Supervised Learning for Microclimatic parameter Estimation in a Greenhouse environment for productive Agronomics

Dr. Samuel Manoharan,
Professor,
Department of Electronics,
Bharathiyar College of Engineering and Technology,
India.
Email: jsamuel@bcetedu.in

Abstract: Maximum crop returns are essential in modern agriculture due to various challenges caused by water, climatic conditions, pests and so on. These production uncertainties are to be overcome by appropriate evaluation of microclimate parameters at commercial scale for cultivation of crops in a closed-field and emission free environment. Internet of Things (IoT) based sensors are used for learning the parameters of the closed environment. These parameters are further analyzed using supervised learning algorithms under MATLAB Simulink environment. Three greenhouse crop production systems as well as the outdoor environment are analyzed for comparison and model-based evaluation of the microclimate parameters using the IoT sensors. This analysis prior to cultivation enables creating better environment and thus increase the productivity and harvest. The supervised learning algorithm offers self-tuning reference inputs based on the crop selected. This offers a flexible architecture and easy analysis and modeling of the crop growth stages. On comparison of three greenhouse environment as well as outdoor settings, the functional reliability as well as accuracy of the sensors are tested for performance and validated. Solar radiation, vapor pressure deficit, relative humidity, temperature and soil fertility are the raw data processed by this model. Based on this estimation, the plant growth stages are analyzed by the comfort ratio. The different growth stages, light conditions and time frames are considered for determining the reference borders for categorizing the variation in each parameter. The microclimate parameters can be assessed dynamically with comfort ratio index as the indicator when multiple greenhouses are considered. The crop growth environment is interpreted better with the Simulink model and IoT sensor nodes. The result of supervised learning leads to improved efficiency in crop production developing optimal control strategies in the greenhouse environment.

Keywords: IoT Sensors; Greenhouse production; Microclimate; simulation models; comfort ratio; Supervised Learning;

1. Introduction

For enabling adaptive strategies for climate control and improving the energy efficiency as well as optimizing solar greenhouses prior to cultivation of crops, it is essential to assess the microclimate parameters of the greenhouse in a dynamic manner [1]. This will help in improving the crop yield and analysis of best suited crop during that time of the year. Automation Culture Environment oriented Systems analysis (ACESYS) should be demonstrated in the current greenhouses for enabling proper growth of crop as well as to provide a uniform microclimatic condition [2]. The agricultural profit is improved and the uncertainties of crop production is reduced with this information processing, data monitoring and sharing on implementation of ACESYS in a successful manner. Variation in the state of the system, complex dynamic nature between ecological and biological systems and variability of microclimate are some of the major uncertainties faced while cultivating in greenhouse [3].

The quality and production yield vary significantly along with preventing or reducing the probability of crop diseases due to the temporal and spatial variability caused by the solar radiation interception that is coupled with the microclimate parameters [4]. In the environment of plant growth, control is to be done based on real-time analysis of various parameters as the production cost is affected especially in places with adverse climatic conditions that does not support the growth of certain plant types in the greenhouse. Optimality degrees are considered for microclimate parameter evaluation in tropical greenhouses [5]. The amount of natural ventilation and active cooling systems should be analyzed for determining the yield of the plant production system and energy

efficiency of the setup. Various sensors are used for collection, interpretation and analysis of the greenhouse parameters. The sensor data is transmitted by means of wireless communication.

The microclimate parameters must be assessed at every stage of growth of the crop in order to establish a conducive environment [6]. In tropical regions where the atmospheric heat is high, cooling systems must be set up in the greenhouse. IoT sensors are used for monitoring the solar radiation, vapor pressure deficit, humidity, temperature, soil fertility and various relevant parameters inside the greenhouse. Three types of greenhouses are considered for this comparison namely single gabble greenhouse, free standing Quonset greenhouse and gutter connected greenhouse. The parameters are also compared to the external environment. Matlab Simulink is used for interfacing the data obtained by the wireless sensors and a comfort ratio model is developed [7]. The growth stages are monitored and the productivity of the crop is improved by providing favorable condition for the crop in the greenhouse setup.

2. Related Works

The greenhouse environment analysis and research published related to it in terms of IoT sensors and supervised learning are presented in this section. The challenges faced by the greenhouses in various regions and the need for evaluation of microclimate and dynamic assessment is studied. The overall crop production can be increased and the negative impact of the variation in microclimate can be reduced [8]. Unnecessary energy consumption is also identified and reduced by monitoring and evaluating the greenhouse parameters efficiently. The growth responses, greenhouse environment and climatic conditions, their interaction the associated long and short term risks can be assessed using simulation models based on the information obtained by the wireless sensors regarding the raw microclimate [9]. The production profit is increased to a large extent by optimizing the microclimate in the greenhouse on replacing the traditional offline systems with cloud- computing and IoT based platforms for data collection and storage. The use of renewable resources and natural ventilation must be increased for energy management and operation sustainability in greenhouse environment [10].

3. Proposed Work

Figure 1 represents the architecture of the proposed system which is categorized into four major blocks. Acquisition of wireless data is performed using an Arduino based microcontroller unit. Low power consumption, affordable cost, improved accuracy and high performance are the features for selection of this module. Sensors used in this system includes light sensor, humidity sensor and temperature sensor along with a Real Time Clock (RTC) module, voltage regulator and a Secure Digital (SD) card. The data acquisition is done using a suitable software and the connectivity board [11]. This hardware setup is completely energy efficient and has the flexibility of battery operation as well as AC supply. The response time of the microcontroller unit is less than a millisecond due to its high clock speed when compared to the traditional computer based system.

These devices can also operate in temperatures over 100°C due to the low power consumption and superior industrial fabrication quality. The RTC module enables monitoring and recoding every measurement with its corresponding date and time [12]. This module can operate with the help of a coin cell battery when the controller is reset or when the main power source is not functional. The power supply is regulated using the power regulator. The SD card is used for storing the sensor data onboard. The SD card as well as the cloud station is updated with the sensor information every minute. This enables secure data storage even when there is an interruption in the communication with the cloud. A web page interface can be created for visualizing the information even from remote location. The data is fed into the Simulink model on Matlab for simulation as well

as in excel sheets for processing and analysis [13]. Further, supervised learning scheme is used for forecasting the greenhouse environment and crop status based on the analyzed values.
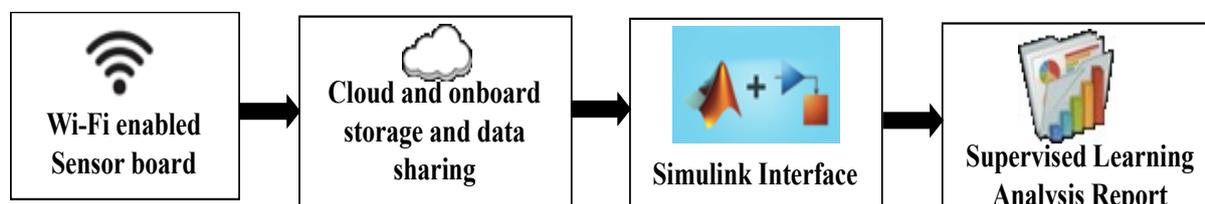

Figure 1: Architecture of the proposed system

The system is developed in a flexible manner that it can be interfaced easily to a PC or onboard computers or even other microcontrollers. The performance of the sensors are compared by setting up a frequency of 1 Hz to monitor the test readings. The ground truth values of a commercial offline data acquisition system is used for validating the measurements. The accuracy of the sensor and the degree of variation is considered to be negligible as the structure is considered to be of a small scale size. The microclimate is assumed to be uniform throughout the area of the greenhouse. Irrespective of the covering material, shape, orientation and dimension, the microclimate parameters must be evaluated using the IoT sensor node for any greenhouse. The characteristics and growth patterns of the crops along with the conducive microclimate parameters can be used for simulation along with the values derived by these sensors.

4. Results and Discussion

The results are analyzed based on the raw IoT sensor information obtained by the evaluation of microclimate within the greenhouse, evaluation based on the recommended values for growth of the crop and reference borders for optimum and critical microclimate. Certain insignificant correlations and minor variations are ignored purposefully as they does not impact the growth or yield of the corp. Simulink model is implemented for various growth stages of the plant and a comfort ratio is generated. The analysis is done over a period of 12 days in outdoor, single gable, free standing Quonset and gutter connected greenhouse environments. Temperature, humidity and the VPD parameters gathered and their mean and standard deviation values at different times of the day is evaluated as shown in table 1.

Table 1: Comparison of microclimate parameters in outdoor and greenhouse environments

Para-meters		Outdoor			Gutter Connected Greenhouse			Free standing Quonset Greenhouse			Single Gable Greenhouse		
	Time (days)	Temp (oC)	Humidity (%)	VPD (kPa)	Temp (oC)	Humidity (%)	VPD (kPa)	Temp (oC)	Humidity (%)	VPD (kPa)	Temp (oC)	Humidity (%)	VPD (kPa)
Mean Sun	12	32	68	1.9	31	70	2.1	30	72	2.0	29	71	2.2

Mean Cloud	12	29	72	1.2	28	75	1.4	27	73	1.3	26	74	1.5
Mean Night	12	26	90	0.4	24	92	0.6	25	96	0.5	23	94	0.7
Mean	12	28	80	0.9	28	86	1.2	27	82	1.1	25	84	1.3
St Dev	12	3	16	0.8	4.5	18	1.0	4	14	0.9	3.5	15	1.2

From the table, it is evident that different times and different days have unequal means of the microclimate data in the greenhouses. Figure 2 and 3 provides the plots of daily average and VPD summary respectively for the 12 days of analysis. There is a variation in the VPD value every day and there is a slight consistence between the 8th to 12th day. The optimal microclimate environment is analyzed for 5 crops namely tomato, brinjal, okra, beans and chilly. The light condition of the greenhouses with respect to the outdoor environment is done. The VPD values vary largely during sunny hours and are quite similar under the cloud and night condition. This is due to the peak temperature during the day. Based on the daily as well as hourly average of the microclimate data obtained by the IoT sensors from the three greenhouses, the correlation is analyzed. Supervised learning is done on training with several nonlinear and linear fitting data with multiple iterations.
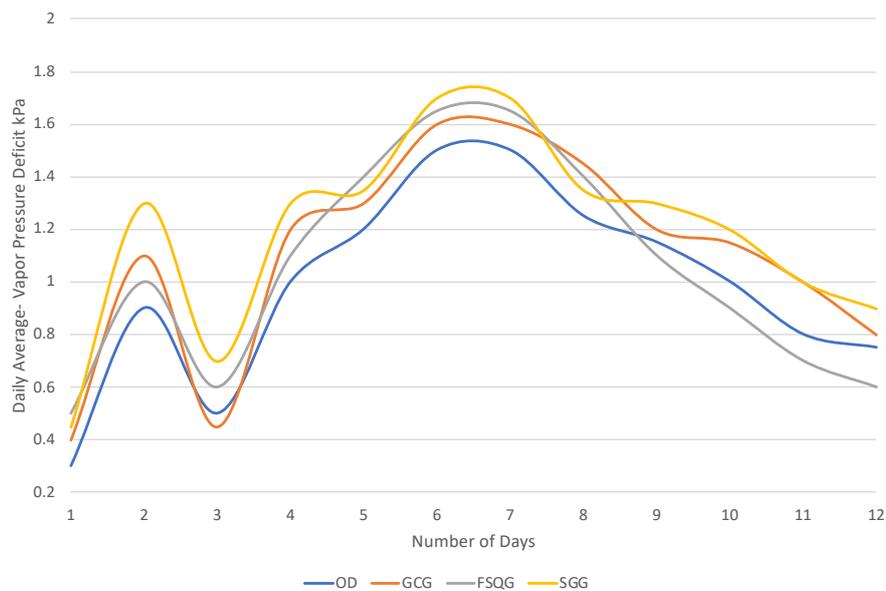

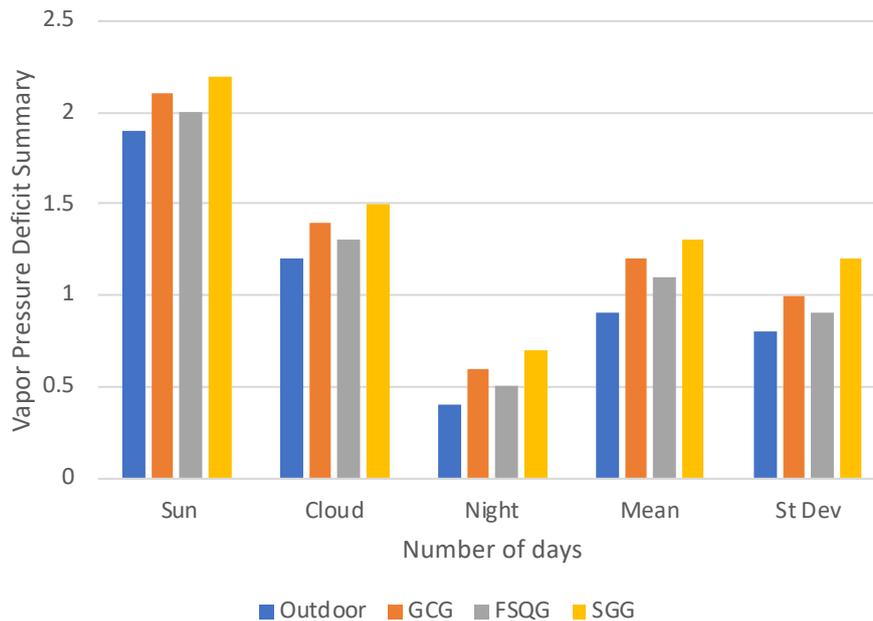**Figure 2: Comparison of the daily average of VPD in outdoor and greenhouse environments**

Figure 3: VPD summary in outdoor and greenhouse environments

Providing optimal microclimatic condition for the various growth stages of the plant has been the main focus in this research. The parameters such as solar radiation, vapor pressure deficit, relative humidity, temperature and soil fertility measured as raw data by the sensors in the greenhouse are analyzed for their influence on the plant growth at various stages. This helps in understanding the precise environmental behavior with respect to the external factors like wind speed and so on. The production risk is minimized and the uncertainties are embraced providing an optimal solution using the model-based analysis. The different stages of plant growth, light conditions, time frames and reference borders are considered along with the microclimate parameters to generate a comfort ratio. This enables better planning prior to cultivation for interpreting the crop growth pattern.

The microclimate parameters are assessed dynamically on comparing the three greenhouses and using the comfort ratio model. Any control action that causes damage to the environment is avoided by simulating different scenarios of plant growth in the greenhouse. A randomized complete block system is used for estimation of the lost energy with high accuracy when the heat transfer model is implemented in the greenhouse. The relationship between the variable inside and outside the greenhouse are compared using the supervised learning algorithm. Farmers can use these forecasts to notice the temperature changes well in advance and prevent damage of crops due to extreme change in temperature. A climate control strategy can be implemented within the greenhouse environment to reduce the risk of planting and make smart energy management decisions. The constructive material usage, equipment management, planting techniques, sound environmental setup, commercial competence, social support and source conservation features of the agricultural greenhouses can be maintained with this research. Reduction of waste production, water and energy consumption, utilization of agro-chemicals are further encouraged.

5. Conclusion

Three greenhouse models are analyzed and their microclimate parameters are evaluated using the data gathered by IoT-sensors that are processed using supervised learning models and comfort ratio model. The environment of crop growth is interpreted with the simulation models that are interfaced with data collection platforms that work on cloud and IoT technologies. This replaces the offline data acquisition boards and wired sensors that are used traditionally and exhibits only the raw data. The time frame and growth stage are compared and any deviation between the reference parameters and raw data obtained are translated to the comfort ratio index. This analysis helps in identifying the suitable evaporative cooling system for the corresponding crop based on the values obtained on comparison. It is found that there is no correlation between the various parameters of the microclimate to the comfort ratio. Before actual cultivation, the microclimate can be assessed dynamically and systematically by the greenhouse managers using Simulink model and IoT sensors. The operational cost and geographic climate of the greenhouse control system and such knowledge-based data helps in foreseeing the expected profit of cultivation. The supervised learning model decides the appropriate control strategy and makes decisions by estimating the growth response and quality of crop. Wireless transmission in the greenhouse environment is made using Wi-Fi technology. This communication gateway is flexible based on the size and requirements of the greenhouse. Future work is directed towards a complete year assessment of the climatic parameters for providing appropriate information regarding cultivation of crop throughout the year.

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