to be included in the modeling process. Wilkie et al. (1990) defined the basic components in a turbine system as wind turbine rotor, low speed shaft, gearbox, high speed shaft, induction generator and control system. Mohamed et al. (2000) modeled a wind turbine connected to the grid, and noted that the system’s four components were the wind turbine, the generator, the rectifier, and the inverter. Several researchers modeled wind turbine power output, such as Sharma et al. (2000), Ezzeldin et al. (2000), and Petru and Thiringer (2002). The focus of those studies was the electrical aspects of the system and modeling system performance and effects on the electrical grid. Omara and Irps (2003) tested a MoWEC system for wind power. This is a mobile system with two rotors and a total swept area of 80 m\(^2\).
4.3.3 Irrigation system modeling

Modeling an irrigation system is a complex task that must incorporate the random factors affecting the system, the desired reliability, economical factors related to system cost, and the expected income generated by the farming operation. Modeling an irrigation system starts with the identifying the factors that will affect system performance and the relation between the factors. Factors affecting an irrigation system design can be classified into two main groups:

- Random factors: mostly factors that are associated with location, such as the weather parameters, soil type, slope, etc. The main denominator between all the factors in this group is that they are uncontrollable. Some of those factors are constants for each individual system, such as the slope or soil type, and the others will change from one year to the next, such as the temperature, solar radiation, wind speed, humidity, etc.

- Design and operation factors: such as the type of system, its reliability, the required degree of irrigation, etc. These factors can be controlled and are somewhat dependent on the random factors. A successful irrigation design would satisfy or exceed its design requirements for all the change in the random factors through the project life.

The final system design will vary from one case to another depending on the purposes of irrigation, climactic conditions, and the available energy sources.

English et al. (2002) emphasized the fact that there is a shift in the way irrigation design is conducted regarding the water regime used in operating the system. The old way of designing the irrigation system to give maximum yields is now replaced by designing to achieve the maximization of net benefits. This may be because of the rising costs of an irrigation system, the limitation of natural resources, and concerns about the
environmental effect of irrigation. According to English et al., the maximization of net benefits could be per unit of water or land, or cost depending on the surrounding circumstances, and the objective of the system. Each different goal will require a different method of analyzing the system and will produce a different final design. Deciding the goal to be achieved by the design will depend on the limiting factors in the design. For example, in arid areas the main concern will be water availability and the design should be aimed at maximizing the net benefit of water unit. In areas where energy is expensive, the design should minimize the energy consumption.

4.3.3.1 Predicting the desired irrigation depth

The first step in designing an irrigation system is to determine the water depth to be applied by the system during each irrigation. Weather is a determinate factor in the amount of water needed for irrigation; the rate of evapotranspiration is directly affected by temperature, solar radiation, wind speed, relative humidity, crop type and stage. Jensen et al. (1990) compared 20 different methods used to determine the reference evapotranspiration. They found the Penman-Monteith method to the most reliable method for both arid and humid climates. Penmen (1948) used a combination method with two terms, one describing the energy input and the other term for the rate of aerodynamic exchange from the surface. Monteith (1965) introduced a new term for the stomatal resistance in the Penmen equation to account for crop type, in addition to the aerodynamic term presented in the original Penmen equation. The original form of the Penman-Monteith equation can be written as:

$$\begin{align*}
ET_0 &= \frac{0.408 \Delta(R_m - G) + \gamma \frac{900}{T + 273} U_z (e_s - e_a)}{\Delta + \gamma (1 + 0.34U_z)} \\
&= (4.3)
\end{align*}$$
where:

\( ET_0 \) is the reference evapotranspiration [\( \text{mm day}^{-1} \)]; \( R_n \) is net radiation at the crop surface [\( \text{MJ m}^{-2} \text{ day}^{-1} \)]; \( G \) is soil heat flux density [\( \text{MJ m}^{-2} \text{ day}^{-1} \)]; \( T \) is mean daily air temperature at 2-height [\( ^\circ\text{C} \)]; \( u_2 \) is wind speed at 2-m height [\( \text{m s}^{-1} \)]; \( e_s \) is saturation vapor pressure [\( \text{kPa} \)]; \( e_a \) is actual vapor pressure [\( \text{kPa} \)]; \( e_s - e_a \) is saturation vapor pressure deficit [\( \text{kPa} \)]; \( \Delta \) is slope vapor pressure curve [\( \text{kPa} ^\circ\text{C}^{-1} \)]; and \( \gamma \) is a psychrometric constant [\( \text{kPa} ^\circ\text{C}^{-1} \)].

Allen (1997) used a self-calibrating model to estimate the solar radiation for use in the estimation of evapotranspiration. He reported the model to perform accurately in arid areas, but it tended to overestimate solar radiation in humid and semi-humid areas. Berliner and Droppelmann (2003) used the Thornton–Running model to estimate solar radiation, and then used the output in estimating the evapotranspiration using Penman’s equation. They reported a systematic underestimation of daily Penman's potential evapotranspiration during the dry summer period, especially if the saturated vapor pressure at min daily temperature was used in the Thornton–Running model instead of the actual measured daily saturated vapor pressure.

The reference evapotranspiration can be related to crop evapotranspiration using a crop coefficient. The value of the crop coefficient is not only different between different crops, but it also differs for the same crop depending on the crop stage. The growing season can be divided into four stages with three crop coefficient values. At the initial stage, the determinant factor controlling the crop coefficient is the soil evaporation. In the crop development stage the determinant factors are ground cover and plant development. The third stage is the mid-season stage where the crop coefficient depends on the crop type, humidity, and wind speed. In the late season stage the crop coefficient depends on
crop type and harvesting date. The crop coefficient is assumed to be constant for the initial stage, increasing from its value at initial to a maximum at the beginning of the mid-season stage, constant at its max value during the mid-season stage, and declining after that until harvest. Tabulated values of the crop coefficient for different crops and different growth stages can be found in FAO Irrigation and Drainage Paper 56 (FAO, 1998).

James (1993) described a water budget technique for determining time of irrigation. The technique calculates the new soil-water content at the end of each day as a function of precipitation, evapotranspiration, irrigation, drainage and runoff.

4.3.3.2 Modeling emitter wetting diameter

Water movement and wetting patterns from an emitter are determinant factors in choosing emitter discharge and number of emitters for each plant. The soil-water dynamics under trickle emitters depends on emitter flow rate, soil infiltration rate, and evapotranspiration. Several types of models are available for modeling these dynamics depending on available data and the purpose of the prediction. Lubana and Narda (2001) reviewed models that described the soil-water dynamics under trickle emitters. They reported five major modeling purposes: infiltration, wetted soil volume, emitter spacing, moisture distribution, and water uptake. Philip (1971), Raats (1971), Brandt et al. (1971), Bresler (1971), Taghavi et al. (1984) and others developed models to predict water flow under an emitter. Risse and Chesness (1989) reviewed the previous models and reported that those models are sometimes complicated and the data needed for the models limits their use.
Bresler (1978) analyzed the interaction between emitted water and soil, assuming the soil to be homogeneous, isotropic, and that the emitter was a small circular ponded source. He also assumed the soil evaporation to be negligible. Dasberg and Bresler (1985) used the approximate solution of the axi-symmetric two-dimensional flow equation to find emitter spacing. Risse and Chesness (1989) modified Dasberg and Bresler’s approach and used it to predict the wetting radius of a trickle emitter. Risse and Chesness’ procedure predicts the relation between the hydraulic conductivity and the soil water potentials as a function of soil texture, then predicts the ultimate wetting radius as a function of the saturated hydraulic conductivity and emitter discharge.

Ben-Asher et al. (1986) used the effective hemi-spherical model to model infiltration and water extraction from a trickle source. The model assumes that water from an emitting source on the soil surface will form a hemisphere around the source, and the radius of this hemisphere is a function of soil evaporation, plant transpiration, and soil infiltration. Lubana (2004) used the hemispherical model in predicting the wetting radius around tomato plants irrigated using a trickle system, and found variation up to 17% in soil water content in some cases, and found wetting radius to be dependent on water application rate from an emitter.

4.3.3.3 Designing system laterals and predicting energy requirement

For any irrigation system, the energy required for system operation depends on the required head and the system discharge. Bralts et al. (1987) used the relationship:

\[ q_e = kh^s \]  \hspace{1cm} (4.4)
where:

$q_e$ is the emitter flow rate($L^3T^{-1}$); $k$ is the emitter constant; $x$ is the emitter exponent; and $h$ is pressure head($L$). Gerrish et al. (1996) indicated that the relation between the flow rate and the pressure head is nonlinear in the transition and the turbulent flow regimes. Von Bernuth (1990) used the Darcy-Wiesbach equation when evaluating the friction losses in a plastic pipe. He expressed the friction loss in the pipe as follows:

$$h_{loss} = \frac{8fsQ}{\pi^2gD^5}$$ (4.5)

where:

$f$ is the coefficient of friction; $Q$ is the flow moving through the pipe; $s$ is the pipe length; $g$ is the gravitational acceleration; and $D$ is the pipe discharge. Hathoot et al. (1993) used the Darcy-Wiesbach equation and calculated the value of $f$ based on the work of Von Bernuth. Hathoot et al. used their equation to calculate the friction coefficient based on the flow regime being laminar, transient or turbulent.

Several researchers, such as Gerrish (1996), Bralts and Segrlind (1985), and Mohtar et al. (1991), used finite element and numerical methods in analyzing trickle irrigation systems. Wood and Rayes (1981) found that the head loss in elbows, tees, and valves can significantly affect the pressure in an irrigation network. Gerrish et al. (1996) proposed a method to incorporate pipe components into the hydraulic network analysis by adding their contribution to the nodal equations instead of treating them as separate items.

Meshkat et al. (1985) and Narayanan et al. (1998) developed a more complete approach for analyzing the entire irrigation system. Narayanan et al. (2000) developed a computer tool to optimize the irrigation system design for small areas in South Dakota. The model considers crop type, soil type, irrigation interval, system layout, and pressure
requirements of the emitter. Some of the parameters needed for the system design were calculated using the generalized equation for predicting parameters, such as the wetting diameter, the shortest irrigation interval, etc.

4.4 METHODS

For this study model development is based on the idea of modeling the random factors that affect the system, and then designing the system based on the trends obtained from the statistical distribution of those factors. Figure 4.1 shows an illustration of the different factors involved in an irrigation system powered by a renewable source. Temperature, wind speed, solar radiation and humidity determine reference evapotranspiration. The proposed crop helps to decide the start and end of the growing season, and the crop coefficient for the different stages, and thus the crop evapotranspiration. Crop evapotranspiration, soil type, root zone depth are factors that affect water demand. Because the value of the reference evapotranspiration will change from one year to another, the water demand will also change and the design water demand should be determined using a statistical distribution.

The soil type, dominate weather conditions, topography, field shape and dimensions, crop type, and availability of water will determine the type of irrigation system to use and design of the system. Water demand, irrigation system design, and the desired reliability of the system help determine the energy needed to achieve design goals. The energy demand, solar radiation and wind speed help determine the suitable power system for energy supply, the size of such a system, and its cost. The model is constructed to be able to design the system and calculate its expected reliability.
4.4.1 Model development

The model is constructed to handle up to 100 years of daily weather record. The main parts of the model are as follows:

- Modeling water demand;
- Designing the irrigation system, predicting energy demand, and calculating efficiency; and
- Designing the renewable energy system and predicting its reliability.
4.4.1.1 Modeling water demand

Reference evapotranspiration: Daily reference evapotranspiration was calculated using the Penman-Monteith method (Equation 4.3), and the calculations were performed according to the FAO Irrigation and Drainage Paper 56 (FAO, 1998).

Net radiation at the crop surface, \( R_n \), was calculated using the procedures described in the FAO paper with the clear day radiation, \( R_e \), calculated according to the method described by Allen (1997). Total solar radiation on any given day was calculated using the model described by Alzoheiry et al. (2006) and in Chapter 3 above. The \( \Delta \) slope of the vapor pressure curve is calculated using Equation 10,

\[
\Delta = \frac{4098 \left( 0.6108 \exp \left( \frac{17.27 T_{\text{ave}}}{237.3 + T_{\text{ave}}} \right) \right)}{(T_{\text{ave}} + 237.3)^2}
\]  \( \text{(4.6)} \)

where: \( T_{\text{ave}} \) is the average daily temperature (°C); and the psychrometric constant \( \gamma \) is calculated using equation 4.7:

\[
\gamma = \frac{c_p P_a}{\epsilon \lambda}
\]  \( \text{(4.7)} \)

where: \( c_p \) is the air specific heat at constant pressure (MJ Kg\(^{-1}\) °C\(^{-1}\)); \( P_a \) is the atmospheric pressure (kPa); \( \epsilon \) is the ratio of molecular weight of water vapor/dry air = 0.622; and \( \lambda \), the latent heat of vaporization = 2.45 (MJ Kg\(^{-1}\)).

Crop evapotranspiration: The growing season was divided into four stages defined with three different crop coefficient values: \( Kc_{\text{ini}} \) is the crop coefficient at the initial stage; \( Kc_{\text{mid}} \) is the max value for the crop coefficient; and \( Kc_{\text{end}} \) is the crop coefficient at the end of the season. The user enters each of the crop coefficient values as well as the date of planting, and the number of days in the initial stage, the crop development stage,
the mid-season stage and the late season stage. Each stage is then represented by a linear equation. Both the initial and the mid stage is represented by a linear model of the form:

\[ Kc = a \]  
(4.8)

where: \( a = Kc_{ini} \) for the initial stage; and \( a = Kc_{mid} \) for the initial stage.

Crop development and late season stages are represented by an equation in the form:

\[ Kc = a + bL \]  
(4.9)

where: \( a = Kc_{ini} \) for the crop development stage; \( a = Kc_{mid} \) for the late season stage; \( b = inc \) for the crop development stage; \( b = dec \) for the late season stage; and \( L \) is the day number in the stage. The parameters \( inc \) and \( dec \) are calculated as:

\[ inc = \frac{Kc_{mid} - Kc_{ini}}{D_{ini}} \]  
(4.10)

and

\[ dec = \frac{Kc_{end} - Kc_{mid}}{D_{late}} \]  
(4.11)

Where \( D_{ini} \), \( D_{late} \) are the length of the crop development and the late season stage, respectively.

Determining design daily irrigation requirements (DDIR): The DDIR is calculated according to the method described by James (1993). Soil bulk density, saturation water content, water content at field capacity, water content at welting point, depth of the root zone, allowable depletion, and daily precipitation are required inputs. A simple water balance is used to describe the change in soil-water content on any given day:

\[ \Delta \theta = P + IR - ET_c \]  
(4.12)
where: $\Delta \theta$ is the change in soil-water content as depth of water (mm); $P$ is the daily precipitation (mm); $IR$ is the irrigation depth (mm); and $ET_c$ is the daily crop evapotranspiration (mm). The modeling is under the assumption that the soil is well drained and the excess water over the filed capacity exits the soil profile 24 hours (time needed to go from saturation to field capacity) after irrigation or precipitation. The new soil-water content is calculated as:

$$\theta_{i+1} = \theta_i + \Delta \theta$$  \hspace{1cm} (4.13)

where: $\theta_{i+1}$ is the soil-water content at day $i+1$; and $\theta_i$ is the soil water content at day $i$.

When the soil-water content reaches the critical water content, the model adds the irrigation depth and sets the new soil-water content to field capacity, recording the interval between irrigation throughout the year. After each year the min interval between irrigation for the year $II_{\text{min}}$ is recorded and the $DDIR$ of the year is calculated as:

$$DDIR_{yy} = \frac{AD}{II_{\text{min}}}$$  \hspace{1cm} (4.14)

where: $AD$ is the allowable depletion water depth (equals irrigation water depth in full irrigation) (mm/day).

The probability distribution of the $DDIR$ values and the data smoothing for interpolation using the Weibull transformation to linearize the relation between the $DDIR$ values and the corresponding probability is according to the method described by Haan (1977). The least squares method is used to determine the slope and the interception of the resulting linear relationship and the $DDIR$ value at the desired reliability level is calculated.
4.4.1.2 Irrigation system design and energy requirement

Emitter capacity and irrigation operation time were calculated according to the method described by James (1993). The emitter capacity requires the calculation of the expected wetting diameter of the emitter.

Determining the expected wetting diameter of the emitter: The wetting diameter of the emitter was modeled using the effective hemispherical model described by Ben-Asher et al. (1986). Two different cases are the determinant cases of the wetted radius around an emitter.

1. When the plants are small, there is very little ground cover and the dominant process of water loss is evaporation:

\[ R_0 = \left( \frac{2I_o}{E} \right)^{\frac{1}{3}} \]  

(4.15)

2. When the plants are grown and the dominant process of water loss is transpiration:

\[ R_0 = \left( \frac{3I_o}{T} \right)^{\frac{1}{3}} \]  

(4.16)

where: \( R_0 \) is the expected wetted radius; \( I_o \) is the soil basic infiltration rate; \( T \) is the plant transpiration; and \( E \) is the soil evaporation.

Soil evaporation was calculated using the method described by Ritchie (1971). Plant transpiration was calculated using the method developed by Ritchie and Burnett (1971). Determining transpiration requires the values of leaf area index (LAI). A second degree equation represents the first stage of the LAI curve then a third degree equation represents the rest of the season. With user provided values and the least squares method, the constants in both equations are determined.
Based on the emitter capacity, and after selecting an emitter, the number of emitters on each lateral and lateral discharge, the head at the end of the lateral can be determined using the back-step method described by Hathoot et al. (1993). However, instead of starting from the beginning of the line, the model starts the iteration from the last emitter on the line and adds the discharge until the beginning is reached. The discharge from emitter $i$ can be calculated using Equation 4.4. The flow velocity $v$ (ms$^{-1}$) is calculated as:

$$v = \frac{4Q}{\pi d^2}$$  \hspace{1cm} (4.17)

where: $Q$ is the total volumetric flow rate in the drip line (m$^3$s$^{-1}$); and $d$ is the diameter of the line (m). The friction coefficient is calculated based on the type of flow in the line and the classification of the flow based on Reynolds number and the corresponding friction factor is as follows:

Friction coefficient for laminar flow $R_N < 2000$

$$f = \frac{64}{R_N}$$  \hspace{1cm} (4.18)

Friction coefficient for turbulent flow $3000 < R_N < 10^5$

$$f = 0.316 \left(\frac{\pi dv}{4Q}\right)^{0.25}$$  \hspace{1cm} (4.19)

Friction coefficient for full turbulent flow $10^5 < R_N < 10^7$

$$f = 0.13 \left(\frac{\pi dv}{4Q}\right)^{0.172}$$  \hspace{1cm} (4.20)

where: $f$ is the friction coefficient in a plastic pipe.
The friction losses in a length of pipe from emitter i to emitter i+1 on the line is calculated using Equation 4.5. The head at point i+1 is calculated by adding the head loss to the head at point i. The discharge of emitter i+1 is calculated using the new head in equation 4.4.

The new total discharge in the pipe length is:

\[ Q_{i+1} = Q_i + q_{i+1} \]  \hspace{1cm} (4.21)

The head at the emitter i+1 is:

\[ h_{i+1} = h_i + \frac{3(Q_{i+1}^2 - Q_i^2)}{2gA} + h_{\text{loss}} + sS \]  \hspace{1cm} (4.22)

where: \( s \) is the slope; and \( S \) is the emitter spacing on the line (m).

The revised value of emitter i+1 discharge is then calculated using the new head and Equation 4.4. A new value of total discharge is calculated using Equation 4.21 and a new head is calculated using Equation 4.22. The iteration process is continued till the change in emitter discharge is less than the desired accuracy.

Because the model focuses on minimizing the energy requirements of the system, the model uses the lateral pressure range at the lower end of the emitter’s operating pressure range. In order to find the lowest permissible head that can be used without compromising the required emission uniformity of the system, the minimum emitter discharge at the end of the system is calculated as:

\[ q_m = \frac{EU}{100\left[1 - \frac{1.27C_v}{\sqrt{n}}\right]}q_a \]  \hspace{1cm} (4.23)

where: \( q_m \) is the discharge of the emitter at the far most end of the line (minimum emitter
discharge in entire system, m$^3$s$^{-1}$); $q_a$ is the nominal discharge of the chosen emitter (average emitter discharge, m$^3$s$^{-1}$); $C_r$ is the manufacturer’s coefficient of variation for the emitters; $n$ is the number of emitters per plant; and $EU$ the desired emission uniformity (%).

The same method is applied for the main line design. A main diameter and a temporary main diameter are selected from a look-up table in the program (Figure 4.2) using a temporary total discharge equal to the number of lines multiplied by the line total line discharge calculated before. The head at the beginning of the new line is calculated using Equation 4.5 and the discharge of the previous line. The new head is then used to estimate the discharge of the emitter at the beginning of the new line and the iteration process using Equations 4.17 to 4.22 is repeated from the beginning of the new line until its end, with Equation 4.21 as follows:

$$Q_{i+1} = Q_i - q_{i+1} \tag{4.24}$$

The process is repeated line by line and the difference between each new emitter discharge and $q_m$ is calculated. The process is repeated until the line closest to the water source is reached or the difference of discharge between the emitter exceeds the $\pm 10$ discharge differences recommended for drip irrigation systems.
Figure 4.2: Look-up table with available main diameters.

If the discharge difference exceeds the allowable difference, the model chooses the next available main diameter from the look-up table, and the process of calculating the head and the discharges through the system is repeated using the new diameter. The look-up table contains the nominal size of the pipe, and its inner and outer diameters. The look-up table also contains the equation to convert the fittings throughout the system into added pipe length of the chosen diameter to account for the secondary losses.
The head losses in the couplers between pipes are converted to equivalent length of pipe according to Sarsfield (1984). The head losses in fittings, tees and other system components are added to the system based on the chosen layout. The model has seven different layouts, and a custom layout for the user to input the energy and the discharge of any system other than the seven available in the program (Figure 4.3). The number of zones in any layout is calculated by dividing the field dimensions by the length of the drip lines obtained in the back-step iteration. System discharge and total head are acquired at the end of the process. The system total head is calculated by adding the initial lift to the operating head, and the pump is chosen based on the total system discharge and the total head. Because of the variation of the head loss in the filter with operation, the maximum allowable pressure drop across the filter before flushing as recommended by the ASAE (ASAE, 2003) is added to the system head to account for the maximum possible pressure head required through the system operation. The ASAE standard for design and installation of microirrigation system requires the flushing of the filter when the head drop across the filter reaches 7.13 m (70 kPa).
The user interface shown in Figure 4.4 allows the user to specify different parameters used in the design of the irrigation system, such as row spacing, spacing between plants in the same row, length and width of the field, slope in each direction, and percentage of coverage of the wetted area. Based on the previous inputs, the model calculates the irrigation time and a suggested value for the emitter capacity, and allows the user to input the specifications of the drip line to be used. The model then recalculates the irrigation time based on emitter capacity. All the calculations assume uniform land slope.
4.4.1.3 Modeling the solar energy system

Several approaches were tested for modeling solar irradiance. The total available daily solar radiation is modeled using the model developed by Alzoheiry et al. (2006) and as presented in Chapter 2 above. The selective model used is a modified form of the Hargreaves and Samani (1982) model. Modeling the expected lower limit of solar
radiation is predicted using the Selective $k_{r3}$ model described by Alzoheiry (2006) and as presented in Chapter 2 above. Solar PV system design is based on the voltage need of the system, the total energy required and the temperature. The total energy output in the location from the selected panels is predicted using the ASTM method. The model requires the max power, the open circuit voltage, the short circuit current, the max power voltage, the max power current and the max power voltage/temperature coefficient at standard testing conditions (STC: irradiance of 1000Wm$^{-2}$, cell temperature of 25$^\circ$C, AM 1.5), and another level of solar irradiance. The amount of available solar energy and the corresponding electric energy from the solar panel system is calculated as a moving average of the energy amount in the min irrigation interval for each year.

4.4.1.4 Modeling the wind energy system

The average values of wind speed at any location helps determine the maximum size of the wind turbine that can be operated at this location. The transformation of the wind data from the available metrological data to the corresponding data at the site requires at least one year of readings at the site, and the corresponding data from the weather station. The Measure-Correlate-Predict approach is used in the model to transform the data from the weather station to the site data. The model allows the user to enter the values of the turbine power coefficient (Cp) and the corresponding wind speeds. The parameter Cp can be expressed as a function of the wind speed using a second-degree equation, the least square method is used to find the constant in that equation using the wind speed, and the corresponding expected power generated from the turbine. After finding the relation between Cp and wind speed, the power generated at each wind
speed level $P_n(U)$ can be calculated. A statistical method is used to predict the expected power output from the turbine using $P_n(U)$ and the probability density function for each wind speed $p(U)$. The 2-parameter Weibull distribution is used to describe the daily wind speed distribution. The values of the hourly wind speeds are used to determine the distribution parameters as described in Chapter 3.

4.4.2 Model testing and evaluation

A computer program was developed for representing the system. The model is a visual basic program with an excel spreadsheet. Visual basic was chosen because of the flexibility in the programming language and the capability of producing a user-friendly interface. The use of the excel sheet enables the program to handle large amounts of data using the optimized function available in excel.

The model is capable of handling up to 65,000 values of daily data. Solar and wind power predictions and model performance are being tested and evaluated in Northeast Ohio. The solar system available is a 26-kW photovoltaic array. The array consists of solar cells with an expected max power of 120 W (STC), the open circuit voltage of the cell $V_{OC} = 21$ V, the short circuit current $I_{SC} = 7.74$ A, the max power voltage $V_{PMAX} = 16.8$V, the max power current $I_{P MAX} = 7.12$ A, and a max power voltage coefficient of $-0.5$ V/$^\circ$C. The measurements recorded include solar irradiance, ambient temperature, module temperature, wind speed at a 2-m height, and amount of energy generated. The panels face south with a tilt angle of approximately $55^\circ$. Figure 4.5 shows the solar array used in evaluating the model.
For wind power generation, the system has a 20-kW rated power wind turbine with a rotor diameter of 9.46 m (31 ft). The turbine cut-in speed is 8 mph and the rated speed is 26 mph, and the generator rotates at 175 rpm. The turbine is mounted on a 30.5-m (100 ft) monopole tower. The tower has three wind anemometers, two of them mounted at 21.4 m (70 ft), and the last anemometer mounted at 15.3 m (50 ft). The wind turbine is shown in Figure 4.5 and the turbine rotor and the anemometers are shown in Figure 4.6. The wind direction in degrees is also recorded. The wind data logger records the wind
parameters and the power generated by the turbine for 1-min, 10-min and 1-hour intervals. The record includes the average and the max wind speed, the wind direction at both levels of the sensors, and the average and max-generated power during each interval. Eighteen month’s of data have been collected. A 50-year data record from a nearby weather station in Cleveland, OH, is used for predicting the upper and lower limits and trends of solar and wind parameters.

Figure 4.6: Wind turbine rotor and anemometer positioning on the tower.
4.5 RESULTS

4.5.1 Irrigation system design evaluation

In order to evaluate the methods used in the irrigation system design, the model was used to solve the design problems presented by Yitayew and Warrick (1988) and Hathoot et al. (1994).

Design Problem:

Design the proper length of a lateral pipe as well as the pressure in the inlet for the following criteria: Pressure head discharge relation \( q = 3.5 \times 10^{-7} \ H^{0.5} \), nominal emitter discharge \( q = 4 \ Lh^{-1} \), distance between emitters on the line \( s = 1 \ m \), uniformity coefficient \( UC = 0.95 \), lateral diameter \( D = 14mm \), and the slope \( S = 0 \). The minimum allowable discharge for an emitter (Equation 4.23) was calculated assuming an average emitter with a \( C_V = 0.05 \) and a design emission uniformity \( EU \) of 85%.

The model run gave the following results: The length of the lateral \( L = 124 \ m \), the pressure head at the inlet of the lateral \( H_{max} = 11.49 \ m \) and the average head \( H_{av} = 8.85 \ m \). Hathoot’s calculation gives \( L = 129 \ m \) and \( H_{max} = 12.69 \ m \). Using Yitayew and Warrick’s calculations, \( L = 126 \ m \) and \( H_{max} = 11.65 \ m \). The difference between the length (124 versus 126) and the head (11.49 m versus 11.65 m) calculated by the model and that from Yitayew and Warrick’s calculations results from the fact that the model is focused on lowering the energy needs of the system, so it starts from the lowest possible emitter discharge. Yitayew and Warrick’s calculations start from the nominal emitter discharge. The difference between the model results and Hathoot’s results is because the model considers the emission uniformity in the calculation while Hathoot’s calculation is based only on the uniformity coefficient. The max emitter discharge on the lateral using
the model was $q_{\text{max}} = 4.37 \text{ Lh}^{-1}$ while Hathoot’s method gives $q_{\text{max}} = 4.59 \text{ Lh}^{-1}$ and Yitayew and Warrick’s method gives $q_{\text{max}} = 4.4 \text{ Lh}^{-1}$.

4.5.2 Evaluating model prediction for solar energy

Figure 4.7 shows the observed and predicted values of total daily solar radiation. The values of solar radiation predicted by the model represent the observed values for solar radiation, for solar radiation values greater than 3 kWhm$^{-2}$. When the values of solar radiation are smaller than 3 kWhm$^{-2}$, the model tends to over-predict the values of solar radiation as illustrated in Figure 4.7. The value of solar radiation calculated as a moving average over the minimum irrigation interval shows the model’s slight tendency to over-predict solar radiation (Figure 4.8). This tendency is results from the model over-predicting the smaller values of solar radiation.

The predicted versus observed values of total electrical energy produced by the solar array is shown in Figure 4.9. The model is more accurate in predicting the electrical output of the array when solar irradiance is between 400 and 800 Wm$^{-2}$. On days with relatively small solar radiation, model accuracy decreases. This is expected because the accuracy of the ASTM method decreases when solar irradiance is less than 400 Wm$^{-2}$. On days with relatively large levels of solar irradiance, the model under-predicts solar array electrical energy output because it was designed to calculate the energy output based on the average daily irradiance and the average daily temperature. This was done to avoid over-predicting energy output.
Figure 4.7: Total predicted and observed daily solar radiation.
Figure 4.8: Total predicted and observed daily solar radiation calculated as moving average over minimum irrigation intervals.
Figure 4.9: Predicted versus observed values of daily total electrical energy produced by the solar array.
4.5.3 Evaluating model prediction for solar energy

The model slightly over-predicts the power generated by the tribune when wind speeds are relatively small and wind flow is consistent. This can be seen in Figure 4.10, where values predicted by the model are greater than the observed values most of the time for all average observed power values less than 3 kW. On days with wind gusts with greater wind speeds, the model under-estimates turbine power output. This is because the average hourly values used in the prediction do not always reflect the greater wind speeds during wind gusting periods, and the power generated by the turbine is proportional to wind speed cubed. The model’s tendency to over-predict power values under 3 kW and at greater wind speeds is illustrated in a predicted versus observed graph in Figure 4.11. Model prediction shows an over-prediction until a value of 3 kW is reached, then the model under-predicts the value of power output.
Figure 4.10: Predicted and observed daily average values of wind turbine power output.
Figure 4.11: Predicted versus observed values of average daily turbine power output.
4.5 SUMMARY AND CONCLUSIONS

A model was developed to simulate and predict the performance of a microirrigation system powered by a renewable energy source. PV solar and wind turbine systems were considered with the modeling. The water demand needed for the irrigation system is predicted using the Penman-Monteith method, and the back-step method is used to design the irrigation system laterals and drip lines. The lower limits of the available solar or wind energy are predicted using the metrological data and stochastic methods. The amount of energy is calculated based on the min irrigation interval available and then the renewable energy system is designed based on the energy needed for the expected power output. For the solar array, the minimum expected voltage is determined using average daily solar radiation and average temperature, and then the number of solar panels required is determined. Wind turbine power and height is suggested based on average wind speeds predicted from the metrological data. The model is more accurate in predicting the electrical output for average daily irradiance values between 400 and 800 Wm\(^{-2}\). The model tended to slightly over-estimate the wind power at relatively smaller wind speeds, and underestimates the power generated on days with wind gusts producing relatively greater wind speeds.
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CHAPTER 5

ECONOMICAL PIPE SIZE FOR MAIN LINES FOR AN IRRIGATION SYSTEM
POWERED BY A SOLAR PHOTOVOLTAIC ARRAY

5.1 INTRODUCTION

The production of high-value crops, such as vegetables and nuts, may require irrigation to assure optimal conditions for plant growth and maximum yield. Because of the high value of the crop and the likelihood that there will be inadequate rainfall during a portion of the growing season for Ohio conditions, it is usually economical to design the irrigation system for full irrigation. Drip irrigation is a suitable type of irrigation for high value crops because of its efficiency in water use, fertilizers and energy. The value of the crop is expected to cover the high investment required for the system.

A drip irrigation system powered by a solar photovoltaic array is one way of using natural resources efficiently and minimizing the impact of the irrigation system on the environment. Other than the solar array and the battery bank, the system will have virtually no impact on the environment. The other advantage of such a system is the independence of the production process from fluctuations in energy prices. The disadvantage of the system would be that it would add to the initial investments required.
Solomon and Keller (1978), Wu (1997), and Valiantzas (2002) used analytical approaches to choose the diameter of irrigation mains and laterals. Computer-aided methods were developed by Bratls and Segerlind (1985), Kang and Nishiyama (1996), and others. Both the analytical methods and the computer-aided designs methods depend on the hydraulics of the system and use the desired efficiency of the system as a means to choose the diameters of the pipes. Valiantzas (2003) said that the methods mentioned above do not take into account the cost of energy when designing the system.

The other approach is to economically choose the pipe size by finding the diameter that minimizes the total cost (fixed investment costs plus operating costs) of the system. Keller (1975) produced a chart to be used in the selection of the economical pipe diameter. Singh et al (2000) developed a method to find the economical diameter in irrigation networks based on the shortest route algorithm. Valiantzas (2003) presented an approach for designing a tapered irrigation system using the inlet pressure head of the laterals.

The decision of choosing the economical diameter for a drip irrigation system is based on minimizing the total cost of the system. The initial cost of the system components such as pipes and fittings is dependent on the pipe size. The larger the pipe size is the larger the initial investment required for the system, but that means lower friction losses and less energy needs for the system thus decreasing the energy cost required for the system operation.

The total cost of the irrigation system can be expressed as follows:

\[ C_{\text{ToT}} = C_{\text{en}} + C_{\text{comp}} \]  

\[ (5.1) \]
Where:

\( C_{\text{ToT}} \) is system total annual cost;

\( C_{\text{comp}} \) is the system components annual cost; and

\( C_{\text{en}} \) is the annual energy cost.

Valiantazs (2003) expressed the annual energy cost of the irrigation system, \( C_{\text{en}} \), as:

\[
C_{\text{en}} = C_{fu} P_p O_t E_{ac}
\]  

(5.2)

Where:

\( C_{fu} \) is the fuel cost ($/kWh);

\( P_p \) is the total power required for pumping (kW);

\( O_t \) is the total annual operation time (h); and

\( E_{ac} \) is the equivalent annualized escalating energy cost factor.

Keller and Bliesner (1990) calculated the value of \( E_{ac} \) as:

\[
E_{ac} = \frac{r \left( 1 + e \right)^t - (1 + r)^t}{\left( e - r \right) \left( (1 + r)^t - 1 \right)}
\]  

(5.3)

Where:

\( e \) is the equivalent annual rate of energy escalation (decimal);

\( r \) is the annual interest rate (decimal); and

\( t \) is the service life of the investment (years).

Valiantazs (2003) also expressed the energy cost as a function of head requirements of the system. Valiantazs concluded that the main factor in the design affecting the energy cost of the system is the inlet pressure head at the submain. This
means that under the same average system discharge, the energy cost is a function of the inlet pressure head. The pressure head used for the operation of the drip irrigation system depends on the type of the emitters used, the friction losses, the desired flow uniformity, and the field topography.

Keller and Bliesner (1990) used an approximation to calculate the inlet pressure head for irrigation lines on a flat topography. They expressed the inlet pressure head as a function of the emitter operating pressure and the friction loss along the average lateral assuming the emitter discharge to be constant along the lateral. Valiantazs (1998) proposed a more general method for calculating the inlet pressure by considering the spatial variation in emitter discharges and the slope. Valiantazs used the solution of the Keller and Bliesner (1990) approximation as an initial guess to calculate an empirical exponent to determine the variation of the flow along the lateral. He reported that the results from his calculations were very close to those of the back step method.

The cost of the pipes, the fittings, the values and other system components depends on the diameter of the laterals and the mains. The cost of system components can be calculated as follow:

$$C_{comp} = C_{in}CRF$$  \hspace{1cm} (5.4)

Where:

$C_{in}$ is the total initial cost of the system components; and

$CRF$ is the capital recovery factor, calculated as:

$$CRF = \frac{r(1 + r)^t}{(1 + r)^t - 1}$$  \hspace{1cm} (5.5)
The cost of energy needed to operate the system decreases as the pipe diameter used becomes bigger, but this causes the cost of the system components to increase as shown in Figure 5.1. The economical pipe size for any irrigation system is the pipe diameter that minimizes the annual total cost of the system.

Figure 5.1 Typical relationships between pipe diameter and annual energy, components, and total costs (James, 1993).
5.2 AIM

The aim of this work is to:

1- Investigate the relationship between the energy, components, and the total cost of an irrigation system powered by renewable energy sources and determine the effect of the size of the field and the storage capability of the system on the economical pipe size for such a system; and

2- Compare the proposed system to a traditional irrigation system powered by a fossil fuel.

5.3 METHODS

A drip irrigation system for a high-value crop, such as tomato, is being considered for this study. In order to investigate the effect of the size of the field on the economics of the system, areas of 4,000 m$^2$ (1 ac), 10,000 m$^2$ (1 ha), 20,000 m$^2$ (2 ha), and 40,000 m$^2$ (4 ha) are being used. The shape of the field is assumed to be square and the water source is assumed to be located at the edge of the field. The land slope is 2% in one direction, and drip laterals are laid down slope. An emission uniformity of 85% was used as a design criterion for the drip system (ASAE, 2003). The whole field is considered as one area and the irrigation system is designed to supply 100% of the crop water needs. The pipe diameter that achieves the hydraulic requirement of the system is calculated using the back-step method (Yitayew and Warrick, 1988). The system annual cost for the irrigation system using fossil fuel is calculated using Equations 5.1-5.5. For the irrigation system powered by the solar panel, the proposed cost of the system is as follows:
• Total annual system cost calculated using Equation 5.1;

• System component cost (not including solar panel system) calculated using Equation 5.4; and

• Annual energy cost of the system calculated as follows:

\[ C_{en} = C_{sys} \cdot CRF + C_{area} \cdot C_{ac} \]  

(5.6)

Where:

\( C_{sys} \) is the cost of the solar panel system components and installation; and

\( C_{area} \) is the lost income due to the area occupied by the solar panel.

The variable \( C_{area} \) is calculated as:

\[ C_{area} = area \times [(Y \times P_{crop}) - VC] \]  

(5.7)

Where:

\( area \) is the area occupied by the solar panel (unit area);

\( Y \) is the yield from tomato (weight/unit area);

\( P_{crop} \) is the expected price of the crop ($/unit weight);

\( VC \) is the variable cost of producing the crop ($/unit area);

\( C_{ac} \) is the equivalent annualized escalating crop factor.

The variable \( C_{ac} \) is calculated as:

\[ C_{ac} = \frac{r \left[ (1 + e_c) \frac{Y}{(1 + r)^t} - (1 + r)^t \right]}{e_c - r \left[ (1 + r)^t - 1 \right]} \]  

(5.8)

Where: \( e_c \) is the equivalent annual rate of escalation for crop net returns (decimal).
The diameter obtained from the back step method is used as the initial diameter for the economical analysis and the cost is calculated for the next available pipe diameter as long as the total cost of the system is decreasing or until there are no available larger diameters.

5.4 RESULTS AND DISCUSSION

The total annual cost for both the traditional irrigation system and the system powered by solar energy was calculated using Equations 5.1-5.8. The total annual cost of the system powered by the renewable energy was greater than the total annual cost for the traditional system for all four simulated field areas. The calculation is based on a 12% annual interest rate, an equivalent annual rate of energy escalation of 10%, an equivalent annual rate of escalation for crop (tomato) net returns of 2%, an energy price of $0.0087 per kWh, an average yield of 175 cwt/ac, and average net income of $1,882 per ac for tomato.

A typical trend of the total annual cost of the system decreasing then increasing was found in both the traditional irrigation system and the system powered by the solar energy. The difference between the total annual cost at the economical diameter and the total annual cost of the smallest diameter that satisfies the hydraulic requirement of the irrigation was very small for the 4000 m$^2$ field area. This was true for both the traditional system and the system powered by the solar energy. For the traditional system the total annual cost for the smallest hydraulic diameter was $154.26, while the total annual cost of the economical diameter was $150.20. The economical diameter for the traditional irrigation system was 2 in and the smallest hydraulic diameter was 1.25 in. For the system powered by solar power the total annual cost of the smallest hydraulic diameter
was $982.20, while the total annual cost for the economical diameter was $980.70. The economical diameter for the system powered by solar power was 1.5 in. Figure 5.2 shows the relation between the total annual cost of the system and its pipe diameter. The system powered by solar energy had a smaller economical diameter than the traditional system (1.5 in versus 2 in), since the cost of material increases as pipe size increases, while the cost of energy is constant. The reduction in the energy requirements by changing from the 1.25-in dia pipe to 1.5-in dia reduces the required number of solar panels from 11 to 10 panels. At a diameter of 6 in, the required number of solar panels to power the system is 9.35, which require the installation of 10 panels. The small reduction of the energy requirements results from the smaller size of the irrigation system itself. For field size areas of 10,000 and 20,000 m², the decline in the total annual cost of the system from the smallest hydraulic diameter to the economical diameter was more obvious than for the 4,000 m² field area.

In the case of the 10,000m² field size, the total annual cost for the smallest hydraulic diameter was $308.7, while the total annual cost of the economical diameter was $263.65 for the traditional system. The economical diameter for the traditional irrigation system was 2.5 in and the smallest hydraulic diameter was 1.5 in. For the system powered by solar power, the total annual cost of the smallest hydraulic diameter was $1,414.70, while the total annual cost for the economical diameter was $1,090.80. The economical diameter for the system powered by solar power was also 2.5 in. The relation between the total annual cost of the system and its pipe diameter for a field size area 10,000 m² is shown in Figure 5.3.
For a field size of 20,000 m$^2$, the total annual cost for the smallest hydraulic diameter was $453.20 while the total annual cost of the economical diameter was $397.80 for the traditional system.

The economical diameter for the traditional irrigation system was 4 in and the smallest hydraulic diameter was 2 in. For the system powered by solar power the total annual cost of the smallest hydraulic diameter was $2,291.70, while the total annual cost for the economical diameter was $1,313.70. The economical diameter for the system powered by the solar power was the same as the traditional system Figure 5.4. At a field size of 40,000 m$^2$, the total annual cost for the smallest hydraulic diameter was $1,783.20, while the total annual cost of the economical diameter was $1,409.70 for the traditional system. The economical diameter for the traditional irrigation system was 5 in and the smallest hydraulic diameter was 3.5 in. For the system powered by solar power, the total annual cost of the smallest hydraulic diameter was $14,859.70, while the total annual cost for the economical diameter was $9,723.40. The economical diameter for the system powered by the solar power was 8 in as shown in Figure 5.5.

The relation between the area and smallest hydraulic diameter and the economical diameter for both systems are shown in Figure 5.6. The economical diameter of the system powered by solar energy is closer to the smallest hydraulic diameter for small areas than that for the traditional system. As the area increases, the amount of energy required to power the system increases and the change in energy requirements with the change of diameter increases. Because of the high cost of energy in the system powered by solar panels, the rate of increase of the economical diameter with the area increase is greater than that for the traditional system, as shown in Figure 5.6.
Figure 5.2: The relation between the total annual cost and the main diameter for a traditional irrigation system and an irrigation system powered by solar energy for an area of 4,000 m².
Figure 5.3: The relationship between the total annual cost and the main diameter for a traditional irrigation system and an irrigation system powered by solar energy for an area of 10,000 m².
Figure 5.4: The relation between the total annual cost and the main diameter for a traditional irrigation system and an irrigation system powered by solar energy for an area of 20,000 m$^2$. 


Figure 5.5: The relation between the total annual cost and the main diameter for a traditional irrigation system and an irrigation system powered by solar energy for an area of 40,000 m$^2$. 
Figure 5.6: The relation between the area and the economical pipe diameter for a traditional irrigation system and an irrigation system powered by solar energy.
The total annual cost of the system powered by the solar panels was always greater than that for the traditional system, but the percentage of the total annual cost of the system powered by the solar panels to the total annual cost of the traditional system decreased as the area increased, until reaching a field area of 20,000 m$^2$, then increased again at a field area of 40,000 m$^2$ (see Figure 5.7).

The closest total annual cost of the system powered by the solar panels to the total annual cost of the traditional system was at 20,000 m$^2$ with a 330% ratio between the total annual costs of both systems. The cost of the materials is the dominant factor in the initial design of the traditional system, as opposed to the traditional system design for a field area of 4,000 m$^2$, where the energy cost is close to the cost of the material. The cost of the materials and the energy cost for field-size areas of 20,000 and 4,000 m$^2$ are shown in Figure 5.8 and 5.9, respectively. The minimum total annual cost for a unit area (1ac) was at a field size 20,000m$^2$ as shown in figure 5.10. The figure shows that as the field size increases the total annual cost for a unit area decreases until the field size reaches 20,000m$^2$ and then it starts to increase again. This implies that a field with an area more than 2 ha should be divided into plots that are 2 ha or smaller when designing the irrigation system.
Figure 5.7: The total annual cost of an irrigation system powered by solar panels as a percentage of the total annual cost of a traditional irrigation system for different field-size areas.
Figure 5.8: Energy cost and material cost of a traditional irrigation system for a field size area of 20,000 m².

Figure 5.9: Energy cost and material cost of a traditional irrigation system for a field size area of 4,000 m².
Figure 5.10: The total annual cost ($/ac) as a function of the pipe diameter for the four field sizes simulated
A sensitivity analysis was performed to determine the possible effects of the change in the equivalent annual rate of energy escalation, \( e \), on the results of the analysis. The \( e \) values used in the analysis were in the range of 0.05 to 0.25. The effect of the change of \( e \) on the economical pipe size diameter, the energy cost of the traditional system, the total cost of the traditional system, and the total annual cost of the irrigation system powered by solar panels as a percentage of the total annual cost of a traditional irrigation system were determined for a field area of 20,000 m\(^2\). The values of \( e \) had no effect on the economical pipe diameter of the traditional system, which had an economical pipe diameter of 4 in for all values of \( e \). The energy cost of the system increased as the value of \( e \) increased from $47.84 at an \( e \) value of 0.05 to $283.95 at an \( e \) value of 0.25.

The total cost for the traditional system showed the same trend as the energy cost. This was expected because the cost of the materials was not affected by the change in the \( e \) values, so the changes in total cost were caused by the changes in the energy cost. The change in the energy cost was proportional to \( e^2 \). The relation between the values of \( e \) and the energy cost and the total annual cost of the traditional irrigation system are shown in Figure 5.11.

The total annual cost of the system powered by the solar panels as a percentage of the total annual cost of the traditional irrigation system decreased as the values of \( e \) increased. The same trend of the values of the percentage being proportional to \( e^2 \) was observed. The value of the percentage decreased from 350% at an \( e \) value of 0.05 to 215% at an \( e \) value of 0.25. The change in the percentage between the total annual costs of the two systems as a result of the change of \( e \) values is shown in Figure 5.12.
Figure 5.11: The effect of different values of the equivalent annual rate of energy escalation $e$ on the energy cost and the total annual cost of a traditional irrigation system.
Figure 5.12: The changes in percentage of the total annual cost of the irrigation system powered by the solar panels to the total annual cost of the traditional irrigation system due to changes in the equivalent annual rate of energy escalation $e$. 
To investigate the effect of the solar panel prices on the results of the analysis, the prices of the solar panels were decreased in steps of 10% of their current price. The price of the solar panels had no effect on the economical pipe diameter for the system, and the 4-in diameter remained the economical diameter of both systems. The energy cost and the total annual cost of the system powered by the solar panels decreased as the price of solar panel decreased. The relation between the price and both the total annual cost and the energy cost can be represented by a linear equation. The energy cost decreased from $985.78 at the current price to $305.67, when the price of the panels was set to 20% of its current price. The total annual cost decreased from $1,313.7 at the current price to $633.6 when the price of the panels was set to 20% of its current price. Figure 5.13 shows the change in the energy cost and the total annual cost of the system powered by the solar panels as a function of the change in price of solar panels. The total annual cost of the system powered by the solar panels as a percentage of the total annual of the traditional irrigation system decreased as the price of the solar panels decreased. The percentage between the total annual costs of both systems decreased from 330.25% at the current price of the solar panels to 159.27% when the price of the solar panels was set to 20% of its current price. Figure 5.14 shows the effect of the price of the solar panels on the percentage between the total annual cost of the solar powered system and the traditional system. Although the cost of operating the solar powered system is considerably greater than the traditional system, the results suggest that if the price of the solar panels reaches 20% of the current price levels and energy prices keep rising, an irrigation system powered by solar panels can be economically feasible in the next few years. Figure 5.15 show the combined effect of both factors. Both systems will have the same total annual cost at a 20% of the present solar panels prices and e=0.25.
Figure 5.13: The effect of the price of the solar panels on the energy cost and the total annual cost of an irrigation system powered by solar panels.
Figure 5.14: The changes in percentage of the total annual cost of the irrigation system powered by the solar panels to the total annual cost of the traditional irrigation system due to changes in the solar panels price.
Figure 5.15: The changes in percentage of the total annual cost of the irrigation system powered by the solar panels to the total annual cost of the traditional irrigation system due to changes in the equivalent annual rate of energy escalation $e$ at different levels of the solar panels prices.
5.5 SUMMARY AND CONCLUSIONS

The economical main pipe diameter for a traditional irrigation system and an irrigation system powered by solar panels were determined. The systems were designed for field areas of 4,000 to 40,000 m². The irrigation system powered by the solar panel showed the same typical relation between the total annual cost of the system and the system diameter. The system powered by the solar panel was more responsive to the change in the field area than the traditional irrigation system. The economical diameter of the system powered by the solar panels was smaller than the economical diameter for the traditional system at the 4,000 m² field area. At the 10,000 and 20,000 m² field areas, the economical diameters of both systems were equal. At the 40,000 m² field area, the economical diameter of the system powered by solar panels was larger than the economical diameter of the traditional system.

The closest total annual cost for a system powered by solar panels to the total annual cost of the corresponding traditional system was at a field area of 20,000 m². This result was because the energy costs of the traditional system in this case were dominated by the material costs. This suggests that the condition that identifies the system powered by solar panels that is closest in the total annual cost to the traditional system is that the material cost of the traditional system is significantly greater than its energy cost. The sensitivity analysis showed that the values of the equivalent annual rate of energy escalation \( e \) had no effect on the system economical pipe diameter for both the traditional system and the system powered by the solar panels. The total annual cost, the energy cost and the percentage between the total annual cost of both systems were proportional to the equivalent annual rate of energy escalation \( e^2 \) and had a linear relationship with the prices of solar panels.
5.6 REFERENCES


6.1 SUMMARY AND CONCLUSIONS

6.1.1 Summary and Conclusions of Chapter 2

Solar radiation data are not available for a lot of locations. Several models have been developed to predict solar radiation based on the available metrological data. Hargreaves and Samani (1982) models predict solar radiation using the location of the site, the elevation, and maximum and minimum daily temperatures. The models are simple to calculation, are not site-specific, and do not need calibration for the model constants. Allen (1997) proposed a self-calibrating model to modify the constant in the original Hargreaves and Samani models. Allen models modify the Hargreaves and Samani model’s constant based on the comparison between the models prediction and the solar radiation for a completely clear day. Solar radiation in humid areas can fluctuate widely from one day to another. Allen 1997 reported the largest error in the prediction of the solar radiation by the self-calibrating model in Gainesville, FL, and North Baltimore, OH. The use of either of the Hargreaves and Samani models (inner and coastal region) does not adequately cover the range of fluctuations in the day to day solar radiation values.
A regression analysis was performed to investigate the possibility of using other metrological parameters to predict the total daily solar radiation. The strongest correlation was between solar radiation and minimum relative humidity, and between solar radiation and the difference between the daily maximum and minimum temperatures. The solar radiation correlations with wind speed, precipitation, and maximum relative humidity were insignificant.

Several models were developed as a modification of the original Hargreaves and Samani models. The selective models chose the values of the constant to use in the Hargreaves and Samani based on the value of the difference between the max and min temperature. The models tested in this work are Hargreaves and Samani coastal regions \( (k_r = 0.19) \), Hargreaves and Samani for interior regions \( (k_r = 0.16) \), Selective \( k_r \) \( (k_r = 0.19 \text{ when } (T_{\text{max}} - T_{\text{min}}) \geq \text{overall } (T_{\text{max}} - T_{\text{min}}) \text{ average}, \ k_r = 0.16 \text{ otherwise}) \), Selective \( k_{r2} \) (Allen self-calibrating model when \( (T_{\text{max}} - T_{\text{min}}) \) is greater than or equal to the overall \( (T_{\text{max}} - T_{\text{min}}) \) average, \( k_r = 0.16 \) otherwise), Selective \( k_{r3} \) (Allen self-calibrating model when \( (T_{\text{max}} - T_{\text{min}}) \) is greater than or equal to the overall \( (T_{\text{max}} - T_{\text{min}}) \) average, self-calibrating using min relative humidity otherwise, and Selective \( k_{r4} \) \( (k_r = 0.19 \text{ when } (T_{\text{max}} - T_{\text{min}}) \geq \text{overall } (T_{\text{max}} - T_{\text{min}}) \text{ average, self-calibrating using min relative humidity otherwise}) \). Three years where chosen to evaluate the models performance in all conditions. The years were identified as a dry year, average year, and a wet (humid) year based on the total annual precipitation and Palmer Drought Index.

The use of models where the value of the constant \( k_r \) is chosen based on the difference between max and min daily temperature can enhance prediction capability.
The value of the RMSE was found to be correlated with the value of the solar radiation and can change from dry years to wet years, and from one season to another in the same year. The greater the average value of solar radiation, the greater the value of the RMSE. The RMSE can be used as an indicator of the total amount of error of the model for the data period, but it is not a good indicator of model prediction performance for short periods, instead the model performance should be evaluated using a relative error term. For long-term predictions of the limits of solar radiation, the chosen model should depend on the application intended for the predicted limit. Because it seems impossible to find a model that will predict the exact upper and lower limits, use a model that tends to underestimate solar radiation with the smallest error, such as the selective $k_{r3}$ model. For the upper limit, use a model that tends to overestimate solar radiation with the smallest lowest error, such as the selective $k_{r4}$ model.

6.1.2 Summary and Conclusions of Chapter 3

Stewart & Essenwanger 1978, Takle & brown 1978, and Van der Auwera et al. 1980 used the Weibull distribution to represent the wind speed distribution. Tuller & Brett 1984 reported that the Weibull distribution gives an approximate but generally good fit of the wind distribution. Weibull distribution could take the form of other distribution depending on the values of the shape factor. Rayleigh distribution is a special case of Weibull distribution with a value of the shape factor $k=2$ (Justus et al. 1978). Rayleigh distribution is the simplest way to express wind speed probability distribution. The focus of this work was to determine the possibility of representing the wind speed in short time intervals (1day) using a statistical distribution and determine the accuracy of such
representation if used to predict the energy output of a wind turbine. The wind turbine used in the experiment where a 20 kW rated Jacob wind turbine with a maximum rated speed of 11.62ms\(^{-1}\) (26mph) and a cut in speed of 3.58ms\(^{-1}\) (8mph). The turbine is installed at a rural area about twenty-five miles east of Cleveland Ohio. The wind speeds were recorded in 1-minute intervals of for 250 days through the whole year. The results showed that the Weibull representation is more accurate in simulating the observed distribution when the Cv of the daily wind speeds is 0.5 or smaller. When the Cv of the daily wind speeds is greater than 0.5 the daily Rayleigh representation is closer to the observed data distribution. The prediction using the Weibull representation appears not to accurately predict the smaller values of the power, but as the observed value increases the Weibull prediction performs better. The power of a wind turbine can be predicted for short intervals such as a day using a statistical representation of the daily wind speeds. The Weibull distribution is the best distribution to represent the daily wind speed distribution. Sometimes the Weibull distribution over predicts the average daily power expected from the turbine when the Cv of the wind speeds is greater than 0.5. In such cases, the Rayleigh distribution performs better in predicting the average daily power. The Cv of the daily wind speeds can be used to choose which distribution is better for predicting the expected average daily turbine power.

6.1.3 Summary and Conclusions of Chapter 4

A model was devolved to simulate and predicted the performance of a microirrigation system powered by a renewable energy source. The model is a visual basic program with user friendly interface and an embedded excel spreadsheet. PV solar
systems and wind turbines were considered for the modeling. The water demand needed for the irrigation system is predicted using the Penman-Monteith method (Allen et al., 1998). The back-step method (Yitayew and Warrick, 1988) is used to design the irrigation system laterals and drip lines. The lower limits of the available solar or wind energy are predicted using the metrological data and the stochastic methods described in chapters 2 and 3. The amount of energy available is calculated based on the minimum irrigation interval, and then the renewable energy system is designed based on the energy needed for the expected power output. For the solar array, the minimum expected voltage is determined using the average daily solar radiation and the average temperature and the number of the panels required is determined according. The wind turbine power and height is suggested based on the average wind speeds predicted form the metrological data. The model is more accurate in predicting the electrical output for average daily irradiance values between 400 and 800 Wm$^{-2}$. The model tends to slightly overestimate the wind power at lower wind speeds and underestimates the power generated in days with high wind gusts.

6.1.4 Summary and Conclusion of Chapter 5

The economical diameter for a traditional irrigation system and an irrigation system powered by solar panels was determined. The systems were designed for field areas from 4,000 to 40,000 m$^2$. The irrigation system powered by the solar panel showed the same typical relation between the total annual cost of the system and the system diameter. The system powered by the solar panel was more responsive to the change in the field area than the traditional irrigation system. The economical diameter of the
system powered by the solar panels was smaller than the economical diameter for the traditional system at the 4,000 m² field area. At the 10,000 and 20,000 m² field areas, the economical diameters of both systems were equal. At the 40,000 m² field area, the economical diameter of the system powered by solar panels was bigger than the economical diameter of the traditional system. The closest total annual cost for a system powered by solar panels to the total annual cost of the corresponding traditional system was at a field area of 20,000 m². This resulted because energy costs of the traditional system in this case are dominated by the material cost. This suggests that the condition that identifies the system powered by solar panels that is closest in the total annual cost to the traditional system is that the material cost of the traditional system is significantly greater than its energy cost.

The sensitivity analysis showed that the values of the equivalent annual rate of energy escalation $e$ had no effect on the system economical pipe diameter for both the traditional system and the system powered by the solar panels. The total annual cost, the energy cost and the percentage between the total annual cost of both system were proportional to the equivalent annual rate of energy escalation $e^2$ and had a linear correlation with the price of the solar panels.
6.2 RECOMMENDATION AND FURTHER RESEARCH

- The model for the solar radiation should be tested in different climates to confirm the results found for Wooster, Ohio.
- The use of the wind energy to power an irrigation system should be evaluated in areas where there are two growing seasons, and in winter, as there may be enough wind to provide the needed energy for the system.
- The use of the renewable energy sources to power an irrigation system with an innovative, energy-reducing solution, such as collecting and reusing drainage water should be investigated.
- Although renewable energy sources are still greater in cost than the traditional systems, the investment in finding new uses for such systems should be encouraged.
- The cooperative use for such systems specially for smaller farms should be investigated.

6.3 REFERENCES


