

**INTEGRATION OF LOGISTIC REGRESSION
AND MULTI-LAYER PERCEPTRON FOR
SINGLE AND DUAL AXIS SOLAR TRACKING
SYSTEMS**

NADIA A. AL-ROUSAN

**UNIVERSITI SAINS MALAYSIA
2018**

**INTEGRATION OF LOGISTIC REGRESSION AND MULTI-LAYER
PERCEPTRON FOR SINGLE AND DUAL AXIS SOLAR TRACKING
SYSTEMS**

by

NADIA A. AL-ROUSAN

**Thesis submitted in fulfillment of the
requirements for the degree of
Doctor of Philosophy**

June 2018

ACKNOWLEDGEMENT

In the name of Allah, the entirely merciful the especially merciful.

Foremost, all my Praises and thanks be to Allah the Almighty, for giving me the courage, the strength, the patience, and the guidance to complete this thesis successfully.

I will not forget to thank the persons who really deserve the credit of my success. I would like to express my warmest acknowledgements to my beloved husband Hazem AL-Najjar and my beloved daughters Logain and Leen for their help, support, patience, and time. I also would like to deeply thank my mother, my brothers, and my sisters for their encouragements, prayers, and support during my studying.

It's my honor to be grateful to the persons who helped me to complete my thesis successfully. I would like to express my sincere gratitude to my supervisor Prof. Ir. Dr. Nor Ashidi Mat Isa and to my co-supervisor Dr. Mohammad Khairunaz Mat Desa for the continuous support to my study and research. I really grateful to them for their patience, efforts, motivation, enthusiasm, and immense knowledge. Without their guidance and help in all the time of research and writing of this thesis, it was very difficult to come with this thesis successfully. I could not have imagined having a better advisors and mentors for my Ph.D study.

TABLE OF CONTENTS

	Page
ACKNOWLEDGEMENT	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	viii
LIST OF FIGURES	xiii
LIST OF ABBREVIATIONS	xvi
LIST OF SYMBOLS	xvii
ABSTRAK	xviii
ABSTRACT	xx
CHAPTER ONE : INTRODUCTION	
1.1 Overview	1
1.2 Problem Statement	4
1.3 Objectives	6
1.4 Research Contributions	7
1.5 Research Scopes	7
1.5 Research Organization	8
CHAPTER TWO : LITRATURE REVIEW	
2.1 Introduction	10
2.2 Renewable Energy	10
2.3 Solar Power Systems	13
2.3.1 Solar Tracking Systems	14
2.3.2 Solar Variables and Parameters	17
2.4 Intelligent Classifiers	25

2.4.1	Multi-Layer Perceptron Neural Networks	26
2.4.2	Cascade Multi-Layer Perceptron Neural Network	30
2.4.3	Adaptive Neural Fuzzy Inference System	31
2.4.4	Logistic Regression	35
	2.4.4 (a) Binomial and Multinomial Logistic Regression	36
	2.4.4 (b) Clustering Algorithms	38
2.5	Statistical Models	43
	2.3.1 Linear Regression	43
	2.3.2 Correlation Analysis	44
2.6	Solar Tracking Systems based on Intelligent classifiers	46
2.7	Summary	70

CHAPTER THREE : METHODOLOGY

3.1	Introduction	72
3.2	The Proposed Solar Tracking Systems Methodology	73
3.3	Solar Tracking Systems Based on Most Effective Variables	74
	3.3.1 Correlation Analysis	76
	3.3.2 Proposing Solar Tracking Models based on Correlation	77
3.4	Proposed Solar Tracking Systems Based on Intelligent Classifiers	80
	3.4.1 Motivation	81
	3.4.2 Linear Regression Based Solar Tracking System	84
	3.4.3 Multi-Layer Perceptron Neural Network Based Solar Tracking System	86
	3.4.4 Cascade Multi-Layer Perceptron Neural Network Based Solar Tracking System	91
	3.4.5 Adaptive Neural Fuzzy Inference System Based Solar Tracking System	93

3.5	Development of Single and Dual Axis Solar Tracking Systems by Integration Multi-Layer Perceptron and Logistic Regression	96
3.5.1	Selection of the Optimum Clustering Algorithm	102
3.5.2	Training of Logistic Regression Based on the Optimum Clustering Algorithm	106
3.5.3	Development of New Single and Dual Axis Solar Tracking Systems	108
3.6	Data Samples and Performance Analysis	111
3.6.1	Data Samples	111
3.6.2	Performance Analysis	117
3.7	Summary	119

CHAPTER FOUR : RESULTS AND DISCUSSION

4.1	Introduction	120
4.2	Results of Solar Tracking Systems based on Most Effective Variables	120
4.2.1	Correlation Analysis Results	121
4.2.2	Proposed Solar Tracking Systems based on Correlation	123
4.3	Results of the Proposed Solar Tracking Systems based on Classifiers	127
4.3.1	Results of the Proposed Single-Axis Solar Tracking Systems	128
4.3.1 (a)	Results of Linear Regression Based Solar Tracking System	128
4.3.1 (b)	Results of Multi-Layer Perceptron Neural Network Based Solar Tracking System	129
4.3.1 (c)	Results of Cascade Multi-Layer Perceptron Neural Network Based Solar Tracking System	134
4.3.1 (d)	Results of Adaptive Neural Fuzzy Inference System	139

	Based Solar Tracking System	
4.3.2	Results of the Proposed Dual-Axis Solar Tracking Systems	142
4.3.2 (a)	Results of Linear Regression Based Solar Tracking System	143
4.3.2 (b)	Results of Multi-Layer Perceptron Neural Network Based Solar Tracking System	144
4.3.2 (c)	Results of Cascade Multi-Layer Perceptron Neural Network Based Solar Tracking System	148
4.3.2 (d)	Results of Adaptive Neural Fuzzy Inference System Based Solar Tracking System	152
4.3.3	Discussion of the Proposed Solar Tracking Systems Based on Intelligent Classifiers	156
4.4	Results of Developed Single and Dual Axis Solar Tracking Systems by Integration of Multi-Layer Perceptron and Logistic Regression	157
4.4.1	Selection of the Optimum Clustering Algorithm	158
4.4.1 (a)	Selection of the Optimum Clustering Algorithm for Multi-Layer Perceptron Network	158
4.4.1 (b)	Selection of the Optimum Clustering Algorithm for Cascade Multi-Layer Perceptron Network	163
4.4.2	Logistic Regression based on the Optimum Clustering Algorithm	167
4.4.2 (a)	Logistic Regression based on the Optimum Clustering Algorithm for Multi-Layer Perceptron	167
4.4.2 (b)	Logistic Regression based on the Optimum Clustering Algorithm for Cascade Multi-Layer Perceptron	170
4.4.3	Results of Developed New Single and Dual Axis Tracking Systems Based on Logistic Regression	172

4.4.3 (a) Results of Developed Single and Dual Axis Solar Tracking System Based on MLP	172
4.4.3 (b) Results of Developed Single and Dual Axis Solar Tracking System Based on Cascade Multi-Layer Perceptron	179
4.4.4 Discussion of The Proposed Solar Tracking Systems Results	186
4.5 Summary	190

CHAPTER FIVE: CONCLUSION AND FUTURE WORK

5.1 Conclusions	192
5.2 Future Works	194

REFERENCES	196
-------------------	-----

APPENDICES

Appendix A: Sample Of Collected Data For Dual-Axis Solar Tracking Systems

Appendix B: Sample Of Collected Data For Single-Axis Solar Tracking Systems

LIST OF PUBLICATIONS

LIST OF TABLES

		Page
Table 2.1	The statistical rule for building most suitable regression models	36
Table 2.2	K-Means, FCM and Hierarchical clustering algorithms	42
Table 2.3	Accepted guidelines for interpreting the correlation coefficients	44
Table 2.4	Comparison between intelligent solar tracking systems controllers	61
Table 3.1	Pairs between input and output variables	77
Table 3.2	Input variables selection for single-axis tracker proposed models	78
Table 3.3	Input variables selection for dual-axis tracker proposed models	80
Table 3.4	Electrical Specification of Module KC120-1	112
Table 3.5	Recommended Average Days for Months and Values of n by Months (Duffie et al, 2013)	115
Table 4.1	Correlation between solar variables and orientation angle for single-axis solar tracking system.	121
Table 4.2	Correlation between solar variables and both tilt and orientation angles for dual-axis solar tracking system	122
Table 4.3	The input variable selection for single-axis solar tracking system	124
Table 4.4	The input variable selection for dual-axis solar tracking system	125
Table 4.5	The input-output variables for single-axis solar tracking system	127
Table 4.6	The input-output variables for dual-axis solar tracking system	127
Table 4.7	The results of prediction rate and MSE for orientation angle of the proposed linear regression based single-axis solar tracking system	128
Table 4.8	Number of nodes for the proposed MLP based single-axis solar tracking system	131

Table 4.9	Overall prediction rate (%) of the proposed MLP based single-axis solar tracking system	132
Table 4.10	Results of MSE rates for the proposed MLP based single-axis solar tracking system	132
Table 4.11	Number of nodes for the proposed CMLP based single-axis solar tracking system	136
Table 4.12	Overall prediction rate (%) of the proposed CMLP based single-axis solar tracking system	137
Table 4.13	Results of MSE rates for the proposed CMLP based single-axis solar tracking system	137
Table 4.14	The number of estimated rules for the proposed ANFIS based single-axis solar tracking system	139
Table 4.15	Overall prediction rate (%) of the proposed ANFIS based single-axis solar tracking system	140
Table 4.16	Results of MSE rates for the proposed ANFIS based single-axis solar tracking system	140
Table 4.17	The structure of Model six with 5 MFs of the proposed ANFIS based single-axis solar tracking system	142
Table 4.18	The results of prediction rate (%) and MSE for both tilt and orientation angles of the proposed linear regression based dual-axis solar tracking system	143
Table 4.19	Number of nodes for the proposed MLP based dual-axis solar tracking system	146
Table 4.20	Overall prediction rate (%) of the proposed MLP based dual-axis solar tracking system	146
Table 4.21	Results of MSE rates for the proposed MLP based dual-axis solar tracking system	147
Table 4.22	Number of nodes for the proposed CMLP based dual-axis solar tracking system	150
Table 4.23	Overall prediction rate (%) of the proposed CMLP based dual-axis solar tracking system	151
Table 4.24	Results of MSE rates for the proposed CMLP based dual-axis solar tracking system	151

Table 4.25	The number of estimated rules for the proposed ANFIS based dual-axis solar tracking system	153
Table 4.26	Overall prediction rate (%) of the proposed ANFIS based dual-axis solar tracking system	153
Table 4.27	Results of MSE rates for the proposed ANFIS based dual-axis solar tracking system	154
Table 4.28	The prediction rate (%) and MSE results of MLP and the three clustering algorithms of single-axis solar tracking system using dataset one	159
Table 4.29	The prediction rate (%) and MSE results of MLP and the three clustering algorithms of dual-axis solar tracking system using dataset one	159
Table 4.30	The prediction rate (%) and MSE results of MLP and the three clustering algorithms of single-axis solar tracking system using dataset two	160
Table 4.31	The prediction rate (%) and MSE results of MLP and the three clustering algorithms of dual-axis solar tracking system using dataset two	160
Table 4.32	The prediction rate (%) and MSE results of CMLP and the three clustering algorithms of single-axis solar tracking system using dataset one	163
Table 4.33	The prediction rate (%) and MSE results of CMLP and the three clustering algorithms of dual-axis solar tracking system using dataset one	164
Table 4.34	The prediction rate (%) and MSE results of CMLP and the three clustering algorithms of single-axis solar tracking system using dataset two	165
Table 4.35	The prediction rate (%) and MSE results of CMLP and the three clustering algorithms of dual-axis solar tracking system using dataset two	165
Table 4.36	The optimum combination of MLP and MLR/BLR to develop single and dual axis solar tracking systems using dataset one and dataset two	168
Table 4.37	Confusion matrix for MLR that trained by k-means clustering when k=7 by using dataset one for single-axis solar tracking system	168

Table 4.38	Confusion matrix for BLR that trained by k-means clustering when k=2 by using dataset one for dual-axis solar tracking system	169
Table 4.39	Confusion matrix for MLR that trained by k-means clustering when k=5 by using dataset two for single-axis solar tracking system	169
Table 4.40	Confusion matrix for BLR that trained by k-means clustering when k=2 by using dataset two for dual-axis solar tracking system	169
Table 4.41	The optimum combination of CMLP and MLR/BLR to develop single and dual axis solar tracking systems using dataset one and dataset two	170
Table 4.42	Confusion matrix for MLR that trained by k-means clustering when k=4 by using dataset one for single-axis solar tracking system	170
Table 4.43	Confusion matrix for BLR that trained by k-means clustering when k=10 by using dataset one for dual-axis solar tracking system	171
Table 4.44	Confusion matrix for MLR that trained by k-means clustering when k=10 by using dataset two for single-axis solar tracking system	171
Table 4.45	Confusion matrix for MLR that trained by k-means clustering when k=4 by using dataset two for dual-axis solar tracking system	171
Table 4.46	The prediction rate (%) and MSE results of the developed dual-axis solar tracking system based on combining MLP and MLR when K= 7 by using dataset one	173
Table 4.47	The prediction rate (%) and MSE results of the developed dual-axis solar tracking system based on combining MLP and BLR when K= 2 by using dataset one	173
Table 4.48	The prediction rate (%) and MSE results of the developed single-axis solar tracking system based on combining MLP and MLR when K= 5 by using dataset two	175
Table 4.49	The prediction rate (%) and MSE results of the developed dual-axis solar tracking system based on combining MLP and BLR when K= 2, by using month, day, time, I_sc, V_oc, and power radiation dataset	175

Table 4.50	A comparison between conventional MLP and MLP-BLR/MLR based systems for dataset one	177
Table 4.51	A comparison between conventional MLP and MLP-BLR/MLR based systems for dataset two	178
Table 4.52	The prediction rate (100%) and MSE results of the developed single-axis solar tracking system based on combining CMLP and MLR when K= 4 by using dataset one	180
Table 4.53	The prediction rate (100%) and MSE results of the developed dual-axis solar tracking system based on combining CMLP and MLR when K= 10 by using dataset one	180
Table 4.54	The prediction rate (100%) and MSE results of the developed single-axis solar tracking system based on combining CMLP and MLR when K= 10 by using dataset two	182
Table 4.55	The prediction rate (100%) and MSE results of the developed dual-axis solar tracking system based on combining CMLP and MLR when K= 4 by using dataset two	182
Table 4.56	A comparison between conventional CMLP and CMLP-BLR/MLR based systems for dataset one	184
Table 4.57	A comparison between conventional CMLP and CMLP-BLR/MLR based systems for dataset two	185

LIST OF FIGURES

		Page
Figure 2.1	Total solar energy consumed in million tons oil equivalent	11
Figure 2.2	Total solar energy consumed in terawatt-hour	12
Figure 2.3	Total solar energy capacity in megawatt	12
Figure 2.4	Longitudes of the Earth (Makhloufi et al, 2014)	18
Figure 2.5	Equator line and latitude (Makhloufi et al, 2014)	19
Figure 2.6	Angle of incidence	19
Figure 2.7	Declination angle	20
Figure 2.8	Elevation and zenith angles	20
Figure 2.9	Solar azimuth angle	21
Figure 2.10	Inclination angle	21
Figure 2.11	Schematic representation of solar angles (Makhloufi et al, 2014)	22
Figure 2.12	Tilt and orientation angles	23
Figure 2.13	The architecture of MLP network for one hidden layers	26
Figure 2.14	The architecture of cascade MLP network with one hidden layer	30
Figure 2.15	General architecture for ANFIS system	32
Figure 3.1	Flowchart of the proposed methodology	73
Figure 3.2	Flowchart of correlation analysis	76
Figure 3.3	The flowchart of proposing single and dual-axis solar tracking systems based on linear regression	85
Figure 3.4	Flowchart of MLP networks for single and dual axis solar tracking systems	89
Figure 3.5	Flowchart of CMLP networks for single and dual axis solar tracking systems	92
Figure 3.6	Flowchart of ANFIS for single and dual axis solar tracking systems	94

Figure 3.7	Block diagram of the developed single and dual axis solar tracking systems	100
Figure 3.8	The conventional concept of neural network controller	101
Figure 3.9	Block diagram of selecting the optimum clustering algorithm process	103
Figure 3.10	Flowchart of clustering phase	105
Figure 3.11	Block diagram of multinomial/binomial logistic regression	106
Figure 3.12	Flowchart of training and testing MLR and BLR	108
Figure 3.13	The flowchart of the developed single and dual axis solar trackers using MLP/CMLP	110
Figure 3.14	Manually solar tracking model with panel of model KC120-1	112
Figure 3.15	Circuit diagram of solar tracking system connected to voltmeter, ammeter, and pyranometer	113
Figure 3.16	Flowchart of data collection for single-axis solar tracking	114
Figure 3.17	Flowchart of data collection for dual-axis solar tracking	116
Figure 4.1	Performance of one hidden layer of MLP based solar tracking system for single-axis solar tracking system with different hidden nodes	130
Figure 4.2	Performance of two hidden layer of MLP based solar tracking system for single-axis solar tracking system with different hidden nodes	130
Figure 4.3	Performance of three hidden layer of MLP based solar tracking system for single-axis solar tracking system with different hidden nodes	131
Figure 4.4	Performance of one hidden layer of CMLP based solar tracking system for single-axis solar tracking system with different hidden nodes	135
Figure 4.5	Performance of two hidden layer of CMLP based solar tracking system for single-axis solar tracking system with different hidden nodes	135
Figure 4.6	Performance of three hidden layer of CMLP based solar tracking system for single-axis solar tracking system with different hidden nodes	136

Figure 4.7	Performance of one hidden layer of MLP based solar tracking system for dual-axis solar tracking system with different hidden nodes	144
Figure 4.8	Performance of two hidden layer of MLP based solar tracking system for dual-axis solar tracking system with different hidden nodes	145
Figure 4.9	Performance of three hidden layer of MLP based solar tracking system for dual-axis solar tracking system with different hidden nodes	145
Figure 4.10	Performance of one hidden layer of CMLP based solar tracking system for dual-axis solar tracking system with different hidden nodes	149
Figure 4.11	Performance of two hidden layer of CMLP based solar tracking system for dual-axis solar tracking system with different hidden nodes	149
Figure 4.12	Performance of three hidden layer of CMLP based solar tracking system for dual-axis solar tracking system with different hidden nodes	150
Figure 4.13	Block diagram of the developed single and dual axis solar tracking systems based on BLR/MLR and MLP	173
Figure 4.14	Block diagram of the developed single and dual axis solar tracking systems based on BLR/MLR and CMLP	176

LIST OF ABBREVIATIONS

ANFIS	Adaptive Neural Fuzzy Inference System
BLR	Binomial Logistic Regression
CMLP	Cascade Multi-Layer Perceptron
FCM	Fuzzy C-Means Clustering
FL	Fuzzy Logic
FNN	Fuzzy Neural network
GA	Genetic Algorithm
I_{sc}	Short Circuit current
LR	Logistic Regression
MFs	Membership Functions
MLP	Multi-Layer Perceptron
MLR	Multinomial Logistic Regression
MPPT	Maximum Power Point
MSE	Mean Square Error
NNs	Neural Networks
PV	Photovoltaic
V_{oc}	Open Circuit Voltage

LIST OF SYMBOLS

\bar{y}_i	The mean of output values
\hat{y}_i	The predicted output values
w_{ik}	The weight from the i -th node in input layer to the k -th node in output layer
x_i	The input variable
y_i	The original output values
μ_{j_i}	The membership functions
h	The number of hidden nodes in the hidden layer
K	The number of clusters
N	Number of Samples
c	The number of output variables
d	The number of input variables
$f(\cdot)$	The transfer function
j	The number of membership functions for each input
n	The number of training samples
v	The number of attributes

INTEGRASI REGRESI LOGISTIK DAN PERSEPTRON BERBILANG LAPISAN UNTUK SISTEM PENJEJAK SOLAR PAKSI TUNGGAL DAN DWI-PAKSI

ABSTRAK

Sistem penjejak suria pintar untuk menjejak pergerakan matahari telah dikaji dan dicadangkan secara aktif pada masa ini. Walau bagaimanapun, pembolehubah penjejak suria terbaik tidak digunakan untuk membina sistem penjejak suria pintar tanpa mempertimbangkan pembolehubah yang dominan dan optimum. Selain itu, beberapa sistem penjejak suria pintar yang telah direka mempunyai prestasi yang rendah kerana kombinasi pembolehubah dan pengelas pintar penjejak suria yang tidak sesuai. Oleh itu, penyelidikan ini bertujuan untuk (i) menyiasat dan menilai pembolehubah yang paling berkesan dan dominan bagi sistem penjejak suria, (ii) menyiasat kombinasi sesuai di antara pembolehubah solar dan pengelas pintar untuk sistem penjejak solar (iii) mencadangkan sistem penjejak suria baharu dengan mengintegrasikan pengelas pintar terselia dan tidak terselia. Hasil kajian mendapati bulan, hari, dan masa adalah pembolehubah yang paling berkesan untuk sistem penjejak suria paksi tunggal dan dwi-paksi. Dengan menggunakan pembolehubah ini, kajian ini telah berjaya menggabungkan antara perseptron berbilang lapisan (MLP) atau perseptron berbilang lapisan kaskad (CMLP) dan model regresi logistik terlatih (LR). Sistem MLP-LR yang dicadangkan dapat meningkatkan kadar ramalan rangkaian MLP kepada 99.13% untuk sistem penjejak paksi tunggal (iaitu peningkatan 2.35%). Sistem ini juga dapat mengurangkan kadar purata ralat kuasa dua (MSE) kepada 0.010×10^{-2} berbanding dengan nilai MSE untuk MLP konvensional. Di samping itu, sistem CMLP-LR yang dicadangkan dapat meningkatkan kadar ramalan

rangkaian CMLP kepada 99.19% untuk sistem pengesanan dua paksi (iaitu peningkatan sebanyak 1.23%), manakala kadar MSE berkurang kepada 6.250×10^{-5} berbanding nilai MSE untuk CMLP konvensional. Model yang telah dibangunkan juga berjaya mencapai bilangan sambungan keseluruhan yang lebih sedikit (iaitu 77.58% dan 86.16% masing-masing peningkatan bagi MLP dan CMLP), bilangan neuron yang lebih kecil (iaitu 63.51% peningkatan untuk kedua-dua MLP dan CMLP) dan kadar kekompleksan yang lebih kecil (iaitu 70.40% dan 99% masing-masing peningkatan bagi MLP dan CMLP). Penemuan kajian mencadangkan bahawa sistem penjejak suria pintar yang dicadangkan mempunyai potensi besar untuk diaplikasikan untuk aplikasi dunia sebenar (seperti sistem pemanasan solar, sistem pencahayaan solar, kilang-kilang dan ventilasi kuasa solar).

INTEGRATION OF LOGISTIC REGRESSION AND MULTI-LAYER PERCEPTRON FOR SINGLE AND DUAL AXIS SOLAR TRACKING SYSTEMS

ABSTRACT

Intelligent solar tracking systems to track the trajectory of the sun across the sky has been actively studied and proposed nowadays. However, different solar tracking variables have been employed to build those intelligent solar tracking systems without considering the dominant and optimum ones. In addition, several low performance intelligent solar tracking systems have been designed and implemented due to the inappropriate combination of solar tracking variables and intelligent classifiers to drive the solar trackers. Thus, this research aims to (i) investigate and evaluate the most effective and dominant variables on solar tracking systems, (ii) investigate the appropriate combination of solar variables and intelligent classifier for solar tracking systems, (iii) propose new solar tracking systems by integrating supervised and unsupervised intelligent classifiers. The results revealed that month, day, and time are the most effective variables for single and dual axis solar tracking systems. By using these variables, this study has successfully integrated between multi-layer perceptron (MLP) or cascade multi-layer perceptron (CMLP) and trained logistic regression (LR) models. The proposed MLP-LR system is able to increase the prediction rate of MLP network to 99.13% for single axis tracking systems (i.e. which is 2.35% of improvement). The system is also able to decrease the mean square error (MSE) rate to 0.010×10^{-2} as compared to value of MSE for the conventional MLP. In addition, the proposed CMLP-LR system is able to increase the prediction rate of CMLP network to 99.19% for dual axis tracking system (i.e. 1.23% of improvement), while

the MSE rate is decreased to 6.250×10^{-5} as compared to value of MSE for the conventional CMLP. The new developed models achieved less number of overall connections (i.e. which are 77.58% and 86.16% of improvement for MLP and CMLP respectively), less number of neurons (i.e. 63.51% of improvement for both MLP and CMLP), and less time complexity (i.e. which are 70.40% and 99% of improvement for MLP and CMLP respectively). The finding suggests that the proposed intelligent solar tracking systems has a great potential to be applied for real-world applications (i.e. solar heating systems, solar lightening systems, factories, and solar powered ventilation).

CHAPTER ONE

INTRODUCTION

1.1 Overview

Recently, there is a huge interest of renewable energy field globally. Renewable energy comes from natural resources including sunlight, wind, rain and geothermal heat. This energy can naturally be replenished, used, and converted to other forms of energy to be more useful for human usages. Solar energy is one of the most important forms of renewable energy. Solar energy is obtained directly from the sun through the form of solar radiation (Sabry et al., 2013). It is a promising alternative energy that could help to replace the fossil fuels energy sources because it is the most readily available source of energy, daily renew, free, and non-polluting (Iqdour et al., 2007; Azman et al., 2011; Borhanazad et al., 2013; Twidell et al., 2015; Kaysal, 2016).

Solar photovoltaic technology, or commonly known as solar PV have been used for decades to convert solar energy into electricity. The solar photovoltaic is a scalable technology depending on the size of the load. Photovoltaic cells can be used to power small electronics. These cells can be wired together to make solar panels to power up bigger size loads (Sabry et al., 2013; British Petroleum, 2017). The panels can be grouped together to make a solar array for large scale power generation (Alexandru, 2013; Samantha et al., 2013).

Solar tracking system is a system that is designed and developed to track the trajectory of the sun across the sky. The solar tracking systems keep the solar panel at optimum angle that can produce the best power output (Ranganathan et al., 2011; Desa et al., 2017). Solar tracking systems have been used in many places globally. Many

solar tracking systems have been built and designed to maximize the output of solar panels. Using the tracker systems can increase the input of solar radiation, therefore, the output of electrical energy could also be increased (Şenkal et al., 2009; Ghassoul et al., 2013; Fonseca et al., 2016; Randall, 2016). Solar tracker can increase the direct exposure to the sunlight compared to stationary solar photovoltaic (Goldemberg et al., 2003; Juswanto, 2016). This increase can be as much as 10 to 30% depending on the geographic location.

Several research studies have focused on designing and implementing solar tracking systems for different geographical regions due to different environmental conditions (Nelson, 2003; Russell et al., 2003; Stand, 2003; Marlein et al., 2007; Kalogirou et al., 2010; Sabry et al., 2011; Shafie et al., 2011; Rahman et al., 2013; Wu et al., 2013; Kamala et al., 2014; Fonseca et al., 2016; Ray et al., 2016; Rezvani et al., 2016; Chabuk et al., 2017).

However, designing and installing solar tracking systems is not a naive task because of many difficulties. Great amount of measurement results is required before employing tracker systems (Twidell et al., 2015; Robles et al., 2017). These results are collected during relatively long period of time to be used when installing solar cells to track the sun (AL-Rousan et al., 2012). Moreover, different pressures may affect the output of solar panel in addition to the panel direction, angle of photons incidence, the time to measure results, the selected variables to install and control the solar panels, the material of solar cells and the conductivity of photovoltaic modules (Goswami et al., 2000; Chong et al., 2009). Moreover, several variables have been used to build solar tracking systems including the orientation and tilt angles, the photovoltaic gained power, the power radiated from the sun, and the current and voltage flow through the photovoltaic.

Solar tracking systems can be mainly divided into two main types depends on the number of axis that can be used to track the sun. Single-axis solar tracking system is a unidirectional system that can move horizontally or vertically each time (Juswanto, 2016). In contrast, dual-axis solar tracking system is the system that can move horizontally and vertically at the same time (El Jaouhari et al., 2018). Increasing the performance of solar tracking systems is a research interest nowadays (Goldemberg et al., 2003).

On the other hand, driving or controlling solar tracking systems is very difficult operation. The optimal position of solar photovoltaic is difficult to obtain due to sensor accuracy, environmental conditions and algorithm complexity that are used on conventional PV trackers (Narendrasinh et al., 2015). Thus, several researchers have studied the topic of improving and increasing the performance of solar tracking systems by selecting the optimal techniques to control or drive solar tracking system to be moved efficiently from one side to another based on the position of the sun.

The operation of finding the best technique that can move the solar photovoltaic into horizontally, vertically, or both is a hot research topic nowadays. So, several research studies have focused on proposing and applying controllers that can maximize the energy of solar tracking systems (Nakkela, 2016; Kaysal, 2016; Gad et al., 2016). These controllers can be algorithms, microprocessors, motors, electronic circuits, technical methods, or artificial intelligence (AI) technique. Artificial intelligence is a science that focuses on using intelligent principles, machine learning techniques, and expert systems to design any type of machine that can behave like humans. Several AI principles have been used to drive the solar photovoltaic modules toward the position of the sun such as fuzzy logic (FL), neural networks (NNs), fuzzy

neural networks (FNNs), adaptive fuzzy neural networks (ANFIS), genetic algorithms (GA), etc (Elmaged et al., 2015; Narendrasinh et al., 2015; Fonash et al., 2017).

1.2 Problem Statement

The addressed problem in this research focuses on the lack of appropriate studies to determine the best situations and ways to exploit better solar tracking systems to collect solar energy in the world, in general, and specifically in Jordan and its neighbors. To the best of author knowledge, there are no reported studies that suggest (i) the optimum intelligent driving methods for solar tracking systems or (ii) the most effective variables on intelligent solar tracking systems controllers to get the maximum output of solar cells based on real experimental data.

On the other hand, choosing the suitable variables to build, install, and drive solar tracking systems is very important issue to track the position of the sun across the sky efficiently. Several variables have been used to drive solar tracking systems including the horizontal and vertical photovoltaic directions (orientation and tilt angles) (Cheikh et al., 2007; Wu et al., 2013), the photovoltaic gained power (AL-Rousan et al., 2012). The power radiation from the sun (Pattanasethanon, 2010; Sindhura et al., 2013), the current and voltage flow through the photovoltaic (Otieno et al., 2009; Zaki et al., 2012), and the time to make measurements (Cheikh et al., 2007; Thiwa et al., 2014). The variation in using solar variables from a work to another has caused a variation in the generated power, performance, and the efficiency of solar tracking systems. Furthermore, many researches have been published in designing and driving solar tracking systems by using some of these variables without referring to a study to select the most appropriate variables to the proposed solar tracking systems (Mousazadeh et al., 2009; Armindariz et al., 2013; Anuraj et al., 2014; Bazyari et al., 2014; Zhang et al., 2015; Rezoug et al., 2016). Besides that, no study in the field explores the effectiveness of each solar variable on the performance of designed solar trackers. In addition,

no published researches to consider the optimal variables that can maximize the performance of solar tracking systems.

Moreover, several studies have been focused on driving solar tracking systems toward the position of the sun across the sky (Al-Rousan et al., 2012, Deb et al., 2012, Wu et al., 2013, Assaf et al., 2014, Juang et al., 2014; Ray et al., 2016; Zahoor et al., 2017). In these studies, artificial intelligent principles have been used to drive solar tracking systems (Bosque et al., 2014, Kiyak et al., 2016, Khosrojerdi et al., 2016, Sharma et al., 2016, Sethuramalingam et al., 2017, Pandiyan et al., 2017). Diverse researches have been published in driving solar tracking systems by using several types of linear and nonlinear intelligent classifiers and different solar variables (AL-Rousan et al., 2012; Zaki et al., 2012; Armendariz et al., 2013; Thiaw et al., 2014; Kadi et al., 2015; Huang et al., 2016; Toylan, 2017). Developing new solar tracking systems to increase the performance of solar photovoltaic systems is very important target nowadays. Proposing such systems is a very complicated process because of the difficulty to get high prediction rate system at the same time it should have a low error rate (Loschi et al., 2015). However, several low performance intelligent solar tracking systems have been designed and implemented (Mousazadeh et al., 2009; Toylan 2017). These inefficient systems are commonly due to use of inappropriate combination of solar variables and intelligent classifiers to drive the solar trackers. This is due to use unnecessary variables to model solar tracking systems, in addition to select an intelligent classifier that not complex enough to deal with the collected data.

Using intelligent classifiers in driving solar tracking systems not guaranteed the efficiency of traditional solar photovoltaic systems (Zaki et al., 2012; Hijawi et al., 2016). Developing new principles to drive and control solar tracking systems by selecting the appropriate intelligent classifiers is a hot topic (Figueiredo, 2009). The main idea is to develop such efficient systems that can improve the field of solar tracking systems. Efficient solar tracking systems should increase the prediction rate, minimize the error rate, simplify the processes and operation while determining the optimum directions, and minimize the

consumed energy (Devi et al., 2012; Sharma et al., 2016). However, using high non-linear and complex intelligent classifiers in driving solar tracking systems will cause many problems. It will slow down the process of predicting tilt and orientation angles, and increase the complexity of the solar tracker, thus, increase the consumed energy.

However, intelligent classifiers can be mainly divided into two types (i.e. supervised and unsupervised). Supervised classifiers can be defined as a learning technique that depends on learning process by mapping an input to output based on what it learnt. While unsupervised classifiers describe the method of finding the hidden structure from unlabeled data (Mizutani et al., 2001; Banman, 2002).

1.3 Objectives

The main objectives for this research are as follow:

- i. To investigate and evaluate the most effective variables on solar tracking systems based on practical data to be used to increase the performance of solar tracking systems.
- ii. To investigate the appropriate combination of solar variables and intelligent classifiers to improve the prediction rate and mean square error of solar tracking systems.
- iii. To propose new solar tracking systems by integrating supervised and unsupervised intelligent classifiers for single and dual axis solar tracking systems.

1.4 Research Contributions

This research is to contribute the field of solar energy by many issues.

- i. The investigation of the most effective solar variables and optimum intelligent technique contributes to the field of solar energy. This is because more such investigations and studies are needed to guide research in the field of solar energy.
- ii. This research has found the optimum single and dual axis solar tracking systems by finding the optimum combination of the most effective variables and intelligent classifiers.
- iii. This research has developed new high-performance single and dual axis solar tracking systems based on integrating MLP and CMLP techniques with logistic regression models. These developed systems have optimized the mean square error (MSE), maximized the prediction rate, and minimized the time complexity compared with conventional systems.
- iv. Using experimental and non-theoretical data has added a good contribution because most of works done are mainly based on theoretical calculations or randomly generated data. Using experimental data gives a strong indication to real weather pressures, thus the most appropriate variables and intelligent techniques will not be affected by faulty data.
- v. This research contributes to the field of solar energy in Jordan and nearby countries that no similar studies have been done for Jordan and its neighbors.

1.5 Research Scopes

The data used in this study were collected for the city of Irbid in northern Jordan, which is a four seasons country. This would bound this research to be tested and evaluated in

the country of Jordan or its neighbors which have the same environmental conditions. On the other hand, testing and evaluating this research for other countries requires collecting specific datasets for these countries. Moreover, several solar variables and parameters are measured during collecting the datasets (i.e. angle of incidence, light intensity, solar time, equation of time, declination angle, inclination angle, azimuth and zenith angles). However, this research is bounded by employing the most popular variables to predict both tilt and orientation angles (i.e. month, day, time, V_{oc} , I_{sc} , and power radiation).

Finally, evaluating this research is mainly based on testing the performance of several proposed solar tracking systems. However, this research focuses on selecting three performance metrics to make the research specific namely prediction rate, mean square error, and time complexity.

1.6 Thesis Organization

This thesis is organized into five chapters. Chapter one presents the overview of solar tracking systems and intelligent classifiers that used to drive solar trackers. Then, the problem statement of solar tracking systems, the research objectives, and the outlines of the thesis are explained.

Chapter two presents the literature review and defines the solar tracking systems issues involved in the field. This chapter then explains several intelligent classifiers that used to control solar tracking systems. Finally, it reviews several research works that used diverse intelligent classifiers to drive solar tracking systems, together with their advantages and disadvantages.

Chapter three explains the research methodology and the experimental procedures that used to solve the problems of the current intelligent solar tracking systems. This chapter presents the procedure to find the most effective variables on solar tracking systems. In addition, it presents the methods to implement and evaluate several proposed solar trackers based on diverse intelligent classifiers. Finally, the procedure to develop new efficient single and dual axis solar tracking systems based on integrating several intelligent classifiers will be presented.

Chapter four presents the results that obtained by implementing the proposed methodology. In addition, it discusses the results and the alignment to harmonize to research objectives. This chapter also compares the new proposed systems with the current solar tracking systems. Finally, Chapter five highlights the conclusions of this research, research limitations, and suggestions for further research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter is dedicated to provide a review of the relevant background information that required to understand the principle concept of solar tracking systems. Section 2.2 covers definitions, concepts, the advantages and disadvantages of non-renewable and renewable energy. Section 2.3 focuses on the definitions, functions, categories, variables and parameters of solar tracking systems. Section 2.4 covers the concept of intelligent classifiers. Section 2.5 reviews the intelligent classifiers based solar tracking systems. The review involves the concept as well as the advantages and disadvantages of these intelligent solar tracking systems. In addition, researches gaps and problem statement will be highlighted clearly at the end of this section. Final section will summarize the reviews on this chapter.

2.2 Renewable Energy

Non-renewable energy is a kind of a finite energy that does not renew itself in a short period for sustainable economic extraction (Apergis et al., 2012; Chang et al., 2014; Jebli et al., 2016). Non-renewable energy comes in five forms including fossil-fuels, petroleum, natural gas, coal, and nuclear fuels (Jebli et al., 2016). Non-renewable energy is cost effective and easier to product and use. In contrast, non-renewable energy can cause damage to the environment. Non-renewable energy contributes to the global warming because burning non-renewable energy causes photochemical pollutions, therefore, could lead to acid rain and greenhouse gasses (Chen et al., 2011).

On the other hand, renewable energy can be used to solve the problems of non-renewable energy. Renewable energy is the energy that comes from natural resources such as sunlight, wind, rain, tides, and geothermal heat. It is the energy that naturally replenished and can be converted from a form to another to be useful for human usage. Numerous researchers in worldwide have devoted increasing attention to a renewable energy development. Renewable energy sources are friendlier to the environment and more sustainable compared to fossil fuels (Goldemberg et al., 2003; Borhanazad et al., 2013; Juswanto et al., 2016; Randall, 2016; Kaya et al., 2017). Recently, renewable energy has gained more attention from researchers due to the high demand to find new sources for energy and due to its friendly nature for environment.

A Solar energy is one form of renewable energy that can be obtained from the sun through the form of solar radiation. It is a promising alternative technology that will help to replace petroleum energy sources. The interest in using a solar energy instead of fossil fuel has increased, and several countries have increased their sharing percentage of solar energy generation. The total amount of consumed solar energy in worldwide in million tons of oil equivalent is shown in Figure 2.1.

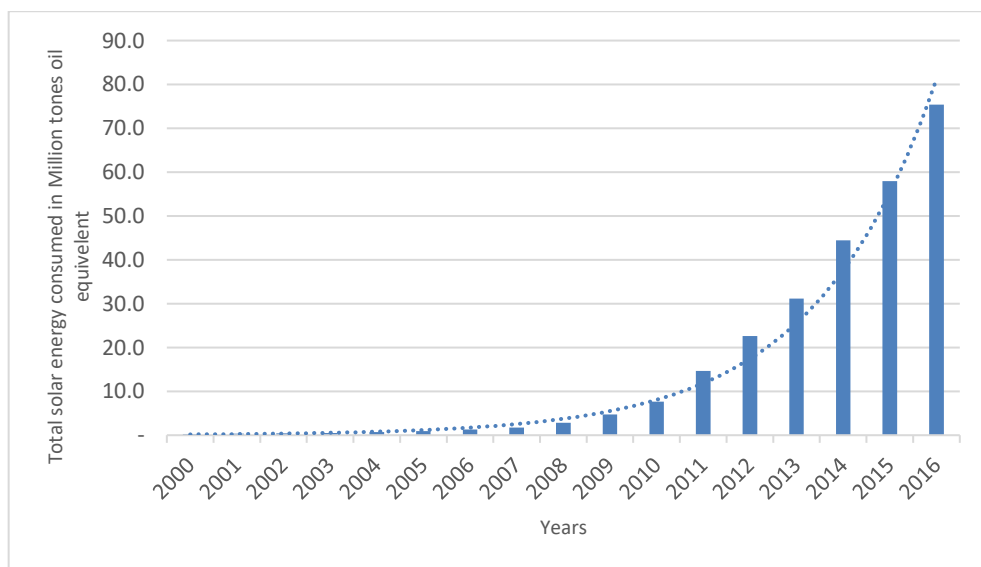


Figure 2.1: Total solar energy consumed in million tons oil equivalent.

As shown in Figure 2.1, the total amount of solar energy which consumed in worldwide increased exponentially from 2000 to 2016. The maximum amount of consumed solar energy was observed in 2016. Official data from various government ministries and statistical offices were used to compile these data (Petroleum, 2017). The total gross generation of a solar energy worldwide in terawatt hours is shown in Figure 2.2. Figure 2.3 shows the total capacity in megawatts. As shown in Figures 2.2 and 2.3, the total capacity, of the generated, and the consumed energy have increased exponentially, and the total growth of solar energy capacity and usage reached 29.6%.

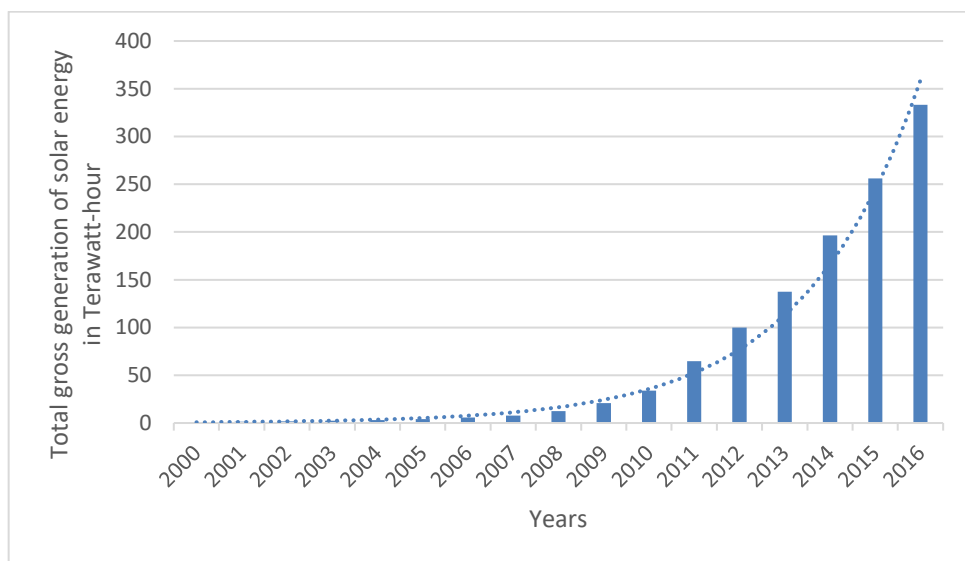


Figure 2.2: Total solar energy consumed in terawatt-hour.

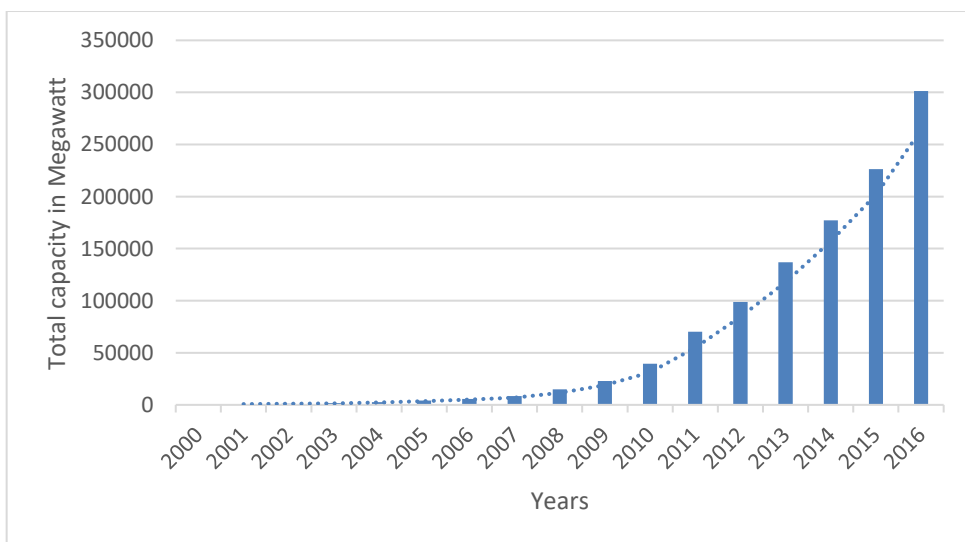


Figure 2.3: Total solar energy capacity in megawatt.

2.3 Solar Power Systems

The solar power systems are the systems that use the solar energy that radiated from the sun to make electricity. Several forms of solar power systems are available such as standalone, battery backup, utility grid-connected power systems, and photovoltaic system (Kaundinya et al., 2009). A photovoltaic system is a solar power system that consists of several components to absorb and convert solar power into electricity. Concentrator photovoltaic, maximum power point tracking (MPPT), and solar tracking systems are the main strategies that can be used to improve the performance of a photovoltaic system (Almonacid et al., 2017; Al-Rousan et al., 2017).

A concentrator photovoltaic is a technology that generates electricity directly from the solar power radiated from the sun (Almonacid et al., 2017). It consists of lenses and curved mirrors to increase the amount of power radiated, thus, increases the efficiency. In contrast, MPPT is a technology that used to track the maximum power point that can be generated by the photovoltaic system (Cheikh et al., 2012; Makhloufi, 2014). The photovoltaic module should be moved from side to side in order to obtain the maximum power (Mathur et al., 2014). On the other hand, solar tracking system is a system that depends on the orientation of the photovoltaic toward the sun, thus minimizes the angle of incidence between the solar beam and the photovoltaic surface (Tudorache et al., 2010; Otieno, 2015).

A solar tracking system is the most popular solar power systems globally (Tudorache et al., 2010; Deb et al., 2012). The definition, functions, categories, types, variables and parameters of solar tracking systems are discussed in the following subsections.

2.3.1 Solar Tracking Systems

A solar tracking system is a device that can be implemented to follow the trajectory of the sun across the sky efficiently. Solar tracking system is used to minimize the angle of incidence between the incoming solar beam and the photovoltaic module surface. Therefore, it helps in increasing the amount of generated energy by using solar photovoltaic modules.

Solar tracking system depends on using photovoltaic cells or solar panels to convert solar energy into electricity. Solar photovoltaic cells are a scalable technology depending on the size of the load. Photovoltaic cells can be used to power small electronics or can be wired together to make solar panels for large loads (Würfel, 2010, Azman et al., 2011; Desa et al., 2016). The panels can be grouped together to create a solar array for large-scale power generation (Clifford et al., 2004; Azman et al., 2011; Twidell et al., 2015; Desa et al., 2016; Kolluru, 2016; Rezvani et al., 2016; Petroleum, 2017; Fonash et al., 2017).

Solar tracking systems have been used in numerous places worldwide. Many solar tracking systems have been built and designed to achieve the optimal amount of solar energy, and many models have been proposed to enhance the advantages of a solar panel usage. Several studies have focused on designing and implementing solar tracking systems for different geographical regions (Lakeou et al., 2006; Hines et al., 2008; Huang et al., 2009; Al-Rousan et al., 2012; Deb et al., 2012; Wu et al., 2013; Assaf et al., 2014; Juang et al., 2014).

Tracker systems track the position of the sun, thereby increasing the input of solar radiation and electrical energy output (Stand, 2003; Iqdour et al., 2007; Wu et

al., 2013). A solar tracking system maintains the solar photovoltaic modules at an angle that produces the best power output.

Moving solar tracking systems from side to side in order to track the trajectory of the sun across the sky is an important task. Solar tracking systems can be manually moved mechanically through the use of cantilevers, gears, or motors. Solar tracking systems can be divided into two main groups based on the techniques that control the photovoltaic module namely active and passive tracking systems (Sözen et al., 2004; Sørensen, 2007; Hines et al.; 2008, Sözen et al., 2008; Chong et al., 2009; Tudorache et al., 2010; Parmar et al., 2015; Racharla et al., 2017). Active tracking systems use motors and gear trains to direct the panel toward the sun, while passive tracking systems use a low-boiling-point compressed gas fluid that originates from a solar heat for that purpose. The main drawback of passive solar tracking systems is their strong dependency on environmental conditions. Although passive solar trackers can maximize heating from the sun, bad environmental conditions can render these trackers inefficient. Active solar tracking system can solve the problems of passive solar tracking systems (Anderson et al., 2003; Gevorkian, 2003; Luque-Heredia et al., 2007; Sabry et al., 2013; Elmaged et al., 2015; Akcin et al., 2016).

Active tracker systems come in several varieties that can be classified into a few categories (Mousazadeh et al., 2009; Elmaged et al., 2015; Loschi et al., 2015; Otieno et al., 2015; Saini et al., 2015). Based on literature review, active solar tracking systems can further be classified into five categories namely (i) sensor driver systems; (ii) microprocessor driver systems; (iii) open–closed loop driver systems; (iv) intelligent driver systems; and (v) a combination of two or more of these driver systems.

Sensor driver systems can control the photovoltaic modules based on inputs driven from sensors and other electronic devices that detect relevant parameters of the sun and send them to a processor that can analyze these parameters to find a suitable output (Tudorache et al., 2010; Pattanasethanon et al., 2010). Microprocessors and computer systems on the other hand, can drive solar tracking systems to the position of the sun by using algorithms and mathematical equations to determine the exact position of the sun (Roth et al., 2005; Kamala et al., 2014; Chabuk et al., 2017). Open-closed loop systems use control device motors or actuators to follow the sun direction based on mathematical equations (Seme et al., 2017; Sidek et al., 2017). Open-loop system uses algorithms based on the control of date and time without using any feedback to evaluate the results or the actions of the trackers (Alexandru, 2013; Melo et al., 2017). By contrast, a closed-loop system can track the sun using sensors. The sensors can sense the position of the sun at all times of the day. The sensed position is used in mathematical equations to make a few calculations, the results of these calculations will be used to find the next tracker direction (Juang et al., 2014; Fonseca-Campos et al., 2016).

On the other hand, intelligent driver systems are the tracking systems that depend on intelligent classifiers to train the system using pre-determined data and use the intelligent principles to predict the next tracker direction (Bosque et al., 2014; Thiaw et al., 2014; Kiyak et al., 2016; Khosrojerdi et al., 2016; Sharma et al., 2016; Pandiyan et al., 2017; Sethuramalingam et al., 2017; Toylan et al., 2017). Intelligent driver systems are the most promising among these tracking systems due to their capability to predict the exact position of the sun by using learning algorithms. Thus, most of the current researches focus on using intelligent principles.

However, multiple measurement variables and parameters are required before employing tracker systems (Biol, 2006; Jazayeri et al., 2013). These variables and parameters are collected and calculated during a relatively long period time to be used when installing solar cells to track the sun (Al-Rousan et al., 2012). Different solar variables and parameters, including panel direction, angle of photon incidence, time to measure the results, material of solar cells, and conductivity of photovoltaic modules, may affect the output of solar panel cells etc. (Almonacid et al., 2017).

Solar tracking system depends on the number of axes used to move solar photovoltaic modules horizontally, vertically, or both. Two main types of solar tracking systems are available. The first one is single-axis tracking, which can be used to move a solar photovoltaic horizontally or vertically. The second type is dual-axis solar tracking, also known as two-axis tracking, which can be used to simultaneously change in both horizontal and vertical directions (Al-Rousan et al., 2012).

2.3.2 Solar Variables and Parameters

Several solar parameters must be considered when designing, implementing, and installing solar tracking systems. Greenwich Time and Solar Time are the basic parameters in the solar energy field. Greenwich Time is a timescale that depends on the rotation of the Earth around itself in one day (Goswami et al., 2000; Makhloufi et al., 2014). This time can be determined based on the meridian that passes through the town of Greenwich in Britain, which is one of the longitudes adopted as a reference point for world timing. Other longitudes are divided into two parts based on their positions along the Greenwich line. The time in all east lines is calculated by adding a number of hours (+) to the Greenwich Time. The time in all west lines is calculated by subtracting a number of hours (-) from the Greenwich Time (Kalogirou et al., 2010;

Akhlaghi et al., 2017). The number that is added or subtracted to each Greenwich Time is determined based on the region of the time zone relative to the Greenwich line. A total of 360 longitudes exist all over the world based on the Greenwich line and each time zone, as shown in Figure 2.4. A variation in longitudes can occur based on the movement of the Earth. The Earth can move by one degree every four minutes, and it rotates around itself once per day (Lambeck, 2005).

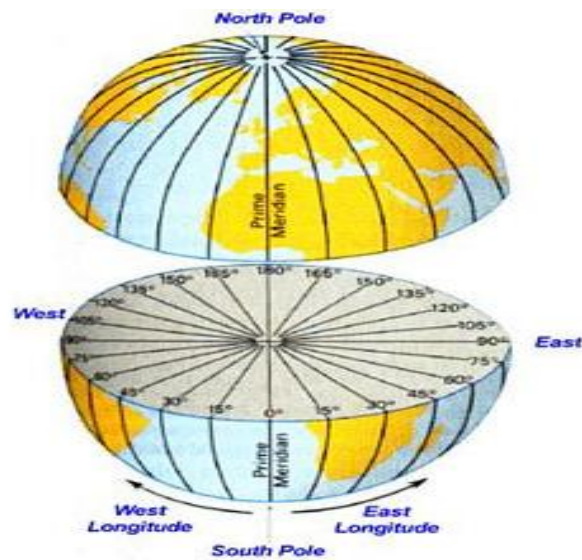


Figure 2.4: Longitudes of the Earth (Makhloufi et al., 2014).

The Solar Time parameter is also important because it is the real time that depends on the position of the sun in the sky. The fundamental unit in this time is the day order in the year, starting from 1 on the 1st of January and ending with 365 on the 31st of December (Grolemond et al., 2011).

In addition to determine the longitude and equation of time, a few parameters should be calculated or measured to determine the best direction and orientation of solar photovoltaic modules and to obtain more output power. Latitude, angle of incidence, light intensity, declination angle, elevation and zenith angles, solar azimuth

angle, and inclination angle are the main parameters that specify the best location and direction of solar tracking systems. Latitude is a parameter used to determine the angular distance (south or north) of the equator in any location on Earth (Lang, 2013). The latitude angle is measured in degrees, as shown in Figure 2.5.



Figure 2.5:Equator line and latitude.

Angle of incidence is the most important parameter in installing solar tracking systems. Angle of incidence is the angle between the rays of the sun falling on the surface and the rays perpendicular to that surface (Kalogirou et al., 2010), as shown in Figure 2.6, where the angle of incidence is indexed by (θ°).

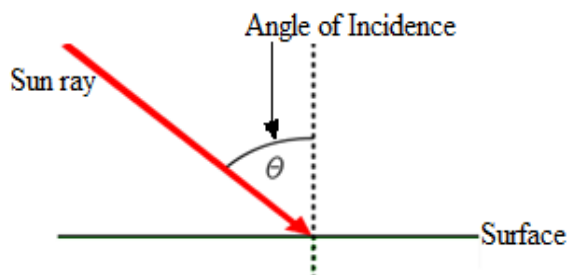


Figure 2.6:Angle of incidence.

However, using the angle of incidence alone is insufficient when installing solar tracking systems. Light intensity, which is commonly called solar irradiance of a light source, is also an important parameter to install tracking systems. Light intensity can be determined by measuring either the power of the light source or the luminous

flux. The light intensity of the sun is measured using specific tools, such as a pyranometer.

Several other parameters have to be measured to sufficiently install solar tracking systems. Declination angle, which is the angle between the equator and a line drawn from the center of the sun to the center of the Earth, is one of these parameters. Declination angle is shown in Figure 2.7. Elevation and zenith angles have close definitions to the declination angle. Elevation angle is the altitude of the sun or the angle between the center of the sun and the horizon. Zenith angle is the angle between the center of the sun and the vertical (Reda et al., 2004). Figure 2.8 shows elevation and zenith angles.

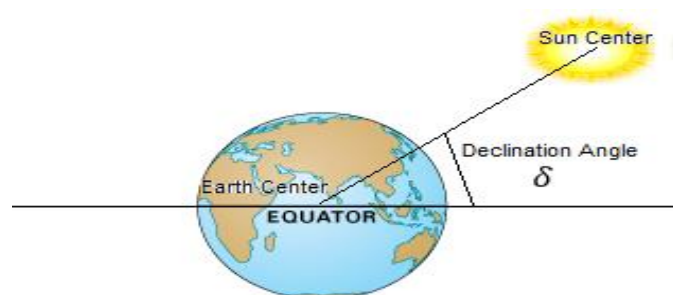


Figure 2.7: Declination angle.

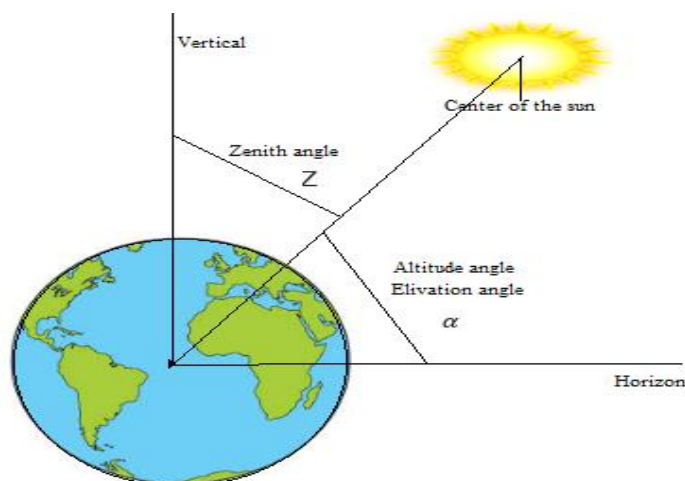


Figure 2.8: Elevation and zenith angles.

Solar azimuth angle is measured with respect to due south; it is the angular distance between the projection of the line of sight to the sun on the ground and due south (Nuwayhid et al., 2001). Solar azimuth angle is indexed by (γ_s) and indicated by a positive sign for the position east of south or a negative sign for the position west of south. Azimuth angle is shown in Figure 2.9.

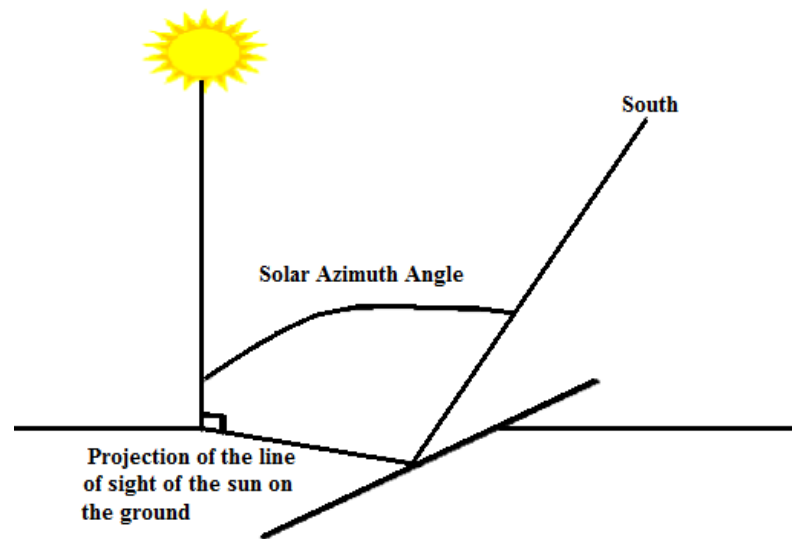


Figure 2.9:Solar azimuth angle.

Inclination angle is the angle between a photovoltaic module and the positive x axis (Peled et al., 2017). This angle is indexed by (β) and it measured in degrees, as shown in Figure 2.10.

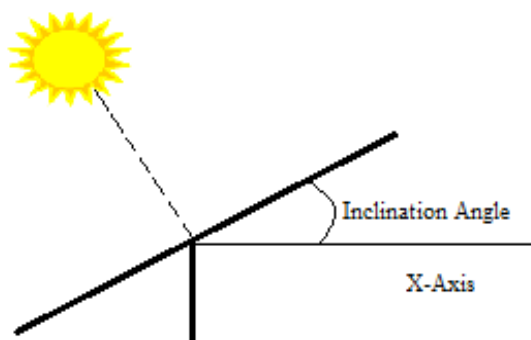


Figure 2.10:Inclination angle.

All of these preceding parameters can be utilized to determine the best location to install solar tracking systems or the best orientation for such systems to obtain higher power, as shown in Figure 2.11.

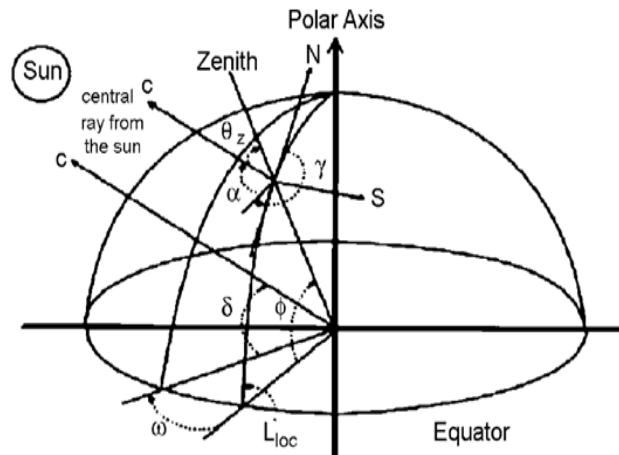


Figure 2.11: Schematic representation of solar angles (Makhloufi et al., 2014).

The work in the field of solar tracking systems does not stop after installing a photovoltaic panel in a suitable place. Solar tracking systems should be evaluated to ensure that they function efficiently and they can be used in the future of solar energy. Numerous evaluation metrics are utilized to evaluate solar tracking systems. The type of driver or controller system is one of the metrics that used to determine the next direction of photovoltaic panels and the axis angle movement.

On the other hand, several solar variables must be considered when designing solar tracking systems. The most important variables that must be considered during building solar tracking systems are tilt (θ°) and orientation (ϕ°) angles. Tilt and orientation angles are used to track the position of the sun sufficiently. The tilt angle can be defined as the angle between the solar tracking system and the horizontal axis while the orientation angle is the angle that can be used to move the solar tracking

system horizontally to ensure that the sun is perpendicular to the solar tracking system surface as shown in Figure 2.12. The main objective of solar tracking systems is to choose the best tilt and orientation angles that allow the systems to gain more power through the form of solar radiation.

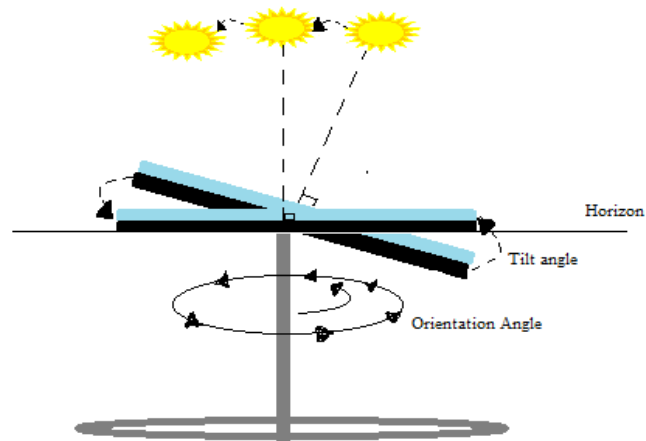


Figure 2.12:Tilt and orientation angles.

However, measuring the best tilt and orientation angles is not enough to build solar tracking system. Other variables must be considered while working on such systems such as measuring the light intensity or as commonly named solar irradiance of the sun. Light intensity is the variable that can represent the power which obtained from the sun and it is measured using specific tools. Open-circuit voltage is another solar variable which can be measured when no external load is connected to the two photovoltaic module terminals, therefore, no external electric current flows between these terminals. Short-circuit current (I_{sc}) is another solar variable which is the current that measured through the photovoltaic module when the voltage across the module is equal to zero. Both of open-circuit voltage and short-circuit current are widely used to ensure about the efficiency of the photovoltaic module and many solar tracking systems depend on using them in tracking the position of the sun (Hohm et al., 2003; Liu et al., 2008; Hardin et al., 2012; Quansah et al., 2017).

The weather variable is also very important variable that can affect on the solar tracking systems principles (Stern et al., 2000; Liu et al., 2008; Duffie et al., 2013). The changing in weather can be presented by using the month variable through the year that the monthly position of the sun is changed because of the interaction between the rotation of the earth around its axis and the orbit of the earth around the sun. The rotation of the earth on its axis causes the changing of time through the day while the orbit of the earth around the sun represents days of a month and a year. Month of the year, day of the month, and time of the day are also used in designing solar tracking systems. Although measuring all the previous variables is very important while designing and installing solar tracking systems, but using all of these variables in building and driving solar tracking system cannot guarantee that the system will give the optimal results, and they can cause more processing time and more energy consumption. Most of the current research tried to select from these variables to build their systems without making any pre-analysis to the used variables (Armendariz et al., 2013).

Controlling or driving solar tracking systems is the most important issue in solar tracking systems. Solar tracking systems can be controlled manually or by using a kind of controllers that can automatically move the photovoltaic toward the optimal positions (Kaya et al., 2017). These controllers can be algorithms, microprocessors, motors, electronic circuits, technical methods, or artificial intelligence (AI) technique. AI controllers are the systems that used intelligent classifiers to control solar tracking systems.