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Hydroponic Greenhouse Crop Optimization*

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***Abstract*—This article describes the work that was developed to model and control the inside environmental conditions, temperature, humidity, nutrients, and luminosity, of a small hydroponic greenhouse prototype to obtain optimal plant growth. Greenhouses are transparent constructions that use solar energy to allow plants to grow in a closed controlled environment. It is expected that greenhouses will play an increasing important role due the impact of climate changes on the traditional methods of food/crop production.**

***Index Terms*—Greenhouse, hydroponics, automation, optimal control, logistic model.**

I. INTRODUCTION

As the world population continues to increase and the expected climate changes impact, there is a need for improvements on the efficiency of crop growth. One possible approach to tackle this problem is to use greenhouses, where environmental variables can be controlled to obtain optimal conditions for plant growth. Greenhouses are transparent constructions that allow plants to grow in a closed controlled environment, where the inside temperature, humidity and luminosity are adjusted. These controlled environmental conditions can be complemented with hydroponics, a method of growing plants without soil. In this way, the plants' roots will get nutrients and oxygen from a water oxygenated solution with dissolved mineral nutrients and improve the plant growth rate.

Greenhouses and hydroponics are not a novelty, but there is a lot of room for improvement with the advance of technology. Greenhouses and hydroponics have been widely used for several decades to increase crop growth. In Doirymple's 1973 review of greenhouse food production [2], besides these two techniques, other strategies of environmental control were tested. Carbon dioxide started to be an object of study on plant growth, in addition to humidity, light and temperature. These variables were controlled through basic mechanical and electronic devices such as timers and fans.

More recently, though, food production benefits from smarter and more complex and efficient technology. Countries such as the US, The Netherlands, and China have been investing heavily in crop growth automation technology that brings much higher yields. By using sensors and actuators, autonomous crop growth can be done [10], reducing thus the burden of time-consuming and physically challenging agriculture tasks. This objective can be done with optimal policies to increase the production efficiency and to decrease costs. Growing plants in extreme conditions, where natural crop growth would not be possible at all is another interesting possibility. Places with extremely adverse weather conditions, and even in space, are motivational examples.

The main goal of this work is to develop an efficient automated soilless greenhouse, that allows users to remotely monitor and control crop growth and environmental conditions. Regarding this systen, four main objectives are considered:

1) Build a physical smart greenhouse with all required sensors, actuators and computers;
2) Fit experimental data to environmental and crop growth models;
3) Develop and implement optimal control strategies to efficiently reduce acting costs while increasing crop growth; and
4) Connect the greenhouse to the Internet and implement a web-based graphical user interface.

This article is organized as follows. Section II describes the greenhouse prototype developed. Section III addresses the modeling and control of the greenhouse temperature and humidity and shows experimental results. The objective is to impose adequate environmental condition for the crop growth. The modeling process and the optimization of the crop growth is described in the section IV. The description of the plant growth is approximated by a logistic model that is used in conjunction with optimal control theory to define optimal strategies, to adjust the nutritive solution concentration, the amount of daily light and the optimal harvest day. The conclusions are presented in the last section.

II. GREENHOUSE PROTOTYPE DESCRIPTION

To explore the application of control methodologies, a cheap, small size ($75cm \times 55cm \times 55cm$), real hydroponic greenhouse was build, pictured in Figure 1(a). With this platform it is possible to run several simultaneous experiments to collect experimental data for model identification of the greenhouse temperature and humidity dynamics and the identification of a plant growth model.

Several hydroponic systems have been proposed such as, Deep Water Culture (DWC) and Nutrient Film Technique (NFT). Inside the greenhouse, a small Deep Water Culture (DWC) hydroponic system was installed. Separate containers are used to allow the independent growth of plants with

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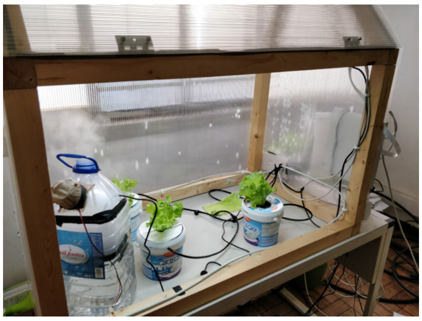
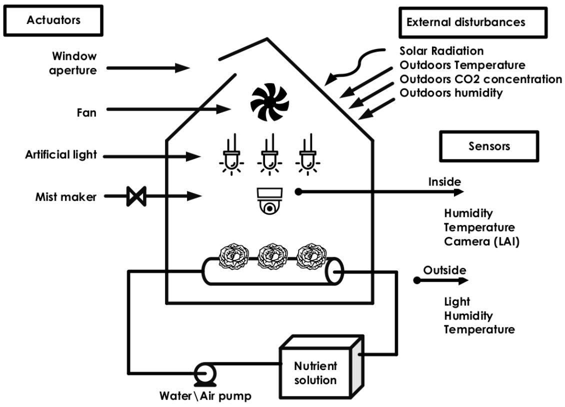


(a) Experimental greenhouse and hydroponic system design.



(b) Diagram depicting the sensing and acting devices..

Fig. 1. General view of the greenhouse prototype.

different nutritive concentrations. This structure allows the acquisition of more data in the same period of time if compared with a Nutrient Film Technique hydroponic system.

There are many variables influencing crop growth. The main ones that should be taken into account are (i) light, (ii) greenhouse temperature, (iii) carbon dioxide concentration, (iv) relative humidity, (v) nutrient solution concentration (EC), and finally (vi) the acidity level, pH.

Figure 1(b) represents the sensing and actuation in the greenhouse, where light, temperature, and humidity sensors are used. To actually measure the growth of plants a top-view camera was installed. On the other hand, to influence the inside greenhouse environmental conditions, a fan and an aperture window were installed. An artificial light allows supplementing available sun light, whereas a mist maker actuator allows to increase the greenhouse inside relative humidity. Nevertheless, some of the initially planed configuration was subject to change. Heating was not necessary because the experiments were taken during Summer time, but cooling was not available to compensate "high" temperatures. Moreover, because the nutritive solution sensors revealed to be quite expensive, neither the pH or EC levels were measured. Finally, during the project period there was not enough time to further develop the control of CO_2. Lettuce was the selected crop since this type of crop has a fast development and easy greenhouse management, also because it is a very well documented hydroponic crop.

The hardware/sofware architecture are based on Arduino and Raspberry PI solutions. The selection of the Arduino platform was motivated by its low price and available extension boards while the Raspberry PI was selected to handle more intensive tasks is needed. The sensors and actuators are connected to the Arduino except for the camera that is attached to the Raspberry Pi. The artificial light, the air pump and the mist maker actuator are attached to an Arduino shield with relays for their higher power supply voltage. Sensors and actuators are connected to digital ports, analog (which have an ADC or a DAC), or PWM ($\sim$). The Pi and the Arduino are connected with an USB cable via Serial communication. The Pi card memory saves experimental data. External users and the programmer are able to connect to the Pi trough the World Wide Web. Figure 2 summarizes this configuration.

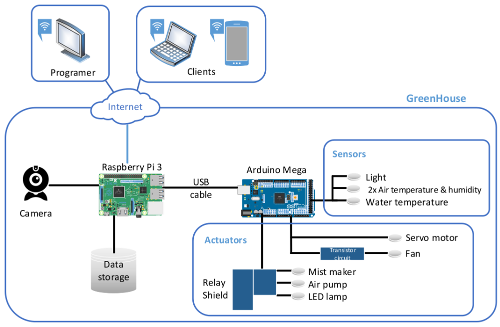


Fig. 2. System architecture

The Arduino Mega is only responsible to interact with the sensors and actuators doing no computation neither control. A simple C code with access to libraries allows the communication with specific sensors and actuators. It also allows the communication with the Raspberry Pi throughout a very simple set\get protocol.

On the other hand, the Pi does all the computation. It uses Experimental Physics and Industrial Control System (EPICS) [7] software to monitor and control the crop and environmental variables. The Pi also serves as a database server storing the variables log. Moreover, it runs the image processing software. Finally, the Pi permits users to connect to a Graphic User Interface (GUI) developed with Control System Studio (CSS)[6] software that works well with EPICS. Figure 3 illustrates the interface developed with CSS to monitor and to control the greenhouse variables.

To measure crop weight, image processing is used. The simple process of counting the leaf 2D area of a top view camera reveled to be quite satisfactory and, for sake of simplicity, this method was adopted.

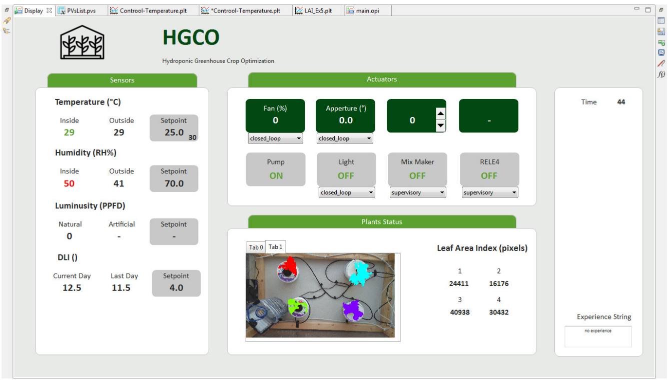


Fig. 3. CSS user interface allowing to monitor and control greenhouse live conditions.

III. MODELING AND CONTROL OF GREENHOUSE TEMPERATURE AND HUMIDITY

In order to control some of the environmental variables that affect plant growth, it is important to develop models of those variables. In this case concentrated parameter models are considered.

A simplified continuous time linear model for the inside temperature was deducted based on energy balance,

$$\frac{dT_{in}(t)}{dt} = -K_{loss}(T_{in}(t) - T_{out}(t)) + K_{sun}L(t) - K_{roof}\Theta(t) - \quad (1)$$

$$-K_{fan}(T_{in}(t) - T_{out}(t))V_{fan}(t) - K_M M(t) \, ,$$

where $T_{in}(t)$ and $T_{out}(t)$ are the inside and outside temperatures, $L(t)$ represents the power(light) received from the sun, Θ and $V_{fan}(t)$ are the window aperture and fan actuators and finally $M(t)$ stands for the mist maker actuator responsible to increase the greenhouse inside humidity. Some terms are more important than others. The parameters represented by K terms are assumed constant for the greenhouse working temperature (plant growth conditions) and are identified off-line from experimental data using the Least-Square Method (LS).

A physical approach to model the greenhouse relative humidity is more complex compared to the temperature due to the humidity temperature dependence. Previous studies [4], [1], [11] show that a heuristic approach leads would still lead to acceptable models.

It is then reasonable to describe the inside relative humidity

$$\frac{dH_{in}(t)}{dt} = -K_{H1}(H_{in}(t) - H_{out}(t)) - K_{H3}\Theta(t) - K_{H4}(H_{in}(t) - \quad (2)$$

$$-H_{out}(t))V_{fan}(t) + K_{H5}M(t) - K_{H6}T_{in}(t),$$

where $H_{in}(t)$ and $H_{out}(t)$ are the inside and outside greenhouse humidities. All K terms were computed experimentally using the LS method.

Supported by these models, linear control is used to regulate the greenhouse temperature and humidity. An on-off controller is implemented to control the amount of light the plant receives daily. Due to budget and time limitations the nutritive solution was not controlled automatically.

A control architecture was defined to coordinate the window aperture with the command of the fun. To reduce the temperature level, the window is operated first, followed by the fan operation. This procedure may decrease the humidity level that must be compensated by the mist maker. The controller is based on a Proportional and Integral feedback loop where feedforward and anti-windup enhancements were implemented. The experimental results obtained with the controller on the real system are presented in figure 4.

The time interval $t \in [10; 11]$ is used to illustrate the operation of the window in conjuntion with the fan. The mix maker is set to the off mode. The controller operates, in first place, the window to extract heat by natural convection, as soon as the $T_{in}(t)$ is above the temperature reference. Followed by the operation of the fun to force air into the greenhouse with a lower temperature. The actuation net effect is that the temperature T_{in} tracks the reference, but other controller gains can be selected to smooth the actuation signals of the actuators (fan and window). For $t > 11.5$ there is a step on the temperature reference, as $T_{in}(t)$ is lower than the temperature reference, the controller stops the fun and decreases the window aperture. The control of the humidity is illustrated in the time interval $t \in [12.5; 13.5]$ where the mix maker is operated using a on-off strategy due to mix maker operational constraints.

IV. OPTIMIZING CROP GROWTH

Plant growth modeling has been addressed in several works. In [5] a quite simple plant growth model it is suggested by splitting its three characteristics phases in different equations, a initial exponential growth, followed by a linear and then a constant function. While this is a simple approach it does not allow to have a single mathematical expression model. One of the most important and accurate works for optimizing the dry matter production in greenhouses is the one done by van Henten and van Straten [13], [12]. The lettuce crop production process is accurately described by a four state variable dynamic model, although this solution is very complex. Other works like [3] proposed simplifications of the van Henten's model, although this still tend to be complex models.

In this project the **Logistic function** is tested as a potential model of plant growth. The paper [9] supports this possibility. This is a first order nonlinear differential equation that is often used to model the growth of a given population in a constrained environment [8]. Using this mathematical expression, plant growth is modeled as

$$\frac{dw(t)}{dt} = K(\mathcal{M} - w(t))w(t) \, , \quad (3)$$

where w denotes the plant biomass, K and $\mathcal{M}$ are constants defining the plant growth rate and its maximum mass achieved, respectively. This is the model chosen because it is simple and, it allows to model the growth during the entire plant lifetime.

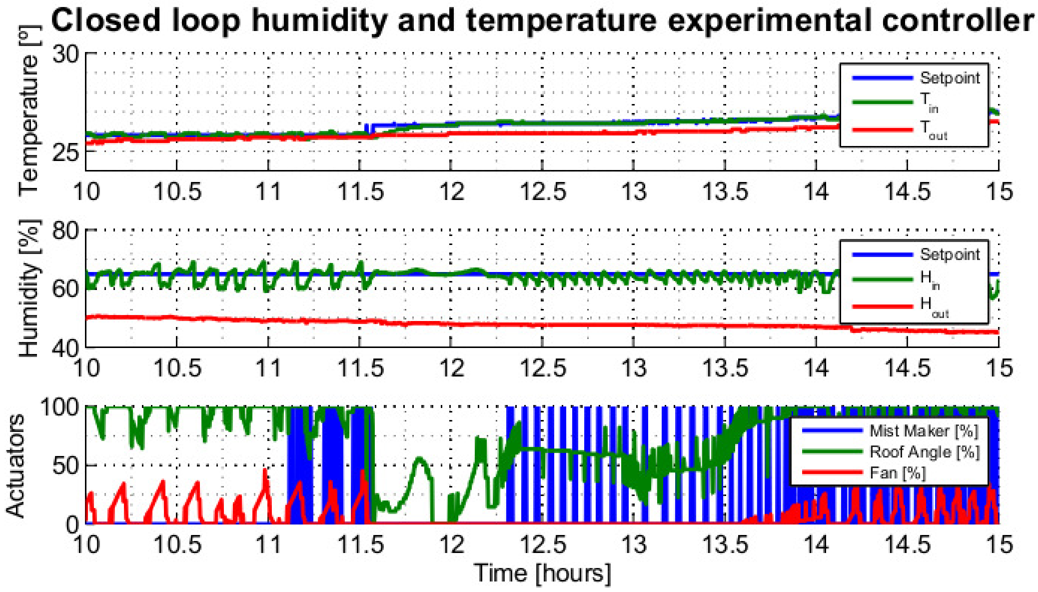


Fig. 4. Closed-loop control of the Humidity and Temperature during a normal day, from 10 to 15 hours. The temperature follows well the set-point within limits of the actuators. The fan operates only when the window aperture saturates to force air with a lower temperature.

A. *Logistic plant model*

Based on the logistic function the following model is explored to describe crop growth

$$\begin{aligned} \frac{dw(t)}{dt} &= K(\mathcal{M} - w(t))w(t)\ , \\ \mathcal{M}(N, L) &= \alpha N + \beta L, \\ , K(L, T, H) &= \gamma L + \delta T + \eta H\ , \end{aligned} \tag{4}$$

where $w(t)$ denotes the mass of the plant, N $[mS/cm]$ represents the nutritive average solution concentration over the plant growth cycle, $\mathcal{M}$ and K define the growth speed and the maximum mass achieved that depend on other accessible variables. The expressions for $\mathcal{M}$ and K are simple candidate expressions that must be validated using experimental data. Although there was no conductivity sensor available, N is measured according to the nutrient dilution factor $[ml/l]$. L represents the average daily light received by the plant (DLI-Daily Light Integral). Finally, T and H are the average inside temperature $[°C]$ and relative humidity $[\%]$ in the greenhouse, respectively. It is important to stress that N , L, T and H represent the average values during the entire grow process. The model assumes that these values are kept to small deviation around the average value. Moreover, these variables must be bounded to $0 < N < N_{max}$, $0 < L < L_{max}$, $T_{min} < T < T_{max}$ and $H_{min} < H < H_{max}$ for a more accurate model. These bounds are obtained both from experimental data and from bibliography.

Several experiments took place at different growth conditions to collect data to estimate the parameters of the model described by equations 4. The procedure encompasses the description of K and $\mathcal{M}$ by minimizing the cost function J that represents the error of the fitting to the experimental data

$$\min_{w} J = \sum_{t=1}^{N_s} [y(t) - w(t, \hat{K}, \hat{\mathcal{M}})]^2\ , \tag{5}$$

where $y(t) \in R^{N_s}$ is the plant biomass experimental data at time t with N_s samples, and $w(t, \hat{\mathcal{M}}, \hat{K}) \in R^{N_s}$ is the plant mass at time t defined by the fitted model with the estimated parameters $\hat{\mathcal{M}}$ and $\hat{K}$. Figure 5 presents an example on estimating these parameters. Knowing the estimators $\hat{K}$ and

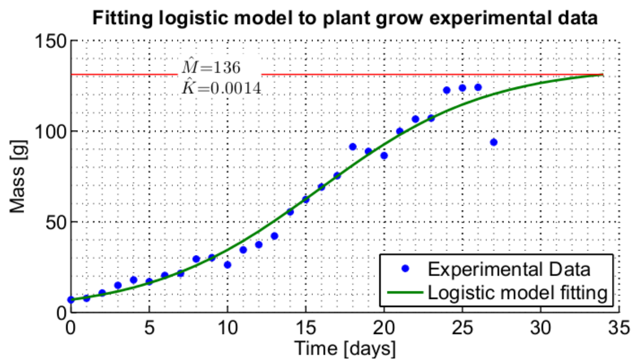


Fig. 5. Example of fitting crop growth experimental data to logistic function using `fminunc` function of `Matlab`.

$\hat{\mathcal{M}}$ that best fit each experiment it is possible to apply the LS method over a group of experiments (N_{exp}) to find out the linear parameters of equations 4. Which in turn will allow to relate the crop biomass with the grow conditions it is subject to.

B. *Optimal control of plant growth*

Knowing a model for the plant growth, it is possible to design an optimal control strategy to improve the efficiency of growing plants in the controlled greenhouse. In order to be able to fully control the crop biomass at harvest time t_f, as described in the model in 4, it is necessary not only to control the nutritive solution concentration at root level N, as well as the amount of light the plant receive on average per day L.

The model is now considered with $u_1(t) = N(t)$ and $u_2(t) = L(t)$,

$$\frac{dw(t)}{dt} = K(\alpha u_1 + \beta u_2 - w(t))w(t), \tag{6}$$

where the rate of growth K is considered as constant, u_1 represents the control of the nutritive solution and u_2 is the control of the amount of light the plant receives daily.

At this stage a cost function can be defined as

$$J(u_1, u_2) = w(t_f) + \int_{t_0}^{t_f} (-u_1(t) - u_2(t))dt, \tag{7}$$

that aims at maximizing the crop weight at the harvest time ($w(t_f)$), while minimizing the associated cost on acting.

This problem was address using the Pontryagin's principle and solved using the gradient method.

The optimal input solution of nutrients and light obtained by solving the problem numerically is presented in Figure 6. This is a bang-bang optimal control solution. Because the

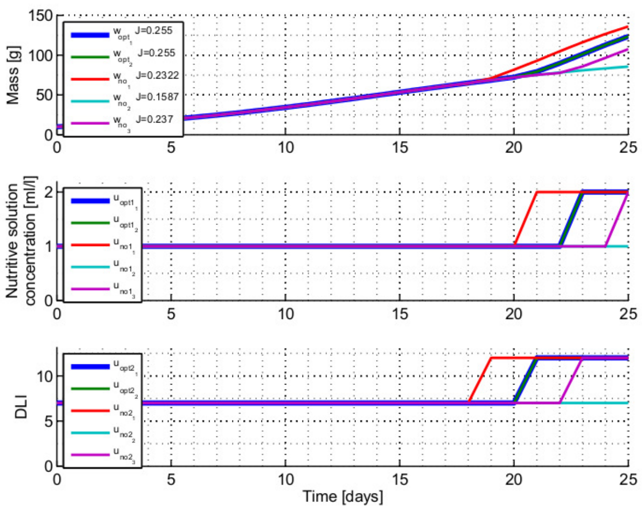


Fig. 6. Optimal control (subscript opt) with the nutritive solution concentration (u_1), and the amount of daily light received (u_2) as the input variables. Other non-optimal solutions (subscript no) are present as well as the corresponding cost function (J).

optimal control is known to be of the bang-bang type it is possible to plot a 3d surface, represented in Figure 7, with the cost of switching the control at different time combinations within the experience. This allows to have a better precision on when should this changes take place. Based on these results, several switching time instants are considered with the bang-banf control strategy where the optimal solution w_{opt2}, is presented in Figure 6, gave the same result as searching for the maximum of Figure 7, although this is not always the case since the gradient method sometimes showed to converge to sub-optimal solutions. Furthermore, this same Figure 7 allows to infer about the optimal controller robustness. Because the cost does not change drastically with the time change around the optimal value it is considered a robust solution. In other words, if one affects the time control switch around its optimal value it is guaranteed that the final profit will not change drastically.

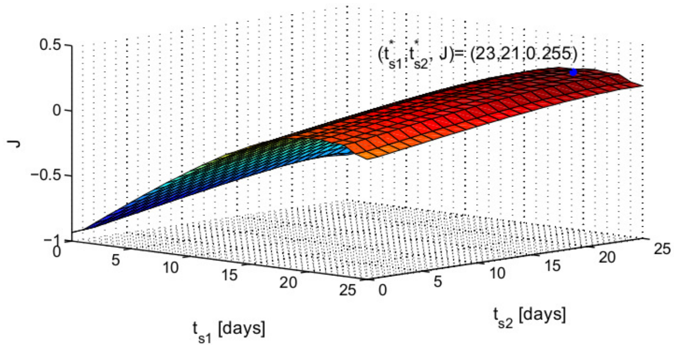


Fig. 7. Cost function evaluated when switching the control variables at different time combinations (t_{s1}, t_{s2}). The optimal combination is given at (t^*_{s1}, t^*_{s2}). The suggest a robust controller.

C. *Optimal harvest day*

Growing plants for longer or shorter time periods will achieve distinct final biomass, which will reflect on different profit values. Therefore, the optimal problem must take the experiment duration in consideration. In this work the same optimal problem is solved for different harvest days (t_f) to find the one that achieves a higher profit value. The optimal day to harvest was computed yielding $t_f^* = 25$ with $J^* = 0.255$.

V. Results and Validation

A final experience was performed to validate the optimal solution proposed in Figure 6 with the optimal harvest day. In this experience growth conditions were the same for the four plants. The nutritive solution was kept at 1 ml/l up to day 22 and raised to 2 ml/l until the harvest time on day 25. On the other hand, the amount of light was kept to $7DLI$ up to day 20 and raised to $12DLI$ until the end of the experience. Moreover, the humidity and temperature were kept at ideal average values of 65% and $27°$, respectively.

Figure 8 overlaps the optimal result of Figure 6 with the four plants experimental growth. It allows to conclude that the four plants grew in similar conditions having thus similar growth rates. Furthermore, the most important experimental evidence is the similar growth of the four plants compared to the optimal solution simulated curve. The error between the curves is initially very small, increasing with time. It is important to remember that the image processing software also gets more inaccurate as the plants size increase, being this a possible justification for an increase of the error. The root mean square error between each experimental curve and the simulation is [14.5136 8.8183 4.5022 8.5963]. These are errors of around 10% compared to its harvest weight, which is considered to be quite satisfactory results. Note that the

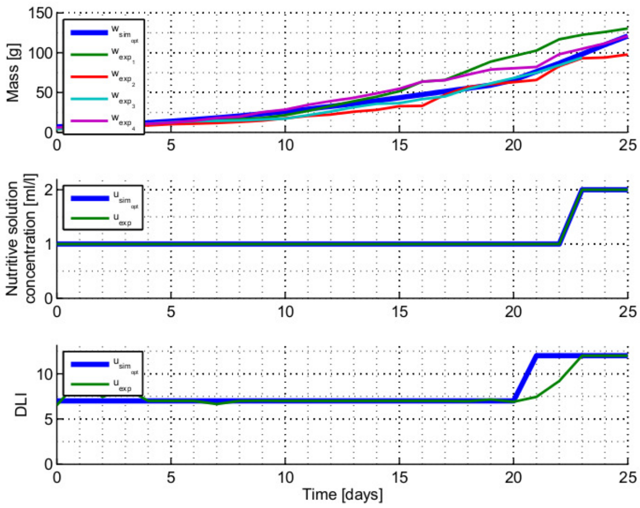


Fig. 8. Final experiment to validate the fitted plant growth model as well as the optimal controller solution proposed. The experimental root mean square error between the experimental growth curves compared to simulation is around 10%.

daily light integral (DLI) control of the experience did not follow precisely the desired values. Sometimes the sunlight captured is bigger than the desired setpoint (although this is free light). Other times the desired setpoint is so big, compared to the captured sunlight, that for the LED to deliver that amount of light daily, it would have to be turned on for so long that the plant would not have night periods (which was set to a minimum of 6 hours). Therefore, not achieving the desired value. Overall, this validation experience brought the confirmation of a successful fitting of the plant growth model, as well as, the possibility to apply the proposed optimal control algorithm in real plants.

VI. CONCLUSIONS

An automated soilless greenhouse was built. Growing plants in a controlled environment with hydroponic technology was proven to be much faster compared to traditional cultivation methods. Experimental Physics and Industrial Control System (EPICS) allowed to develop a reliable control system, although its configuration and installation is not the easiest one, for example extra plugins or required third party software. The possibility to easily develop a GUI using Control System Studio (CSS) revealed to be very satisfactory, only falling short if a web interface is required. It was possible to remotely connect to the greenhouse throughout a graphical interface, where manual and autonomous control and monitoring features are available. The greenhouse experimental data allowed to model temperature and humidity dynamics. With these models, PI and optimal control design was successfully implemented to regulate the temperature and humidity values to the desired setpoints. It was possible to follow plant growth through image processing. Description of the plant growth was done using a logistic model where the parameter were estimated from experimental data. Optimal control was applied to obtain control strategies that maximize the yield.

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