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Building a Diagnostic Model for Climate Controlled Greenhouse using Bayesian Network

Pitaya Poompuang[1*], Nipat Jongsawat[2] and Mano Suwannakam[3]

[1] Division of Computer Science, Faculty of Science and Technology,
Rajamangala University of Technology Thanyaburi, Khlong Luang, Pathum Thani 12110, Thailand
[2] Division of Computer Technology, Faculty of Science and Technology,
Rajamangala University of Technology Thanyaburi, Khlong Luang, Pathum Thani 12110, Thailand
[3] Division of Agricultural Engineering, Faculty of Engineering,
Rajamangala University of Technology Thanyaburi, Khlong Luang, Pathum Thani 12110, Thailand
* Email: pitaya_p@rmutt.ac.th

Abstract

Greenhouse crop production is directly influenced by climate conditions. The aim of this study is to achieve adequate inside climate conditions (mainly air temperature, photosynthetically active radiation, CO2 concentration, and humidity) of controlled greenhouses located in Pathum Thani province of Thailand. The adequacy of Bayesian diagnosis to model the environmental conditions of a greenhouse as essential parameters including disturbances such as external temperature, external radiation, wind speed, wind direction, external humidity, external CO2, and soil temperature. The system is built and tested using data gathered from a real greenhouse located in Pathum Thani province under closed-loop control. The Bayesian network has demonstrated to provide a good approximation of a control signal and the results show the performance and applicability of Bayesian networks within the proposed climate controlled greenhouse solution.

Keywords: Bayesian networks, Greenhouse climate control, air temperature control, photosynthetically active radiation control, CO2 concentration, humidity control

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1. Introduction

Climate conditions directly affect greenhouse crop production. An improvement in quality and volume of crop production is the primary focus of greenhouse crop production. Internal and external factors such as air temperature, photosynthetically active radiation, CO2 concentration, and humidity need to be considered carefully. The manipulation of these factors allows growers to produce consistently high yields of high quality crops, throughout the year. An automated greenhouse control system is introduced to manipulate these factors. It helps keeping plants healthy and prosperous under the best possible growing environment. An automated greenhouse control system is necessary to provide real-time updates. Air temperature, photosynthetically active radiation, CO2 concentration, and humidity are very important and need to be considered as monitoring conditions.

Bayesian Network has demonstrated to provide a good approximation of a control signal based on control actions implemented in the automated greenhouse control system (based on predefined setpoints), as well as on the environmental conditions. In this paper, we introduce a Bayesian network to achieve adequate inside climate conditions (mainly air temperature, photosynthetically active radiation, CO2 concentration, and humidity) by acting on actuators based on the value of different state variables and disturbances acting on the system. The system is built and tested using data gathered from a real greenhouse located in Pathum Thani province under closed-loop control. The results show the performance and applicability of a Bayesian network model within the proposed climate controlled greenhouse solution.

The rest of the paper is organized as follows. Section II presents the related work. In Section III, we discuss some of the typical usages of Bayesian network. In Section IV, we discuss a framework of climate controlled greenhouse using Bayesian network and results gathered from the Bayesian model and its applicability. Finally, Section V concludes the paper.

2. Literature Review

Relevant works has been published in designing and implementing smart farming. Deepak Idnani [1] presented a conceptual study of sensor for smart farming: humidity, temperature, and moisture measurement. Various sensor nodes are deployed at different locations in the farm. Controlling these parameters are through any remote device or internet services and the operations are performed by interfacing sensors, with microcontroller. Their proposed concept is created as a product and given to the farmer's welfare. This system generates irrigation schedule based on the sensed real time data from field and data from the weather repository. It can recommend farmer whether or not, is there a need for irrigation.

Alipio, et al. [2] presented a smart hydroponics farming system using exact inference in Bayesian network. They developed a smart hydroponics system that is used in automating the growing process of the crops using exact inference in Bayesian network. Sensors and actuators are installed in order to monitor and control the physical events such as light intensity, pH, electrical conductivity, water temperature, and relative humidity. The sensor values gathered were used to build the Bayesian network in order to infer the optimum value for each parameter. A web interface is developed where the user can monitor and control the farm remotely via the Internet. The fluctuations in terms of the sensor values were minimized in the automatic control using BN as compared to the manual control.

The authors in [3] proposed an architecture Bayesian event prediction model which uses historical event data generated by the IoT cloud to predict future events. He demonstrated the architecture by implementing a prototype system to predict outbound flight delay events, based on inbound flight delays, based on historical data collected from aviation statistics databases.

Patrick J. de Nijs, et al. [4] developed a simple model that incorporates climate projections, local environmental data, information from peer-reviewed literature and expert opinion to account for the adaptation benefits derived from climate-smart agriculture activities in Malawi. This approach allows assessment of vulnerability to climate change under different land use activities and can be used to identify appropriate adaptation strategies and to quantify biophysical adaptation benefits from activities that are implemented. They suggest that multiple-indicator Bayesian belief network approaches can provide insights into adaptation planning for a wide range of applications and, if further explored, could be part of a set of important catalysts for the expansion of adaptation finance. Brett Drury, et al. [5] presents a survey of the applications of Bayesian networks in agriculture.

3. Bayesian Network

This section is intended to describe the background of Bayesian networks and some perspectives of qualitative causal relationships in the Bayesian approach. Bayesian networks (also called belief networks, Bayesian belief networks, causal probabilistic networks, or causal networks) are acyclic directed graphs in which nodes represent random variables and arcs represent direct probabilistic dependencies among the nodes [6]. Bayesian networks are a popular class of graphical probabilistic models for research and application in the field of artificial intelligence. They are motivated by Bayes' theorem [7] and are used to represent a joint probability distribution over a set of variables. This joint probability distribution can be used to calculate the probabilities for any configuration of the variables. In Bayesian inference, the conditional probabilities for the values of a set of unconstrained variables are calculated given fixed values of another set of variables, which are called observations or evidence. Bayesian models have been widely used for efficient probabilistic inference and reasoning

[1], [8], and numerous algorithms for learning the Bayesian network structure and parameters from data have been proposed [9], [10], [11]. The causal structure and the numerical parameters of a Bayesian network can be obtained using two distinct approaches [12]. First, they can be obtained from an expert. Second, they can also be learned from a dataset or data residing in a database. The structure of a Bayesian network is simply a representation of independencies in the data and the numerical values are a representation of the joint probability distributions that can be inferred from the data [13], [14]. In practice, some combination of these two approaches is typically used. For example, the causal structure of a model is acquired from an expert, while the numerical parameters of the model are learned from the data in a database.

4. BUILDING A BAYESIAN NETWORK MODEL FOR CLIMATE CONTROLLED GREENHOUSE

In this section, we present a framework of climate controlled greenhouse using Bayesian network. External and internal factors are identified and the relationships among factors are given. The results obtained from the model can be used for controlling internal devices.

Fig. 1 shows a framework of climate controlled greenhouse using Bayesian network. External factors include Outside Global Radiation (O_G_R), Outside Photosynthetically Active Radiation (O_PAR), Outside Temperature (O_T), Outdoor Humidity (O_H), Outdoor CO2 (O_CO2). The outside global radiation as well as the actual outside temperature have to be considered for the calculation of heat consumption. Photosynthetically Active Radiation is defined as the electromagnetic radiation in the waveband between 400 and 700 nm, which can be used as the source of energy for photosynthesis by green plants. We use the outdoor humidity sensor and temperature transmitter to measure the relative humidity and temperature of air outside. The outdoor humidity and temperature transmitter converts the measurands into standard signals of 0-10 Vdc or 4-20 mA. We use the CO2 gas detectors to detect levels of carbon dioxide from 0 - 20,000 ppm. Higher levels of CO2 would be expected (>2,000 ppm), including breweries, wineries, or plant greenhouses. The outdoor CO2 level serves as a baseline for comparison to indoor CO2 concentration.

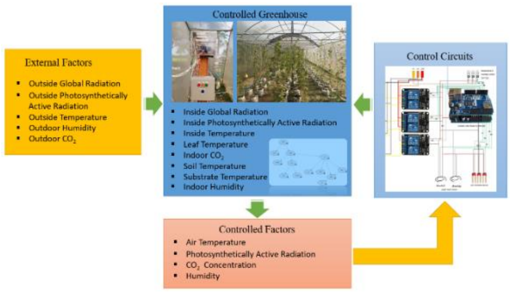

Figure 1. Bayesian network used for climate controlled greenhouse.

Internal factors of controlled greenhouse include Inside Global Radiation (I_G_R), Inside Photosynthetically Active Radiation (I_PAR), Inside Temperature (I_T), Leaf Temperature (L_T), Indoor CO2 (I_CO2), Soil Temperature (S_T), Substrate Temperature (S_T), and Indoor Humidity (I_D). These following inside measurements were taken. This paper focuses on controlling these measurements inside the greenhouse. The causal relationships of internal and external factors are identified using Bayesian network. Finally, air temperature, photosynthetically active radiation, CO2 concentration, and humidity are captured and monitored to maintain constant temperature, humidity and other environmental factors within desired ranges for crop growing. Obviously, controlled factors relate to each other. For example, when the photosynthetic rates are higher, the concentration of CO2 falls below the atmospheric producing a growth deficit that is increased when the crop reaches its maximum development. Photosynthesis rate indirectly affects the humidity content because when the leaves stomata are opened to capture the CO2, the plant emits water vapor through the transpiration process increasing the humidity inside the greenhouse. The values of each state of each controlled factor (node) in a Bayesian network is passed to the control circuit which can be used to control sensors and mechanical devices to achieve optimal growth and plants development.

Fig. 2 shows the applicability of Bayesian networks to inside and outside climate conditions. A Bayesian network can be used as a predictor simply by considering one of the variables as the class and the others as predicting variables. Most importantly, it can perform powerful what- if problem analyses. The variables were discretized based on class values and the information in the data set. Each node has 3 states: low, medium, and high values. It means that the value must fall into each state. Data were recorded daily in a database at 5 minute intervals and then fed to the Bayesian network model.

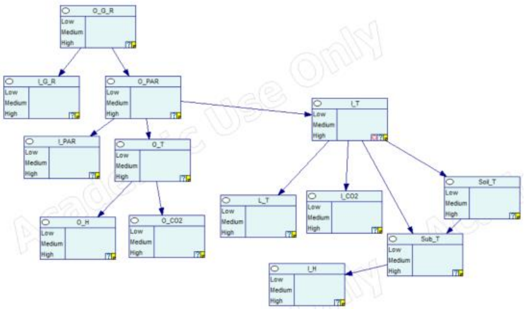

Figure 2. Applicability of Bayesian networks to inside and outside climate conditions

From Fig. 2, it shows that outside global radiation has an impact on inside global radiation and outside photosynthetically active radiation. Outside photosynthetically active radiation has an impact on inside photosynthetically active radiation and outside temperature. Outside temperature directly impacts on outdoor humidity and outdoor CO2. Outside photosynthetically active radiation has an impact on inside temperature. Inside temperature directly impact on leaf temperature, indoor CO2, substrate temperature, and soil temperature. Soil temperature affects substrate temperature and then substrate temperature affects indoor humidity.

Fig.3 shows Bayesian network used for climate controlled greenhouse after updating belief. Bayesian inference is used for probability computations. The numerical data provided for the model are captured by internal and external sensors and transmitted signals are sent to a preprocessing process that converts signals to numerical data. A set of conditions are given in the child node. After updating the model or update belief, the results obtained from observable nodes will be used to control internal devices. For example, a solenoid valve for temperature control is opened when the internal temperature is higher than the threshold set (possibility = 0.5). The water sprays to lower temperature in a greenhouse. Plant growth is driven by photosynthetically active radiation (PAR). The amount of photosynthetically active radiation changes seasonally and varies depending on time of day. Measuring internal PAR can help determine the light levels in a greenhouse. The photosynthetic radiation can be measured and observed (low, medium, high) to predict plant growth. Threshold values for climatic conditions like humidity, temperature, moisture can be fixed based on the environmental conditions in a preprocessing process. If the internal temperature and internal humidity values are higher than the threshold set (possibility = 0.5), the signals are sent to the control box to start fans, blowing a water wall.

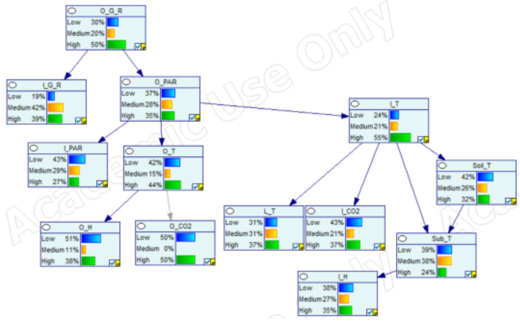

Figure 3. Bayesian network used for climate controlled greenhouse after Updating Belief.

5. Conclusion

Crop growth in greenhouses is basically determined by the climate variables in the environment. In this paper, a Bayesian network is used to achieve adequate inside climate conditions so that we can take effective decisions to ensure efficient crop growth. This work was designed and implemented in a smart farm located in Pathum Thani province of Thailand. The data received from the sensors are processed, are sent to an IoT platform, and then a preprocessing process that converts signals to numerical data. Analyses are based on the static inputs as time goes these sensors collect data periodically. Data were recorded daily in a database at 5 minute intervals and then fed to the Bayesian network model. The Bayesian network model is re-computed every 5 minute. The values of each state of each controlled factor (node) in a Bayesian network is passed to the control circuit which can be used to control sensors and mechanical devices to achieve optimal growth and plants development. It means that it can perform predictive analysis that gives output decisions to automatically control the system.

Future research will focus on how to effectively improve the system. The data gathering procedure must be longer as larger data would have produce better results for data analytics. Finally, we can examine the best suit crop that satisfies all the necessary condition defined in the control system and determine the right time to crop.

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