IoLT Smart Pot: An IoT-Cloud Solution for Monitoring Plant Growth in Greenhouses

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Abstract: According to a recent Beecham Research report, food production have to be increased by 70 percent till 2050 to feed 9.6 billion global population predicted by the United Nations Food and Agriculture Organisation. Since Cloud Computing and the Internet of Things (IoT) have already opened new ways for revolutionizing industrial processes, these technologies could be important for the farming industry. Smart farming has the potential to improve productivity and reduce waste to transform agriculture. Plant phenotyping is an important research field that gained a high attention recently due to the need for complex monitoring of development and stress responses of plants. However, the current phenotyping platforms are very expensive, and used in large central infrastructures, which limit their widepread use. The newly emerging ICT technologies together with the availability of low cost sensors and computing solutions paved the way towards the development of affordable phenotyping solutions, which can be applied under standard greenhouse conditions. The Internet of Living Things (IoLT) project has been launched to integrate IoT technological research with applied research on specific, biological applications. In this paper we introduce our research results for developing a low cost plant phenotyping platform for small sized plants, which is one of our goals in this project. The proposed IoLT Smart Pot is capable of monitoring environmental parameters by sensors placed above the plant and into the pot, managed by a Raspberry Pi board placed under the pot. We have also developed a private IoT-Cloud gateway for receiving, storing, visualizing and downloading the monitored parameters sent by the pot devices. We have performed the evaluation of our proposed platform both with simulated and real smart pots.

1 INTRODUCTION

The United Nations Food and Agriculture Organisation predicts that by 2050 global population will grow to 9.6 billion. A recent, corresponding Beecham Research report (Beecham Research, 2017) states that food production have to respond to this growth by 70 percent increase till 2050. Agriculture also need to be reformed since it is currently responsible for a fifth of greenhouse gas emissions and for 70 percent of the worlds fresh water usage. They also argue that smart farming has the potential to improve productivity and reduce waste by exploiting new ICT technologies, such as the Internet of Things (IoT). IoT represents a dynamic global network infrastructure with self configuring capabilities (Sundmaeker et al., 2010), in which things can interact and communicate among themselves and with the environment through the Internet by exchanging sensor data, and react autonomously to events and influence them by triggering actions with or without direct human intervention. Such systems can be utilized in many application areas, thus they may have very different properties. According to recent reports in the IoT field (e.g. (Mahoney et al., 2011)), there will be 30 billion devices always online and more than 200 billion devices discontinuously online by 2020. Such estimations call for smart solutions that provide means to interconnect and control these devices in an efficient way.

Cloud computing (Buyya et al., 2009) enables flexible resource provisions that have become hugely popular for many businesses to take advantage of responding quickly to customers demands. There is a growing number of cloud providers offering IoT-specific services, since cloud computing has the potential to serve IoT needs such as hiding data generation, processing and visualization tasks. With the help of these virtualized solutions, user data can be stored in a remote location and can be accessed from any-

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where.

Plant phenotyping covers high throughput approaches, which make possible to monitor the growth, physiological parameters, and stress responses of plants with high spatial and temporal resolution by using the combination of various remote sensing methods. Until recently typical plant phenotyping platforms used very expensive instrumentation to monitor several hundreds to few thousands of plants. Although these large infrastructures are very powerful, their high cost, in the range of few mEUR per platform, limited their widespread, everyday use. Due to the recent development in computer, sensor, and IoT technology a promising alternative, called affordable phenotyping, started to develop, which applies low cost sensors and computing solutions for monitoring fewer number of plants with high flexibility in standard greenhouse environment.

The goal of our research is the development of a low cost plant phenotyping platform for small sized plants, which enables the montoring of growth of leaves and shoots in parallel with the monitoring of environmental parameters, as well as the development of an IoT Cloud platform capable of collecting, storing and visualizing environmental data.

The remainder of this paper is presented as follows: Section 2 introduces related works, and Section 3 discusses the background, the research goals and the applied idea. Section 4 presents our proposed support gateway using IoT Cloud technologies, and also shows its evaluation about its scalability and device management features. Finally, the contributions are summarized in Section 5.

2 RELATED WORK

Nowadays, we can find smart solutions in the commercial world for many household areas, including indoor plant monitoring, e.g. Xiaomi Flora (Sharma, 2018) and Parrot pot (Parrot Pot, 2018). They are mostly capable of monitoring light, humidity and salt content of the plant soil, and able to communicate with nearby devices via Bluetooth. For professional usage, there are only very few commercially available platforms for affordable phenotyping (e.g. PhenoBox (CzedikEysenberg et al., 2018)). However, they are typically limited to monitoring only a single plant.

Brogi et al. (Brogi et al., 2018) have developed a hands-on lab activity for educational purposes by monitoring a single plant. Their goal was to exemplify the use of IoT, Fog and Cloud technologies. We exploit a similar idea for using these technologies, but we propose a complex platform usable for real world greenhouse application.

Dagar et al. (Dagar et al., 2018) proposed a model of a simple smart farming architecture of IoT sensors capable of collecting information on environmental data and sending them over wireless networks to a server. There are also generic solutions to monitor IoT systems including agriculture applications, such as the Kaa IoT Platform (Kaa project, 2018). It is a commercial product that is able to perform sensor-based field and remote crop monitoring. It also has an open source version called the Kaa Community Edition. Such generic toolkits are quite complex and heavy-weight, so they are not well suited to specific needs.

Concerning generic IoT gateways, Kang et al. (Kang et al., 2017) introduced the main types and features of IoT gateways in a detailed study, which presents the state-of-the-art and research directions in this field. This solution is also too generic for our needs.

In contrast to these solutions, our approach aims to provide a low-cost solution using the latest IoT and Cloud techniques to enable a robust and scalable solution to be used for groups of plants with user friendly management.

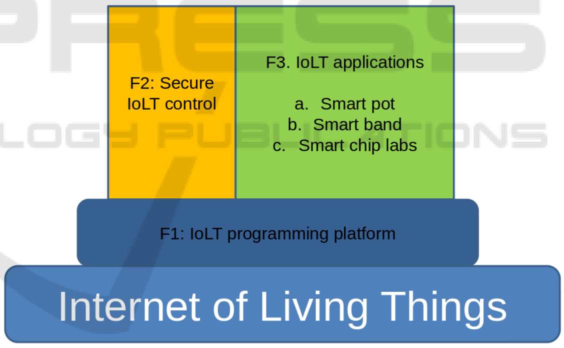

Figure 1: IoLT project tasks.

3 THE IOLT SMART POT

3.1 The Internet of Living Things Project

The University of Szeged and the Biological Research Centre of the Hungarian Academy of Sciences work together to create a Network of Excellence called the Internet of Living Things (IoLT) since 2017. This project aims to integrate IoT technological research with applied research on specific, biological IoT applications. The project will create an opensource IoLT programming platform based on JavaScript. It will be able to execute applications on cheap, low capacity IoT devices by providing easy to use programming interfaces, thus enabling application development for researchers of any discipline. Technological developments will address the JavaScript executor engine, software-hardware porting, programming environment, secure management algorithms and software quality.

Figure 1 depicts the main development tasks (denoted by F1, F2 and F3) of our project. The IoLT application areas (within F3) address (a) the development of a smart pot for plants enabling complex plant phenotyping using medium-high throughput characterization of plant growth and physiological status, (b) the development of a smart watch for performing actigraphy to investigate ultradian activity levels of patients in psychosocial treatments, and (c) the development of Lab-on-a-chip systems for enhanced microfluidic diagnostic technologies for high-throughput cell analysis.

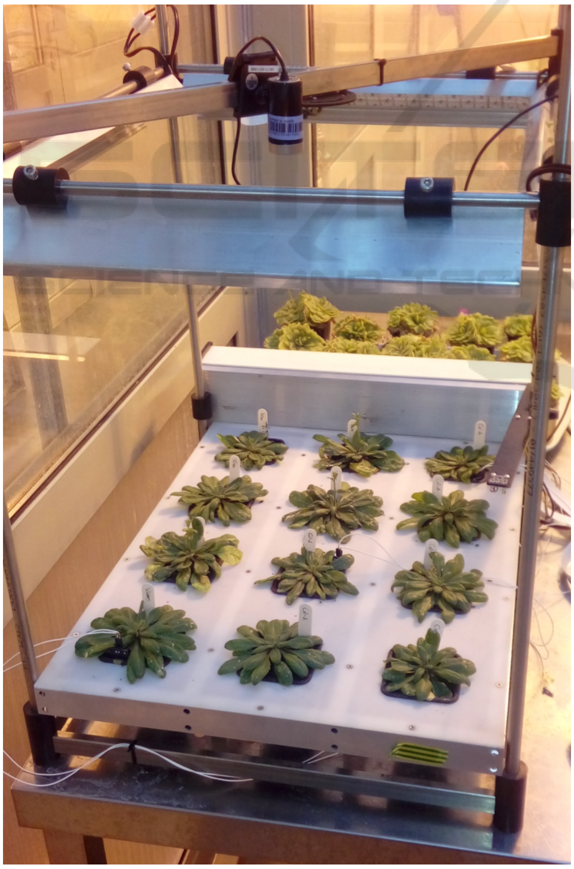

Figure 2: IoLT Smart Pot prototype.

3.2 Designing and Assembling the IoLT Smart Pot

We have developed a low cost plant phenotyping platform for Arabidopsis and other small sized plants. The platform consists of a cluster of 12 pots (in 4x3 matrix) with individual plants, and uses a low-cost computer based system to monitor plant growth and environmental parameters. Plant growth is monitored by using an RGB camera, located above the plant cluster, as shown in Figure 2. The cluster is also equipped with an LED-based illumination system, which allows supplementing the natural light, if needed. The usual frequency of image capture is one hour, but it is possible to increase it up to one minute for higher time resolution. Environmental parameters are monitored by sensors (light intensity, air temperature, relative air humidity), placed above the plants, as well as soil humidity sensors placed into selected pots. The data are stored temporarily on a memory card of the computer, and it can be transferred via WiFi connection to a database located in a local server or in the cloud. Segmentation of plant related green pixels and calculation of projected leaf area is performed by a home-developed software. The system was tested during a one-month growth period with WT Arabidopsis plants. The used one hour image capture frequency revealed a circadian change in the projected leaf area due photoperiod dependent leaf movements. The proposed IoLT Smart Pot system allows to monitor the effect of various stress factors (drought, nutrition, salt, heavy metals, etc.), as well as behavior of various mutant lines.

4 IOT-CLOUD GATEWAY FOR DATA MANAGEMENT

4.1 Overview of the Gateway Application

The architecture of our proposed IoT-Cloud gateway can be seen in Figure 3. It is composed of three services. We have developed a (i) Node.js Webapp application to provide a web-based graphical interface for grouping and managing pots and users in the form of projects. Users can register pots, and create projects for a certain time interval, to which additional users and already registered pots can be assigned. It is also capable of visualizing the sensor values gathered from one or more pots added to a project. In Figure 4, we visualized experimental results of a cluster of pots (called *BRC_Smartpot_1*) of a project (titled *Real BRC*

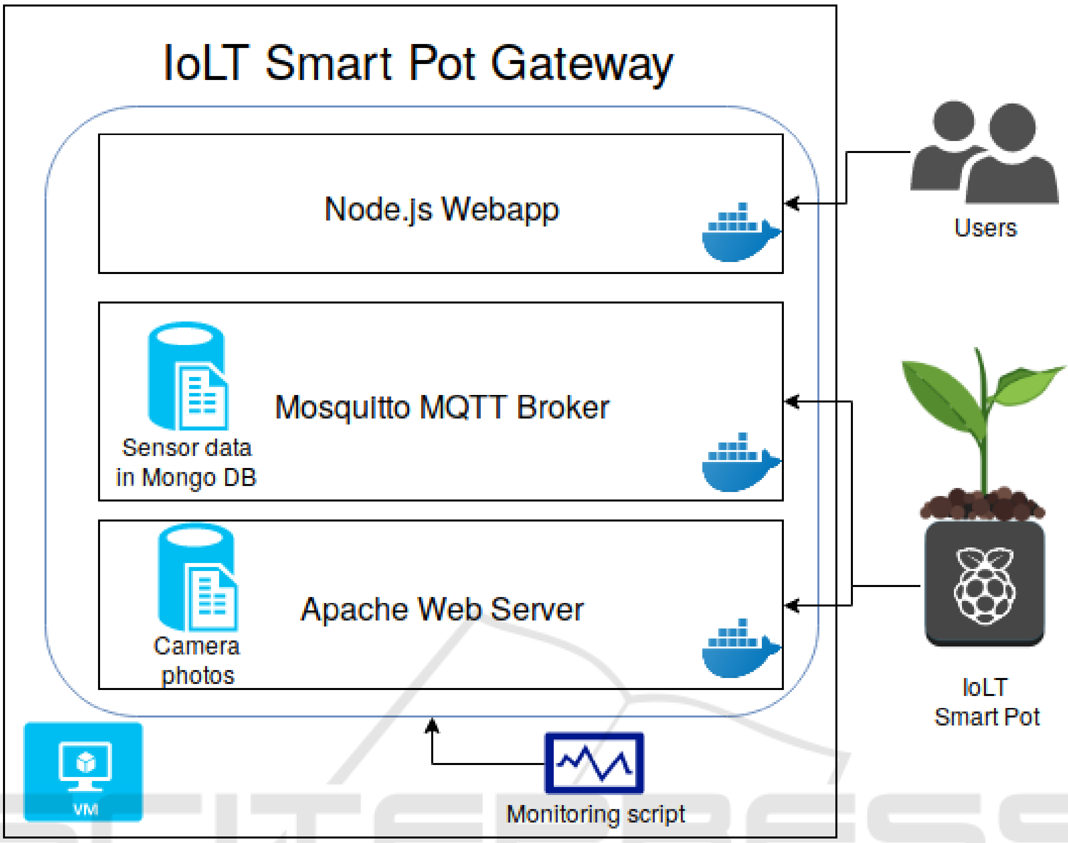

Figure 3: The architecture of the IoLT Smart Pot Gateway.

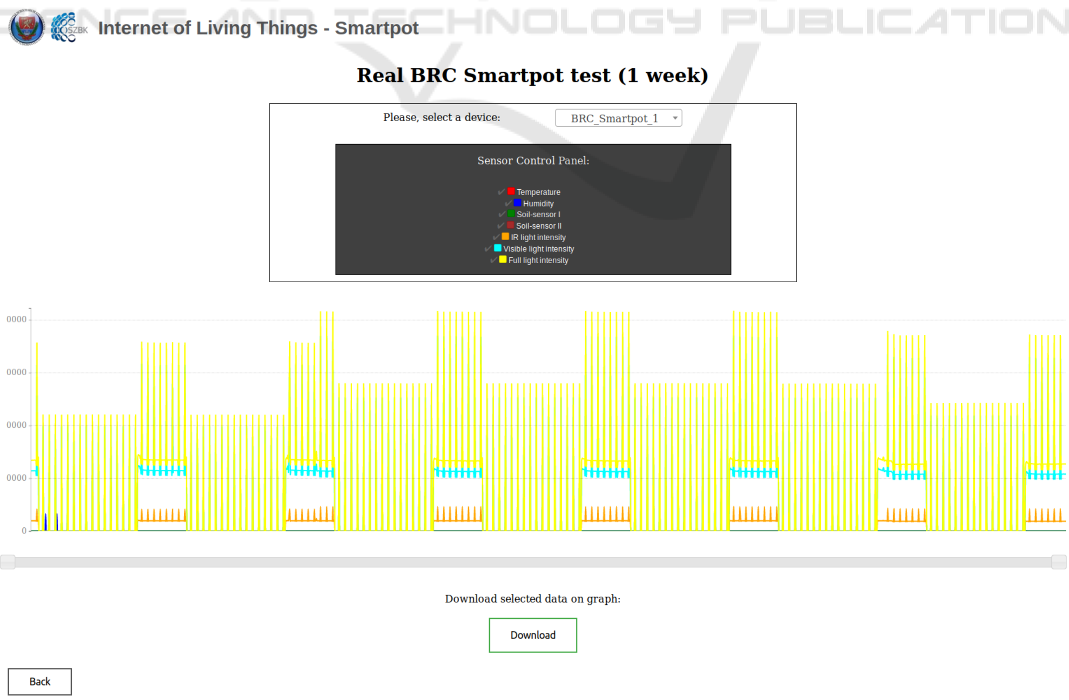

Figure 4: Historical sensor data visualization in the IoLT Smart Pot Gateway.

Smartpot test (1 week)) depicting values of 7 sensor types for a week of utilization. As we can see, if all of the sensor types are selected on the graph, some curves may overlap. We can adjust the time interval (on the x-axis, while the y-axis denotes the actual sensor values), and switch on and off the sensor types, and download the set of values according to the defined visualization parameters in CSV format. The downloaded file can be used by the associated researchers for further processing.

We have also developed a microservice called Mosquitto MQTT Broker (ii), which is built on the open-source Mosquitto tool (Mosquitto, 2018), using a MongoDB (MongoDB, 2018) database to store the received sensor values. The monitored 7 sensor types of a pot are described by a JSON document, regularly sent by the Smart Pot to the MQTT broker of this microservice directly. The sensors of a pot is managed by a python script implementing an MQTT client. This script can be configured with a pot identifier, sensor value sampling frequencies and picture taking frequencies, hence each IoLT Smart Pot (which is a cluster of pots in our case) is equipped with a camera. The pictures taken are sent directly to our third microservice called Apache Web Server (iii) via SFTP connection.

The source code of our proposed gateway is available at (IoLT Smart Pot Gateway Source, 2019). Concerning the implementation of these microservices, we used the Docker container technology (Docker, 2018). Each microservice is placed in a Docker container, and the three of them are composed together, since the Node.js Webapp reads the sensor values stored in MongoDB and the pictures stored at the Apache server. Finally, the composed microservices are placed in a virtual machine (VM), in which the container performance values are monitored by a script (which we use for the evaluations in the next section). The VM containing the microservices can be placed to any cloud. In our case, it is instantiated in the MTA Cloud (MTA Cloud, 2018) with a small VM flavor (having 1 virtual CPU core and 2 GB RAM memory). The MTA Cloud is an OpenStack-based national community cloud financed by the Hungarian Academy of Sciences in order to provide cloud services for scientists from the academy.

4.2 Evaluation with Simulated Smart Pots

In order to evaluate our proposed phenotyping platform, first we performed a detailed evaluation by means of simulation. After some initial measurements, we got to know the exact, real data value


```
{
  "Project": "SampleProjekt",
  "Soil-sensor II": "434.437",
  "Full light intensity [lux]": 16901.38,
  "Time": "2019-01-14 14:02:56",
  "Humidity [%]": "41.1",
  "Soil-sensor I": "594.940",
  "IR light intensity [lux]": 15865.80,
  "Temperature [C]": "21.8",
  "Visible light intensity [lux]": 1035.58
}
```


Figure 5: Sample JSON message of 7 sensor values of a pot.

ranges for the installed sensors, therefore we designed a simulated Smart Pot represented by python scripts capable of sending generated sensor data via the MQTT protocol. Figure 5 presents a generated sample JSON file for the considered sensor types.

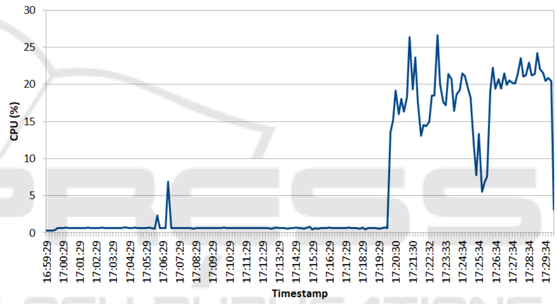

Figure 6: CPU measurement results for 250 pots.

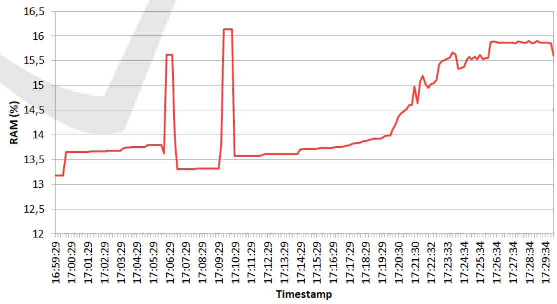

Figure 7: Memory measurement results for 250 pots.

First, we created 250 simulated pots with scripts that sent generated sensor data to our IoLT Smart Pot Gateway service (deployed at MTA Cloud) for 30 minutes. We divided the total experiment time-frame to the following periods:

- in the first 10 minutes we applied sensor data generation frequency of 30 seconds (which means that each pot sent a message of 7 sensor values every 30 seconds);

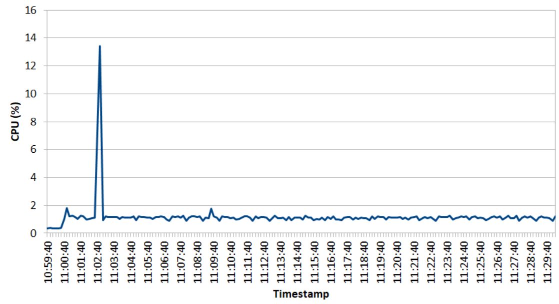

Figure 8: CPU measurement results for 50 pot clusters.

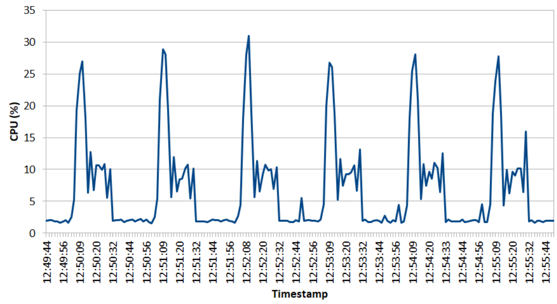

Figure 10: CPU measurement results for 100 pot clusters.

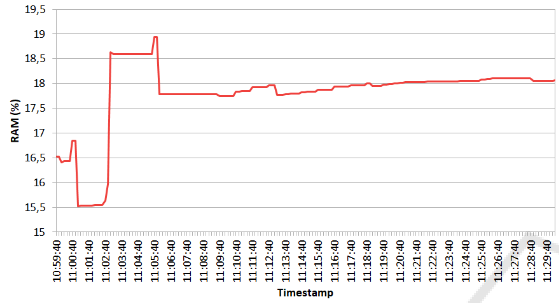

Figure 9: Memory measurement results for 50 pot clusters.

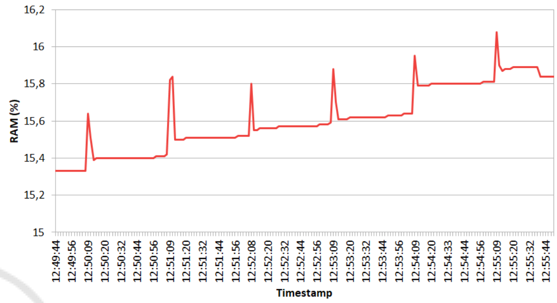

Figure 11: Memory measurement results for 100 pot clusters.

- in the second 10 minutes we applied sensor data generation frequency of 10 seconds;
- in the following 5 minutes we applied sensor data generation frequency of 2 seconds;
- and in the last 5 minutes we applied sensor data generation frequency of 10 seconds, again.

The resource usage sampling by the monitoring scripts were set to 10 seconds. They queried CPU and memory resource utilization for all containers, and we summed them to get the total resource consumption of the composed service (thus of the whole VM). We can see the measurement results for this initial round simulating 250 pots in Figure 6 and Figure 7. The x axis denotes the timestamps of resource usage sampling, while the y axis denotes the resource usage percentage. We can see that there are some spikes in both resource usage percentages after the first 10 minutes, when we start to send more messages, and from the 20th minute the utilization is clearly rising. (Note that the resource using sampling is less frequent than the arrival rate of the messages.)

Next, we set the simulation parameters in a way to mimic future, real world utilization. Our proposed IoLT Smart Pot is basically a cluster of 12 pots, as shown in Figure 2. To evaluate the scalability of our gateway solution, we performed three simulation measurements with 50, 100 and 250 clusters (composed of 600, 1200 and 3000 pots respectively). In all cases we performed the measurements for half an hour, and the simulated smart pot platform sent sensor values with the following periods:

- in the first 10 minutes we applied sensor data generation frequency of 5 minutes (which means that each pot sent a message of 7 sensor values every 5 minutes: resulting 2 messages in this period per pot);
- in the second 10 minutes we applied sensor data generation frequency of 1 minute;
- and in the last 10 minutes we applied sensor data generation frequency of 5 minutes, again.

Table 1: Comparison of the three evaluation rounds.

No. of clusters	50	100	250
No. of pots	600	1200	3000
Max. CPU util. (%)	13.42	30.91	39.29
Max. Mem. util. (%)	18.94	18.1	24.73

In the first simulation for 50 clusters we set the sampling of resource usage (processor and memory usage) in every 10 seconds, while for the second and the third one (100 and 250 clusters) we set it to 2 seconds (to have a better resolution of resource loads).

We can see the measurement results for the first round simulating 50 clusters with 600 pots in Figure 8 and Figure 9 for 30 minutes. Here we can see that the average CPU load varies between 1 and 2 percent,

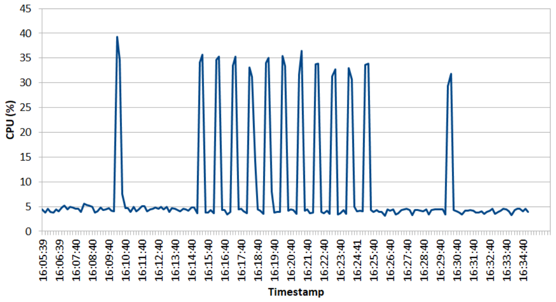

Figure 12: CPU measurement results for 250 pot clusters.

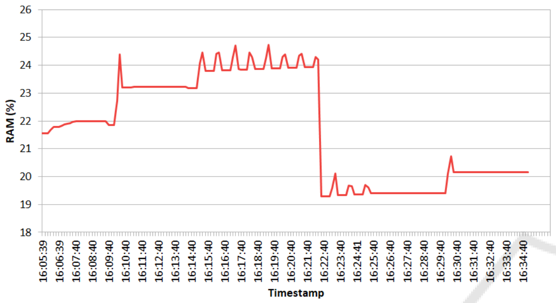

Figure 13: Memory measurement results for 250 pot clusters.

and the memory usage fluctuates between 15 and 19 percent. In this experiment we also observed that the time of an actual data processing (receiving a message and writing its contents to the database) and the time of the resource usage sampling are rarely matched. One matching example can be seen right after the 3rd minute in Figure 8, which shows a spike with almost 14 percent of CPU utilization.

For the second round we doubled the number of clusters to 100, and performed the simulation only for 5 minutes with detailed resource usage sampling of 2 seconds. We can see the measurement results for this round simulating 100 clusters with 1200 pots in Figure 10 and Figure 11. Now the results reveal a periodic resource usage fluctuation denoting the data processing activities.

Finally, for the largest experiment we further increased the number of pot clusters to 250 arriving to a total number of 3000 simulated pots. For this third round, we performed the simulation for 30 minutes, again, with the same periods as defined for the first round (of 50 clusters). We can see the measurement results in Figure 12 and Figure 13. If we take a look at the middle 10 minutes period we can see the periodic resource usage spikes, as in the previous round.

To summarize our investigations, Table 1 compares the maximum resource utilization values measured during the experiments. We can see that by increasing the number of pots to be managed by the gateway service, the utilization raises. As expected, the CPU utilization was the highest in the third round managing 3000 pots at a time with more than 40 percent, and the memory utilization is also the highest with almost 25 percent. These results show that we can easily serve numerous phenotyping projects monitoring up to thousands of pots with a single gateway instance in a Cloud.

4.3 Evaluation with Real Pots

After the simulation experiments proved the usability of our gateway service, we have tested the IoLT Smart Pot platform with real world utilization. We placed 12 Arabidopsis plants in small pots to the prototype cluster (as shown in Figure 2), and configured the smart pot (its python scripts running in the Raspberry Pi board under the cluster) to send the sensor values regularly to the IoT-Cloud gateway service. The wiring of the smart pot prototype allowed us to consider the whole cluster as a single IoT device, meaning that 7 sensors was placed in the cluster in total (for some of the 12 pots). We performed the monitoring of the growth of Arabidopsis plants under standard greenhouse conditions for more than a month. RGB imaging was performed every one hour, and sensor sampling frequency was set to 5 minutes (resulting in one JSON message per 5 minutes). Figure 14 shows a query at the gateway web interface for one week of monitoring the real IoLT Smart Pot prototype. Figure 15 shows the pictures taken on 2018.12.01., and one month later, revealing the growth of the monitored plants.

The biologists performed a post-processing of the monitored data by downloading them from the gateway portal. Figure 16 depicts the time course of leaf area growth of Arabidopsis plants. The red curve shows the time dependence of projected leaf area in an 8 days time window, while the blue curve in the inset shows the same for the whole 29 days of the experiment. The data represent the mean value for the 12 plants placed in Smart Pot cluster. The time course of the projected leaf area revealed a cirkadian oscillation pattern due to periodic leaf movement (flattening in the dark and erection in the light period).

5 CONCLUSION

Agriculture takes a significant role in greenhouse gas emissions, therefore smart farming solutions have started to be developed to improve productivity and reduce waste by exploiting new ICT technologies, such as the Internet of Things. Affordable pheno-

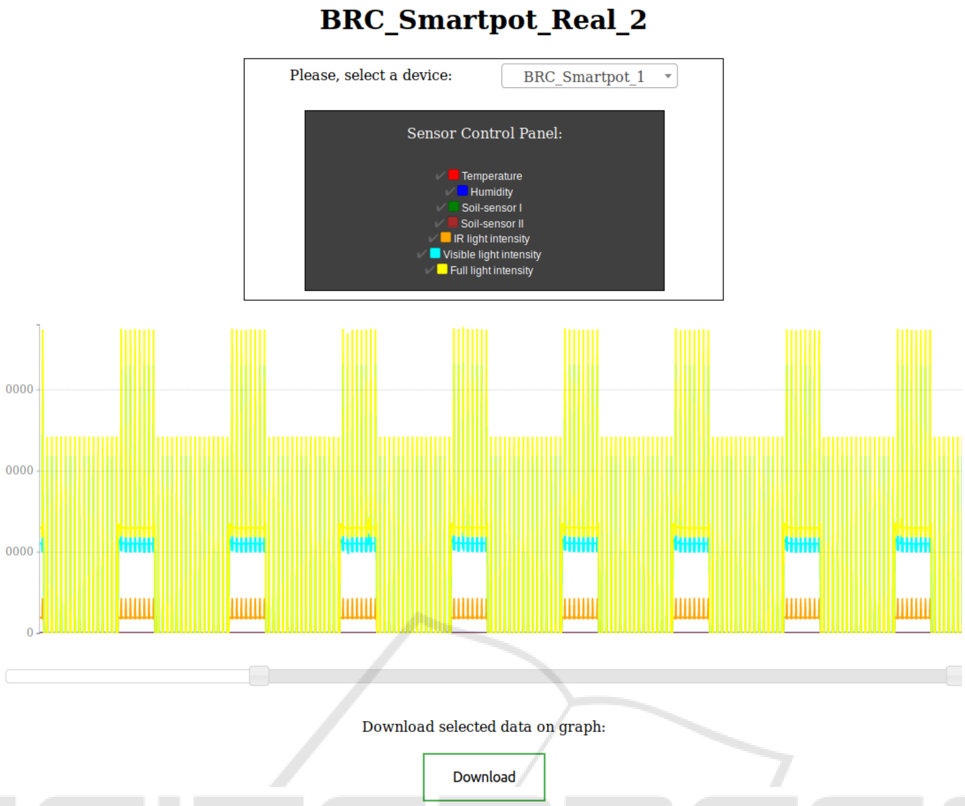

Figure 14: Real world measurement data visualization in the IoLT Smart Pot Gateway.

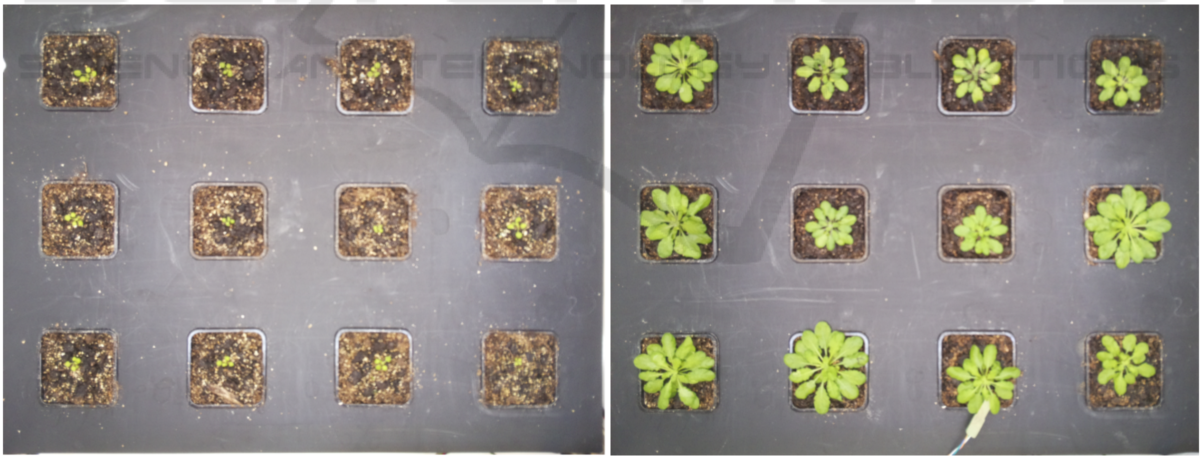

Figure 15: Pictures of a Smart Pot cluster taken at 2018.12.01 (left), and 2019.01.01 (right).

typing represents a related research area that aims to apply low cost sensors and computing solutions for smart monitoring of plants with high flexibility in standard greenhouse environments.

To contribute to this aim, in this paper we proposed the IoLT Smart Pot Platform, which is capable of monitoring environmental parameters with IoT technology by placing sensors above the plants and into the pots. We also developed a private IoT-Cloud gateway for receiving, storing, visualizing and downloading the monitored parameters sent by the IoT devices of the pots. We have performed the evaluation of our proposed platform both with simulated and real smart pots, and the results proved the scalability and flexibility of our platform.

Our future work will address further improvements of the smart pot by attaching further sensors, and we also plan to extend the IoT-Cloud gateway

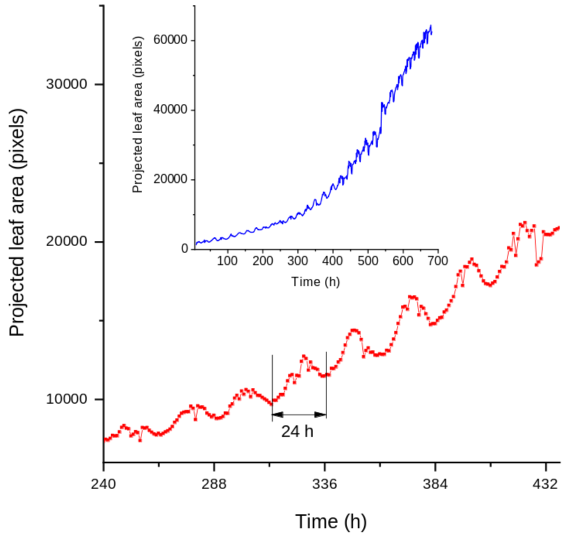

Figure 16: Post-processed environmental results of the real experiment.

with additional services for postprocessing the monitored environmental data.

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