# Toward Autonomous Farming—A Novel Scheme Based on Learning to Prediction and Optimization for Smart Greenhouse Environment Control

Israr Ullah, Muhammad Fayaz, Muhammad Aman, and Dohyeun Kim

***Abstract*—The greenhouse industry has received great attention and experienced tremendous growth in the recent past across the globe. However, energy consumption and labor cost in greenhouses account for more than 50% of the cost of greenhouse production. This demands an Internet of Things (IoT)-based smart solution for automation of greenhouse environment-related activities to ensure maintenance of the desired climate inside the greenhouse to maximize plant production with optimal resource utilization. To this end, several models are proposed in the literature that is based on a selected artificial intelligence (AI) algorithm which is once trained and then deployed. The drawback of such systems is that the trained models are fixed (locked) and, therefore, unable to adapt to dynamically changing conditions, which results in performance degradation. Second, the existing studies on the subject matter are focused on the individual key component (i.e., prediction, optimization, and control). In this article, a novel scheme is presented based on the integration of the key components, and the performance of prediction and optimization components is further enhanced through the exploitation of artificial neural network (ANN)-based learning modules to support autonomous greenhouse environment monitoring and control. For experimental analysis, the greenhouse environment is emulated through the mathematical formulation of essential greenhouse processes, considering the impact of actuators' operations and external weather conditions. Real environmental data collected for Jeju Island, South Korea is used for model validation and result analysis. Proposed learning-based optimization scheme results are compared with two other schemes, i.e., baseline scheme and optimization scheme. Comparative analysis of the results shows that the proposed model maintains the desired indoor environment for maximizing plant production with reduced energy consumption, i.e., it achieves 61.97% reduced energy consumption than the baseline scheme, 11.73% better than the optimization scheme without learning modules. Furthermore, the proposed model achieves 67.96% and 12.56% reduction in cost when compared to the baseline scheme and optimization scheme without learning modules, respectively.**

***Index Terms*—Artificial neural network (ANN), energy efficiency, Internet of Things (IoT), optimization, prediction, smart greenhouse.**

## I. INTRODUCTION

THE WORLD population is increasing over time and to fulfill the food requirements of the growing population, it is ultimately necessary to discover new ways of food production. In this respect, smart farming is one of the most relevant choices and is considered to be a key solution for meeting the needs of the rising population. Conventional farming faces a lot of challenges due to global changes in climate conditions, such as heavy rainfall, floods, insufficient fresh water, etc. In 2050, the population of the world is expected to be approximately 9.7 billion [1], hence, the Food and Agriculture Organization (FAO) of the United Nations (UN) urges and promotes the use of modern instruments and technology in all kinds of formation to achieve the desired food requirements. Worldwide food production will need to increase by 50% [2]. At present, 821 million people are suffering due to undernutrition [3], and it will rise with population growth if corrective steps are not taken. The UN, therefore, gives great importance to achieve Zero Hunger (Sustainable Development Goals (SDGs)-2) by 2030 [4]. Just as aquaculture supports fish production, greenhouses—having the capacity to achieve 10–12 times higher production than open-air cultivation—can also increase agricultural production. A greenhouse is a transparent-covered framed environment that offers a partially or fully managed atmosphere for maximum productivity throughout the year. Fig. 1 shows the standard greenhouse model with critical components. Effective greenhouse operation and management include a comprehensive and sound understanding of various relevant greenhouse processes, including photosynthesis, transpiration, environmental relative humidity, respiration, vegetative and generative plant growth, etc.

Generally, the size of the greenhouse ranges from 30k–50k $ft^3$, and over time the number is increasing. To care about the greenhouse environment and manage the resources,

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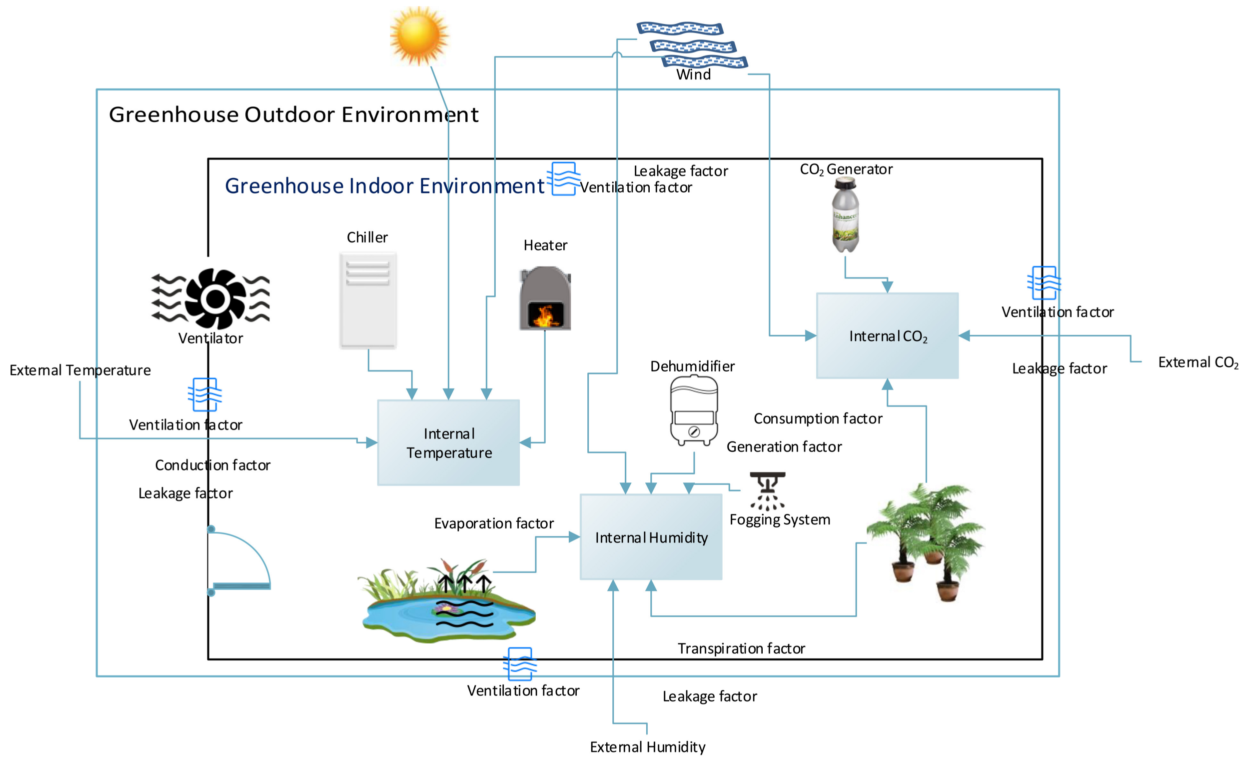


Fig. 1. Greenhouse environment model with essential components and processes.

experienced farmers are required. The hiring of expert farmers requires time and money as it is extremely hard to find expert farmers and they demand high salaries. Hence, it is the need of the day to develop an Internet of Things (IoT)-based system that has the capability to monitor the greenhouse environment in a regular manner and facilitate the farmer. The system can efficiently utilize farm resources and maintain a productive environment for plant growth in the greenhouse by monitoring various crucial parameters, e.g., temperature, humidity, $CO_2$ level, etc. Optimal resource utilization results in cost reduction, i.e., farm equipment is operated only when required. The system can assist in data collection regarding the farm for long-term assessment and accurate decision making to utilize the resources in an effective way and maximize the profit. Additionally, it enhances the productivity of the farmers by informing them through timely notifications, reminders, and alarms. The system also helps in reducing the cost involved in hiring an experienced farmer by enabling the common farmer to effectively manage and maintain the farm after minimal training.

IoT has brought a lot of improvements in different areas, improving the efficiency and the accuracy of the systems while maximizing the net profit. Technologies based on IoT are extremely beneficial in order to realize the smart cities concept. IoT devices are tiny devices that are connected to everyday life objects in order to facilitate remote control and monitoring [5]. These small devices can communicate; hence, it is possible to access them from remote locations by using the Internet. Among many potential applications of IoT, effective usage and management of energy are considered the second-most important area for IoT application in South Korea [6]. Small sensors are attached with IoT devices that have the capability of gathering sensing data about the indoor building environment, hence, the appliances can be controlled in a smart manner based on user-desired settings [7]. It also minimizes the consumption of energy by allowing the operation of electrical appliances only when needed. Nevertheless, it is worth mentioning here that such kinds of solutions shall have a minimal adverse effect on user comfort or crop production. In short, we have a multiobjective optimization problem with contradictory goals, i.e., minimize energy consumption and maximize production rate. IoT-based smart agriculture systems offer numerous advantages and challenges. A detailed discussion on the future tendencies and opportunities in this domain can be found in [8] and [9].

Most of the proposed models in the literature are based on a selected artificial intelligence (AI) algorithm which is once trained and then deployed. The drawback of such systems is that the trained models are fixed (locked) and, therefore, unable to adapt to dynamically changing conditions, which may result in performance degradation. Second, the existing studies on the topic are focused on the individual key component (i.e., prediction, optimization, and control). We believe that instead of using the components individually, the integration of these components may enhance the performance of prediction and optimization components through the exploitation of artificial neural networks (ANN)-based learning modules to support autonomous greenhouse environment monitoring and control—an attempt to take AI-based IoT applications to the next level. The objective of this study was to develop an AI-based IoT solution to maximize greenhouse production with reduced energy consumption. A summary of the four major contributions presented in this study is as follows.

1) A novel scheme is proposed based on the integration of prediction, optimization, and control components, and the same is demonstrated for greenhouse environment optimization.
2) Enhanced the performance of the proposed approach by introducing ANN-based learning modules for autonomous control of the greenhouse environment with reduced energy consumption.
3) The mathematical model of the greenhouse environment is developed, considering the impact of essential processes, actuators' operations, and external weather conditions.
4) The proposed model evaluation and experimental analysis are conducted in a realistic greenhouse environment to demonstrate the feasibility and effectiveness of the proposed approach.

The remainder of this article is structured as follows. Section II presents a brief overview of related studies. The proposed IoT-based optimization system with learning modules is presented in Section III. For emulator development, greenhouse environmental parameters' modeling is presented in Section IV. Section V presents the details about the experimental setup and comprehensive performance analysis, including the comparative study of cost and power consumption is presented in Section VI. Finally, this article is concluded in Section VII along with future work directions.

## II. Related Work

Akkaş and Sokullu [10] presented an IoT-based monitoring system for greenhouse temperature, light, pressure, and humidity using Micaz motes. They have recorded network performance data in terms of packets sent, forwarded, dropped, and retried attempts along with node battery level. Data were collected for 36 h and consistent network performance was observed.

Virtual Grower is a very nice and useful tool specifically designed for greenhouse energy and heating requirement estimation. This tool is being developed by the greenhouse production research group (GPRG) [11]. This tool allows users to specify their greenhouse location, and environmental data regarding external temperature and outdoor solar radiation is selected from historical data for a given location. Users can also specify greenhouse size and other parameters and the tool can then perform the computation to calculate the estimated heating cost.

Shen *et al.* [12] developed a prediction model for energy demand while unknown parameters of the prediction model are tuned using genetic algorithm (GA), differential evolution (DE), and particle swarm optimization (PSO) optimization algorithm. Eight unknown parameters in the mathematical model are optimized via three optimization algorithms using collected data. Afterward, the model is validated by comparing predicted and actual energy consumption in the greenhouse. Finally, they use the model for optimizing daily average temperature which achieves a 9% reduction in energy cost. Chen *et al.* [13] developed an energy demand model for energy demand prediction in a greenhouse environment. In the proposed model, certain parameters are difficult to measure as they tend to change over time. To find the optimized values for these unknown parameters, they develop a hybrid PSO+GA-based solution such that the difference between model-predicted and actual energy consumption is reduced. The proposed hybrid solution performs better in terms of convergence and accuracy than individual PSO and GA algorithms. Trejo-Perea *et al.* [14] have studied and developed a cascaded model based on ANN for energy prediction in the greenhouse. They have used two ANN models in a cascaded fashion such that the output of the first network serves as input for the second network. The first network is used to predict the indoor temperature and humidity using four inputs, i.e., wind speed, outside temperature, outside relative humidity, and solar radiation. The predicted output of the first network (temperature and humidity) then serves as input for the second network along with time and energy consumption at time $k$. The output of the second ANN network is the predicted power consumption for time $k + 1$. They have compared ANN predicted results with the regression model and found that the proposed solution performs better in terms of accuracy. Besides energy, machine learning algorithms are actively used in greenhouse production environments to detect plant diseases. To this end, Fatima *et al.* [15] proposed an approach based on deep learning algorithms to predict diseases in an IoT-based smart greenhouse. An efficient deep learning approach has been applied on leaf images for disease identification. Likewise, Delnevo *et al.* [16] developed an approach based on deep learning and social IoT for plant disease prediction to facilitate sustainable agriculture. Social IoT is used for sensing environmental conditions, deep learning models are used to detect plant disease. Images of plant leaves are collected and classified through crowdsourcing. The proposed method is then evaluated by using various performance metrics and encouraging results are reported.

Energy is one of the most precious resources and its demand is increasing day by day. Optimal utilization of energy is highly desirable in smart cities and IoT-based technologies can be useful in building such solutions. Home users to industries, energy production companies, and regulatory authorities, all are equally interested in promoting energy-efficient solutions. Smart home users are ready to embrace energy-efficient products and procedures that can somehow reduce their monthly billing. The smart home energy management system (SHEMS) is a system developed for this purpose [17]. Pedrasa *et al.* [18] developed a decision-support tool for smart home users so that they can control and optimize their electrical energy services acquisition. Their proposed system enables users to specify their desired energy service and then optimize the schedule to maximize the net benefits. The PSO algorithm is used for schedule optimization. In smart grids, demand response (DR) programs are very important and it provides an opportunity for home users to shuffle back and forth their energy demand during peak periods. Manual adjustments are not effective and it requires an intelligent solution to optimize the energy usage schedule such that user requirement is fulfilled while peak load hours are avoided. If the start-up time for a particular user appliance is considered as a binary decision variable then it is very difficult to solve the resultant mixed-integer combinatorial optimization problem using straightforward methods. Tsui and Chan [19] proposed a DR optimization framework using versatile convex programming (CP) to facilitate load management of different household appliances in a smart home environment.

A comparative study of various optimization techniques is presented in [20] for energy scheduling in a smart environment. Evaluation is performed in monetary terms and the relative utility of each scheme is highlighted and quantified. As the energy scheduling problem is a linear optimization problem; therefore, the linear programming (LP) algorithm outperforms all other schemes. Other optimization techniques also provide comparative solutions and are expected to perform well for more complex optimization problems where LP will fail. They observed that in online configuration, PSO works well, however, in extended offline scenarios, PSO can achieve a significant reduction in cost. Lorestani *et al.* [21] developed an invasive weed optimization (IWO) algorithm for energy management controller (EMC) in order to optimize energy scheduling of associated resources to generate enhanced lookup tables. They determine the power generation schedule for connected resources over hourly intervals. During the optimization process, constraints regarding operational limitations of power generating resources are considered along with varying electricity tariffs. To study the impact on the operational cost of SHEMS, several scenarios are investigated. Zhang *et al.* developed a framework for home energy management to support DR program for domestic users in [22]. The proposed framework, i.e., a home energy management system (HEMS) allows the integration of domestic renewable energy resources in a future smart grid along with plug-in electric vehicles. Their proposed optimization scheme for scheduling flexible home appliances takes into account various factors, such as predicted outdoor temperature, renewable resources output power, users' preferences, and electricity price. Through simulations, they verify the effectiveness of the proposed scheme and have reported a 47.76% reduction in energy cost.

Tripathy *et al.* [23] suggested an IoT-based approach for smart greenhouse farming. Numerous sensors have been used to monitor different parameters, such as humidity, water nutrients solution level, pH and electrical conductivity value, temperature, etc. for early faults detection and diagnosis. A decision support module is designed that works as the main operating system for governing and coordinating entire activities. This system is dynamic and can be adapted to the changing environment. A cloud-based approach for building an IoT platform for greenhouse has been proposed in [24]. The model is being deployed and tested in a greenhouse crop production context. Web services are made available to access real-time and historical data along with prediction models. The proposed approach has the capability that new users can register IoT devices and their greenhouse data by using the FIRWARE platform. The user can also interact with the system by using a Web-based application.

Bozchalui *et al.* [25] developed an optimization model for greenhouse resources utilization with minimum energy consumption. Zhuang *et al.* [26] presented a formulation for optimal energy management using a multitime scale Markov decision process (MMDP) to reduce the operational cost using renewable energy sources. Hasni *et al.* [27] developed an optimization model for temperature and humidity by controlling the fog system, the vent opening, the soil, and the air heating using GA and PSO algorithms. Wang *et al.* [28] developed a simulation model to analyze and optimize the greenhouse construction design for improving its thermal performance. Another technique based on PSO and DE algorithm has been proposed by Pérez-González *et al.* [29] for parameters identification in the smart greenhouse. The proposed model has been implemented in a LabViewTM code. The experimental results exhibit that the proposed approach is far better as compared to counterpart algorithms. A greenhouse controller has been developed in [30] for adjustment of artificial light, indoor temperature, and humidity within appropriate limits. The purpose of the controller is to maximize crop photosynthesis rate and minimize water and energy usage. Applications of the IoT in order to evaluate models for microclimate factors inside two greenhouse crop production systems have been presented in [31]. A comprehensive literature review has been done by Iddio *et al.* [32] and different strategies for energy efficiency in the greenhouse have been discussed with detailed explanation. In this review, different areas have been identified for future research. Ghoulem *et al.* [33] have also conducted a detailed literature review with as objective to analyze different designs and systems that are commonly used for cooling purposes in greenhouses in hot climate zones. Technical and theoretical attributes of greenhouse cooling techniques have also been discussed in detail. In [34], the precision and sustainable agricultural techniques for production enhancement have been discussed in detail. The comparison and analysis of conventional and state of the art for production maximization and energy saving have been also carried out. IoT plays a vital role in boosting smart agriculture. It helps in increasing the production rate and decreasing the usage of resources, thus minimizing the production cost. Yuanping *et al.* have studied a greenhouse temperature optimization problem and they have developed an online decision strategy based on the surrogate-assisted multiobjective optimization algorithm by making a tradeoff between final crop production and total energy consumption [35].

Recently, several automated approaches are developed to assign optimal values to the tunable parameters in the optimization algorithm "optimizee" by an intelligent optimizer that receives feedback and continuously improves the performance of optimizee [36], [37]. Hu *et al.* [38] developed a tuning model for proportional–integral–derivative (PID) controller using evolutionary algorithm NSGA-II in a greenhouse environment. del Sagrado *et al.* [39] developed a Bayesian network-based control system for ventilator opening/closing to adjust greenhouse climate. Atia and El-madany conducted a comparative study to analyze the performance of four different controllers PID, fuzzy logic control (FLC), ANN, and adaptive neuro-fuzzy inference system (ANFIS) for the heating system.

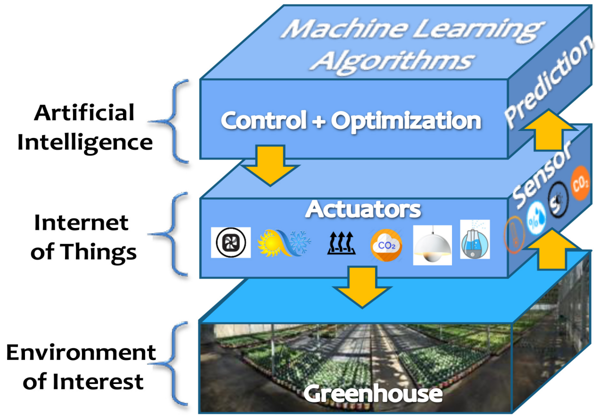


Fig. 2. Layered view of the proposed system for smart greenhouse.

They found that the ANFIS-based controller outperforms all other [40]. Azaza *et al.* [41] designed a fuzzy logic-based control system for greenhouse climate control using sensing data. By extending the point control objectives into the interval or region control objectives, Hu *et al.* [42] developed an advanced compatible control algorithm, namely expanding the point targets to intervals or regions to ensure energy-saving and the existence of control solutions.

**Algorithm 1:** Greenhouse Environment Control Based on Learning to Prediction and Optimization

$initSysConfig()$
$C = LoadConstraints()$
$GHP_d = getDesiredSettings()$
/* Repeat While loop until stopped by User */
**while** $Stop \neq true$ **do**
  /* Context Data Collection */
  $GHP_c = getGHParamData()$
  $Ext_c = getExtWeatherData()$
  $A_c = getGHActuatorsStatus()$
  /* Phase 1 - Prediction part */
  $R_{new} = ANNComputeKFR(GHP_c, A_c, Ext_c)$
  $GHP_p = KFPredict(R_{new}, GHP_c)$
  **if** $GHP_p \notin GHP_d$ **then**
    /* Phase 2 - Optimization part */
    $GHP_d^{new} = ANNComputeMinMaxAdj(GHP_p, GHP_d, Ext_c)$
    $GHP_{opt} = ComputeOptimalGHP(GHP_p, GHP_d^{new}, C)$
    /* Phase 3 - Control part */
    $A_{level}^{dur} = CascadedFuzzyCont(GHP_p, GHP_{opt}, Ext_c)$
    $ActivateActuators(A_{level}^{dur})$

## III. Proposed Optimization Scheme Based on Learning in Smart Greenhouse

The proposed system is an integrated solution based on AI and IoT technologies for greenhouse environment control. Fig. 2 presents the layered view of the proposed system for a smart greenhouse. IoT technology provides contextual information to the machine learning algorithms using various sensors. The collected data are processed and optimal parameters are computed using AI algorithms and, finally, control commands are generated to activate actuators accordingly, to bring the desired changes in the greenhouse environment.

We have developed an integrated system having three main components, that is: 1) prediction; 2) optimization; and 3) control. The design of the proposed system is given in Fig. 3 where prediction and optimization components are continuously tuned by the associated learning module. An incremental approach is used for proposed system implementation in three phases as shown in Algorithm 1.

The process is initiated by loading the initial system configuration, constraints data, and desired user settings. Afterward, the operations are performed in a continuous loop starting with context data collection that includes getting current values of greenhouse selected parameters, and getting current actuators' operational status and external weather data. This gives us the current context of the greenhouse indoor and outdoor environment. In Phase 1, the ANN algorithm is activated to compute the updated value for the Kalman filter parameter $R_{\text{new}}$ and the same is then used to compute the predicted greenhouse parameter values $\text{GHP}_p$. If the predicted greenhouse parameter values $\text{GHP}_p$ are within the user-desired settings then no action is required or otherwise $\text{GHP}_p$ are passed to the second module, i.e., the optimization component. In Phase 2, to enhance the performance of the optimization scheme, parameter tuning and adjustment in the user-desired setting are done using ANN-based learning algorithms. Afterward, optimal greenhouse parameters are computed using the CPLEX solver [43]. Subsequently, the cascaded fuzzy controller module is used to compute the optimal operational level and duration for greenhouse actuators in Phase 3. Finally, activation commands are generated to start/stop corresponding actuators in order to maintain the desired indoor conditions for the plant growth with optimal resource utilization. A detailed description of the system's key components is presented in the remaining sections.

Greenhouse indoor climate control includes various crucial parameters that need to be kept within a certain desired range to ensure a productive environment for plant growth. Among such crucial parameters includes temperature, humidity, illumination, $CO_2$ level, watering, fertilization, etc. Among the various greenhouse parameters, three parameters are considered in this study and are controlled through the operation of seven actuators as shown in Fig. 3. The Kalman filter algorithm is used to remove noise from sensing data. For optimization, a novel objective function is developed that achieves a balance between optimal parameter setting and energy consumption. A cascaded fuzzy controller is used to control the operation of greenhouse actuators based on optimized parameter values. Learning modules for prediction and optimization components are based on ANN. A description of the prediction component is skipped here for brevity, interested readers are advised to consult [44]. A detailed description of the optimization and control components is given in the next sections.

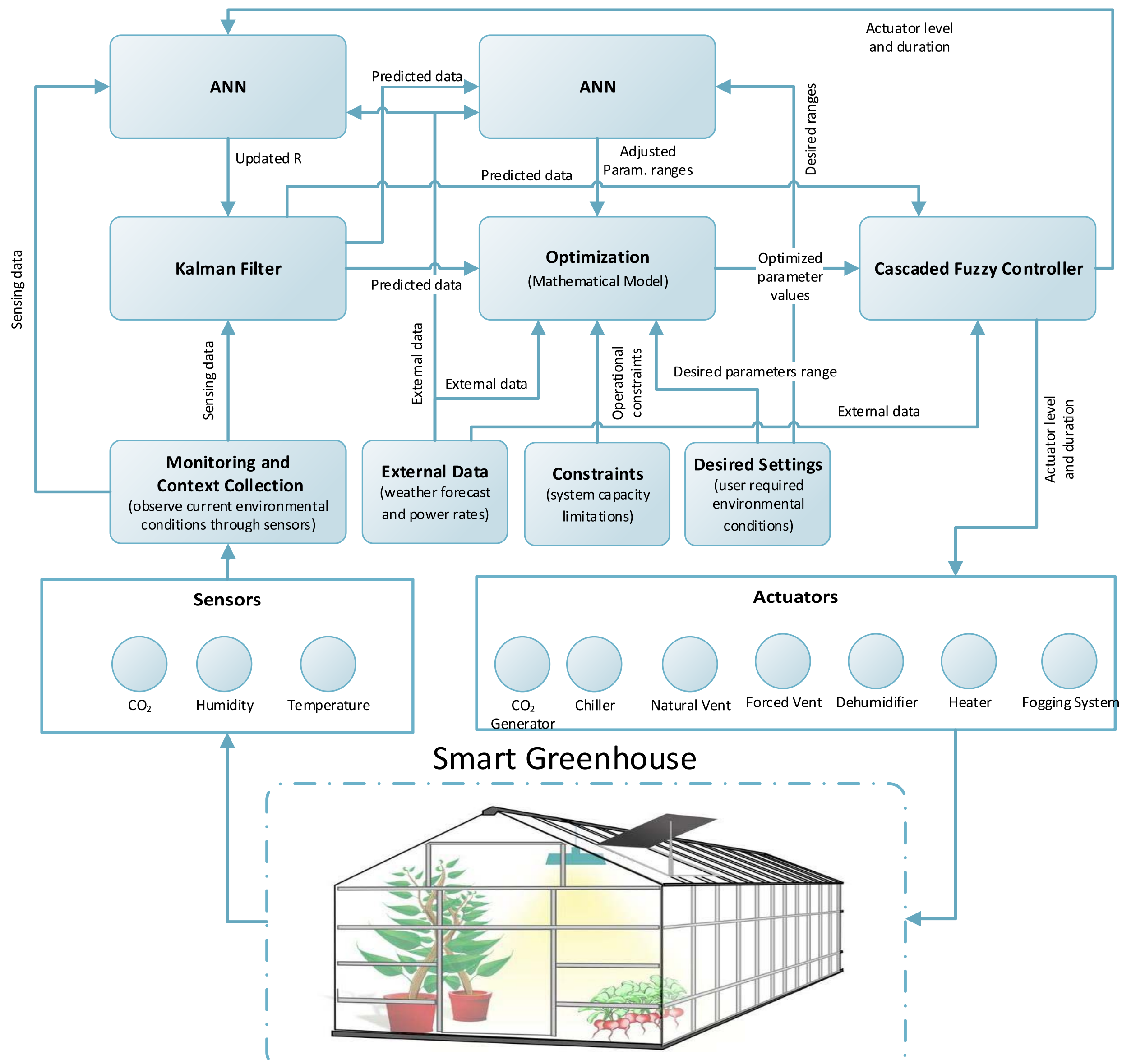


Fig. 3. Design of the proposed learning-based prediction, optimization, and control of smart greenhouse environment.

### *A. Formulation for Optimization*

Let us assume, the greenhouse parameters current readings for temperature, humidity and $CO_2$ level in greenhouse are denoted as $\text{GHP}_c = [T_c, H_c, C_c]$. Greenhouse user/farmer specifies his/her preferred setting using a range of acceptable values for each greenhouse indoor climate parameter referred to as user-set points, i.e., desired settings for greenhouse parameters can be expressed as follows:

$$\text{GHP}_d = [T_d, H_d, C_d] \tag{1}$$

where $T_d$, $H_d$, and $C_d$ are the allowed minimum and maximum ranges for each parameter such that

$$T_d = [T_{\min}, T_{\max}] \tag{2}$$
$$H_d = [H_{\min}, H_{\max}] \tag{3}$$
$$C_d = [C_{\min}, C_{\max}]. \tag{4}$$

There is an underlying assumption here that if energy cost was not an issue, then every farmer would certainly like to maintain the greenhouse indoor climate as per the extreme value for each parameter to boost productivity. However, this will surely result in increased cost; therefore, we establish a tradeoff between the desired setting and energy consumption to maximize the plant growth rate with minimal cost. For the sake of brevity, we express the range length of each parameter as

$$\Delta T = |T_{\max} - T_{\min}| \tag{5}$$
$$\Delta H = |H_{\max} - H_{\min}| \tag{6}$$
$$\Delta C = |C_{\max} - C_{\min}|. \tag{7}$$

For model simplicity, we consider seven greenhouse actuators (heater, chiller, dehumidifier, fogging system, $CO_2$ generator, and forced and natural ventilation) that are operated to maintain the desired environmental settings in the greenhouse. If $T_c < T_{\min}$, then the heater is operated to increase

TABLE I
DESCRIPTION OF VARIOUS NOTATIONS USED IN THE FORMULATION

| Notation | Description |
|---|---|
| $GHP_d$ | Desired greenhouse parameters |
| $GHP_c$ | Current greenhouse parameters |
| $GHP_o$ | Optimal greenhouse parameters |
| $T_c$ | Current temperature |
| $T_o$ | Optimal temperature |
| $T_{min}$ | Minimum limit of desired temperature |
| $T_{max}$ | Maximum limit of desired temperature |
| $H_c$ | Current humidity |
| $H_o$ | Optimal humidity |
| $H_{min}$ | Minimum limit of desired humidity |
| $H_{max}$ | Maximum limit of desired humidity |
| $C_c$ | Current $CO_2$ |
| $C_o$ | Optimal $CO_2$ |
| $C_{min}$ | Minimum limit of desired $CO_2$ |
| $C_{max}$ | Maximum limit of desired $CO_2$ |
| $E_{opt}$ | Energy consumption in maintaining optimal settings |
| $E_{min}$ | Energy consumption in maintaining minimal desired settings |
| $E_{max}$ | Energy consumption in maintaining maximal desired settings |
| $\alpha_p$ | Weight for greenhouse indoor climate settings |
| $\alpha_e$ | Weight for energy savings |
| $w_X$ | Weight for selected greenhouse parameters $X$ |
| $G_p$ | Gain in maintaining optimal greenhouse climate settings |
| $G_e$ | Gain in energy savings |
| $P_a$ | Power consumption in per unit change in indoor parameters by operation of actuator $a$ |
| $D_X$ | Deficiency in achieving optimal settings for parameter $X$ |

greenhouse temperature. Similarly, if $T_{\max} < T_c$ then we need to operate a chiller to cool down greenhouse indoor temperature. Likewise, $H_c < H_{\min}$, then fogging system is activated, and if $H_{\max} < H_c$ then we need to operate a dehumidifier. For $CO_2$ level maintenance, if $C_c < C_{\min}$, then $CO_2$ generator needs to be activated and if $C_{\max} < C_c$ then we need to perform forced ventilation to bring fresh air to lower down $CO_2$ concentration inside greenhouse. Let us assume that power consumption by the heater and chiller per unit change in temperature is estimated by $P_h$ and $P_c$, respectively. Similarly, power consumption by the dehumidifier and fogging system per unit change in the humidity level is estimated by $P_{\text{deh}}$ and $P_{\text{fog}}$, respectively. Whereas, power consumption by forced ventilation and $CO_2$ generator system in per unit change in $CO_2$ level is estimated by $P_{fv}$ and $P_g$, respectively. Table I provides a short description of the different notations used in this formulation.

Let us assume that the optimal settings that can achieve a tradeoff between the ideal environmental settings and the energy consumption are determined by

$$\text{GHP}_o = [T_o, H_o, C_o] \tag{8}$$

whereas, the optimum value of each parameter must be within the desired range, i.e.,

$$T_o \in [T_{\min}, T_{\max}] \tag{9}$$
$$H_o \in [H_{\min}, H_{\max}] \tag{10}$$
$$C_o \in [C_{\min}, C_{\max}]. \tag{11}$$

We can now compute the total energy required for maintaining optimal settings $E_{\text{opt}}$ in the greenhouse which is given by

$$E_{\text{opt}} = E_{T_o} + E_{H_o} + E_{C_o} \tag{12}$$

where $E_{T_o}$, $E_{H_o}$, and $E_{C_o}$ are the required energy for optimal settings of the greenhouse temperature, humidity, and $CO_2$ level, which can be computed as follows:

$$E_{T_o} = \begin{cases} P_h \times (T_o - T_c), & \text{if } T_c < T_{\min} \quad (13a) \\ P_c \times (T_c - T_o), & \text{if } T_{\max} < T_c \quad (13b) \end{cases}$$

$$E_{H_o} = \begin{cases} P_{\text{fog}} \times (H_o - H_c), & \text{if } H_c < H_{\min} \quad (14a) \\ P_{\text{deh}} \times (H_c - H_o), & \text{if } H_{\max} < H_c \quad (14b) \end{cases}$$

$$E_{C_o} = \begin{cases} P_g \times (C_o - C_c), & \text{if } C_c < C_{\min} \quad (15a) \\ P_{fv} \times (C_c - C_o), & \text{if } C_{\max} < C_c. \quad (15b) \end{cases}$$

The above formulation is about the total power consumption in maintaining optimal greenhouse parameter settings. We can compute the lower and upper limits of power consumption as follows:

$$E_{\min} = E_{T_{\min}} + E_{H_{\min}} + E_{C_{\min}} \tag{16}$$
$$E_{\max} = E_{T_{\max}} + E_{H_{\max}} + E_{C_{\max}} \tag{17}$$

where

$$E_{T_{\min}} = \begin{cases} P_h \times (T_{\min} - T_c), & \text{if } T_c < T_{\min} \quad (18a) \\ P_c \times (T_c - T_{\max}), & \text{if } T_{\max} < T_c \quad (18b) \end{cases}$$

$$E_{T_{\max}} = \begin{cases} P_h \times (T_{\max} - T_c), & \text{if } T_c < T_{\min} \quad (19a) \\ P_c \times (T_c - T_{\min}), & \text{if } T_{\max} < T_c \quad (19b) \end{cases}$$

$$E_{H_{\min}} = \begin{cases} P_{\text{fog}} \times (H_{\min} - H_c), & \text{if } H_c < H_{\min} \quad (20a) \\ P_{\text{deh}} \times (H_c - H_{\max}), & \text{if } H_{\max} < H_c \quad (20b) \end{cases}$$

$$E_{H_{\max}} = \begin{cases} P_{\text{fog}} \times (H_{\max} - H_c), & \text{if } H_c < H_{\min} \quad (21a) \\ P_{\text{deh}} \times (H_c - H_{\min}), & \text{if } H_{\max} < H_c \quad (21b) \end{cases}$$

$$E_{C_{\min}} = \begin{cases} P_g \times (C_{\min} - C_c), & \text{if } C_c < C_{\min} \quad (22a) \\ P_{fv} \times (C_c - C_{\max}), & \text{if } C_{\max} < C_c \quad (22b) \end{cases}$$

$$E_{C_{\max}} = \begin{cases} P_g \times (C_{\max} - C_c), & \text{if } C_c < C_{\min} \quad (23a) \\ P_{fv} \times (C_c - C_{\min}), & \text{if } C_{\max} < C_c. \quad (23b) \end{cases}$$

Our objective is to maximize greenhouse productivity by maintaining the desired setting with reduced energy consumption. Let $G_p$ be the gain in maintaining optimal climate settings in the greenhouse and $G_e$ be the corresponding gain in energy saving. Now, if $\alpha_p$ and $\alpha_e$ are the user-assigned weightage to optimal parameter settings and energy saving, respectively, then our objective function can be formulated as follows:

$$\text{Max}\left(\alpha_p.G_p + \alpha_e.G_e\right) \tag{24}$$

such that $\alpha_p + \alpha_e = 1$. The gain in achieving optimal environmental settings $G_p$ can be computed as follows:

$$G_p = \sum_{X \in T,H,C} w_X.\left(1 - {D_X}^2\right) \tag{25}$$

where $D_T$, $D_H$, and $D_C$ express the deficiency, i.e., failure to achieve optimum temperature, humidity, and $CO_2$ level settings, respectively. $w_T$, $w_H$, and $w_C$ are the weight assigned to each parameter, depending on its importance for plant productivity, such as $w_T + w_H + w_C = 1$. To maximize the gain in achieving the desired optimal setting of $G_p$, we need to minimize the deficiency component for each of the parameters given below the formula

$$D_T = \begin{cases} \dfrac{T_{\max} - T_o}{\Delta T}, & \text{if } T_c < T_{\min} & (26a) \\ \dfrac{T_o - T_{\min}}{\Delta T}, & \text{if } T_{\max} < T_c & (26b) \end{cases}$$

$$D_H = \begin{cases} \dfrac{H_{\max} - H_o}{\Delta H}, & \text{if } H_c < H_{\min} & (27a) \\ \dfrac{H_o - H_{\min}}{\Delta H}, & \text{if } H_{\max} < H_c & (27b) \end{cases}$$

$$D_C = \begin{cases} \dfrac{C_{\max} - C_o}{\Delta C}, & \text{if } C_c < C_{\min} & (28a) \\ \dfrac{C_o - C_{\min}}{\Delta C}, & \text{if } C_{\max} < C_c. & (28b) \end{cases}$$

We need to minimize the $D_X$ deficiency component for each parameter to get optimal settings for indoor parameters. If $T_c < T_{\min}$, then $T_o \approx T_{\max}$ will be our ideal optimal setting. As $T_o \to T_{\max}$, $D_T \to 0$ helps to optimize the $G_p$ needed. The same holds valid for humidity and $CO_2$ level optimization.

The energy-saving gain of $G_e$ can be estimated as follows:

$$G_e = 1 - \left( \frac{(E_{\text{opt}} - E_{\min})}{(E_{\max} - E_{\min})} \right)^2. \tag{29}$$

We need to minimize the energy consumed in order to optimize energy savings to achieve optimum settings, i.e., $E_{\text{opt}}$. If $E_{\text{opt}} \to E_{\min}$, then $G_e \to 1$ helps to optimize the $G_e$ energy saving component. Thus, our ultimate objective function can be formulated as follows:

$$\text{Max}\left( \alpha_p . \sum_{X \in T,H,C} w_X . \left(1 - {D_X}^2\right) + \alpha_e . \left(1 - \left(\frac{E_{\text{opt}} - E_{\min}}{E_{\max} - E_{\min}}\right)^2\right)\right). \tag{30}$$

Constraints

$$\begin{aligned} &T_c < T_{\min} \le T_o \le T_{\max} && \text{for cooling case} && (31a)\\ &T_{\min} \le T_o \le T_{\max} < T_c && \text{for heating case} && (31b)\\ &H_c < H_{\min} \le H_o \le H_{\max} && \text{for fogging} && (31c)\\ &H_{\min} \le H_o \le H_{\max} < H_c && \text{for dehumidification} && (31d)\\ &C_c < C_{\min} \le C_o \le C_{\max} && \text{for } CO_2 \text{ generation} && (31e)\\ &C_{\min} \le C_o \le C_{\max} < C_c && \text{for forced ventilation} && (31f)\\ &0 < E_{\min} \le E_o \le E_{\max} && \text{for energy optimization.} && (31g) \end{aligned}$$

*1) Illustration of the Proposed Optimization Function:* The proposed multiobjective optimization function given in (30) has mainly two components. The first component signifies the gain in maintaining greenhouse climate parameters as per user-desired settings whereas, the second component relates to the corresponding energy consumption. The contribution of each component to the overall optimization value can be controlled by adjusting the weights $\alpha_p$ and $\alpha_e$. While maintaining a greenhouse climate, we consider the three crucial parameters, i.e., temperature, humidity, and $CO_2$ in this study. The relative importance of each parameter can be expressed by adjusting their corresponding weights $w_T$, $w_H$, and $w_C$.

TABLE II
CONFIGURATION OF GREENHOUSE MODEL PARAMETERS USED FOR ILLUSTRATION

| Param/Metric | Cur | Min | Max | wx | Alpha (α) | | |
|---|---|---|---|---|---|---|---|
| | | | | | Set-1 | Set-2 | Set-3 |
| Temperature | 18 | 25 | 30 | 0.4 | 0.3 | 0.5 | 0.8 |
| Humidity | 86 | 50 | 60 | 0.3 | | | |
| $CO_2$ | 387 | 400 | 1500 | 0.3 | | | |
| Energy | | | | | 0.7 | 0.5 | 0.2 |

To illustrate the working and significance of the proposed objective function, we have performed several experiments with the configuration given in Table II. These experiments are conducted to analyze and highlight the contribution of each component to overall system optimization.

Given the user-desired minimum and maximum setting for each parameter, we can have different valid combinations (total $6 \times 11 \times 1100 = 72\,600$ if we consider precision with zero decimal places). The proposed formulation helps in the selection of the best combination that results in maximum value for the objective function. For the sake of simplicity, we have considered only $6 \times 11 \times 4 = 264$ combinations, i.e., temperature values to be $25, 26, \ldots, 30$, humidity values varying from 50 to 60, and CO2 values to be $400, 765, 1130$, and $1500$.

Fig. 4 shows the piecewise contribution of each greenhouse parameter with varying values. This is a visual representation of (25). The contribution value of each component is controlled by weights $w$ values, and we can observe that the total sum of all components can never exceed 1.0. The best combination of the greenhouse parameters is where all the components get maximum contributing values, i.e., toward the end of the graph in Fig. 4. However, maintaining the best parameter setting results in more energy consumption and consequently less energy saving and the same is evident from the results given in Fig. 5. For the sake of illustration, we consider a simplified model of the greenhouse where the same amount of energy is consumed per unit change in all parameters. The actual model used in the experimental results (Section VI) is more complex to closely reflect the real-world conditions.

Next, we study the impact of the increase in greenhouse parameter values over the gain in optimal parameter setting and corresponding energy savings. Fig. 5 is the visual representation of the two main components given in (30). The blue line reflects the overall optimization gain for varying parameter values and we can observe a gradual growth in the gain for optimal parameter setting with the increase in greenhouse parameter values. This component approaches its maximum value of 1 when for greenhouse parameter gets the maximum desired values. On the other hand, a gradual decrease in energy saving (red line) can be observed with an increase in greenhouse parameter values as more energy will be consumed. The energy-saving component approaches its minimum value of 0 when for greenhouse parameter gets the maximum desired

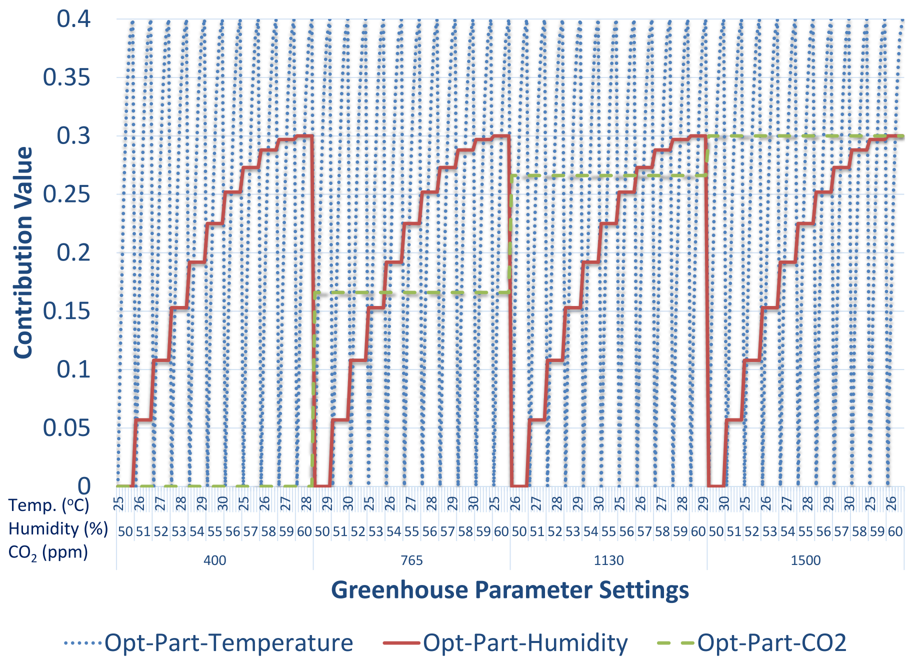


Fig. 4. Piecewise contribution of greenhouse parameter settings with varying values.

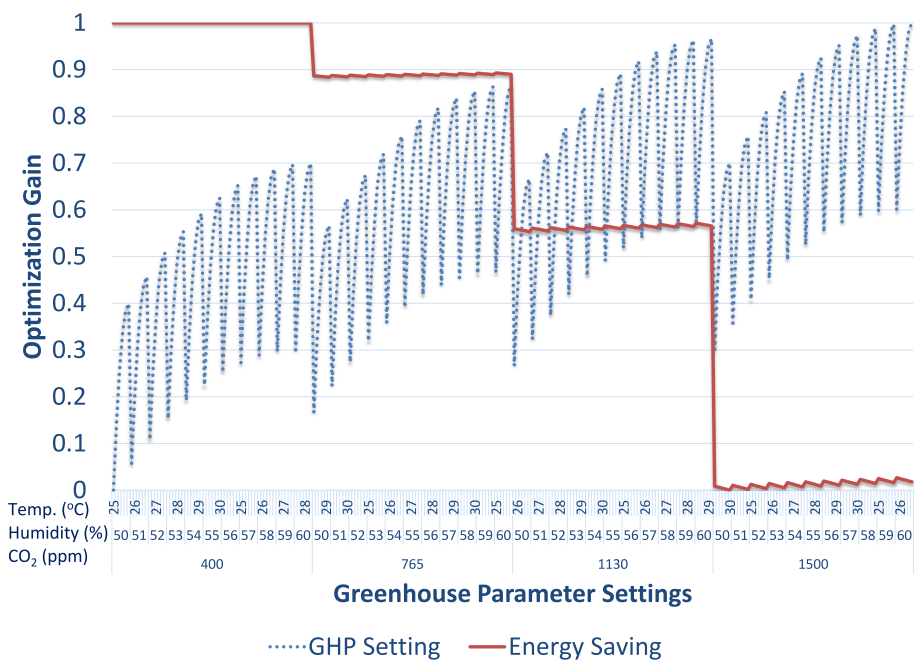


Fig. 5. Analysis of the optimization gain for optimal parameter setting and corresponding energy saving.

values. This is where a need a tradeoff between optimal parameter settings and corresponding energy saving. The proposed multiobjective optimization formula given in (30) achieves this tradeoff by adjusting the weights $\alpha_p$ and $\alpha_e$.

Fig. 6 shows the results for the overall optimization values of the objective function given in (30) with varying alpha weights. Three sets of alpha values are considered in this example and the corresponding values for $\alpha_p$ and $\alpha_e$ are given in Table II. Set-1 assigns more weight to energy savings as compared to the optimal parameter setting and the maximum value of the objective function resides on the left side of the graph as depicted with a solid blue vertical line. Referring to the same position in Fig. 5, we can observe that it corresponds to a significant gain in energy-saving components with a slight compromise in greenhouse parameter settings. In Set-2, we consider equal weights for both components and the maximum value of the objective function resides right in the center of the graph as depicted with a solid red vertical line. Referring to the same position in Fig. 5, we can observe that it corresponds to the same gain for both components. Finally, Set-3 assigns more weight to the optimal parameter setting and the maximum value of the objective function is indicated with a solid green

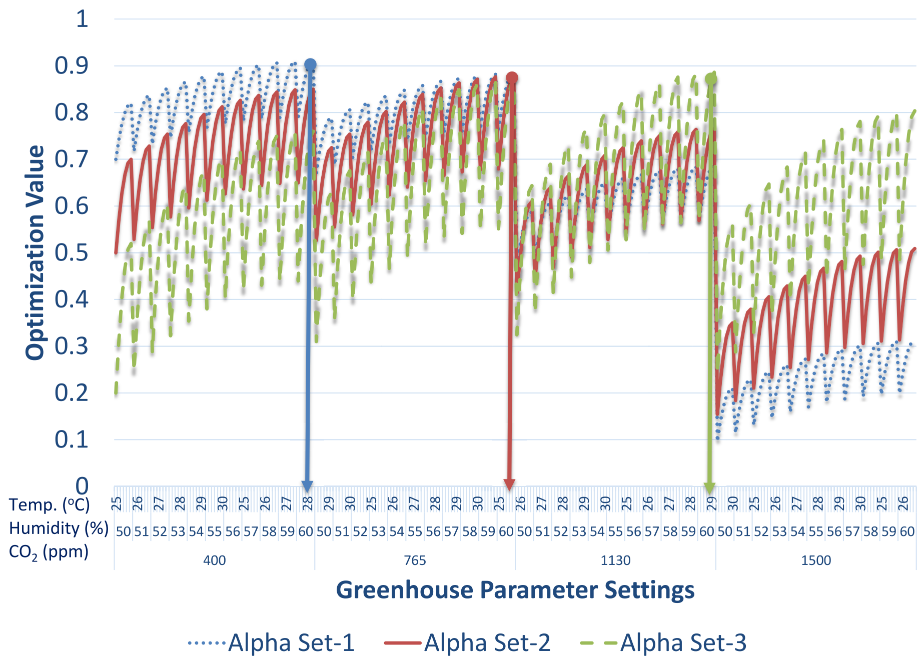


Fig. 6. Overall optimization values of the objective function given in (30) with varying alpha weights.

vertical line which corresponds to a significant gain in optimal parameter settings at the cost of low energy saving.

### B. Learning to Optimization Using ANN

The objective function given in (30) has two main contributing factors, i.e., optimal parameter settings and energy consumption. The optimal parameter settings part further includes the three indoor parameters, i.e., temperature, $CO_2$ level, and humidity. Users can control the weight assigned to each optimization component by appropriately adjusting the $\alpha$ and $w$ values. Optimal point selection depends upon the parameters allowed ranges and their current settings. In order to improve optimal point selection, an ANN-based learning module is developed. The abstract diagram of the ANN-based learning module is given in Fig. 7. This is based on the fact that optimal point settings within the user-predefined ranges have a significant impact on corresponding actuator operation. When external environmental conditions are favorable then it can have little impact on indoor climate and *vice versa*. For instance when the external temperature is very low then choosing an optimal temperature close to $T_{\min}$ will not be a good choice as the external temperature will quickly drag the indoor temperature below $T_{\min}$. As a result, corresponding actuators will need to be operated frequently consuming more energy. The same holds valid for the other two indoor parameters, i.e., $CO_2$ and humidity levels. Similarly, when electricity prices are cheap and farmers can tolerate the maximum operation of actuators to bring the desired change in the indoor climate. Thus, the user-defined ranges are adjusted for indoor parameters such that optimal point selection can be made intelligently.

Fig. 7 presents abstract diagram of proposed learning to optimization scheme. As three parameters (temperature, $CO_2$, and humidity) are under observation in this study, therefore three separate instances of ANN-based learning algorithms are used. Each ANN algorithm takes its relevant inputs and produces estimated adjustment values in minimum and maximum limits of the corresponding parameter-desired ranges. The ANN algorithm is used to estimate and adjust the minimum and maximum limits of indoor parameters based on user-desired settings, current parameter values, and external environmental conditions. Table XII presents the configuration summary of learning modules for predicting adjustment in user-defined settings for temperature, $CO_2$, and humidity level.

### C. Cascaded Fuzzy Controller

Fig. 8 presents a detailed flow diagram of cascaded fuzzy controller for greenhouse actuators. It takes a total of 11 different input parameters, including predicted indoor parameter values for temperature, $CO_2$, and humidity, optimized parameters values for temperature, $CO_2$, and humidity, and external parameters values for temperature, $CO_2$, and humidity, and external wind speed and solar radiation. There are a total of eight fuzzy inference systems (FIS) cascaded together. The first one is actuator selection FIS for temperature setting. Based on predicted indoor temperature, external temperature, and optimized temperature, it selects an appropriate actuator for activation among heater, chiller, natural, or forced ventilation. If the current indoor temperature is below the minimum desired level and the external temperature is higher than the optimized temperature, then ventilation can help in temperature settings; otherwise, the heater actuator will be operated. Likewise, if the current indoor temperature is above the maximum desired level and external temperature is lower than the optimized temperature, then ventilation can help in temperature settings; otherwise, the chiller actuator will be operated. Each of these FIS takes selected input parameters and computes appropriate values for the corresponding actuator level and duration.

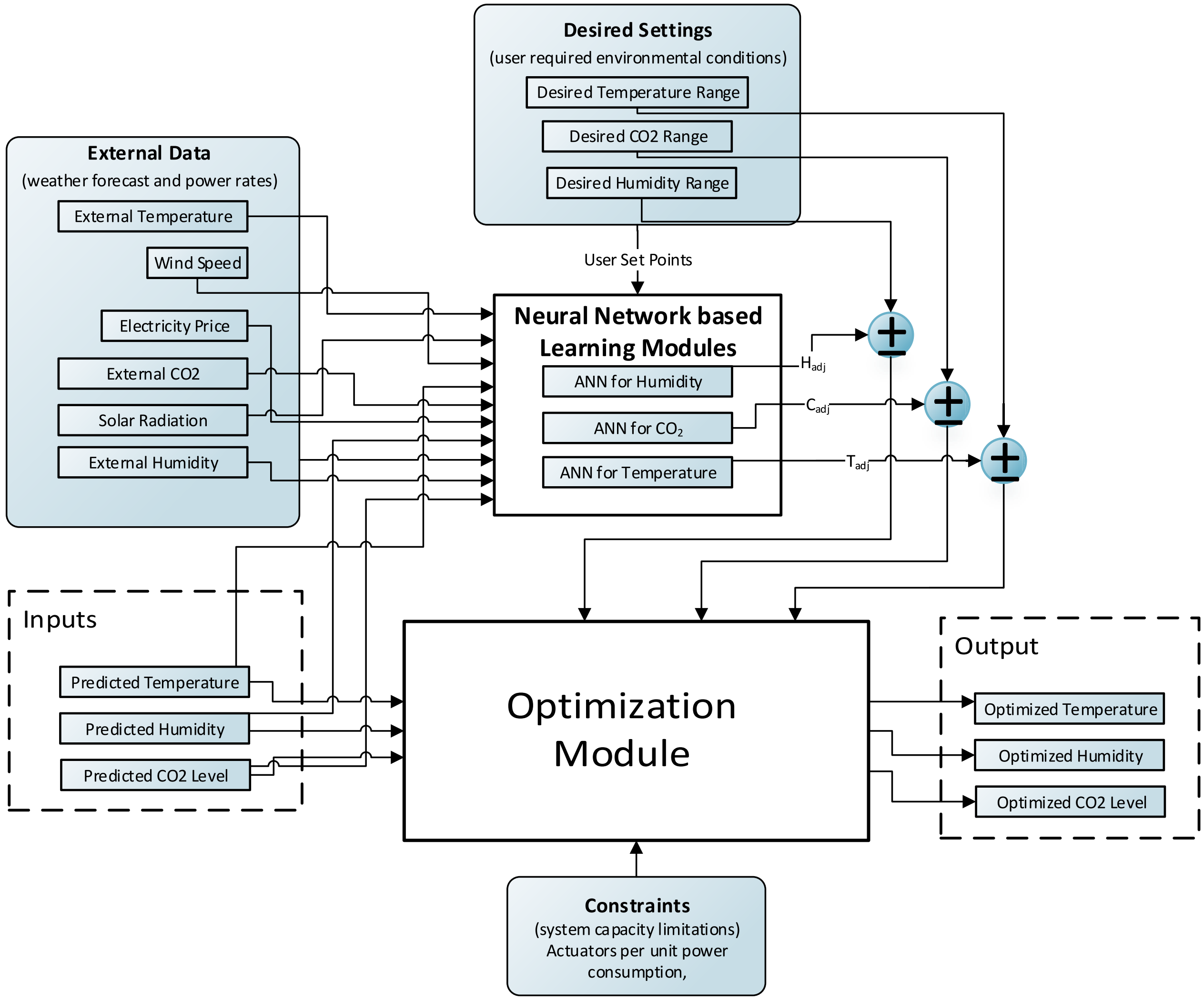


Fig. 7. Proposed ANN-based learning to optimization algorithm.

Indoor $CO_2$ and humidity is changed if ventilation is performed, therefore the estimated value for adjusted $CO_2$ and humidity levels is computed by considering the effect of total ventilation operation. After computing the adjusted humidity level, first, check if the adjusted humidity level is within the desired range, then no actuator is operated for humidity control. If the adjusted humidity level is outside the desired range then a dehumidifier or fogging system is activated to maintain the desired humidity level in the greenhouse. Similarly, the estimated value for an adjusted $CO_2$ level is also computed by considering the effect of total ventilation operation. After computing the adjusted $CO_2$ level, first, check if the adjusted $CO_2$ level is within the desired range, then no actuator is operated for $CO_2$ control. If the adjusted $CO_2$ level is below the desired range, then the $CO_2$ generator is activated to maintain the desired $CO_2$ level in the greenhouse.

## IV. Greenhouse Environment Modeling

For experimental analysis of the proposed learning-based optimization scheme, the greenhouse environment is modeled using the mathematical formulation for various greenhouse processes based on studies presented in [25] and [45]. As stated earlier, three parameters are considered in this study for maintaining a greenhouse indoor environment, i.e., temperature, $CO_2$, and humidity, Fig. 1 shows essential components and processes that have a significant impact on these parameters. For instance, the indoor temperature depends upon three external factors (i.e., solar radiation, wind speed, and external temperature) and two actuators, i.e., heater and chiller. In the next subsections, a detailed mathematical formulation is presented for modeling indoor parameters, i.e., temperature, $CO_2$, and humidity levels.

### A. Greenhouse Indoor Temperature Modeling

Let $T_{\text{in}}(t)$ be the indoor temperature at interval $t$, then intermittent indoor temperature $\acute{T}_{\text{in}}(t)$ changed due to air exchange can be estimated using principals of materials mixing [46] as follows:

$$\acute{T}_{\text{in}}(t) = \frac{G_{\text{vol}} - A_{\text{total}}(t)}{G_{\text{vol}}} \cdot T_{\text{in}}(t) + \frac{A_{\text{total}}(t)}{G_{\text{vol}}} \cdot T_{\text{ext}}(t) \quad (32)$$

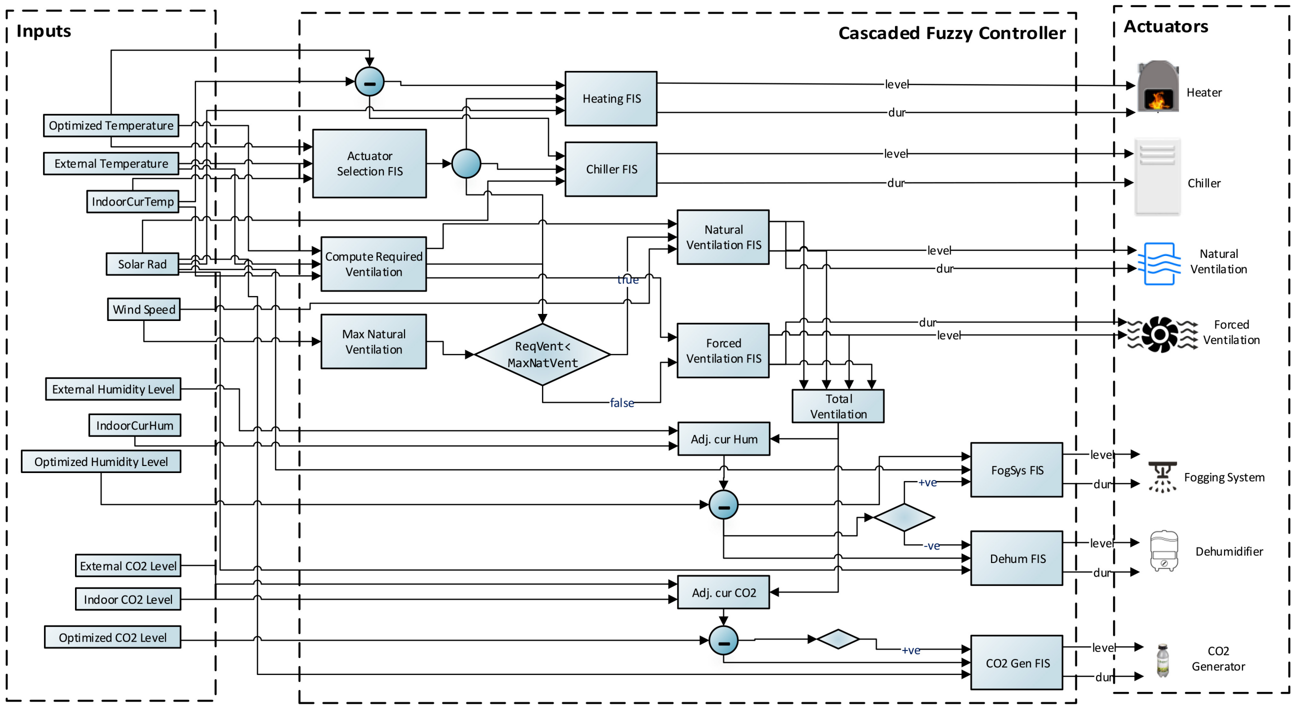


Fig. 8. Flow diagram of the cascaded fuzzy controller for greenhouse actuators.

where is $A_{\text{total}}(t)$ total air exchange, $T_{\text{ext}}(t)$ is the external temperature during interval $t$, and $G_{\text{vol}}$ is the volume of greenhouse. We assume the specific heat of indoor and outdoor air to be the same.

An increase in temperature due to solar radiation can be formulated [25] as follows:

$$\theta_{\text{solar}}(t) = \phi_{sr} \cdot \text{SR}(t) \cdot \frac{G_{\text{area}}}{C} \tag{33}$$

where $\phi_{sr}$ is the light transmission factor of greenhouse material (cover), $\text{SR}(t)$ is the solar radiation during interval $t$, $G_{\text{area}}$ is the area of greenhouse, and $C$ is the total heat capacity of the greenhouse.

The change in temperature due to heat conduction through greenhouse walls is given by the following equation [25]:

$$\theta_{wl}(t) = \phi_{wl} \cdot G_{sa} \cdot \frac{T_{\text{ext}}(t) - T_{\text{in}}(t)}{C} \tag{34}$$

where $\phi_{wl}$ is the heat transfer coefficient of greenhouse walls, $G_{sa}$ is the greenhouse surface area.

An increase in temperature due to the heater is given by

$$\theta_h(t) = \theta_{h_{\max}} \cdot \frac{H_{\text{level}}(t)}{H_{\text{level}_{\max}}} \cdot \frac{H_{\text{dur}}(t)}{\text{sim}_{\text{interval}}} \tag{35}$$

where $\theta_{h_{\max}}$ is the max change in greenhouse temperature when the heater is operated at maximum level $H_{\text{level}_{\max}}$ for the complete duration of an interval. $H_{\text{level}}(t)$ and $H_{\text{dur}}(t)$ is heater level and duration during interval $t$.

Similarly, a decrease in temperature due to the chiller is given by

$$\theta_c(t) = \theta_{c_{\max}} \cdot \frac{C_{\text{level}}(t)}{C_{\text{level}_{\max}}} \cdot \frac{C_{\text{dur}}(t)}{\text{sim}_{\text{interval}}} \tag{36}$$

where $\theta_{c_{\max}}$ is the max change in greenhouse temperature when the chiller is operated at maximum level $C_{level_{\max}}$ for the complete duration of an interval. $C_{\text{level}}(t)$ and $C_{\text{dur}}(t)$ is chiller level and duration during interval $t$.

The final indoor temperature of the greenhouse for the next time interval is given by

$$T_{\text{in}}(t+1) = \acute{T}_{\text{in}}(t) + \theta_{\text{solar}}(t) + \theta_{wl}(t) + \theta_h(t) - \theta_c(t). \tag{37}$$

## *B. Greenhouse Indoor $CO_2$ Modeling*

Let $C_{\text{in}}(t)$ be the indoor $CO_2$ concentration at interval $t$, then intermittent $CO_2$ level $\acute{C}_{\text{in}}(t)$ changed due to air exchange can be estimated using principals of materials mixing [46] as follows:

$$\acute{C}_{\text{in}}(t) = \frac{G_{\text{vol}} - A_{\text{total}}(t)}{G_{\text{vol}}} \cdot C_{\text{in}}(t) + \frac{A_{\text{total}}(t)}{G_{\text{vol}}} \cdot C_{\text{ext}}(t) \tag{38}$$

where is $A_{\text{total}}(t)$ total air exchange and $C_{\text{ext}}(t)$ is the external air $CO_2$ level during interval $t$.

Plants convert glucose to get energy through the process of respiration and release water and $CO_2$ to the air. The respiration process takes place continuously but it almost ceases during mid-day when photosynthesis is maximum and reaches its maximum during night time when photosynthesis is stopped. An increase in $CO_2$ level due to plants' respiration can be found in [25] and, here, we use a simplified formulation as follows:

$$\vartheta_{\text{res}}(t) = \varphi_{\text{res}} \cdot \vartheta_{\text{res}_{\max}} \cdot \left(1 - \frac{\text{SR}(t)}{\text{SR}_{\max}}\right) \tag{39}$$

where $\varphi_{\text{res}}$ is the respiration coefficient by the greenhouse plants, $\vartheta_{res_{\max}}$ is the maximum increase in $CO_2$ concentration due to respiration. $\text{SR}(t)$ and $\text{SR}_{\max}$ is the solar radiation during interval $t$ and maximum solar radiation, respectively.

Photosynthesis is the most important process for plant growth through which plants produce glucose from $CO_2$ and water in presence of light and chlorophyll. Oxygen is released as a byproduct of this process. Due to the process of photosynthesis, indoor $CO_2$ concentration quickly drops down during the daytime and the decrease in $CO_2$ due to photosynthesis can be formulated as follows:

$$\vartheta_{ps}(t) = \varphi_{ps} \cdot \vartheta_{ps_{\max}} \cdot \frac{\text{SR}(t)}{\text{SR}_{\max}} \tag{40}$$

where $\varphi_{ps}$ is the photosynthesis coefficient of the greenhouse plants, $\vartheta_{ps_{\max}}$ is the maximum decrease in $CO_2$ concentration due to photosynthesis. $\text{SR}(t)$ and $\text{SR}_{\max}$ is the solar radiation during interval $t$ and maximum solar radiation.

To overcome, $CO_2$ deficiency in the greenhouse indoor environment, $CO_2$ generators are often used to ensure sufficient provision of $CO_2$ for plant growth. An increase in $CO_2$ due to the $CO_2$ generator can be formulated as follows:

$$\vartheta_{\text{gen}}(t) = \vartheta_{\text{gen}_{\max}} \cdot \frac{\text{CG}_{\text{level}}(t)}{\text{CG}_{\text{level}_{\max}}} \cdot \frac{\text{CG}_{\text{dur}}(t)}{\text{sim}_{\text{interval}}} \tag{41}$$

where $\vartheta_{\text{gen}_{\max}}$ is the max increase in the $CO_2$ concentration when the $CO_2$ generator is operated at maximum level $\text{CG}_{\text{level}_{\max}}$ for the complete duration of an interval. $\text{CG}_{\text{level}}(t)$ and $\text{CG}_{\text{dur}}(t)$ is $CO_2$ generator level and duration during interval $t$.

The final indoor $CO_2$ concentration of the greenhouse for the next time interval is given by

$$C_{\text{in}}(t+1) = \acute{C}_{\text{in}}(t) + \vartheta_{\text{res}}(t) - \vartheta_{ps}(t) + \vartheta_{\text{gen}}(t). \tag{42}$$

### C. Greenhouse Indoor Humidity Modeling

Let $H_{\text{in}}(t)$ be the indoor humidity at interval $t$, then intermittent humidity level $\acute{H}_{\text{in}}(t)$ changed due to air exchange can be estimated using principals of materials mixing [46] as follows:

$$\acute{H}_{\text{in}}(t) = \frac{G_{\text{vol}} - A_{\text{total}}(t)}{G_{\text{vol}}} \cdot H_{\text{in}}(t) + \frac{A_{\text{total}}(t)}{G_{\text{vol}}} \cdot H_{\text{ext}}(t) \tag{43}$$

where $A_{\text{total}}(t)$ is the total air exchange and $H_{\text{ext}}(t)$ is the external air humidity level during interval $t$.

Internal humidity in the greenhouse also gets increased due to the process of evaporation and transpiration. Evaporation is the process of water conversion into vapors from water bodies and plant canopies. During the transpiration process, water leaves the plant in the form of vapors mostly through leaves (stomata). Both of these processes get increased in the presence of sunlight and almost get stopped during night time. An increase in the humidity level due to evaporation and transpiration can be found in [25] and, here, we use a simplified formulation as follows:

$$\sigma_{ev}(t) = \phi_{ev} \cdot \sigma_{ev_{\max}} \cdot \frac{\text{SR}(t)}{\text{SR}_{\max}} \tag{44}$$

where $\phi_{ev}$ is the evaporation and transpiration coefficient of the greenhouse plants, $\sigma_{ev_{\max}}$ is the maximum increase in humidity due to evaporation and transpiration. $\text{SR}(t)$ and $\text{SR}_{\max}$ is the solar radiation during interval $t$ and maximum solar radiation.

When indoor humidity gets too low then it has a negative impact on plant growth as it leads to dehydration in plants. Humidity can be increased through the operation of a fogging system to maintain the desired humidity level in a greenhouse indoor environment. An increase in humidity due to the fogging system can be formulated as follows:

$$\sigma_{\text{fog}}(t) = \sigma_{\text{fog}_{\max}} \cdot \frac{\text{FS}_{\text{level}}(t)}{\text{FS}_{\text{level}_{\max}}} \cdot \frac{\text{FS}_{\text{dur}}(t)}{\text{sim}_{\text{interval}}} \tag{45}$$

where $\sigma_{\text{fog}_{\max}}$ is the max increase in the humidity when fogging system is operated at maximum level $\text{FS}_{\text{level}_{\max}}$ for complete duration of an interval. $\text{FS}_{\text{level}}(t)$ and $\text{FS}_{\text{dur}}(t)$ are the fogging system level and duration during interval $t$.

Conversely, when indoor humidity gets too high, then it also has a negative impact on plant growth as transpiration gets stopped. Humidity can be decreased through dehumidifiers to maintain the desired humidity level in the greenhouse indoor environment. A decrease in humidity due to a dehumidifier can be formulated as follows:

$$\sigma_{\text{deh}}(t) = \sigma_{\text{deh}_{\max}} \cdot \frac{\text{DH}_{\text{level}}(t)}{\text{DH}_{\text{level}_{\max}}} \cdot \frac{\text{DH}_{\text{dur}}(t)}{\text{sim}_{\text{interval}}} \tag{46}$$

where $\sigma_{\text{deh}_{\max}}$ is the max decrease in the humidity when the dehumidifier is operated at maximum level $\text{DH}_{\text{level}_{\max}}$ for the complete duration of an interval. $\text{DH}_{\text{level}}(t)$ and $\text{DH}_{\text{dur}}(t)$ are the dehumidifier level and duration during interval $t$.

The final indoor humidity of the greenhouse for the next time interval is given by

$$H_{\text{in}}(t+1) = \acute{H}_{\text{in}}(t) + \sigma_{ev}(t) + \sigma_{\text{fog}}(t) - \sigma_{\text{deh}}(t). \tag{47}$$

## V. METHODS

### A. Experimental Setup

Performance evaluation of the proposed learning-based optimization scheme is performed using a custom-built simulator based on greenhouse indoor environment modeling (as discussed in Section IV) by taking into consideration the impact of external environmental parameters and actuator operational level on indoor parameters. The greenhouse environment emulator model is developed to interact with our optimization application. The proposed optimization model is solved through a mathematical programming language (AMPL) [47] using CPLEX solver [43]. Visual Studio C# is used for the development of these applications and Table III includes the tools, system specifications, and other resources used in the development process. To implement the ANN-based learning module, we have used the Accord.NET [48] framework to tune the optimization algorithm performance. Fig. 9 illustrates the interaction among the various modules/applications used in the experimental setup.

We used 15 days of weather data collected from the online weather site Meteoblue [49] for Jeju, South Korea, for experimental analysis which includes outdoor temperature, humidity, wind speed, and solar radiation information. Our target in this study is to maintain the desired level of indoor temperature,

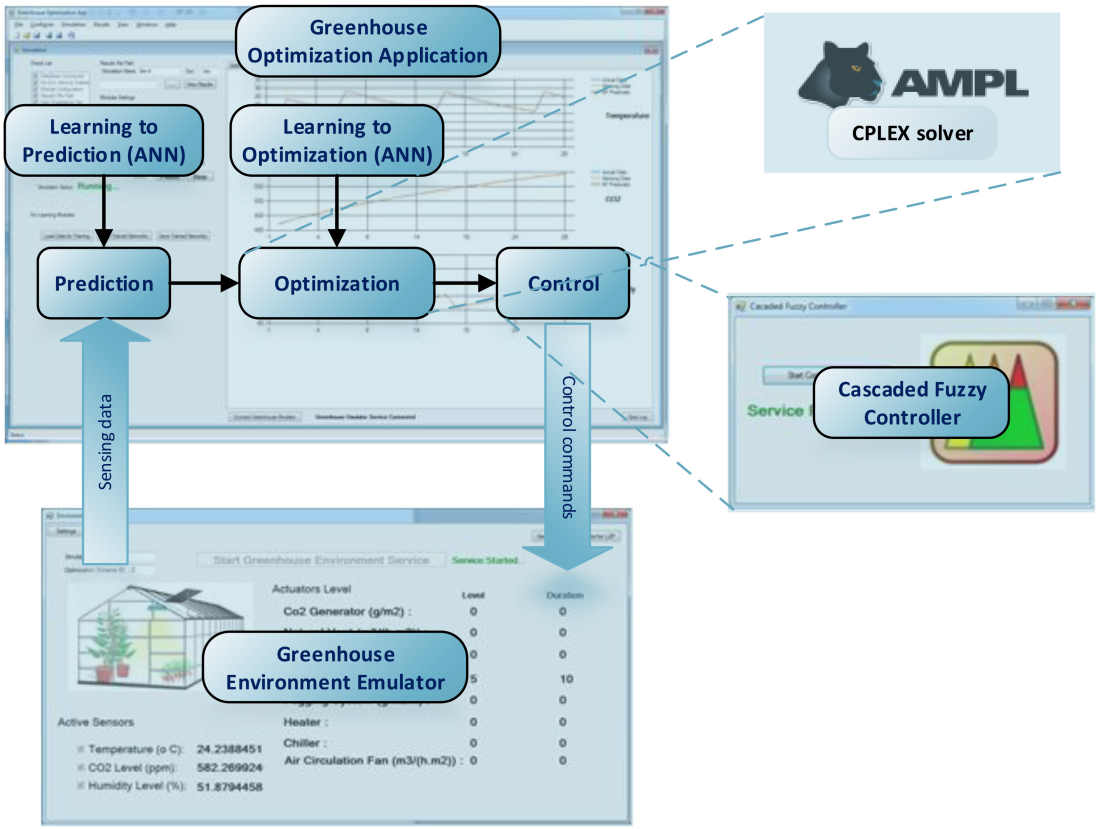


Fig. 9. Illustration of the interaction among the various modules/system components used in the experimental setup.

TABLE III
SYSTEM SPECIFICATION AND TOOLS USED IN THE APPLICATION DEVELOPMENT

| Module | Specifications |
|---|---|
| CPU | Intel Core i3 CPU @3.30GHz |
| Graphics | NVIDIA GeForce 9600 |
| RAM | 16GB |
| Operating System | Window 7 |
| Development Environment | Visual Studio (C#) 2015 |
| Libraries and tools | Accord.Neuro<br>.Net Framework version 4.7 |

$CO_2$, and humidity settings. In addition to these three parameters, these experiments consider solar radiation and wind speed data as these two external parameters are very critical and have a profound impact on the indoor parameters. Table IV provides a short description of the data collected and the desired user settings.

Regarding greenhouse environment modeling, results reported in this study are collected with parameter settings given in Table XI.

### *B. Schemes for Comparative Analysis*

*1) Baseline Scheme:* This approach does not use any optimization scheme and just selects the midpoint of the user-specified range for each parameter when the parameter's current value is outside the desired range. It is expected that this scheme will result in an average level of performance. Its mechanism is straightforward, i.e., the environment inside the farm is checked continuously, and when values of any parameter are observed outside the user-desired range, then respective actuators are activated to control the indoor environment. Technically, this scheme seems to be reasonable, but the outcomes are not according to the expectation. The main aim of the method was to achieve baseline performance. Results labeled as *Optimal (Baseline)* refer to the results obtained through this scheme.

*2) Optimization Scheme (Without Learning Modules):* In this scheme, we have used the objective function given in (30) for the optimization of indoor parameters, i.e., temperature, $CO_2$, and humidity) without learning modules. This scheme considers the fixed values of desired user settings and tries to achieve a tradeoff between energy consumption and the desired indoor environment in order to maintain a productive environment inside the greenhouse from maximizing plant production. This system provides the foundation for our proposed learning to the optimization system.

### *C. Training and Testing of Learning Algorithms*

Repeated experiments are conducted to collect training data for learning modules. Log/trace files were maintained to record essential data during each experiment, e.g., current indoor parameter values, outdoor environmental conditions, and the corresponding operational status of the actuators. The final data set contained 750 records, and 75% of the available data for training and the remainder 25% is used for testing. Various settings of ANN algorithms were tested with different numbers

TABLE IV
DATA SUMMARY AND DESIRED USER CONFIGURATION

| Particulars | | Temperature ($^oC$) | Rel. Humidity (%) | $CO_2$ (ppm) | Solar Radiation (W/m2) | Wind Speed (m/sec) | Electricity Price (won/Kwh) |
|---|---|---|---|---|---|---|---|
| Outdoor parameters values | Min | 11.2 | 42.1 | 403.6 | 0 | 1.22 | 50.1 |
| | Avg. | 17.59 | 85.16 | 405.1 | 115.49 | 19.25 | 85.59 |
| | Max | 26.17 | 98 | 406.75 | 800.14 | 58.87 | 135.5 |
| User desired settings | Min | 25 | 50 | 400 | NA | | |
| | Max | 30 | 60 | 1500 | | | |

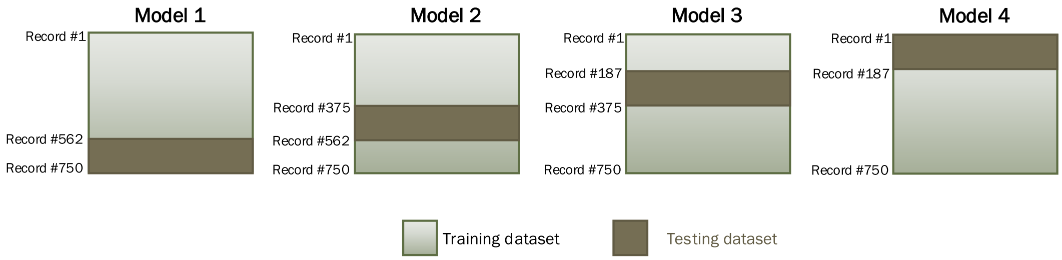


Fig. 10. Training and testing data sets using 4-fold cross-validation model.

of neurons in the hidden layer, adjusting learning rates and activation functions using a 4-fold cross-validation technique to remove training bias as shown in Fig. 10.

For every configuration of ANN, multiple independent experiments are conducted for training and average results are reported to factor out stochastic elements in ANN network weights initialization. Furthermore, to avoid biasness in the training process, a 4-fold cross-validation technique is used for every configuration in all experiments. Fig. 10 illustrates the training and testing data set used for each model in our 4-fold cross-validation process. As per this scheme, 75% of the data is used for training and the remaining 25% is used for testing of ANN algorithm with the selected configuration in each experiment. Table V provides detailed information regarding the selected configuration for ANN and corresponding prediction accuracy in terms of Root mean squared error (RMSE) for training and testing data sets in each model. ANN training algorithm is based on the Levenberg–Marquardt algorithm which is considered to be the best and fastest method for moderate-size neural networks [50]. The maximum number of epochs used to train the ANN network is 100.

Best case results (highlighted in bold) are achieved for the ANN algorithm with a sigmoid activation function for $\alpha = 2$ having 20 neurons in the hidden layer with a learning rate of 0.1. The best trained model is further used for tuning the minimum and maximum values of each greenhouse parameter to boost the performance of the optimization module.

For the best training models, absolute prediction error was within [−0.01, +0.01] for adjustment in minimum and maximum limits of temperature, [−2, +2] for $CO_2$, [−0.02, +0.02] for humidity. RMSE for the error prediction in minimum and maximum values of temperature, $CO_2$ and humidity was 0.006 and 0.006, 1.391 and 3.676, and 0.021 and 0.018, respectively. These trained models were used for making necessary adjustments in the minimum and maximum limits of each parameter during the prediction and optimization process for performance tuning.

TABLE V
ANN ALGORITHM PREDICTION RESULTS IN TERMS OF RMSE FOR TRAINING AND TESTING DATA SETS WITH DIFFERENT CONFIGURATIONS USING 4-FOLD CROSS-VALIDATION MODEL

| ANN Configuration | | | Experiment. No. | Model 1 Accuracy (RMSE) | | Model 2 Accuracy (RMSE) | | Model 3 Accuracy (RMSE) | | Model 4 Accuracy (RMSE) | | Model Avg. | Experiment. Avg. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hidden Layers | Activation Function | Learning Rate | | training set | test set | training set | test set | training set | test set | training set | test set | | |
| 15 | Linear | 0.1 | 1 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | 5.53 |
| | | | 2 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | | | 3 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | | 0.2 | 1 | 0.79 | 1.00 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 4.25 | 5.11 |
| | | | 2 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | | | 3 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | Sigmoid | 0.1 | 1 | 1.05 | 1.25 | 0.97 | 1.20 | 0.97 | 1.19 | 1.10 | 1.31 | 1.24 | 1.18 |
| | | | 2 | 0.96 | 1.14 | 0.97 | 1.21 | 0.96 | 1.19 | 0.81 | 1.05 | 1.15 | |
| | | | 3 | 0.98 | 1.17 | 0.85 | 1.08 | 0.89 | 1.11 | 0.98 | 1.23 | 1.15 | |
| | | 0.2 | 1 | 0.91 | 1.12 | 0.93 | 1.15 | 0.97 | 1.21 | 0.97 | 1.22 | 1.17 | 1.18 |
| | | | 2 | 0.96 | 1.20 | 0.89 | 1.15 | 0.92 | 1.18 | 0.93 | 1.19 | 1.18 | |
| | | | 3 | 0.86 | 1.16 | 0.97 | 1.19 | 0.97 | 1.19 | 0.98 | 1.22 | 1.19 | |
| **20** | Linear | 0.1 | 1 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | 5.53 |
| | | | 2 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | | | 3 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | | 0.2 | 1 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | 5.53 |
| | | | 2 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | | | 3 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | **Sigmoid** | **0.1** | **1** | **0.70** | **0.84** | **0.56** | **0.73** | **0.70** | **0.87** | **0.67** | **0.87** | **0.83** | **0.85** |
| | | | **2** | **0.72** | **0.85** | **0.66** | **0.85** | **0.73** | **0.90** | **0.98** | **0.99** | **0.90** | |
| | | | **3** | **0.74** | **0.86** | **0.57** | **0.76** | **0.54** | **0.71** | **0.77** | **0.96** | **0.82** | |
| | | 0.2 | 1 | 0.76 | 0.89 | 0.65 | 0.83 | 0.79 | 0.98 | 0.80 | 1.00 | 0.92 | 0.94 |
| | | | 2 | 0.81 | 1.00 | 0.76 | 0.95 | 0.75 | 0.93 | 0.74 | 0.94 | 0.95 | |
| | | | 3 | 0.80 | 0.92 | 0.71 | 0.89 | 0.80 | 0.97 | 0.78 | 0.96 | 0.94 | |
| 25 | Linear | 0.1 | 1 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | 5.53 |
| | | | 2 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | | | 3 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | | 0.2 | 1 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | 5.53 |
| | | | 2 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | | | 3 | 5.19 | 6.15 | 5.79 | 4.14 | 5.25 | 6.01 | 5.31 | 5.84 | 5.53 | |
| | Sigmoid | 0.1 | 1 | 1.89 | 1.87 | 1.02 | 1.31 | 1.08 | 1.29 | 0.99 | 1.23 | 1.42 | 1.29 |
| | | | 2 | 0.87 | 1.07 | 0.98 | 1.21 | 0.97 | 1.16 | 1.05 | 1.27 | 1.18 | |
| | | | 3 | 1.32 | 1.41 | 1.08 | 1.32 | 0.97 | 1.18 | 0.94 | 1.19 | 1.28 | |
| | | 0.2 | 1 | 1.02 | 1.19 | 1.31 | 1.87 | 0.93 | 1.19 | 1.14 | 1.36 | 1.40 | 1.26 |
| | | | 2 | 0.99 | 1.17 | 0.97 | 1.21 | 1.01 | 1.26 | 0.95 | 1.19 | 1.21 | |
| | | | 3 | 0.99 | 1.15 | 0.94 | 1.20 | 0.96 | 1.18 | 0.96 | 1.21 | 1.18 | |

## D. *Noise Model for Evaluating Accuracy of Prediction*

The results of simulations are gathered with a maximum-based model of the error to illustrate the gain in accuracy by learning the prediction scheme. Variable error in sensor readings is supposed to be dependent on external parameters and operational level actuators using uniform distribution to produce dynamically changing conditions. The amount of

TABLE VI
SUMMARY OF ERROR MEASURES USING MAXIMUM BASED MODEL IN TEMPERATURE, $CO_2$, AND HUMIDITY SENSOR READINGS

| Measure | Temperature | $CO_2$ | Humidity |
|---|---|---|---|
| Min Error | -5 | -49 | -5 |
| Average Error | 0.05 | -0.39 | -0.26 |
| Max Error | 4 | 33 | 4 |

error is introduced randomly but is proportional to the maximum error component accumulated for each parameter. In other words, noisy sensor readings using the following expressions are produced for temperature ($\text{sen}_T$), humidity ($\text{sen}_H$), and $CO_2$ ($\text{sen}_C$):

$$\text{sen}_T = GH_T + \text{err}_T \cdot N(-1, 1) \cdot S_T \tag{48}$$

$$\text{sen}_H = GH_H + \text{err}_H \cdot N(-1, 1) \cdot S_H \tag{49}$$

$$\text{sen}_C = GH_C + \text{err}_C \cdot N(-1, 1) \cdot S_C \tag{50}$$

where $GH_T$, $GH_H$, and $GH_C$ denotes the real temperature, humidity, and $CO_2$ level of the greenhouse. The error scaling factor for temperature, humidity, and $CO_2$ level is $S_T$, $S_H$, and $S_C$ and in this study, the results are collected with $S_T = 5$, $S_H = 5$, and $S_C = 50$ using the maximum-based model. Using uniform distribution, $N(-1, +1)$ is a random number generator between $-1$ and $+1$. The cumulative error factor for temperature ($\text{err}_T$), humidity ($\text{err}_H$), and degree of $CO_2$ ($\text{err}_C$) are determined based on the maximum normalized error factor.

Table VI provides the description of the resulting error in temperature, $CO_2$ and humidity sensor measurements obtained from experimental results.

Table VII presents the configuration summary for the three schemes used in the experimental analysis. The cascaded fuzzy controller is used with all schemes and the maximum-based model is used for generating an error in sensor readings.

## VI. RESULTS AND DISCUSSION

### A. Comparative Analysis of Prediction Results

A comparative analysis of the prediction module shows that in predicting the real indoor parameter values from noisy sensor readings, the proposed learning to prediction scheme performs better than the other two schemes. A detailed discussion can be found in [44] on the results of the prediction module. For quantifiable comparative analysis, four different methods are used to statistically evaluate the prediction results: mean absolute deviation (MAD), mean squared error (MSE), RMSE, and mean absolute percentage error (MAPE). In order to summarize the results in the form of a single statistical value, statistical measures are used. Table VIII presents the statistical overview of the prediction results of the three different schemes for each of the greenhouse parameters. We used $R = 10$ for the Kalman filter in the case of experiments performed without a learning module for the Kalman filter. Similarly, the Kalman filter with the ANN learning module is collected with the best error factor value, i.e., $F = 0.1$. Comparative analysis reveals that on all statistical tests, the Kalman filter with proposed learning to predict model outcomes outperforms the two other schemes.

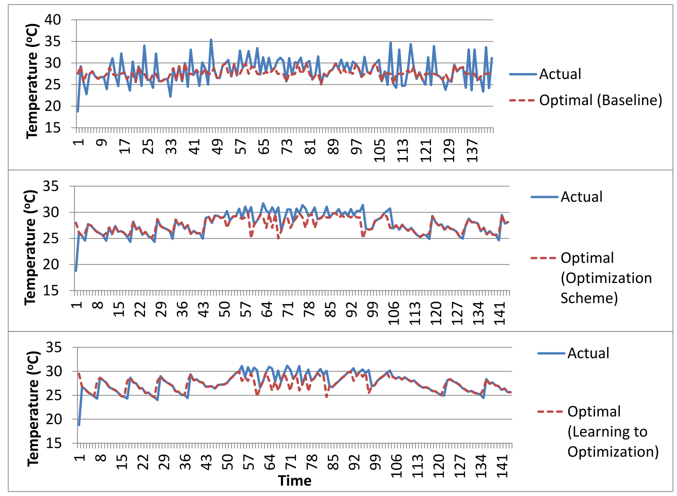


Fig. 11. Temperature optimization results for the three schemes.

In comparison with the results of the baseline and Kalman filter without a learning module, substantial relative improvement is observed in the prediction accuracy of the proposed learning to prediction model and this is proportional to the amount of error. In $CO_2$, for example, absolute error is greater and, thus, relative improvement of the proposed scheme is also greater for sensor readings of $CO_2$. Finally, predicted parameter values serve as input to the next part, i.e., optimization which treats these predicted values as actual parameter values of the greenhouse.

### B. Analysis of Optimization Results

We consider external environment parameters to remain the same for 10 min in our simulation model as per the collected data. The first part of our optimization formula (30) controls the greenhouse parameters level such that the maximum productive environment can be maintained as per user-specified settings. Getting the optimal setting for each parameter will result in increased energy consumption, which is controlled in the second part of the optimization function to achieve energy optimization.

As previously described that the optimal values for indoor parameters shall be within the user-desired range [Min, Max] as shown in Table IV. Our proposed optimization scheme attempts to select an optimal point that results in minimum power consumption while maintaining the desired climate condition in the greenhouse. Fig. 11 presents optimized settings for greenhouse temperature as per the three schemes.

Actual data indicate the environmental parameter values before optimization. These results illustrate the impact of optimization on the indoor parameters, and one can easily extract the amount of change made in each parameter by comparing the corresponding actual and optimized values. For instance, in Fig. 11, the initial indoor temperature is 17.49 °C and the corresponding optimal temperature was set to 27.5 °C in the baseline scheme, 28 °C in the optimization scheme, and 29.47 °C in the proposed learning to optimization scheme. The heater actuator is operated accordingly to rise the greenhouse indoor temperature level.

TABLE VII
SIMULATION SCENARIOS FOR PERFORMANCE ANALYSIS

| **Scheme** | **Prediction** | **Optimization** | **Control** | **Noise Model** |
|---|---|---|---|---|
| Baseline | - | Rule based optimization (Baseline) | Cascaded Fuzzy Controller | Maximum based Model |
| Optimization | Kalman filter | Mathematical model (optimization scheme) | | |
| Learning to optimization | Learning to Kalman filter | Mathematical model with learning module | | |

TABLE VIII
STATISTICAL SUMMARY OF PREDICTION PART RESULTS

| **Indoor Parameter** | **Scheme** | **Statistical Measure** | | | |
|---|---|---|---|---|---|
| | | **MAD** | **MSE** | **RMSE** | **MAPE** |
| Temperature | Baseline Scheme | 0.3 | 0.64 | 0.8 | 1.05 |
| | Predicted (Optimization Scheme) | 0.09 | 0.07 | 0.26 | 0.34 |
| | Predicted (Learning to Optimization Scheme) | **0.07** | **0.04** | **0.2** | **0.28** |
| $CO_2$ | Baseline Scheme | 2.19 | 39.19 | 6.26 | 0.38 |
| | Predicted (Optimization Scheme) | 0.81 | 5.16 | 2.27 | 0.14 |
| | Predicted (Learning to Optimization Scheme) | **0.37** | **1.67** | **1.29** | **0.07** |
| Humidity | Baseline Scheme | 0.34 | 0.97 | 0.98 | 0.61 |
| | Predicted (Optimization Scheme) | 0.09 | 0.06 | 0.25 | 0.16 |
| | Predicted (Learning to Optimization Scheme) | **0.05** | **0.02** | **0.14** | **0.09** |

The rise in indoor temperature can be observed in the second interval. Next, constant fluctuation in indoor temperature can be seen, that is because of low external temperature which is dragging down the indoor temperature. The optimization scheme is trying to maintain the indoor temperature within the user-desired range, i.e., [25–30]. More fluctuation in indoor temperature values indicates the improper setting of optimal points and improper operation of actuators which results in more energy consumption. Temperature optimization results for the Baseline scheme show that its fluctuation is much higher than the other two schemes so as the resultant energy consumption. Moreover, it can be noticed that the Baseline scheme does not always set the mid-point as the optimal point and this is when the current temperature is within the user's desired range. In which case, no need of performing optimization. Whenever actual temperature values go out of use desired range (i.e., [25, 30] for temperature) then the Baseline scheme simply set midpoint (27.5 °C) as optimal temperature. The optimization scheme selects the optimal point using (30) to establish a tradeoff between desired environmental settings and corresponding energy consumption. In the proposed learning to optimization scheme, first, we compute the necessary adjustment values in user-defined ranges through ANN-based learning modules and afterward, optimization is performed using adjusted ranges. Furthermore, optimization results also show that temperature values suffer more fluctuation during the daytime and this is where greenhouse temperature rises due to solar radiation which also results in an increase in humidity. More activity is performed during the daytime, therefore, it is relatively harder to maintain a stable environment in the greenhouse.

Similarly, in Fig. 12, initial indoor $CO_2$ level is 420 (ppm) which is within user-desired range for $CO_2$, i.e., [400, 1500]. However, a gradual increase in the $CO_2$ level can be observed and this is due to the respiration process by plants in the greenhouse. Around 07:00 A.M. in the morning after sunrise, then a gradual decrease in $CO_2$ can be observed due

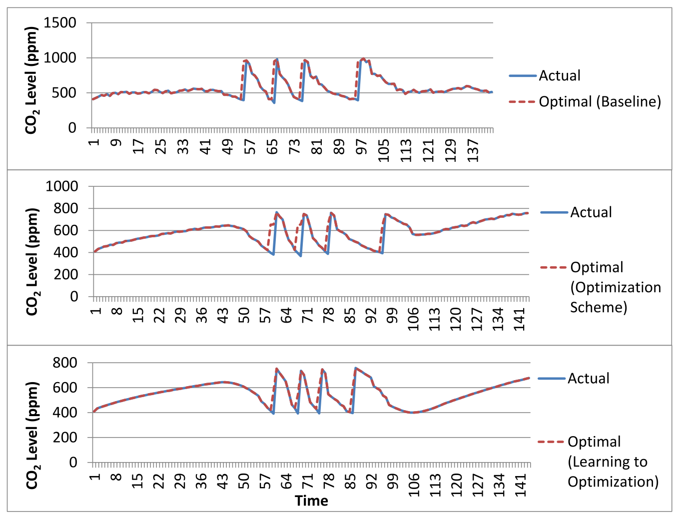


Fig. 12. $CO_2$ optimization results for the three schemes.

photosynthesis process. Around 09:00 A.M., $CO_2$ drop below 400 ppm and then the $CO_2$ generator is operated and the $CO_2$ level is increased. The optimization process ensures the indoor $CO_2$ level to be inside the user-preferred settings, i.e., [400, 1500]. Whenever, actual $CO_2$ values goes below the minimum limit (i.e., 400 ppm for $CO_2$) then Baseline scheme simply set midpoint $((400 + 1500)/2 = 950$ ppm) as optimal $CO_2$ level. The optimization scheme selects the optimal point using 30 to establish a tradeoff between the desired environmental setting and corresponding energy consumption. In the proposed learning to optimization scheme, first, we compute the necessary adjustment values in user-defined ranges using ANN-based learning modules, and afterward, optimization is performed using adjusted ranges. Just like temperature results, optimization results of $CO_2$ also suffer more fluctuation during the daytime and this is when the photosynthesis process is active in the greenhouse and indoor $CO_2$ drops quickly below

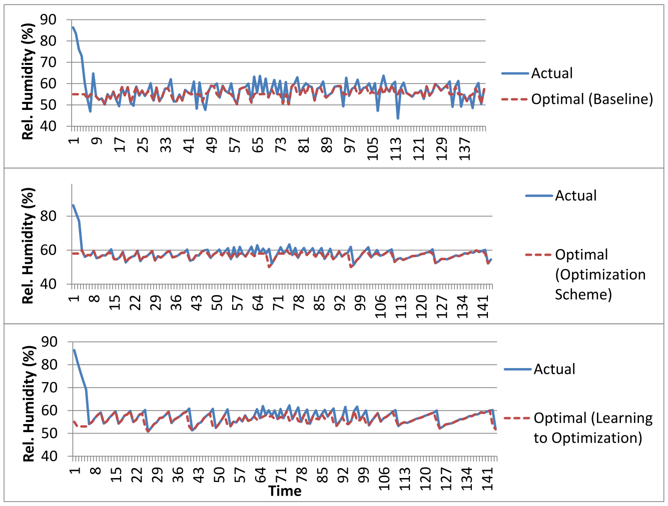


Fig. 13. Humidity optimization results for the three schemes.

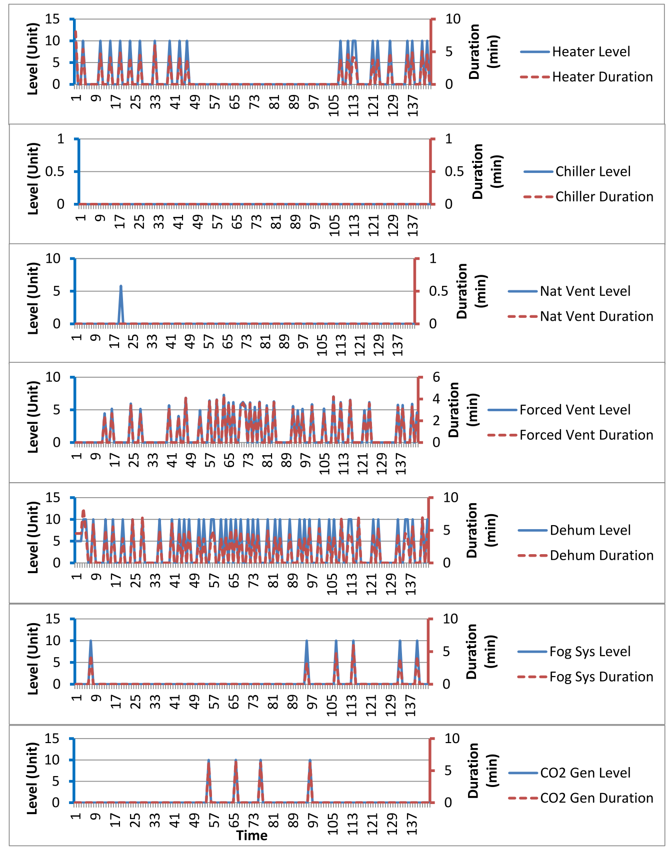


Fig. 14. Actuator operational results for the Baseline scheme.

the desired range. Furthermore, ventilation operation also has a negative impact on indoor $CO_2$ concentration. Toward the end of the day, i.e., after sunset, a gradual rise in $CO_2$ can be observed due to respiration.

Similarly, optimization results for indoor humidity are given in Fig. 13. Weather data used in these experiments are collected for Jeju Island during the month of October and external humidity is very high during this time of year. The initial indoor humidity of the greenhouse is 86.08% and the corresponding optimal humidity level was set to 55% in the baseline scheme, 58% in the optimization scheme, and 55.02% in the proposed learning to optimization scheme. The dehumidifier actuator is operated accordingly to reduce greenhouse indoor humidity levels. The gradual decrease in indoor humidity can be observed from the second interval. Afterward, a constant fluctuation in indoor humidity is observed, which is due to the high external humidity level, which results in the increase of the indoor humidity, whereas the optimization process is trying to keep it within the user-desired range [50, 60]. More fluctuation in indoor humidity values indicates the improper setting of optimal points and improper operation of actuators which results in more energy consumption. Humidity optimization results for the Baseline scheme shows that its fluctuation is much higher than the other two scheme so as the resultant energy consumption. Moreover, it can be noticed that the Baseline does not always set the mid-point as an optimal point and this is where is current humidity is within the user's desired range. In which case, no need of performing optimization. Whenever indoor humidity goes above of maximum desired limit (i.e., 60 for humidity) then the Baseline scheme simply sets the midpoint (55%) as the optimal humidity level. The optimization scheme selects the optimal point using 30 to establish a tradeoff between the desired environmental setting and corresponding energy consumption. In the proposed learning to optimization scheme, first, we compute the necessary adjustment values in user-defined ranges for humidity using an ANN-based learning module, and afterward, optimization is performed using the adjusted ranges. Furthermore, optimization results also show that humidity values also suffer more fluctuation during the daytime because greenhouse humidity rises due to an increase in evaporation due to solar radiation.

Fluctuations in indoor parameters can be better explained and understood when these results are analyzed together with the corresponding actuators' operation. In the next section, we present a detailed discussion on the actuator's control results for each scheme.

### C. Analysis of Actuators Control Results

In this case study, the cascaded fuzzy controller is used for all three schemes but corresponding actuator operation results are different for each scheme. This is due to the fact that this module makes the decision based on the inputs received from previous parts, i.e., prediction parameters values and optimized parameters. Fig. 14 presents actuator operational status results for the baseline scheme for the duration of one day. It can be seen that a chiller is never used as the outdoor temperature is cold in the collected environmental data used in this study (cooling of the greenhouse is not needed). Similarly, external humidity is very high, therefore, no need to use a fogging system. In the beginning, the indoor temperature is very low (17.49 °C) and humidity is very high (86.08%), therefore the heater and dehumidifier are activated to maintain desired settings. Afterward, the heater and dehumidifier are operated after certain intervals when

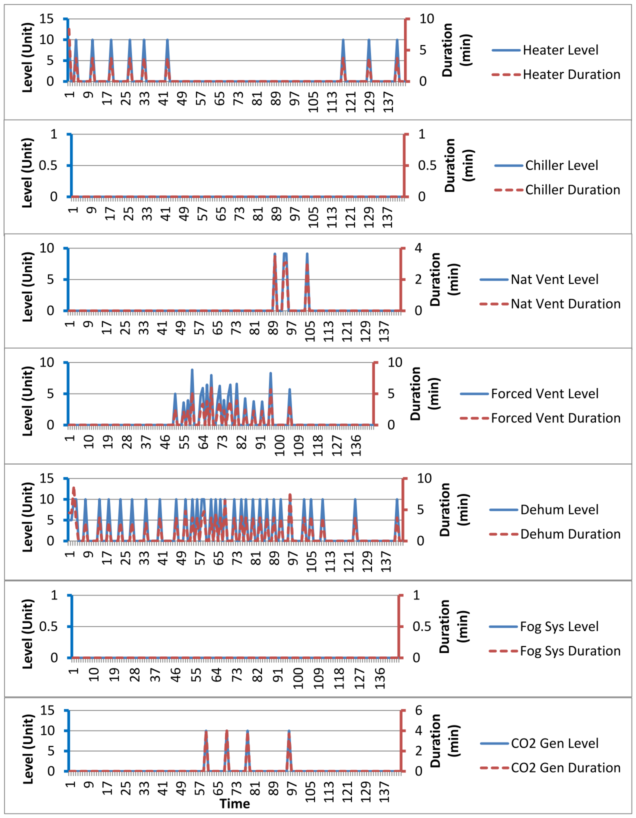


Fig. 15. Actuator operational results for the Optimization scheme.

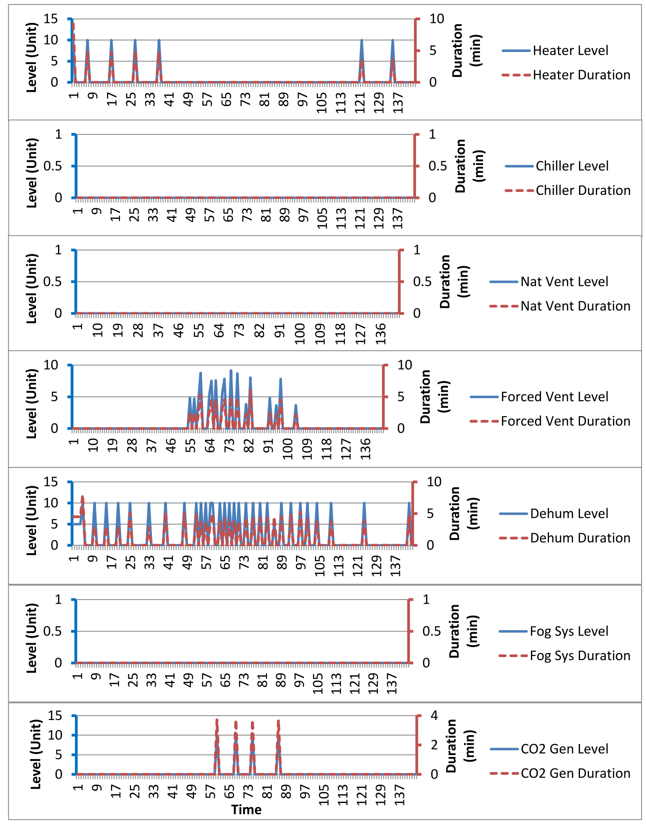


Fig. 16. Actuator operational results for learning to optimization scheme.

indoor temperature drops below the desired minimum level and humidity increases above the maximum limit. However, during mid-day, the heater and dehumidifier are frequently operated and this can be better explained and understood if these results are analyzed together with corresponding indoor parameter settings. During the daytime, temperature values suffer more fluctuation because greenhouse temperature rises due to solar radiation which also results in an increase in the humidity. More activity is performed during the daytime, therefore, it is relatively harder to maintain a stable environment in the greenhouse. Whenever the indoor temperature level goes beyond the desired range then forced ventilation is performed which helps in maintaining the indoor temperature. But as a result of forced ventilation, indoor humidity rises as outdoor humidity is very high therefore dehumidifier is operated.

During the daytime, the indoor temperature rises frequently and then very rapidly dropped due to forced ventilation. However, forced ventilation results in an increase in the humidity due to higher external humidity levels and, hence, the dehumidifier needs to be operated frequently.

Fig. 15 presents actuator operational status results for the optimization scheme for the duration of one day. Just like the baseline scheme results, in the optimization scheme, the chiller is never used as the outdoor temperature is cold in the collected environmental data used in this study (cooling of the greenhouse is not needed). Similarly, external humidity is very high therefore no need to use a fogging system. In the beginning, the indoor temperature is very low (17.49 °C) and humidity is very high (86.08%) therefore, the heater and dehumidifier are activated to maintain desired settings. Afterward, the heater and dehumidifier are operated after certain intervals when indoor temperature drops below the desired minimum level and humidity increases above the maximum limit. However, during mid-day heater and dehumidifier are frequently operated and this can be better explained and understood these results are analyzed together with corresponding indoor parameter settings. During the daytime, temperature values suffer more fluctuation due to solar radiation which also results in an increase in the humidity. More activity is performed during the daytime and, therefore, it is relatively harder to maintain a stable environment in the greenhouse. Whenever the indoor temperature level goes beyond the desired range then forced ventilation is performed which helps in maintaining the indoor temperature. But as a result of forced ventilation, indoor humidity rises as outdoor humidity is very

TABLE IX
POWER CONSUMPTION RATINGS OF GREENHOUSE ACTUATORS

| S. No. | Actuators | Power Rating (Watts) |
|---|---|---|
| 1 | Heater | 20500-25000 |
| 2 | Chiller | 20500-25000 |
| 3 | Forced ventilation Fan | 703-1000 |
| 4 | Natural Ventilation | 110-200 |
| 5 | Dehumidifier | 703-1000 |
| 6 | Fogging System | 230-500 |
| 7 | $CO_2$ Generator | 230-550 |

TABLE X
COMPARATIVE ANALYSIS OF TOTAL POWER CONSUMPTION AND TOTAL OPERATIONAL COST

| Scheme | Total Power Consumption (kWh) | Total Cost(won) |
|---|---|---|
| Baseline Scheme | 48.46 | 3937.03 |
| Optimization Scheme | 20.88 | 1442.48 |
| Learning to Optimization Scheme (proposed) | 18.43 | 1261.28 |

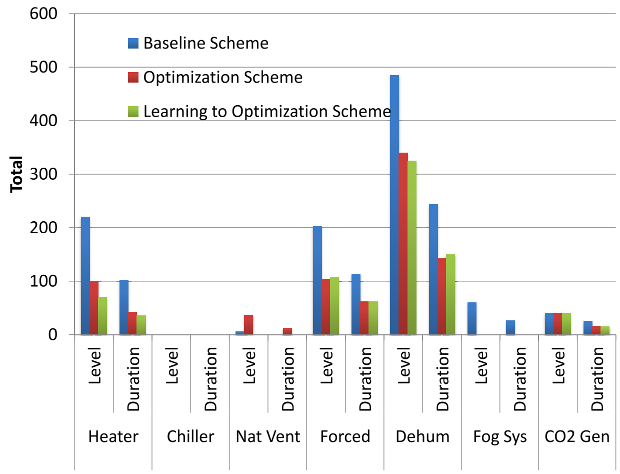


Fig. 17. Comparative analysis of greenhouse actuators' total level and duration results.

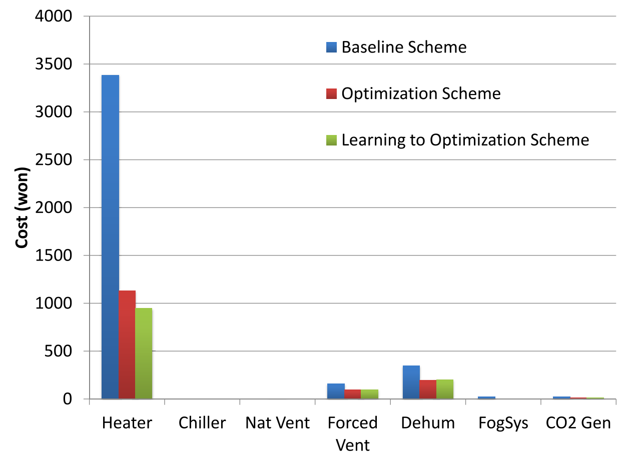


Fig. 19. Comparative analysis of greenhouse actuators' operational cost.

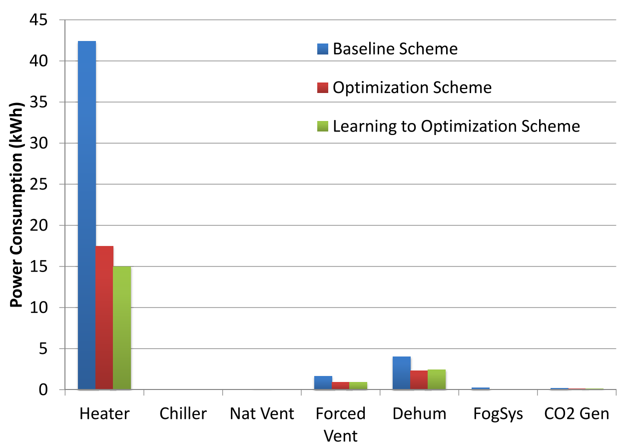


Fig. 18. Comparative analysis of greenhouse actuators' power consumption.

high so the dehumidifier is operated. Compared to baseline scheme results, optimization scheme results for heater operation is relatively stable, i.e., the heater is less frequently operated. This is due to a better optimal point selection by the optimization scheme. During the daytime, when the temperature rises above 30 °C, then the optimization algorithm selects the optimal point closer to 25 °C. Afterward, there is a gradual increase in indoor temperature and after some time, ventilation is performed again to stabilize the indoor temperature. The $CO_2$ generator is also operated a few times during the daytime to overcome $CO_2$ deficiency as a result of the high photosynthesis process in the presence of sunlight.

Fig. 16 presents actuator operational status results for the proposed learning to optimization scheme for the duration of one day. Just like the other two schemes' results, in this scheme, the chiller and fogging system are never operated. In the beginning, the indoor temperature is very low (17.49 °C) and humidity is very high (86.08%) therefore, the heater and dehumidifier are activated to maintain desired settings. Afterward, the heater and dehumidifier are operated after certain intervals when indoor temperature drops below the desired minimum level and humidity increases above the maximum limit. Compared to the other two schemes, the heater and dehumidifier are less frequently operated in the proposed learning to optimization scheme. This can be better explained and understood if these results are analyzed together with the corresponding indoor parameter settings. Whenever indoor temperature level goes beyond the desired range then depending upon the environmental conditions, learning to optimization scheme intelligently pushes the boundaries of user-desired settings either toward lower or upper bound. Through this manipulation of user-defined ranges, the underlying optimization process is forced to select the optimal points within desired limits, i.e., either closer toward lower or upper bounds. For instance, during mid-day, when the temperature crosses the upper bound then learning to optimization scheme selects an optimal point very close to 25 °C and it takes a longer period of time for the indoor temperature to rise and cross the upper bound. Thus, the heater is turned off for a longer period of time, i.e., less frequently operated and more energy is saved. Similarly, in the beginning, and toward the end, learning to optimization scheme selects an optimal point closer to the upper bound such that it takes more time in temperature dropping to cross the lower bound under the influence of external cold temperature. As a result, more energy is saved. The same holds true for humidity-level maintenance. As external humidity is high and indoor humidity can quickly rise above the upper bound, therefore learning to optimization

TABLE XI
PARAMETER SETTINGS FOR THE GREENHOUSE MODEL SIMULATION

| S. No. | Parameter | Description | Values/Range |
|---|---|---|---|
| 1 | $G_l$ | Length of greenhouse | 100ft |
| 2 | $G_w$ | Width of greenhouse | 25ft |
| 3 | $G_{sh}$ | Greenhouse side height | 9ft |
| 4 | $G_{rh}$ | Greenhouse roof height | 13ft |
| 5 | $G_{area}$ | Greenhouse area | 2500ft$^2$ |
| 6 | $G_{sa}$ | Greenhouse surface area | 3500ft$^2$ |
| 7 | $G_{vol}$ | Greenhouse volume | 27500ft$^3$ |
| 8 | $sim_{interval}$ | Simulation interval length | 10min |
| 9 | $\tau$ | Number of intervals per hour | 6 |
| 10 | $\mu_{leak}$ | Percentage air exchange per hour due to large and small gaps | 0.20% |
| 11 | $SR_{max}$ | Maximum solar radiation | 1000W/m$^2$ |
| 12 | $\mu_{nv}$ | Percentage air exchange per hour due to natural ventilation level 1 | 0.50% |
| 13 | $WS_{avg}$ | Average wind speed | 18Km/h |
| 14 | $CFM_{fv}$ | Air exchange cubic feet per minute by forced ventilation level 1 | 1750ft$^3$/min |
| 15 | $\varphi_{sr}$ | Light transmission factor of greenhouse material (cover) | 0.70% |
| 16 | $\varphi_{wl}$ | Heat transfer coefficient of greenhouse walls | 2.78kJ/tCm$^2$ |
| 17 | $C$ | Total heat capacity of greenhouse | 625000kJ/C |
| 18 | $\theta_{h_{max}}$ | Max change in greenhouse temperature when heater is operated at maximum level | $10^oC$ |
| 19 | $\theta_{c_{max}}$ | Max change in greenhouse temperature when chiller is operated at maximum level | $10^oC$ |
| 20 | $H_{level_{max}}$ | Maximum operational level of heater | 10 |
| 21 | $C_{level_{max}}$ | Maximum operational level of chiller | 10 |
| 22 | $\varphi_{res}$ | Respiration coefficient by the greenhouse plants | 0.5g/m$^2$tC |
| 23 | $\vartheta_{res_{max}}$ | Maximum increase in $CO_2$ concentration due to respiration | 20ppm |
| 24 | $\varphi_{ps}$ | Photosynthesis coefficient of the greenhouse plants | 0.5g/J |
| 25 | $\vartheta_{ps_{max}}$ | Maximum decrease in $CO_2$ concentration due to photosynthesis | 100ppm |
| 26 | $\vartheta_{gen_{max}}$ | Max increase in the $CO_2$ concentration when $CO_2$ generator is operated at maximum level | 1000ppm |
| 27 | $CG_{level_{max}}$ | Maximum operational level of $CO_2$ generator | 10 |
| 28 | $\varphi_{ev}$ | Evaporation and transpiration coefficient of the greenhouse plants | 0.50% |
| 29 | $\sigma_{ev_{max}}$ | Maximum increase in humidity due to Evaporation and transpiration | 10 |
| 30 | $\sigma_{fog_{max}}$ | Max increase in the humidity when fogging system is operated at maximum level | 20 |
| 31 | $FS_{level_{max}}$ | Maximum operational level of fogging system | 10 |
| 32 | $\sigma_{deh_{max}}$ | Max decrease in the humidity when dehumidifier is operated at maximum level | 20 |
| 33 | $DH_{level_{max}}$ | Maximum operational level of dehumidifier | 10 |

scheme selects optimal point for indoor humidity very close to the lower bound, i.e., 50%. Thus, the dehumidifier is less frequently operated.

Fig. 17 presents the summary of the actuator's performance by the three schemes in terms of total operational level and duration for each actuating device. We can see that heater,

TABLE XI
*(Continued.)* PARAMETER SETTINGS FOR THE GREENHOUSE MODEL SIMULATION

| | | | |
|---|---|---|---|
| 34 | $\alpha_p$ | Weight assigned to desired parameters settings | 0.5 |
| 35 | $\alpha_e$ | Weight assigned to energy savings | 0.5 |
| 36 | $w_T$ | Weight assigned to temperature settings | 0.4 |
| 37 | $w_H$ | Weight assigned to humidity settings | 0.3 |
| 38 | $w_C$ | Weight assigned to $CO_2$ settings | 0.3 |
| 39 | $T_{min}$ | User specified minimum temperature | 25$^o$C |
| 40 | $T_{max}$ | User specified maximum temperature | 30$^o$C |
| 41 | $H_{min}$ | User specified minimum humidity | 50% |
| 42 | $H_{max}$ | User specified maximum humidity | 60% |
| 43 | $C_{min}$ | User specified minimum $CO_2$ | 400ppm |
| 44 | $C_{max}$ | User specified maximum $CO_2$ | 1500ppm |

TABLE XII
CONFIGURATION SUMMARY OF ANN-BASED LEARNING MODULES FOR GREENHOUSE INDOOR PARAMETER OPTIMIZATION

| S. No. | Learning Module | Inputs | Hidden Layer | Outputs |
|---|---|---|---|---|
| 1 | ANN based Learning Module for making adjustment in user defined ranges for Temperature | 1. External Temperature<br>2. Wind Speed<br>3. Electricity price<br>4. Predicted indoor temperature<br>5. $T_{min}$<br>6. $T_{max}$ | 20 Neurons,<br>Activation Function= Sigmoid ($\alpha = 2$),<br>Learning algorithm= Levenberg-Marquardt<br>Learning rate=0.1 | Predicted adjustment $A_{min}$ and $A_{max}$ in minimum and maximum temperature i.e.<br>$T_{min}$ = $T_{min}$ +$A_{min}$<br>$T_{max}$ = $T_{max}$ +$A_{max}$ |
| 2 | ANN based Learning Module for making adjustment in user defined ranges for $CO_2$ | 1. External $CO_2$ level<br>2. Solar radiation<br>3. Electricity price<br>4. Predicted indoor $CO_2$<br>5. $C_{min}$<br>6. $C_{max}$ | 20 Neurons,<br>Activation Function= Sigmoid ($\alpha = 2$),<br>Learning algorithm= Levenberg-Marquardt<br>Learning rate=0.1 | Predicted adjustment $A_{min}$ and $A_{max}$ in minimum and maximum $CO_2$ i.e.<br>$C_{min}$ = $C_{min}$ +$A_{min}$<br>$C_{max}$ = $C_{max}$ +$A_{max}$ |
| 3 | ANN based Learning Module for making adjustment in user defined ranges for Humidity | 1. External Humidity<br>2. Electricity price<br>3. Predicted Humidity<br>4. $H_{min}$<br>5. $H_{max}$ | 20 Neurons,<br>Activation Function= Sigmoid ($\alpha = 2$),<br>Learning algorithm= Levenberg-Marquardt<br>Learning rate=0.1 | Predicted adjustment $A_{min}$ and $A_{max}$ in minimum and maximum humidity i.e.<br>$H_{min}$ = $H_{min}$ +$A_{min}$<br>$H_{max}$ = $H_{max}$ +$A_{max}$ |

forced ventilation, and dehumidifier are three actuators that are most frequently operated. The $CO_2$ generator is almost equally utilized by the three schemes. Furthermore, it also shows that learning to optimization scheme achieves the best performance as it maintains the desired environment in the greenhouse through the minimal operation of actuators. Although the dehumidifier is the most used actuator, it is not as expensive as the heater. Next, we present a performance analysis in terms of cost and power consumption.

### *D. Cost and Power Consumption Analysis*

In order to conduct cost and power consumption analysis, power ratings are assigned to the greenhouse actuators. Table IX presents the typical power ratings for greenhouse actuators. Every actuator is assumed to operate at multilevels (level 1 to level 10) with different power consumption. For instance, the power rating for heater level 1 is 20 500 W and it gradually increases and the highest level 10 has a maximum power rating, i.e., 25 000 W. The same applies to all other actuators.

As heater and chiller power ratings are significantly higher than the other actuators' power ratings, therefore, it is very important to carefully operate these actuators to save maximum energy. Fig. 18 presents the comparative analysis of power consumption by the three schemes. Power consumption by the heater is the dominating factor in all three schemes and the proposed learning to optimization scheme achieves minimal power consumption as compared to the other two schemes.

For the performance comparison of operational cost, variable pricing rate is considered for a typical winter day [51] as the data used in this study were collected for October (which is the beginning of winter in Jeju). Fig. 19 presents the comparative analysis of actuators' operational cost by the three schemes. Being the most expensive actuator, the operational cost of the heater is the dominating factor, and the proposed learning to optimization scheme achieves minimal operational cost as compared to the other two schemes.

Table X shows the total power consumption and the corresponding cost of the three schemes. Comparative analysis shows that the proposed model maintains the desired indoor environment for maximizing plant production with reduced energy consumption, i.e., it achieves 61.97% reduced energy consumption than the baseline scheme, 11.73% better than the optimization scheme without learning modules. Furthermore, the proposed model achieves 67.96% and 12.56% reduction in cost when compared to the baseline scheme and optimization scheme without learning modules, respectively. Improved energy efficiency in the simulation environment gives us the confidence to further explore the application of the proposed system in a real environment for achieving better energy efficiency.

## VII. Conclusion and Future Work

In this article, we have proposed an integrated solution based on prediction, optimization, and control components with learning modules to efficiently control the greenhouse environment with reduced energy consumption. The contributions of this study are briefly summarized as follows.

1) An integrated solution based on prediction, novel optimization scheme, and control components was developed and demonstrated for greenhouse environment optimization. The Kalman filter algorithm was used for prediction, a mathematical model for optimization, and a cascaded fuzzy controller for greenhouse actuators control.
2) For the performance improvement of the proposed approach, ANN-based learning modules were used, which helped in the autonomous control of the greenhouse environment with reduced energy consumption.
3) The mathematical model of the greenhouse environment was presented, considering the impact of essential processes, actuators' operations, and external weather conditions. The greenhouse environment was emulated through mathematical modeling.
4) The proposed model evaluation and experimental analysis were conducted in a realistic greenhouse environment to demonstrate the feasibility and effectiveness of the proposed approach. In the simulation environment, improved energy efficiency gives us motivation to further explore the implementation of the proposed system in a real-world environment. To that end, the system design was kept sufficiently flexible to serve as a basis for a complete solution and to provide various other sensor details, such as lighting level, watering schedule, etc.

The proposed learning-based optimization scheme results were compared with two other schemes, i.e., baseline scheme and optimization scheme. The comparative analysis showed that our proposed model maintains the desired indoor environment for maximizing plant production with reduced energy consumption, i.e., it achieved 61.97% reduced energy consumption than the baseline scheme, and 11.73% better than the optimization scheme without learning modules. Furthermore, the proposed model achieved 67.96% and 12.56% reduction in cost when compared to the baseline scheme and optimization scheme without learning modules, respectively.

In the future, we look forward to expanding this research in two directions: 1) explore the utility of deep learning algorithms (instead of ANN) for parameter tuning of the underlying prediction and optimization modules and 2) performing experimental analysis with big data in more complex real-world applications to further assess the validity of the proposed learning to prediction and optimization schemes.

## Appendix

See Tables XI and XII.

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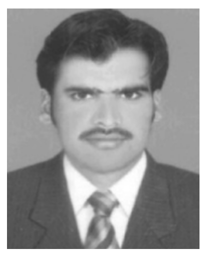

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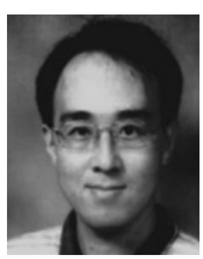

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