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Crop weight measurement sensor for IoT based industrial greenhouse systems

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Abstract. Nowadays the industrial management systems are changing by means of implementing various Internet of Things (IoT) technologies, allowing a simple integration of sensor technologies with wireless communications and development of cloud based database solutions. The industrial greenhouse management systems are not the exception in this regard, as they are becoming more and more popular with the use of various sensors for the automation of the vegetable and other crop cultivation process.The general aim they have is to raise the level of process automation, quality, energy efficiency and other important parameters. The implemented technologies and environment of industrial greenhouse can be different fir the research type laboratories, as they are focused on production, therefore this research is conducted in cooperation with tomato producing industrial greenhouse of SIA 'Latgales darzenu logistika' focusing on IoT based crop weight measurement.

Key words: Crop, Weight measurement, IoT, Greenhouse systems.

INTRODUCTION

Each automation system obtains a control signal from feedback loop, typically gained from some physical sensor, controlling in that way the irrigation process of tomatoes. It is necessary to monitor the weight of tomato plants and its soil pod (Van Straten et al., 2011; Chen et al., 2016). Weight measurements show the tendency of water (fertilizer) consumption and give a precise timing when irrigation must be started and stopped (the changing in moisture level between start and the end of watering is about 7 to 13%). Furthermore, it helps to show the tendency of crops biomass increasing, plants overall health, balance between parts of the plant according to the programmed greenhouse climate values (Ehret, 2001).

One of the most important factors hindering wider implementation of weighting system in greenhouse is their high price, where the largest costs are related to the weighing sensors themselves. In addition to the price factor, the weight sensor systems are often characterized on the market by known structural and functional limitations, which can be solved if developing a new weighting system (Paskal, 2018).

The initial studies show that in the existing industrial greenhouse weighing systems and their prototypes, mostly S-type weighting sensors are used, that simplifies the measurements of the weight of hanged objects. In this case, weight sensors of high-precision with temperature compensation and high output signal linearity are in use for obtaining the accurate measurement data, increasing also the costs of the sensor (Carrasquilla-Batista et al., 2016; Alberta, 2018).

The authors assume that the price of a high-quality sensor cost system can be reduced by using considerably cheaper sensor solutions, embedding electronics that automatically processes the readings of this sensor. The adapting of it to the variations of the ambient temperature meets the requirements of temperature compensation and non-linearity of the weight sensor in all possible operating modes (De Koning & Bakker, 1992). This fact raises a number of scientific research tasks related to the digitization of high-resolution analogue signal of the weight sensors, obtaining of the data filtering post-processing, and subsequently data transmission to the server database.

MATERIALS AND METHODS

In order to obtain the data of the periodic crop weight measurements, an IoT based crop measurement system shown in Fig. 1 is used. The main block is the Load Sensor Module (LSM) with such elements:

- LSM – Load Sensor Module;
- L – Load;
- WS – Weight Sensor;
- ADC – Analog-to-Digital Converter;
- MC – Microcontroller with Built in Wi-fi Module;
- R – Wi-Fi Router;
- S – Data Server (IoT Cloud).

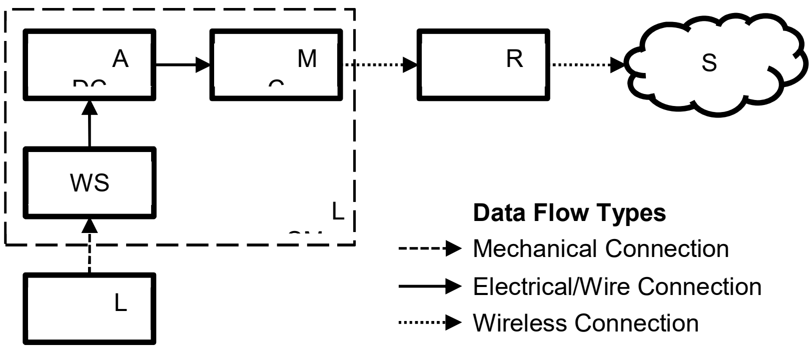

Figure 1. Block diagram of Load Sensor Module (LSM) for IoT application.

LSM uses a microcontroller (MC) with embedded Wi-Fi module (similar to ElectricImp, ESP8266, etc); and two main aspects determine such approach:

- Using the existing 2.4 GHz WiFi network (with the latest ElectricImp and ESP microcontroller versions also 5 GHz) within LSM working zone, the selected MC allows measurement data transmission to cloud based server S (in this case MS Azure based platform), but any other wireless system can also exist, like described by K. Kondratjevs et al. (2016), where data is stored and post-processed without any hardware element of external wireless communication.

- Selected MC also has a distant reprogramming and status monitoring function, which is very useful for the IoT solutions, especially at research and development stages, as it allows a distant changing of control, calculation algorithms, calibration coefficients and other LSM working parameters by means of Internet (mobile or wireless network).

In this case, separate WiFi router R can ensure a stable Wi-Fi network for the experiments.

The output signal of the Weight Sensor (WS) is processed with 24-bit analogue-to-digital converter (ADC) module. The reason to select such high precision is a relatively low working range of WS output signal (2–5 mV at rated regime of LSM). Furthermore, this ADC module has integrated a signal pre-amplifier, which allows the simplification of LSM circuitry, decreasing of the elements and costs, obtaining at the same time the measurement resolution with precision of 0.02 grams.

The first LSM prototype has been tested and verified under the laboratory conditions, where the experimental testing is based on the continuous weighing of a mass object under different external temperature conditions. These experiments clarified that temperature changes of the WS itself affect the measurement readings of WS. After the analysis of the results of the measurements, a hypothesis can state , that if the data of the weight and temperature measurements are post-processed in real-time, the precision of the load weight will be increased. In this case, formula (1) describes the transfer function of measurement data post-processing:

$$m_C = m_M + (T_i - T_C) \cdot K \quad (1)$$

where m_C – calculated weight (true weight from LSM); m_M – measured weight (raw data from WS); T_i – current WS temperature; T_C – WS temperature at LSM calibration; K – linear calculating coefficient.

The linear calculating coefficient is obtained for each LSM, according to the first testing results. The assumption is that in future coefficient K will be more precise due to self-learning algorithms, using various calibration weights.

Various temperature impact tests (sunlight, extra heat, etc.) were carried out within the laboratory environment; and the most characteristic measurements are shown in Fig. 2, where $m_{measured}$ – raw data from WS, g; $m_{calculated}$ – calculated weight (true weight from LSM), g; m_{real} – real weight of the object, g; T_{sensor} – WS temperature.

The horizontal axis represents serial number of a measurement. For all the experiments the measurement interval was 15 seconds.

According to the obtained results at the dynamic WS temperature reading changes, two important factors of the chosen WS exist:

- Transition processes within WS temperature changes cause significant fluctuations in the weight readings and opposite to the temperature process direction (see Fig. 2). This effect can be reduced by using filtration of WS signal, and creating more stable environment inside the WS sensor casing.
- At rapid temperature changes WS sensor readings have a significant reaction delay, which could be reduced by means of actual WS measurement data and historical temperature data use in formula (1).

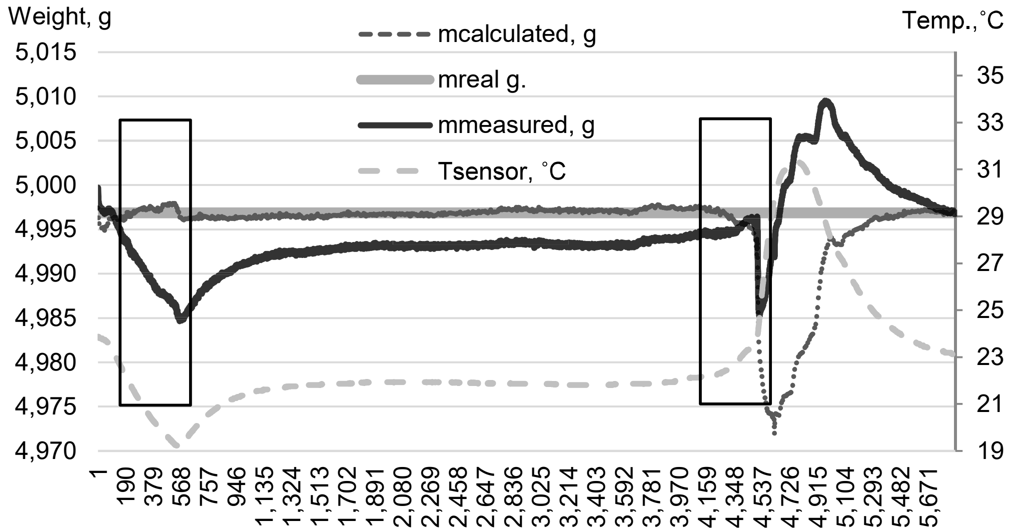

Figure 2. LSM reading stability experiment (impact of temperature test result).

Experiments at slow WS temperature changes (much closer to a real greenhouse environment), show, that in comparison to the the real load weight the calculated weight absolute error does not exceed 0.5%.

RESULTS AND DISCUSSION

Currently the first three LSM prototypes are installed in real industrial greenhouse environment at Mezvidi from 15.12.2017 (see Fig. 3.), thus collecting 179732 measurement points in IoT database by 30.01.2018., with 1 min resolution.

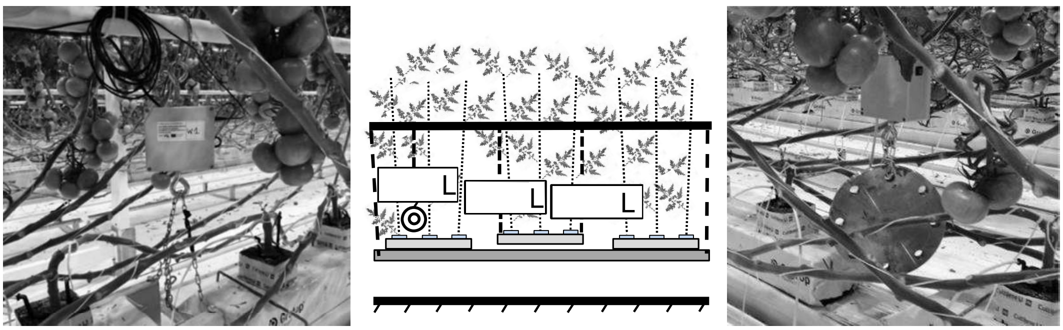

Figure 3. LSM testing in real greenhouse environment, LSM_3 for constant weight (right).

Two sensors (LSM_1 and LSM_2) are used to weight base with three tomato plants (see Fig. 3.), but the third weight sensor (LSM_3) is equipped with a reference weight of 5,770 g, to evaluate LSM measurement precision in industrial greenhouse environment, obtaining long term data. As all measurement data are stored in IoT cloud database, weight changes during twenty-four hour period, can be observed in Fig. 4.

As it can be seen in Fig. 4., from LSM_1 and LSM_2 measurements, it is possible to determine the trend in water consumption and accurately detect the time to start and stop watering system. It is also obvious that the water weight changes between watering system start and stop are about 8%, that meets the rules of the greenhouse irrigation system.

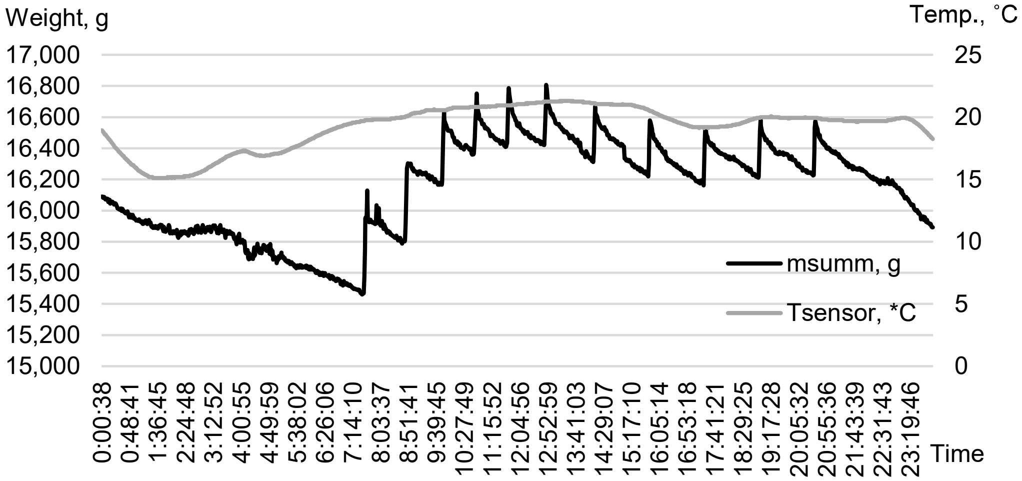

Figure 4. LSM_1 and LSM_2 calculated weight.

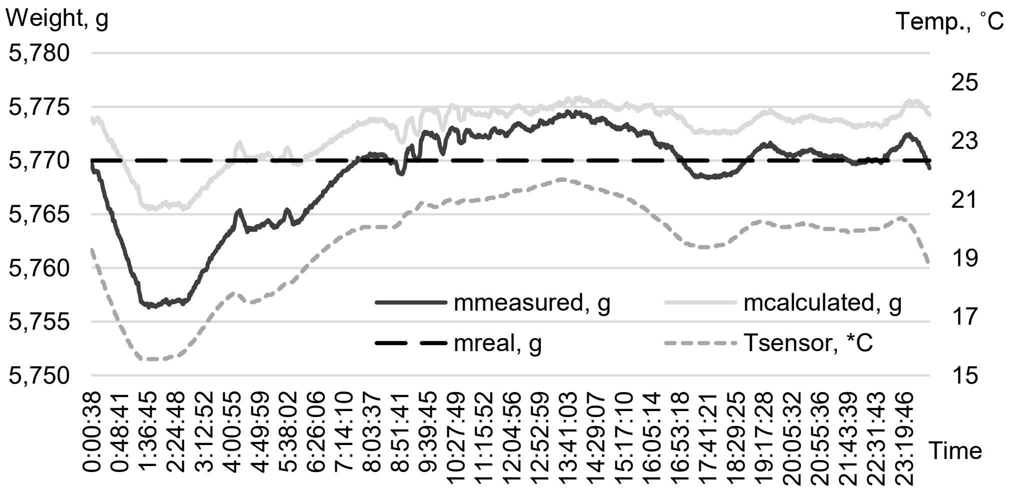

Figure 5. LSM_3 output data.

LSM_3 measurements give an opportunity to analyse LSM measurement precision under real working conditions, to evaluate LSM construction parameters and efficiency of WS data post-processing algorithm, where the error of measurements in this case does not exceed 0.1% (see Fig. 5).

Both laboratory and industrial greenhouse experimental measurement results show, that LSM weight precision can be increased if WS working temperature is stable. As the dynamic temperature changes have a great impact on readings, thus the previous or historic WS temperature readings could be used in data post-processing algorithms.

Measurement experiments of 30 h using constant weight of 5 kg show that, the use of linear data post-processing method (temperature changed 18–32 °C with max raise of 2 °C h^{-1}) gives the measurement errors from 0 to 0.6% (in average 0.1%). In its turn the use of the second and the third grade polynomial data post-processing (temperature changed 19–42 °C with max raise of 10 °C h^{-1}) gives the measurement errors from 0 to 1.5% (in average 0.9%). During calibration process, a transition process takes place, and 'stretching' effect must be taken into account at the first moment after applying calibration load, to avoid 'floating' readings later in the working regime.

At this stage LSM testing results prove their ability to work in industrial greenhouse environment (high humidity, voltage drops, etc). The obtained data can be used to improve greenhouse irrigation control systems and to enable the high accuracy detection of crop biomass growth.

CONCLUSIONS

Experimental measurements show, that both electrical and mechanical design properties of the sensor must be taken into account to get stable thermal operating mode and other operating conditions. Furthermore, the first testing results show that theuse of a S-type sensor of medium precision, it is possible to make post-processing of their raw output data, that results in the required resolution and sampling level of weight measurement data. As a result the logging of the measured weight data and subsequent statistical processing can be carried out with the aim to apply them for the energy efficient control of the total greenhouse management system.

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