Greenhouses within the Agricultura 4.0 interface

Casas de vegetação dentro da interface Agricultura 4.0

Edilson Costa[1]*, Murilo Battistuzzi Martins[1], Eduardo Pradi Vendruscolo[1], Abimael Gomes da Silva[2], Tiago Zoz[1], Flávio Ferreira da Silva Binotti[1], Travis Wilson Witt[3] and Cássio de Castro Seron[1]

ABSTRACT - Global technological advances can be applied to all production sectors to improve people's daily lives, efficiently deliver information, and product safety. This study is a literature review of the use of the Agricultura 4.0 interface in greenhouses and the improvements that these technologies have made to the industry. For the agricultural sector, especially intensive plant production in protected environments, Agricultura 4.0 technologies are widely used to reduce human error and ensure high quality plant products. Mathematical modeling, computer software, electronic meters, robotics, intelligent real-time system decisions, and automatic activity control throughout the production cycle guarantees extreme production safety in protected cultivation systems and precision planting environments. The accuracy, precision, and performance of Agricultura 4.0 in greenhouses depends, as in others agricultural sectors, on improved communication between digital platforms as well as in stable Internet for machine programming and operation in the production systems.

Key words: Robotics. Real time. Intensive production. Information technology.

RESUMO - Os avanços tecnológicos, no atual contexto mundial, atingem todos os setores de produção, melhorando o cotidiano das pessoas, trazendo rapidez na informação e segurança do produto. O presente trabalho apresenta uma revisão de literatura do uso da interface Agricultura 4.0 em casas de vegetação e as melhorias que essas tecnologias trouxeram ao setor. Para o setor agropecuário, em especial a área de produção vegetal intensiva em ambientes protegidos, as tecnologias da Agricultura 4.0 são amplamente aplicadas diminuindo erros humanos e garantindo produtos de elevada qualidade. A modelagem matemática, os softwares, os medidores eletrônicos, a robótica, as decisões dos sistemas inteligentes em tempo real, o controle automático das atividades em todo ciclo de produção garante a segurança de produção intensiva nos sistemas de cultivo protegido e uma ambiência vegetal de precisão. A exatidão, precisão e desempenho da Agricultura 4.0 em estufas dependem, como em outros setores agrícolas, de uma melhor comunicação entre as plataformas digitais e também de uma internet estável para a programação das máquinas e operação nos sistemas de produção.

Palavras-chave: Robótica. Tempo real. Produção intensiva. Tecnologias da informação.

[1]Unidade Universitária de Cassilândia, Universidade Estadual de Mato Grosso do Sul/UEMS, CEP 79540-000, Cassilândia-MS, Brasil, edilson.costa@uems.br (ORCID ID 0000-0002-4584-6611), murilo.martins@uems.br (ORCID ID 0000-0002-8759-0917), eduardo.vendruscolo@uems.br (ORCID ID 0000-0002-3404-8534), zoz@uems.br (ORCID ID 0000-0003-2991-5485), binotti@uems.br (ORCID ID 0000-0002-2248-8954), cassio.seron@uems.br (ORCID ID 0000-0003-4289-931X)

[2]Universidade Estadual Paulista/UNESP, *Campus* de Ilha Solteira, Ilha Solteira-SP, Brasil, 15.385-000, ag.silva@unesp.br (ORCID ID 0000-0001-7146-9226)

[3]Department Of Agriculture, USDA/Agricultural Research Service, U.S. travis.witt@usda.gov (ORCID ID 0000-0003-4501-4230)

INTRODUCTION

High technology applied to industrial, commercial, and agricultural production systems has provided entrepreneurs with high financial security and consumers with product reliability, cooperating with all production sectors to ensure the harmony and satisfaction of both. The use of digitization in agriculture, with big data, Internet of Things (IoT), augmented reality, robotics, sensors, 3D printing, system integration, future Internet, ubiquitous connectivity, artificial intelligence, digital twins, and blockchain has recently intensified to transform the reality of agricultural production. Indeed, high technology has been applied to all farming sectors, particularly intensive greenhouse production, where it assists at all production cycle stages from sowing to harvesting, which promotes an integrated chain of digital products and services and provides production and trading security and user satisfaction, as well as a precision planting environment. The structural construction materials are made of galvanized steel to increase the service life of the protected environment constructions, further allowing for the use of several automated and robotized systems to control and manage the planting environment, irrigation, fertigation, fertilization, nutrition, and growing, harvesting and post-harvesting software.

In greenhouses, the use of technologies such as electronic sensors, software, equipment and systems, can be integrated and connected, an application that began in the 1980s and has been quickly improving as the demand for trackable and reliable products has increased. Today's consumers demand products with consistent quality, that are certified and tracked for food safety, which require intensive crop production to be a fully controlled environment. This type of crop production demands mechanization, automation, digitalization, and robotics as the human workforce becomes more and more expensive and scarce. With Agricultura 4.0, real microclimate data, nutrition correction, fertilization, and irrigation, as well as pesticide or phytosanitary control can be collected by technologies and instantly transmitted over the Internet to optimize the protected, technical and robotized cultivation at all production steps, which ensures the sustainability of the sector. However, internet connectivity and/or instability and the communication between different digital platforms need to be improved to meet the demand of machine programming and operation in production systems. Thus, sensors, software, operating platforms, and machines collecting can act and communicate with each other to promote management actions in real time and initiate immediate problem solving and/or greenhouse production improvements.

This literature review follows the trajectory of digital technologies that began in the last century and are being perfected by the interconnection of data/internet/machine/management to improve production and by the recurrent demands of the intensive greenhouse crop production sector within the context of Agricultura 4.0.

TECHNOLOGY DYNAMICS APPLIED TO GREENHOUSE CULTIVATION

Before assimilating and intensifying Agricultura 4.0 technologies, planting environments consisted of studying and changing physical variables of the intensive protected production environment. The studies were aimed at correlating production with environmental conditions, and improving types of coverage material that would promote adequate light incidence, temperature and relative air humidity because these variables interfere with physiological processes that can affect growth, development and productivity (PAULA *et al.*, 2017; SILVA *et al.*, 2018; SILVA *et al.*, 2020; TAIZ *et al.*, 2017). Without technologies that enable the accurate prediction of interested outcomes, planting environments used decision-making tools as models for best planting practices (COSTA; LEAL; CARMO JÚNIOR, 2004; PROCHNOW *et al.*, 2019). Increasingly dynamic research in which differential details are analyzed to demonstrate the effects of factors on plants, has used equipment, software, and mathematical models as potential decision-making tools (GOSTEV *et al.*, 2019). Such elements changed data collection methods and decreased the need for manpower and the number of required equipment (GALLARDO; SAUERS, 2018).

In addition to research-based needs, it is clear that increased population brings a number of new demands to food production sectors, which need to increase according to population survey institution estimates (CLERCQ *et al.*, 2018). These demands are related not only to the quantity of food, but also to its quality. Thus, the use of technology helps these sectors meet the global food demand by increasing production and improving product quality (CLERCQ *et al.*, 2018; ZAMBON *et al.*, 2019). The simple generation of data in the agricultural sectors results in a static image of its situation in a given moment in time, while data compilation from different periods shows the behavior of a variable. However, the processing of this set of data by software, provided with mathematical models, may result in a behavior prediction, influencing decisions that will optimize the use of resources such as time, space and inputs (WELTZIEN, 2016; EASTWOOD *et al.*, 2017; JANSSEN *et al.*, 2017; WOLFERT *et al.*, 2017). In addition to improving the control of complete

environmental control conditions, the automation of systems has also effectively decreased negative effects on the environment, how to use inputs and water efficiently and effectively, reducing waste (ROSE; CHILVERS, 2018). Automatous irrigation systems can identify the water needs of a plants species at different development phases and it reduce over watering and water waste (KALANTARI *et al*., 2017; OZDOGAN *et al*., 2017; ZAMBOM *et al*., 2019). Thermal sensors identify changes in protected crops in greenhouse, activating temperature regulation mechanisms for optimal plant development (BENERJEE; ADENAEUER, 2014). These are model-based actions predefined in an existing database.

Automation processes are controlled and executed by mechanical or electronic means, and are composed of an active system based on a set of techniques that use sensors to collect data, which is then used to calculate the most appropriate corrective action for optimal medium efficiency (ROSÁRIO, 2009). Souza and Rocha (2020) reported that protected cultivation using automation is a viable alternative to achieve expected success by the small farmer. This automation facilitated the production work and provided greater control of the quality of the final product by using reports generated from cultivation data obtained by sensors and actuators; thus, combining technical knowledge and the information generated by the system for better decision making.

Commercial greenhouse automation and climate control began in the 1970s and 1980s, while research with robotics began in the late 1990s. Computer studies for greenhouse climate control using radiation, ventilation, humidity, and temperature sensors were implemented in the 1970s. The development of technologies in subsequent decades, including sensors, photovoltaic cells, data collectors, intelligent systems, computers, neural networks, software, controllers, robots, wireless technologies, the internet, and the web, improved greenhouse climate control and production operations like nutrition, irrigation, harvesting, and management; which became automated to meet the demands of Agricultura 4.0. Beyond executing actions, the software used in plant production also automatically collects and analyzes data, making the process progressively more efficient because it results in a growing database (WOLFERT *et al*., 2017). Thus, over a short time, the increased implementation of these automated forms of cultivation will result in a great amount of information that contributes to maximizing resource savings and profitability of these systems (CLERCQ *et al*., 2018; WOLFERT *et al*., 2017).

Socially, the use of automated cultivation systems in controlled environments reduces the distance between producers and consumers through the development of agricultural activities in urban centers (BENKE; TOMKINS, 2017). This reduced distance is also reflected in less post-harvest, transport, and storage losses (MILES; SMITH, 2016). In addition, automated systems can decrease the consumption of fossil fuels required for transport and, consequently, the emission of greenhouse effect gases (ADEKOMAYA *et al*., 2016). However, despite all the advantages, the implementation of these systems is still relatively costly. A limited number of companies have developed specific technologies for automaton crops, which increases implementation costs (BENERJEE; ADENAEUER, 2014). Also, equipment that functions expressively increases the demand for electric energy (KALANTARI *et al*., 2017), although these problems tend to decrease over time with technology improvement. Also, despite the high costs, once paid for, the systems have high profitability that should continue to return on the investment as the population generates greater demands for high quality food (BENERJEE; ADENAEUER, 2014; BENKE; TOMKINS, 2017).

In covered areas, such as orchards and forests, GPS signals are not as accurate as in open areas because the treetops block satellite signals or cause reflection errors (SUBRAMANIAN *et al*., 2006). This can also occur in greenhouses due to their plastic covering and metallic structures that can generate positioning errors and inaccurate GPS signal return (BECHAR; VIGNEAULT, 2016). Thus, the accuracy, precision, and performance of Agricultura 4.0 in greenhouses also depends on GPS communication improvement and the machines inside greenhouse.

GREENHOUSE AUTOMATIC MODELING, MONITORING, AND CONTROL

The modeling of micrometeorological conditions in greenhouses are not recent and are increasingly being perfected. In northern China, the deterministic and stochastic microclimate modeling of a single, naturally ventilated slope greenhouses have presented reasonable results of the internal conditions of the greenhouse (YANG; LIU; YANG, 2019).

Plant growth modeling and control in greenhouses and the strategies for environmental and irrigation improvements always aim to obtain a hierarchical control that is governed by an high level, multi-objective optimization approach that maximizes profit, fruit quality, and water use efficiency. Controller industry advances have stimulated technology transfer in control engineering and have had an impact on industrial engineers, academic researchers, and agriculture, chemistry, and process control

professionals (RODRIGUEZ *et al.*, 2015). Modeling is widely used in greenhouses and several models have been developed for plant growth, internal environmental control, energy consumption, and crop predictions. For example, modeling is used in prediction and optimization of the plant transpiration and air humidity of the greenhouse as a function of the outside climate (JOLLIET, 1994), as well as temperature (LINKER; SEGINER, 2004) and internal microclimate prediction (KOTHARI; PANWAR, 2007), plant growth (GUPTA *et al.*, 2012; RODRÍGUEZ *et al.*, 2015), transpiration rate (XANTHOPOULOS *et al.*, 2014), heating based on energy prediction and fluid dynamics (CHEN *et al.*, 2015), transpiration prediction for automatic irrigation management (WANG *et al.*, 2017), environmental variables in stationary semi-solar greenhouses (MOHAMMADI; RANJBAR; AJABSHIRCHI, 2018), and to predict the need of heating per hour in greenhouses in cold weather regions using heat transfer (AHAMED; GUO; TANINO, 2018).

The use of neural networks in modeling is commonly used in greenhouses to control optimal CO_2 (LINKER; SEGINER; GUTMAN, 1998), compare sigmoid and hybrid models in temperature prediction (LINKER; SEGINER, 2004); to predict temperature in tropical regions (PATIL; TANTAU; SALOKHE, 2008), air temperature and relative humidity (LU; VILJANEN, 2009), and energy consumption (TREJO-PEREA *et al.*, 2009); monitoring tomato productivity (EHRET *et al.*, 2011; TAKI; HADDAD, 2012); to analyze the performance of an integrated photovoltaic system (PÉREZ-ALONSO *et al.*, 2012); to estimate leaf area index for a transpiration model for irrigation based on external climatic conditions (WANG *et al.*, 2017); and in control systems (MANONMANI *et al.*, 2018).

At Iran, heat transfer models, multilayer perception (MLP), and dynamic and multiple linear regression (MLR) artificial neural networks have been used to predict internal environmental variables and energy loss in a semi-solar greenhouse (TAKI *et al.*, 2016). This work showed no significant difference between the actual air and roof temperature data and the data simulated by the models, but the output of the environmental parameters data by the MLR model were not correctly predicted for inside air and roof temperature because of autocorrelation between input variables. The best model for estimating actual data and greenhouse energy loss and exchange was the MLP, which can be used online to minimize the costs associated with sensors and data loggers (TAKI *et al.*, 2016).

The use of dynamic modeling to predict environmental conditions in semi-solar greenhouses is not a simple task because internal conditions are totally dependent on external conditions. A dynamic model developed in Iran showed that air and soil temperatures were estimated with a relative accuracy of 10.2% and 7.7%, respectively; and that the model could be used to predict fuel consumption, CO_2 emission, and production yield. These findings help to advance modeling based on social parameters (MOHAMMADI; RANJBAR; AJABSHIRCHI, 2018).

A evolution from protected cultivation to controlled agriculture using fully digitized agriculture has resulted in urban plant production in multi-story buildings and plant production factories in fully controlled environments in response to population growth, environmental degradation, and urbanization, all of which threaten food security (SHAMSHIRI *et al.*, 2018). Automatic greenhouse control with wireless sensor networks and AVR microcontrollers that controlled temperature and humidity, measured carbon dioxide content, and collected light intensity information, provided accurate plant growth data at a low cost, suggesting they are robust and effective decision-making systems (SONG *et al.*, 2011).

Mekki *et al.* (2015) reported that wireless data communication between sensors and control systems could eliminate the need for complex cable connections, which reduced the risk of accidents and system breakdowns. Bajer and Krejkar (2015) used the platform Arduino™ to create a greenhouse control system using SD card data with a system connected to the internet. Vatari *et al.* (2016) evaluated the operation of two greenhouse control systems and presented innovations in sensor data acquisition and uploading data to clouds based on the Internet of Things (IoT) concept, further illustrating that electronic and computer technology positively boosts precision farming in greenhouses.

Data compiling and analysis on the effects of various factors such as luminosity, space, water requirement, temperature, and nutrition in vegetables provided environments with a potential efficiency that was 390 times superior to conventional cultivation systems, which has been illustrated by vertical crop production in controlled environments (CLERCQ *et al.*, 2018). In this system, the automation during the whole process of cultivation development allows sensors to make minimal adjustments so that conditions are as appropriate as possible for maximum crop development. In addition, the system reduced waste due to its specific application of inputs and other resources through monitoring and adjusting for specific species demand (BENKE; TOMKINS, 2017; KALANTARI *et al.*, 2017).

The production management system and the future used of the internet through an intelligent and precision agriculture has replaced complex, monolithic, and outdated systems, tools and software. However,

the internet has many flaws, especially when managing a large number of devices and network devices (IoT) (KALOXYLOS *et al*., 2012). Distributed data acquisition and radio frequency control systems that use network-based hardware and software have made it possible to acquire weather information, capture and process images, detect events, and improve decision-making and management in greenhouses (SERÔDIO *et al*., 2001). When interconnected with data analysis and rapid-decision making, neural networks in greenhouses, such as microclimate prediction, energy expenditure, and carbon dioxide control, allow technology development and research to adapt to new technologies such as the IoT and machine learning (ESCAMILLA-GARCÍA *et al*., 2020), further promoting a robotic agriculture system with less human manual labor.

The advances in greenhouse automation and controlled environment cultivation have increased indoor cultivation, also called plant factories in urban agriculture, as these advances have enabled scientific solutions for efficient cultivation in populated cities using vertical cultivation. Fully controlled environments require high technology that involves the structure material, perception and sharing of internal data, micrometeorological control, and energy consumption optimization (SHAMSHIRI *et al*., 2018), in addition to production system robotization. With the rapid development of technologies, environmental monitoring has become important in greenhouse automation to achieve energy economy and rapid plant growth. Wireless sensor monitoring (e.g., temperature, humidity, infrared, optic brightness and Hall sensors) that is associated with controllers has demonstrated energy saving efficiency and protected environment automation (HUANG; HUANG, 2013).

An intelligent network of wireless sensors (Zigbeewireless) for monitoring, managing, and controlling air temperature, relative humidity, and soil humidity in automated greenhouses. These networks transmit these data to web applications and remote monitoring in real time to allow for the visualization of the network nodes that assist *ad hoc* crop management. This system is a flexible and reliable solution for the development of a greenhouse automated management system (VYTLA; AHAMED, 2015).

The rapid development of information technology, particularly IoT, which combines electronic devices, sensors, and the internet to manage data and applications, allows its use in greenhouse control and management (i.e., precision farming or precision planting environments). The development of low cost and easy access IoT in greenhouses, such as the Arduino microcontroller or the Raspberry Pi microcomputer, transmit data wirelessly (e.g., Bluetooth, ZigBee Protocol and Wi-Fi) and are

designed so that technicians with limited information technology knowledge can use them to manage production in the protected environment (ARDIANSAH *et al*., 2020). An automated plant monitoring system guided by machine vision for the diagnosis in the Nutrient Film Technique (NFT) hydroponic lettuce cultivation in greenhouse that is based on color resources (e.g., red-green-blue, hue-saturation-luminance and color brightness), textural resources (e.g., contrast, energy, entropy and homogeneity), morphological characteristics (e.g., projected upper area of the canopy), plant indices (e.g., NIR and color band ratio), and thermal radiation of the plant, showed that the system could detect water stress two hours before human visual detection (STORY; KACIRA, 2014). For example, the monitoring of mango production with a three-part wireless network sensor technology (e.g., sensor, radio communication, and gateway modules) reported plant growth, carbon dioxide, temperature, and humidity level in real time and showed that the environmental conditions were favorable to the flowering and fruiting of sweet and succulent mangoes (SAAD *et al*., 2014).

Precise irrigation and nutrition recommendations and environmental control management strategies can be performed by machine learning using hyperspectral sensor data that integrates the crop physiology with real-time artificial intelligence systems. A study on automation to detect water and nitrogen deficit stress in soilless tomatoes based on spectral indices showed that the combination of the modified soil-adjusted vegetation index (MSAVI) with the modified red-edge normalized difference vegetation index (mrNDVI) and the photochemical reflectance index (PRI) could detect 89.6% of the water deficit stress and 91.4% of the nitrogen deficit stress, which provided promising support for greenhouse automation and control (ELVANIDI; KATSOULAS; KITTAS, 2018).

ROBOTICS IN PROTECTED ENVIRONMENTS

Efficient greenhouse task control and automation systems involve artificial neural networks that manage the enterprise and optimize production using sensors and remote monitoring, as well as data clouds that are integrated into internet measurement systems and artificial intelligence (YAHYA, 2018), IoT to solve market demands, operation and supervision accuracy (LI *et al*., 2019), learning activation algorithms, and functions in machine learning scenarios (ESCAMILLA-GARCÍA *et al*., 2020). In the Netherlands, research on greenhouse robotics started in 1998 with the development of robotic cucumber harvesting (HEMMING, 2018). The use of robotics for cucumber harvesting through color detection was not

feasible, since both fruit and leaves were green; however, with a tailor-made double spectral camera could detect 94% of ripe fruit with a harvest success of 74-80% (VAN HENTEN *et al.*, 2002, HEMMING, 2018). Moreover, deep learning that predicted tomato yields and *Ficus benjamina* growth in controlled greenhouses using deep recurrent neural network with short-lived long neurons in predictions showed to be promising in Belgium and the UK, achieving high precision in predictions and small errors (ALHNAITY *et al.*, 2019). Automatic intelligent systems and robots require several highly complex, correctly synchronized and integrated subsystems for the efficient task performance and successful information transfer that is necessary for any process or product. These systems must be even more sophisticated in agricultural production when operating in unstructured environments, and have been considerably improved in recent decades (BECHAR; VIGNEAULT, 2016).

With the decreasing number of farmers, robotics have been increasingly applied in agriculture to improve productivity and efficiency, particularly at the stage of fruit and vegetable harvesting for fresh food consumption, as this phase can be lengthy, tiresome, and particularly demanding and costly, ranging from 50% to 66.6% of the total labor costs of crop production (FOGLIA; GENTILE; REINA, 2008). One example of a robot used for fruit harvesting is the SWEEPER, which is used for pepper harvest and has demonstrated a 61% success rate under best conditions and 18% under current conditions in commercial greenhouses. However, this indicates a need for improved growing conditions and varieties for a successful robotic harvest systems (ARAD *et al.*, 2020). Additionally, in strawberry harvesting, the Dogtooth (http://www.dogtooth.tech/) is an autonomous rail navigation robot that locates, collects, classifies, and packs ripe fruits. Most greenhouse harvesting robots use rails and therefore, use position control algorithms rather than navigation algorithms (FUE *et al.*, 2020). In addition to harvesting, the Dogtooth robot, which moves on a monorail along the area of greenhouse, can be used for weed removal between cucumber plants (HERAVI *et al.*, 2018).

Due to labor becoming increasingly scarce and expensive, especially in European countries, an autonomous vehicle steering control algorithm was developed to assist in harvesting and spraying tasks in greenhouses using a suspended guide built into the environmental structure that marks the desired path for the vehicle, which is connected to a rigid bar upon which the vehicle drives and corrects itself by detecting the angle and distance of the guide. A prototype vehicle was developed and the algorithm was successful in a set of experiments (GAT; GAN-MOR; DEGANI, 2016).

A greenhouse tomato harvesting robot with a final effector was designed with four foam-padded fingers to reduce damage when gripping the fruit during harvesting. The grip of the final effector is adjusted by a solenoid to hold the fruit with suction; the best performance in a laboratory setting was obtained with vacuum suction nozzles 15.0 mm in diameter and a force of 8.1 N/cm^2. Thus, the mean successful suction fixation rate was 95.3% and the mean harvesting time was 74.6 s per fruit (CHIU; YANG; CHEN, 2013). The authors also reported that before harvesting the fruit, the final effector must be rotated until the fruit is 60° counterclockwise in relation to the initial alignment. This orientating mush be repeated three times in relation to the fruit, and further field tests are necessary to validate the process.

Even a low-cost multifunctional robot prototype with very low spraying and fertilizing application rate (400-500 plants/h) in greenhouses in preliminary experiments can continuously perform tasks for several hours and perform tasks that are inaccessible to human operators (BERFORT *et al.*, 2006). These authors reported that the next steps in greenhouse automation efficiency requires the development of tools and algorithms to manage as many different tasks as possible so that a robot can perform most of the operations in a complete cultivation cycle. A clamp-type collection robotic device developed for automatic seedling transplantation in greenhouses was evaluated in the laboratory to show that the substrate moisture had the greatest effect on seedling collection success rates, followed by other factors such as penetration angle, seedling age, extraction speed, root/substrate abrasion force, and penetration depth (MAO *et al.*, 2014). The ideal parameters that ensure the successful transplantation of 30-day cauliflower seedlings were a substrate humidity of 55% to 60%, 8° penetration angle, 35 mm penetration depth, a root/substrate abrasion force of 4 N, and an extraction speed of 600 mm/s. The mean success rate in harvesting seedlings was 90.14% for a transplant rate of 22 seedlings/min (MAO *et al.*, 2014). These examples exemplify that use of robotics in protected environments benefits from current intensive study and testing to improve the machines and controllers for replacing human labor and improving cultivation accuracy. Machine and digital system interactions make this area of automation the largest Agricultura 4.0 application in precision planting environments.

IRRIGATION AUTOMATION IN PROTECTED ENVIRONMENTS

Automation can be applied to several systems in a greenhouse, including structural, production and irrigation

systems. The development of smart technologies has made this evolving technology available to researchers and engineers in the agricultural sector. The intelligent irrigation system aims to ensure that the crops have the required amount of water throughout its development (KPONYO *et al.*, 2019) and reduce the use of drinking water resources in agriculture (KALANTARI *et al.*, 2017; OZDOGAN *et al.*, 2017; ZAMBOM *et al.*, 2019). The irrigation blade is determined by monitoring the water flow from the soil-plant-atmosphere system. Monitoring uses several detection technologies to determine and characterize humidity dynamics on a space-time field scale and the water used by the plant. These detection methods can be based on soil, climate, and plant sensing (ADEYEMI *et al.*, 2017).

Other research has demonstrated the use of intelligent irrigation systems through automation that is based on sensors that read soil moisture, environmental temperature and humidity, and soil pH. These parameters are the basis for determining the functional success of the water pump, as well as central data collection and storage (ARCHANA, *et al.*, 2016; CHAVAN *et al.*, 2014; HARISHANKAR *et al.*, 2014; KANSARA *et al.*, 2015; MINZ *et al.*, 2019; SONAIL *et al.*, 2015). Precision irrigation can use two strategies. One is system management that uses an open cycle strategy of compiled historical data to set irrigation volumes at predefined intervals. This strategy is not based on any form of sensor response to indicate water content in the soil or in the plant, or climate variables (LOZOYA *et al.*, 2014). The second strategy prompts irrigation when the soil moisture content reaches a level (DABACH *et al.*, 2013) at which the plants indicate a certain stress limit (SHAUGHNESSY *et al.*, 2012), or with feedback from crop simulation models for better physiological response or economic objective (MCCARTHY *et al.*, 2014). These closed-circuit irrigation strategies are shown to improve the water use efficiency of vegetable production in protected environments (ADEYEMI *et al.*, 2017). Indeed, the use of a closed-circuit irrigation control system in a protected crop production system provided 83% water savings (CHAPPELL *et al.*, 2013). The precise control with closed-circuit systems in irrigation via a wireless sensor network used for flower production in a protected environment resulted in 65% increased profits due to improved harvest quality and yield, which resulted from precise irrigation (SAAVOSS *et al.*, 2016).

Precision irrigation simulation models are a form of management that defines the necessary irrigation in a cultivation system using models based on physiological responses, soil physical parameters, and environment hydrology (DELGODA *et al.*, 2016). Artificial intelligence has a high potential for solving precision irrigation problems that are often complex due to being non-linear and poorly defined. Therefore, the use of algorithms that can simulate human decision-making processes can be used to solve agricultural problems (PRASAD *et al.*, 2007; HARDAHA *et al.*, 2012). Its use also includes artificial neural networks that are mapping non-linear structures that can model undefined underlying relationships in the data. These networks can predict the outcome of new sets of independent data, making them a useful tool for predictive modeling. The use of artificial neural networks is appropriate for decision support in irrigation troubleshooting, which can often be complex and uncertain. Artificial neural networks can continuously provide optimal solutions to dynamic system problems (ADEYEMI *et al.*, 2017).

Another algorithm used in artificial intelligence is fuzzy logic, which can classify a data set into associated classes to promote decision-making. It can also analyze imprecise information because it is efficient at making decisions using vague and uncertain phenomena (KWEON, 2012; MOUSA; ABDULLAH, 2014). Giusti *et al.* (2015) used fuzzy logic for decision support in an irrigation system and reported 13.55% water saving based on a predictive soil moisture model. Mendes *et al.* (2019) performed an experiment using fuzzy logic for variable irrigation rate and described that it can be widely used in agricultural areas as a decision support system.

FINAL CONSIDERATIONS

Protected environment structures and process and production management digitization has been adapted to intensive cultivation system automation for the efficient use of water and nutrients and to control the growth climate. These automated management systems use intelligent decision-making that function in time real in several production operations to decrease the use of inputs and energy in precision planting environments to increase safety for the entrepreneur and the consumer. The digitalization of protected environments using mathematical modeling, software, electronic meters, controllers, robotics, IoT, and intelligent real-time system management throughout the production cycle with the Agricultura 4.0 ensures the safety of intensive production in protected cultivation systems with accuracy, traceability, precision and, performance in greenhouses. The success of Agricultura 4.0 in greenhouses as well as in other farming sectors depends on improved communication between digital platforms and stable internet services to perfect machine programming and performance in intensive production system processes.

ACKNOWLEDGMENTS

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