Remote control of greenhouse cucumber production with artificial intelligence - results from the first international autonomous greenhouse challenge

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Remote control of greenhouse cucumber production with artificial intelligence – results from the first international autonomous greenhouse challenge

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Abstract

The world population is increasing rapidly together with the demand for healthy fresh food. Greenhouse industry can play an important role, but encounters difficulties finding skilled staff to manage crop production. Artificial intelligence (AI) reaches breakthroughs in several areas, however, not yet in horticulture. An international competition on "autonomous greenhouses" aims in combining horticultural expertise with AI to make breakthroughs in fresh food production with fewer resources. Five international teams with different background in horticulture and AI participated in a growing experiment. Each team had a 96-m² modern greenhouse compartment at WUR to grow remotely a cucumber crop ('Hi-Power') during a 4-months period. Each compartment was equipped with standard actuators and sensors, heating, ventilation, screening, artificial lighting, fogging, CO_2 supply and irrigation. Climate control set points were remotely determined by teams using own AI algorithms, actuators were operated by a climate and irrigation process computer. Additionally, teams sent instructions for the crop pruning strategy. Measurements and set points were exchanged via a digital interface. Achievements in AI-controlled compartments were compared with a reference compartment, operated manually by three commercial growers. Teams used additional individually chosen sensors such as RGB or thermal cameras, temperature-humidity-light-sensor-networks, root-zone sensors, sap-flow meters or crop-weighing sensors. Teams' strategies for remote control ranged from supervised, unsupervised and reinforcement machine learning. Teams were judged and received points on several aspects: 50% for net profit, 20% for sustainability indicators, energy- and water-use-efficiency and CO_2 consumption, 30% for their artificial intelligence algorithms, novelty, level of autonomous control, robustness and scalability. The results obtained by different teams in terms of climate and growing strategies, different resource use efficiency and net profit are presented in this paper. One of the AI-controlled compartments achieved overall better results than the manual grown reference compartment.

Keywords: artificial intelligence, climate control, energy, water use efficiency, CO_2 supply, crop growth and development, cucumber

INTRODUCTION

The world population is increasing rapidly together with the demand for healthy fresh food (FAO, 2018). Greenhouse industry can play an important role, but encounters difficulties finding enough skilled staff to manage crop production (Brain, 2018). A crop manager must have a high level of knowledge and experience in order to control crop growth and monitoring all details of the various greenhouse compartments as farms become larger and resources (water, fossil energy) become scarcer. Automated greenhouse climate control algorithms have already been developed decades ago (e.g., Bot, 1983; Tantau, 1980; Van Straten et al., 2010; Takakura et al., 1971; Seginer, 1980; Hashimoto, 1980). Modern high-tech greenhouses are today equipped with process computers which are able to control greenhouse actuators based

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on set points manually fed by the grower. Earlier, experiments have been conducted to control greenhouse climate and crop growth remotely based on computer models only (Buwalda et al., 2006; van Henten et al., 2006; Ramírez-Arias et al., 2012).

Moreover, research attention had been paid toward the use of machine learning algorithms to be used for greenhouse climate control with the aim to take over decisions of the grower. Diverse methods have been applied, such as K-algorithms (e.g., Kurata, 1988), bayesian networks (e.g., Hernández et al., 2015), support vector machines regression (e.g., Wang et al., 2009; Yu et al., 2016; Zou et al., 2017), neural networks (e.g., Dariouchy et al., 2009; Ehret et al., 2011; Linker and Seginer, 2004; Seginer, 1997; Taki et al., 2018), reinforcement learning (e.g., Tchamitchian et al., 2005) or genetic algorithms (e.g., Blasco et al., 2007; Dai et al., 2008).

Next to that, the use of artificial intelligence (AI) has reached major breakthroughs in several areas of daily life and society, such as medical applications (He et al., 2019), autonomous cars (Waldrop, 2015) or robotics (Goldberg, 2019).

In order to combine the use of modern AI algorithms and greenhouse climate, irrigation and crop growth control, in 2018 an international challenge on "autonomous greenhouses" has been conducted at the high-tech research greenhouses of Wageningen University & Research in cooperation with different multi-disciplinary international teams. The challenge aimed at combining horticultural expertise with AI to make breakthroughs in fresh food production with fewer resources. The experiment was set-up to benchmark the use of state-of-the-art AI algorithms for cucumber production. In the experiment existing commercial greenhouse equipment, standard sensors for control and a standard process computer was combined with latest AI technology in order to maximise net profit and minimise resource use while controlling the greenhouse crop growing remotely. This paper presents an overview of the results obtained in the experiment.

MATERIALS AND METHODS

The greenhouse compartments, actuators, sensors and remote control

Six identical greenhouse compartments were available for the growing experiment. Each compartment was equipped with standard actuators also available in commercial high-tech greenhouses. Two pipe heating systems, a rail heating on the floor and a heating on crop height (peak capacity 180 and 30 W m^{-2}, respectively), were available, both controllable by different set points. Continuous roof ventilation (ventilation area of 0.3 m^2 opening m^{-2} greenhouse, equipped with anti-thrips netting), two types of screens (LUXOUS 1547 D FR energy screen and OBSCURA 9950 FR W light blocking screen), HPS artificial lighting system (capacity of 187 μmol m^{-2} s^{-1}), fogging system (max. capacity of 330 g m^{-2} h^{-1}), CO_2 supply (max. capacity 15 g m^{-2} h^{-1}) were available, all controllable by set points determined by the teams remotely. All climate control set points (minimum rail pipe temperature (°C), minimum crop pipe temperature (°C), minimum ventilation opening (%), humidity deficit set point (g m^{-3}), energy screen position (0-100%), blackout screen position (0-100%), artificial illumination (0 or 100%), CO_2 concentration (ppm) and time between last and next irrigation turn (min), were remotely determined by teams using own AI algorithms. Set points were sent via a digital interface (LetsGrow.com) to a central climate control process computer, which was then operating the actuators accordingly. Continuously measured and calculated data was sent back to teams (cumulative outside global radiation (J cm^{-2} d^{-1}), outside PAR (μmol m^{-2} s^{-1}) air temperature outside (°C), outside relative humidity (%), wind speed (m s^{-1}), outside global radiation forecast (W m^{-2}), outside air temperature forecast (°C), outside relative humidity forecast (%), wind speed forecast (m s^{-1}), air temperature inside (°C), air humidity deficit inside (g m^{-3}), heating pipe temperature (°C) and heating power used (W m^{-2}) of both heating systems, lamp status (on/off), CO_2 dosage (on/off), screen position (%) of both screens, irrigation supply (L m^{-2}), drain (L m^{-2}), drain EC (dS m^{-1}), drain pH). Teams were able to control the operation of all actuators remotely. Measurements and set points are exchanged at a 5-min-interval. The following data was calculated from the measured data: inside PAR sum (mol m^{-2}), heating energy used (kWh m^{-2}), electricity used (kWh m^{-2}), CO_2 dosage (kg m^{-2}), water consumption (L m^{-2}) and provided to the teams as well.

Nutrient solution for fertigation was prepared by a central fertigation computer and then stored in a buffer tank for each compartment. The composition, concentration (EC) and pH of the nutrient solution was determined by teams. Based on detailed chemical analysis of the drain water provided every second week the teams could send requests to change the composition, EC and pH of the nutrient solution. Plants were grown on rockwool slabs placed on hanging gutters allowing for accurate drain measurements. Fertigation was supplied with drippers.

Teams were allowed to install additional sensors at the start of the experiment. They have chosen for different types, such as RGB camera's, thermal camera's, sensors for net radiation, root zone, crop and substrate weight, stem diameter, crop sap flow meters, stem diameter, wireless temperature-humidity-light-sensor-networks or no additional sensors.

The crop

'Hi-Power' cucumbers were sown on July 20, 2018 in rockwool cubes, which were transplanted to the greenhouse growing compartments on August 14, 2018 at the start of the experiment. The crop was grown in a high-wire growing system. Plant density and stem density had to be chosen by the teams before the start, choices differed from 2.6 to 3.6 stems m^{-2}. The reference was 2.6 stems m^{-2}. First harvest has been obtained on September 6, 2018. Last harvest was on December 7, 2018. Date of topping had to be chosen by the teams and ranged from November 19 to 28, 2018. The reference was topped on November 9, 2018.

During the experiment, teams sent instructions to the greenhouse workers, who then carried out harvest and all other crop handling (wiring, pruning, leaf picking) manually. The same workers obtained crop related measurement data and then sent these back to the teams via the digital interface.

Teams sent weekly instruction for fruit and leaf pruning in the top of the canopy weekly. Strategies ranged from a more stable procedure which kept removing 50% of the fruits for the whole cropping period to a more variable strategy, which removed alternately 50 and 67% of the fruits. With respect to leaf pruning, the majority of the teams decided for no pruning (0%) or a small amount of leaves (33%). One team used a deviating strategy with removing 50% of the leaves throughout the whole cropping period (and kept pruning after the topping date). As a standard procedure, not controlled by the teams, the greenhouse staff removed leaves below last harvested fruits.

Three harvest quality categories were distinguished (A: >375 g; B: 300-374 g; C: <300 g $fruit^{-1}$), harvest data such as number and weight of fruits (# m^{-2} and kg m^{-2} per quality category A-C) was measured manually by the workers. Crop related parameters such as stem elongation (cm $week^{-1}$), fruit development time (d $fruit^{-1}$), leaves formation rate (# $stem^{-1}$ $week^{-1}$) and cumulative number of leaves (# $stem^{-1}$) were also measured.

AI algorithms

Five different teams were controlling a separate greenhouse compartment based on their AI algorithm remotely (Sonoma, iGrow, deep_greens, The Croperators, AiCU). A team of Dutch growers controlled a sixth compartment manually as a reference (Grower = Reference). Each team determined their own AI algorithms which varied from supervised, unsupervised and reinforcement machine learning (Dynamic Regression, Deep Reinforcement Learning DRL, Deep Deterministic Policy Gradient DDPG, Generative Adversarial Network GAN, Convolutional Neural Network CNN, Recurrent Neural Network RNN). In order to use AI techniques, training data are essential. Since training data with a large variability for the described application was scarce, an artificial training data set was created and provided to the teams before the start of the experiment using the broadly validated dynamic greenhouse climate model KASPRO (De Zwart, 1996) and a modified version of the cucumber crop model INTKAM (Marcelis et al., 2009).

Judgement criteria

1. Sustainability factor.

20% of the total score of a team was given for sustainability. The following aspects were calculated based on measured data: energy use efficiency (MJ kg^{-1} cucumber), CO_2 dosage (kg kg^{-1} cucumber), water use efficiency (m^3 kg^{-1} cucumber), pesticide usage as registered.

2. Net profit.

50% of the total score of a team was given for the net profit. Net profit was calculated based on the following obtained data: Number of fruits harvested × price per fruit and category. The price was determined by a jury at the start of the experiment per week, however, only communicated with teams weekly during the ongoing experiment. At the start of the experiment costs of young plants × number of young plants placed in the compartment and costs of substrate were calculated once. Other greenhouse equipment used was identical and therefore not considered in the calculation of the net profit. Resource use of electricity, heating, CO_2, water, pesticides/biologicals and labour were measured during the experiment per greenhouse compartment, thus per team. Multiplied with the given price, costs were calculated and communicated with teams weekly during the ongoing experiment.

3. AI algorithm.

30% of the total score of teams was given by a jury based on novelty of the AI algorithm with respect to overall scientific community, novelty with respect to application on horticultural domain (novelty), capacity to operate autonomously on a distance without manual interventions (functionality), capacity to operate without too many additional sensors (robustness), easiness of implementation on large scale (scalability).

RESULTS AND DISCUSSION

In Figure 1 the cumulative cucumber production per team in the different greenhouse compartments during the experimental period is given. From the beginning one team (Sonoma) had a more accelerated start and was able to continue with the highest amount of cucumber harvest. They found out that with a higher light sum more harvest could be obtained and they focused their AI algorithms on this particular aspect. The algorithm allowed to obtain a high light sum (Figure 2) by maximizing the amount of artificial light (Figure 3) while taking into consideration potential limiting factors such as temperature and CO_2.

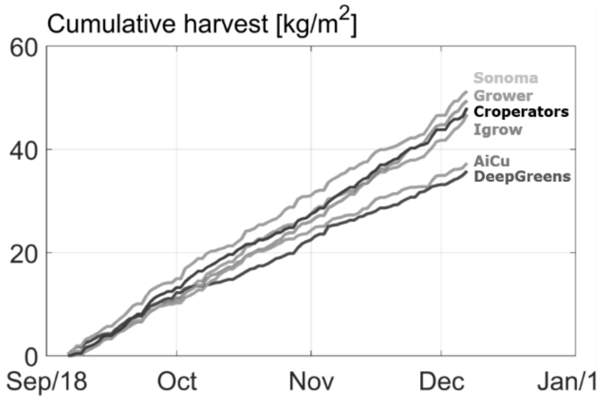

Figure 1. Cumulative cucumber production of different teams.

Another team (The Croperators) increased the daily light sum after a short period at the beginning of October (Figure 2), however, this did not lead to a higher light use efficiency of the crop (data not shown), since at the same time they maintained a low CO_2 concentration (Figure 4). In addition, they opted for a crop pruning strategy which created an unbalance between vegetative and generative growth (data not shown). From these results we can see that high light sum and high CO_2 concentration are important factors for cucumber production together with the crop management (stem density and pruning strategy).

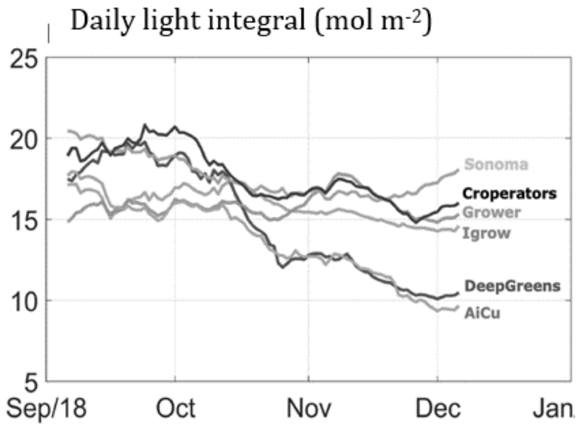

Figure 2. Course of daily light integral (natural and artificial light) in mol m^{-2} inside the greenhouse on crop height, composed of both artificial light and natural light, realized by different teams.

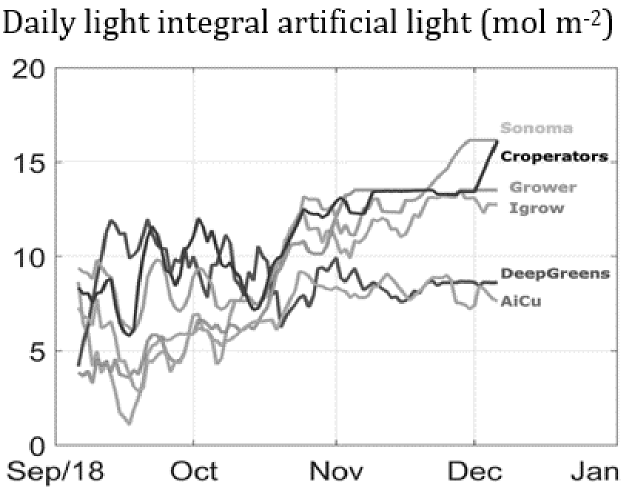

Figure 3. Course of daily light integral of artificial light only inside the greenhouse on crop height realized by different teams.

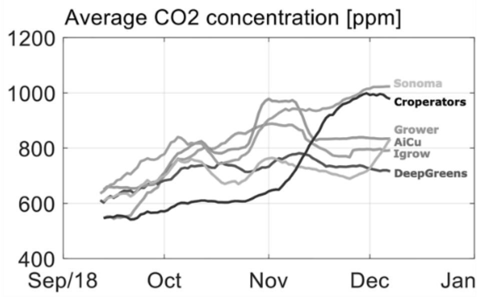

Figure 4. Course of CO_2 concentration in ppm in different compartments during the cucumber experiment.

Manual growers started with a lower harvest (Figure 1). They allowed lower daily light sums at the beginning, they only used low amounts of artificial light (Figure 3). However, they were able to balance the crop very well with their crop pruning strategy (data not shown) which therefore, resulted in a high light use efficiency of the crop. In fact, the manual growers were able to realize the highest light use efficiency during almost the whole cropping cycle (data not shown).

Figures 4 and 5 show the CO_2 concentration realized per team and the CO_2 dosage, respectively. All teams started with relatively low CO_2 concentration, but most teams increased CO_2 dosage from half October onwards. From half November toward the end of the experiment, most teams lowered the concentration, only team Sonoma increased it continuously during the total cropping period. The Croperators suddenly doubled the concentration toward the end of the crop (Figure 4) and were able to catch up with their harvest (Figure 1).

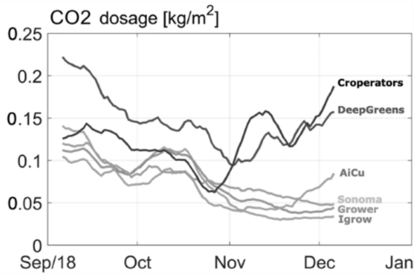

Figure 5. Course of CO_2 dosage in kg m^{-2} in different compartments during the cucumber experiment.

Figures 6 and 7 show the temperature in the greenhouse during fruit development and the heating energy used, respectively. Team Sonoma gave the crop a boost with high temperatures at the beginning of the experiment. Together with the high amount of light (Figure 2) and CO_2 (Figure 4) this led to an early high harvest (Figure 1). Also, team deep_greens tried to boost the fruit development with high temperatures at the beginning. Together with high daily light sums, mainly from artificial light source (Figure 3), they were able to have a good harvest during the first weeks. Unfortunately, in October, technical problems (connection of AI remote control) led to low irrigation (data not shown) and therefore, a dip in harvest which they were not able to catch up again. Team AiCU handled relatively low temperatures (Figure 6) and low daily light sum, while maintaining a high crop/fruit density (data not shown), which together explain the low light use efficiencies (data not shown) and large amount of small fruits (data not shown). The Croperators, due to the detection of small fungal disease spots in their compartment in November, lowered the relative humidity levels that caused, in turn, a steep increase in heating energy demand in the same period (Figure 8), but did not lead to higher temperatures due to high ventilation rates (data not shown).

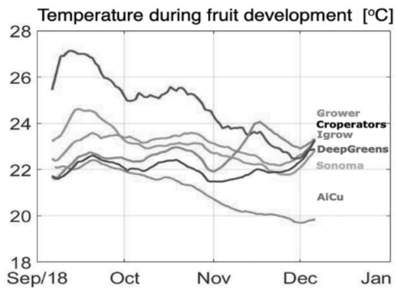

Figure 6. Course of greenhouse air temperature in different compartments during the cucumber experiment.

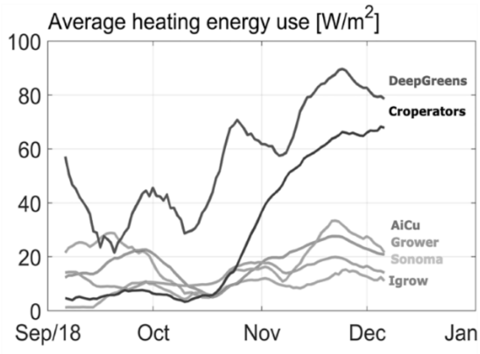

Figure 7. Course of heating energy use in different compartments during the cucumber experiment.

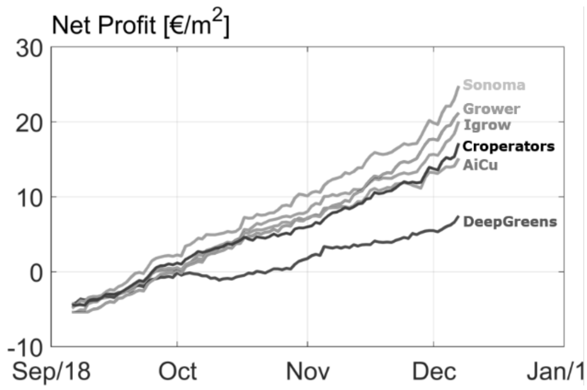

Figure 8. Course of net profit of different teams obtained during the cucumber growing experiment.

In Table 1 the sustainability factors obtained during the growing experiments are presented. In general, team Sonoma was able to realize the lowest resource use kg^{-1} cucumbers produced. Only on electricity use for artificial light they realized average values. Here, manual growers (reference) had the lowest usage. In total deep_greens had the highest resource use for heating, electricity and CO_2 (Table 1), which together with low harvests also led to a low net profit (Figure 8). Highest net profit was obtained by team Sonoma, who were able to perform better with their AI strategy than the manual growers and who won the challenge. We can conclude that most teams were able to have a good harvest, low resource use and reach a net profit better or close to the performance of manual growers. Highest score for their AI strategy was obtained by team iGrow, followed by team The Croperators and Sonoma.

Table 1. Sustainability factors of different teams obtained m^{-2} greenhouse area during the cucumber growing experiment.

	kg CO_2	kWh electricity	kWh heat	L water	mL pesticide
	kg^{-1} cucumber				
Reference	0.20	3.02	3.20	5.52	0.34
Sonoma	0.20	3.59	2.49	4.91	0.35
iGrow	0.20	3.12	2.94	5.89	0.39
deep_ greens	0.47	4.39	13.61	5.87	0.49
The Croperators	0.29	3.82	4.87	5.98	0.35
AiCU	0.26	3.17	3.13	7.62	0.48

All data of the growing experiment is published under doi 10.4121/uuid:e4987a7b-04dd-4c89-9b18-883aad30ba9a. A description of data analysis can be found under Hemming et al. (2019). More details on cucumber crop reaction will be described in a separate paper published in *Acta Horticulturae*.

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