Improving Hydroponic Agriculture through IoT-enabled Collaborative Machine Learning

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Abstract. This paper presents ongoing work in the development of a scalable hydroponics monitoring system. Our system leverages using wireless IoT technology and applies machine learning techniques on gathered data to provide recommendations to agronomists. Hydroponics is a method of growing plants in a water based nutrient rich solution system, instead of soil. By monitoring the parameters of the solution and the environmental parameters inside the greenhouse, farmers can increase the production while decreasing the need for manual labor. Multiple networked sensors can measure these parameters and send all the necessary information to an Internet of things (IoT) platform (i.e., Thingsboard) in order the farmer to be able to control and adjust current operating conditions (e.g. environmental controls) and plan the nutrition schedule. Machine Learning can be used to detect anomalous operating conditions and to provide operational recommendations to assist farmers. The novelty presented in our system is that data contributed by multiple farming sites can be used to improve the quality of predictions and recommendations for all parties involved.

Keywords: Internet of Things · Precision Agriculture · Hydroponics · Machine Learning.

1 Introduction

The Internet of Things (IoT) is an active research area where sensors and smart devices facilitate the provision of information and communication. In IoT, one of the main concepts is wireless sensor networks in which data is collected from all the sensors in a network characterized by low power consumption and a wide range of communication. Wireless sensor networks (WSNs) consist of multiple sensor nodes in a wireless communication-based environment. Each sensor node is to detect physical phenomena such as temperature, humidity, and moisture with limited energy and memory. WSNs are the combination of embedded system and wireless communication which allows data transmission among the sensor nodes over ad-hoc wireless networks. The heart of each WSN node is the microcontroller which processes readings from its own sensors and/or readings from adjacent nodes.

IoT systems have found significant application opportunities in the agricultural sector, however, a recent review of IoT applications in agriculture has shown that research in this area is not yet fully developed [4]. For agricultural applications, IoT devices consist of sensors to measure soil properties (e.g. moisture, electrical conductivity), environmental conditions (e.g. temperature, humidity, rainfall) and ambient light conditions (e.g. irradiation, light levels). All these parameters relate closely to the growth of plants and their monitoring enables precision agriculture, with associated savings in energy and water consumption, as well as reduction of fertilizer and chemicals used to support plant growth. A more recent trend in agriculture involves the move away from soil-based farming towards hydroponic agriculture. In this mode of cultivation, a greenhouse contains rows of substrate material (e.g. rockwool) on which plants are placed. Since this substrate contains no nutrients, it is continuously watered with a nutrient-rich solution. Hydroponic agriculture requires careful balancing of the nutrient solution contents against outdoor and indoor environmental conditions, and is thus subject to impact from even very small fluctuations away from optimal conditions. On the positive side, it is attractive to farmers because maximizes yield and provides yield level guarantees, while allowing for less use of pesticides and other control chemicals, leading to very high quality products produced in less land than would otherwise be required. On the negative side, hydroponic agriculture is far more energy-demanding compared to traditional farming [5]. The scope of this paper is to the application of IoT systems in precision hydroponics, which is currently understudied compared to the rest of the agricultural IoT.

2 Related work

Hydroponic agriculture is a natural fit for IoT system applications. Setting aside back-yard and small installations, professional hydroponic sites require constant monitoring and control to achieve optimal growth conditions. In typical installations, automation is provided in terms of indoor environmental controls via HVAC systems and automated window or shading mechanisms. However, the nutrient feeding schedule is typically set by human experts (agronomists), through a feedback cycle of manual monitoring of selected plant growth ("witness plants"). Agronomists manually measure the growth parameters of witness plants, and adjust the feeding schedule for the whole site accordingly [8]. This, however, is a suboptimal solution. In larger sites, the microclimate can vary significantly across the site. Due to leakages, blockages and other technical issues, irrigation can be uneven. Therefore, impacts measured on witness plants, may not evenly apply to all the site, and growth problems may go unnoticed until it is too late. In this respect, the IoT can offer automated precision monitoring in real time, and across an entire site.

Previous work on IoT-enabled hydroponic systems has focused mostly on system properties and architecture (e.g. [10]), with most research focusing on monitoring specific types of sensor values, such as water quality (e.g. [6]). In

[7], the authors focus on the performance of the MQTT protocol, showing that server load and throughput is not significantly affected by large numbers of IoT nodes (1000 in this case). This demonstrates that large installations can benefit from IoT deployments without needing to rely on resource-rich servers. IoT applications using simple temperature and humidity sensors only, demonstrate that significant savings in electricity (22%) and water consumption (38%) can be obtained [9]. Similarly, in [3] and [2], a system where agronomists could define logical rules for the operation of a system is presented, using a continuous feedback loop to the agronomist, so they can observe the effect of the rules they set. However, in such systems, the weak point here remains the need for heavy agronomist involvement in the process [1]. To address this problem, [12] propose a fuzzy logic control system to automatically adjust system operation, in order to maintain predetermined operational parameter specifications (in this case, solution electrical conductivity and PH). In [11], the use of machine learning is proposed in two ways, to assist hydroponic installations. Firstly, it is used to obtain an indication of witness plant growth levels by analysing images of witness plants, replacing the need for manual measurement. Secondly, it is used to model and forecast optimal lighting policy conditions for the site, based on previous data. So far, this is the only example in literature where data has been used in an assistive manner, i.e. to automatically propose operation guidance to agronomists.

3 System overview

For this system, we developed an embedded wireless sensor network for a hydroponic greenhouse in the area of Mesolongi in Western Greece, producing tomatoes (Fig.1). Contrary to most previous research, the system is applied to a large commercial installation. The conceptual diagram of our system is shown in Fig.2 and consists of the wireless sensor network inside the greenhouse which transmits all the necessary environmental parameters to an Internet of things (IoT) platform.

3.1 Hardware and virtual Sensors

The system consists of a variety of off-the-shelf indoor and outdoor sensor types. All sensors operate between 3.3 - 5.0 Volts. The following hardware sensors are used (e.g see Fig.3):

- Indoor environment sensors: A DHT-11 sensor is used to temperature and humidity levels. We also use a light level and solar irradiation sensor.
- Substrate sensors: To measure nutrition solution parameters on the substrates, we use a capacitative soil moisture sensor and soil temperature sensor.
- Outdoor sensors: For external environmental conditions, we use mast-mounted wind speed, wind direction, light level and waterfall sensor.

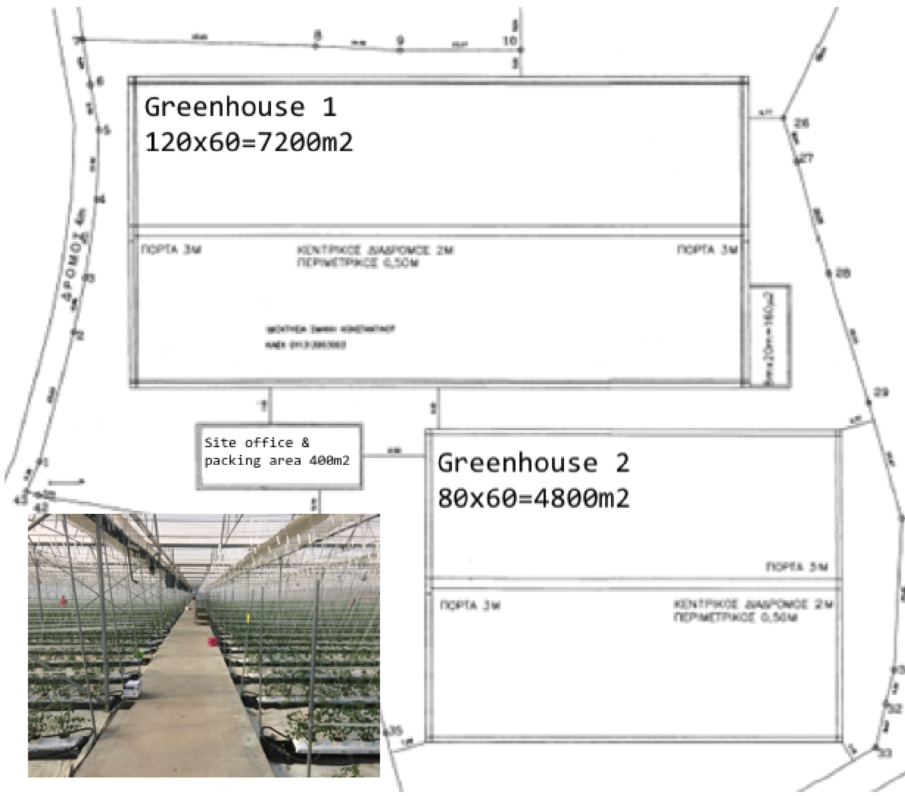

Fig. 1: The hydroponic site of our system, with a total cultivation area of $12,000m^2$ and a site office and packing area of $400m^2$

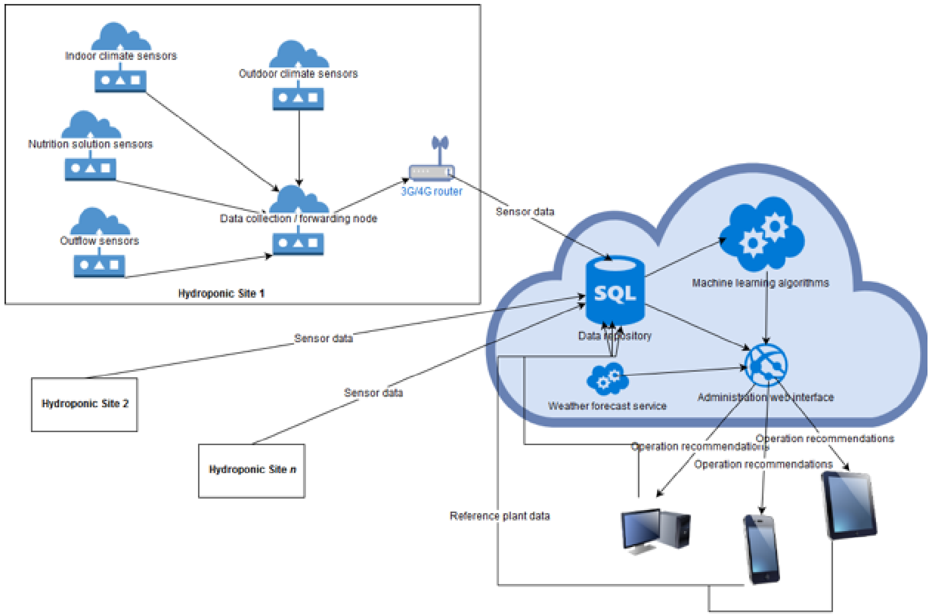

Fig. 2: System architecture depicting site hardware and software platform components

- Water quality sensors: A PH and electric conductivity sensor is used on the water outflow collection points.

Furthermore, we support what we term “virtual” sensors, which are essentially data obtained from external APIs or other internal data sources:

- Virtual weather station: We use the OpenWeathermap.org API to obtain current and forecasted meteorological conditions in the area. This data is used for interpolation with outdoor sensor data, and to obtain weather forecasts from established climate models.
- Nutrition scheduling: The agronomist maintains an accurate record of the nutrition schedule, including watering times and duration, and nutritional content composition, in the form of spreadsheet files. These data are fed to the system at regular intervals.

3.2 Sensor integration and connectivity

We bundle multiple sensors on Arduino Uno boards, building what we call ”sensor packs” with various sensor configurations. The various sensor packs connect via XBee modules based on the IEEE 802.15.4/Zigbee Wireless Personal Area Network (WPAN) in a star configuration, to coordinator nodes. Coordinator nodes aggregate and forward data to the server, via wired Ethernet connections.

The following wireless sensor pack configurations are supported (e.g. Fig.3 left and Fig.4):

– Plant row packs: These support multiple (6) soil moisture sensors and, optionally, a soil temperature sensor. These sensors are positioned along individual plant rows.
– Indoor climate packs: These support the temperature, humidity, light level and irradiation sensors. They are placed in various equidistant locations across the site.
– Outflow packs: These support the PH and electric conductivity sensor and are placed in the outflow collection points across the entire site.

We also support the following wired Ethernet pack configurations (e.g. Fig 3 right):

– Weather station packs: One Arduino board is used to integrate all the outdoor sensors for the site. This sends data directly to the server using a wired Ethernet connection.
– Coordinator packs: Each coordinator node collects data wirelessly (via Xbee) from multiple other sensor packs (plant row, indoor climate and outflow. Its role is to collect, store, pre-process and transmit the data to the server, using a wired Ethernet connection. Because of the heavier computation demand, coordinator packs are integrated using the Arduino Mega board.

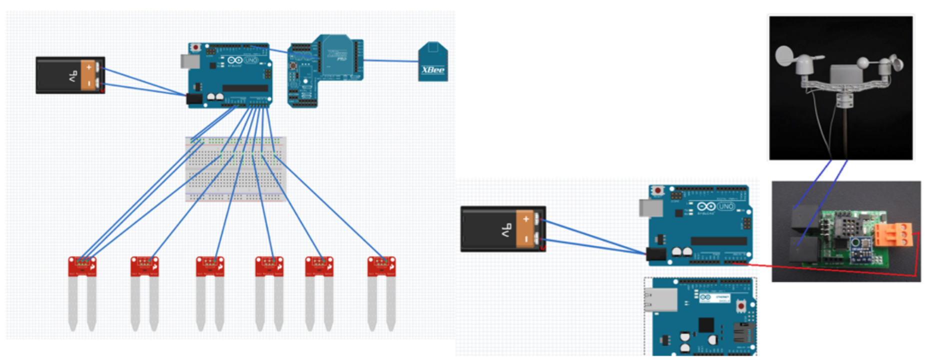

Fig. 3: Schematics for the plant row and outdoor weather station sensor packs

3.3 Manual data collection

The site agronomist takes regular observations from the various witness plants in the site. These observations are collected using a mobile device, running a web-based application to collect the relevant data (foliage, plant height, stem width, fruit size and state etc.). Data is uploaded directly to the server using a wireless (Wi-Fi) connection.

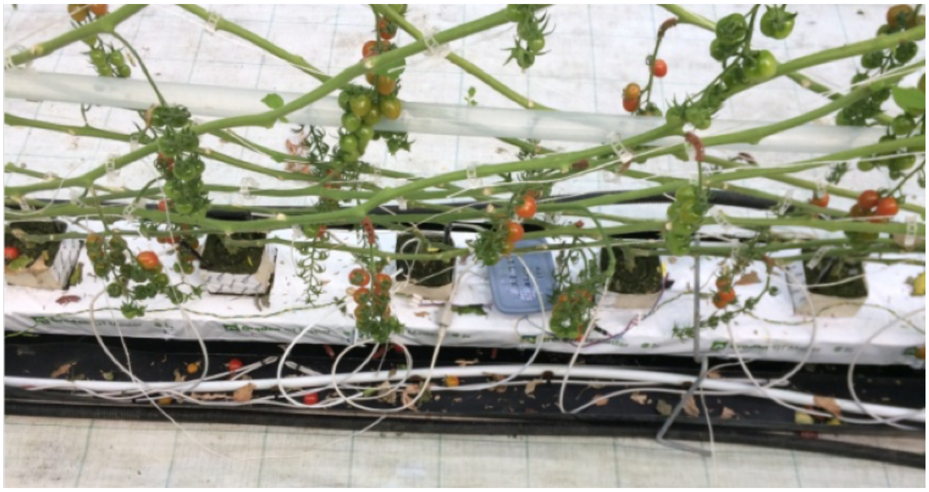

Fig. 4: Deployed plant row sensor pack

3.4 IoT data management platform

For the collection of data, we use the open-source ThingsBoard IoT platform. This platform is configured to model the site as a set of assets (there are two greenhouses, each one being an individual asset), devices (each sensor pack or virtual sensor is modelled as a single device) and operators with various roles (site supervisor, agronomist). The platform offers the ability to visualise the data at an aggregate or individual sensor basis (using custom-designed data visualisation dashboards, Fig. 5), and to establish alerts for operating conditions exceeding specified thresholds. The sensor packs and virtual sensors communicate data to the platform using HTTP REST APIs. Further from the data collection platform, ML modules for training models and performing predictions are also hosted on the server. These modules are currently under development, but the aim is to feed their output back into the platform, and integrate their output on the user's dashboard, in numeric and graphical form.

4 Monitoring Actuator Operation

The hydroponic site is equipped with a proprietary climate control system (by Priva S.A.) which is used to automatically drive various control elements that help maintain optimal indoor climate parameters, as required. These include ventilation fans, overhead curtains, moisture sprayers and CO_2 pumps, which are activated depending on specific rules set by the agronomist. This proprietary system does not have an open interface, therefore it is not possible to access data produced by it from a third-party system such as ours. However, strategic positioning of sensors can be used to infer the system operation.

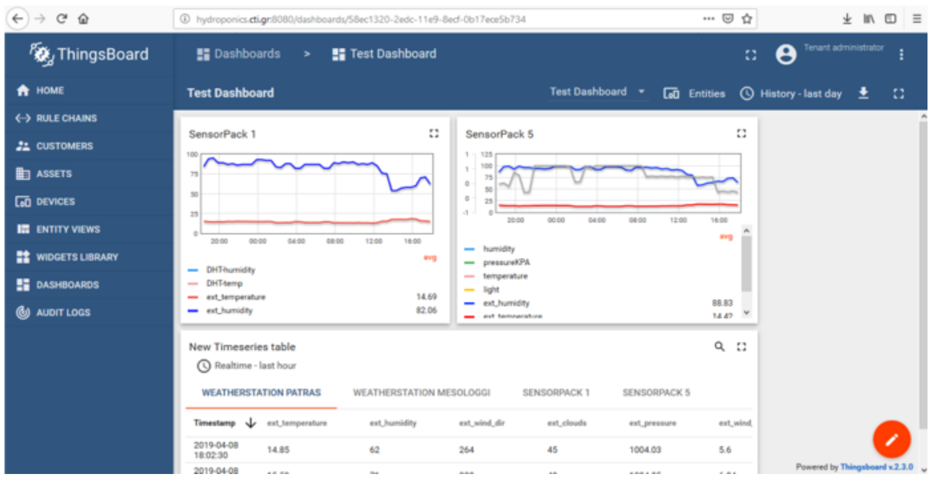

Fig. 5: Sample view of the hydroponic sensor dashboard provided by the Things-Board IoT platform

(a) Under-curtain sensor pack (b) Over-curtain sensor pack

Fig. 6: Positioning of indoor environment sensor packs to detect system operation

Fig. 7: Data captured by the over-curtain and under-curtain indoor environment sensor packs

As an example, we demonstrate the data acquired by two indoor environment sensor packs, positioned over, and under the overhead curtains (Fig. 6). In this example, the green line shows the under-curtain sensor values, while the blue line shows the over-curtain values. As can be seen in Fig. 7, when the solar irradiation intensity spikes (blue line, top chart), the automatic curtains begin to operate, therefore "smoothing" the effect of intense light in the greenhouse. Simultaneously, because of the high light intensity and resulting increased temperature, humidity begins to drop rapidly, hence the moisture sprayers help maintain the humidity levels within better tolerances. By capturing this behaviour, we are able to detect system operation events, as well as threatening emergent conditions in the greenhouse during operation.

5 Machine Learning Experiments

Our work regarding the integration of ML recommendation components is ongoing. However, in this section, we demonstrate an example of how ML can provide advanced insights and recommendations to hydroponic site agronomists, based on the prediction of ambient light levels in the greenhouse. We use a deep neural network model on a six day dataset, ranging between 27/4/2019 and 2/5/2019 (144 cases), with the layer node count $\{3, 5, 5, 5, 3\}$, ReLU activation function and $\epsilon = 1.0^{-}8, \rho = 0.99$. Input features are the hour of day ($[0, 23]$), and reported cloud coverage level ($[0\%, 100\%]$) from the virtual weather station, while the predicted value is the ambient light levels in the greenhouse in lux units ($[0-, +\infty)$). Raw data is aggregated to obtain their hourly average. Data preprocessing includes the normalisation of lux values to a range between [0,1]. The deep learning model can produce arbitrary positive or negative values. The latter, in our case, make no logical sense (since lux values cannot be below 0). Hence we post-process the predictions to transform negative values to zero. To evaluate the model performance, we use k-fold cross validation ($k = 10$) with random sampling, and also use a leave-one-out approach. The results are shown in Table 1 and Fig. 8. Interestingly, just two features (cloud cover, hour of day) are reasonable predictors for light intensity (between 5.7% and 11.4% RMSE), despite inaccuracies caused by plant foliage, worker and equipment movement and the OpenWeatherMap API model inaccuracy. Further, lux data in this analysis comes from a single, uncalibrated sensor, whose values are not cross-related with those of nearby sensors.

Table 1: Deep learning model evaluation

Evaluation approach	**Root mean squared error**	**Correlation (Spearman's ρ)**
k-fold cross validation	$0.114 (\sigma = 0.091)$	$0.877 (p < 0.01)$
Leave-one-out	$0.057 (\sigma = 0.086)$	$0.892 (p < 0.01)$

6 Conclusions

We have presented the architecture and on-going deployment effort for an IoT-enabled hydroponic installation. Our work aims to be amongst the first to produce recommendations to facilitate the workload of professional agronomists, using ML techniques. A further innovation which we are in the process of implementing, is to enhance the quality of predictions by collecting data from multiple contributing sites. In this way, a community of hydroponic installation operators can benefit from the knowledge contributed by others, and therefore solving the "starting problem" associated with the inability to obtain recommendations when no, or little data, has been obtained for the site. A further advantage of this approach is that it may minimize the need for IoT equipment installation, as fewer sensors on each site will be necessary to obtain accurate monitoring and prediction results.

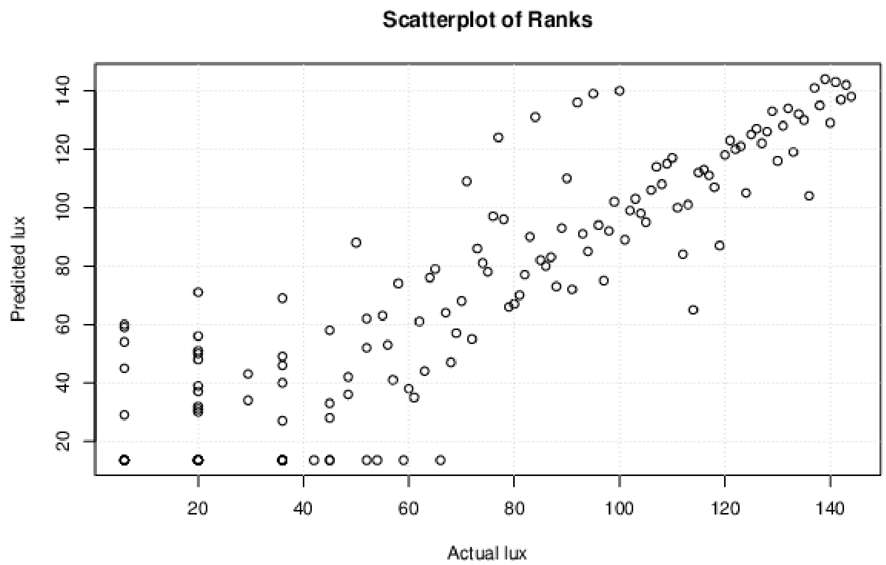

Fig. 8: k-fold cross validation Spearman rank correlation

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