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ScienceDirect

Procedia Computer Science 200 (2022) 517–526

Procedia Computer Science

www.elsevier.com/locate/procedia

3rd International Conference on Industry 4.0 and Smart Manufacturing

Data Conceptual Model for Smart Poultry Farm Management System

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Abstract

Internet of things provides ways to obtain information about farm production; however, the more data there is, the harder it is to determine the correct way to process these data. The solutions on the market are aimed specifically at gathering data, rather than processing and analyzing them. Poultry farming is one of the fields, where the application of Industry 4.0 principles is becoming a necessity, especially in the case of greenhouse gas control. Minimum standards and rules in the poultry management are regulated by EU Directives and required parameters must be ensured at all times, therefore, real-time environmental monitoring must be performed. The only practically viable approach is to automate data gathering using appropriate sensors, which is only possible if a standardized data structure model is defined.

In this research the Cyber-Physical Model is the proposed as a basis to development of smart poultry farm management system that is adjustable to particular production needs. Three main data groups are defined – necessary data to ensure requirements of EU Directives, farm monitoring data for business analysis and optimization, and additional data that can influence overall poultry farm management. The proposed data set was implemented into the existing infrastructure of a Baltic poultry farm. Multiple CO_2 (carbon dioxide) and NH_3 (ammonia) sensors were installed in order to gather data, measurements of which previously were taken manually by the farm's staff. The solution was developed on centralized cloud-based data processing system, where MQTT Broker was used for security measures. The processed data is used by the decision support system with the aim to define optimal feeding and housing.

Keywords: Precision poultry farming; data aggregation; data fusion; sensor data; production data.

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1877-0509
10.1016/j.procs.2022.01.249

1. Introduction

While Smart Poultry term, defined by IoT solution implementation into poultry sector becomes more widely used [1, 2], the aspects of proper data appliance are deepening [3]. Internet of things (IoT), in accordance with Industry 4.0, provides ways to obtain information about farm production; however, the more data there is, the harder it is to determine the correct way to process these data [4]. Firstly, there are no legal regulations pertaining how exactly data must be processed. In addition, the solutions on the market are aimed specifically at gathering data, rather than processing and analysing them. Secondly, the ownership of the data, especially aggregated data, is becoming a hot topic [5, 6] – should farm owners keep data private, or should they share them in order to promote overall Smart Poultry sector development? Aggregated data can be used to develop accurate decision support systems and analysis systems that are not limited to one particular farm.

In general, Industry 4.0 aims to replace manual labouring with automatically and often digitally operated manufacturing and production [7] by implementing such principles as decentralized decision making and information transparency. This is done by introducing multiple layers of digitalization, starting from measuring environmental variables by taking simple measuring devices' readings to optimize production algorithms according to various multiple measures taken in a prolonged period of time. From a technological perspective Industry 4.0 found a use for cloud computing [8], IoT [9], blockchain technology [10]. To summarise, Industry 4.0 tends to answer the question of how the data gathered prior to and during manufacturing can be used in order to optimize the said manufacturing processes.

Poultry farming is one of the fields where the application of Industry 4.0 principles is becoming a necessity. It is especially important in the case of greenhouse gas (GHG) control, the levels of which are to be managed according to the EU climate policy [11] and Kyoto Protocol treaty [12]. Multiple GHG affecting factors are diet composition and feed conversion ratio, manure production, and manure management; all of them, directly or indirectly, affect environmental parameters [13, 14] – temperature, humidity and air composition gases - ammonia (NH_3), carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O).

There are various European Union (EU) directives aimed to limit, regulate and/or manage aspects of keeping and rearing laying hens, including requirements for housing types [15], indoor environment [16], the welfare of poultry farm staff [17]. There are also strict EU regulations regarding marketing standards for eggs [18]. The problem lies in the perception and application of these directives, especially considering that these directives are recommendatory. Most farm owners will ignore directives unless they invoke some sort of legal penalty, large enough to affect business. For instance, according to minimum requirements that must be ensured [16], the main parameters to be constantly monitored and managed are the concentration of NH_3 which should not exceed 20 ppm, concentration of CO_2 which should not exceed 3000 ppm, indoor temperature which should be no more than 33 °C, indoor humidity which should not exceed 70 % averaged over 48 hours with an outdoor temperature lower than 10 °C.

With respect to the protection of laying hens and chickens kept for meat production, the minimum standards and rules are regulated by Directive 1999/74/EC of 19 July 1999, and Directive 2007/43/EC of 28 June 2007, such us lighting intensity in the building. The Directive, however, does not point to a particular approach of obtaining these parameters. According to the Directive previously mentioned parameters must be ensured at all times, therefore, real-time environmental monitoring must be performed. The only practically viable approach is to automate data gathering using appropriate sensors. This, however, is only possible if a standardized data structure model is defined. The aim of this research has therefore been to propose Cyber-Physical Model as a basis for the development of a smart poultry farm management system (SPFMS) that is adjustable to particular production needs.

2. Concept of cyber-physical model

The common [19] approach to poultry farm management without any sensors is to monitor animal behaviour manually and correlate it with positions in the appropriate ethogram. It is typically [20] performed as a post-factum analysis, based on the data collected weekly. The main disadvantages are related to the problems being detected at the later stage while simultaneous various animal medical treatment and production loss may be happening unbeknownst to poultry management. With the implementation of IoT these problems are mostly eliminated; however, the implementation process has not been defined and requires case-specific analysis and adjustments. The main goals of such a system are 1) to ensure the quality and quantity of data for further analysis and 2) to reduce the workload on farm workers who otherwise would be responsible for gathering these data manually.

2.1. Data Source Fusion

From the data necessity perspective three main groups can be defined – necessary data to ensure requirements of EU Directives, farm monitoring data for business analysis and optimization, and additional data that can influence overall poultry farm management (see Fig. 1).

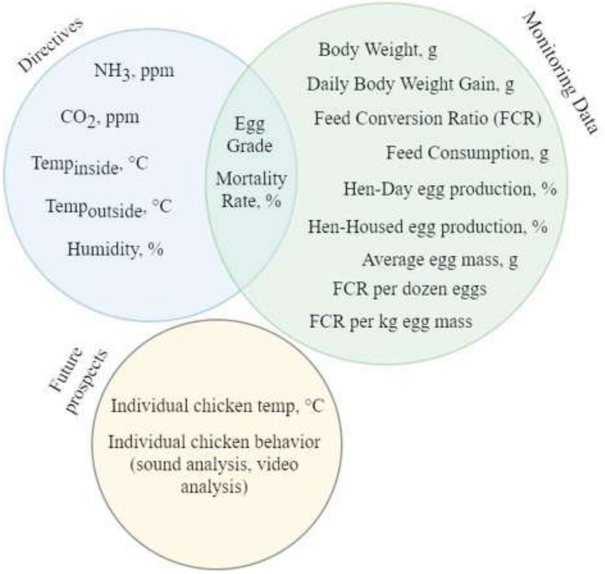

Fig. 1. Synergy of collected data in smart poultry farm.

Recently, this issue of data source fusion has been addressed on the market by providing several solutions [21, 22, 23]. The main features of these solutions pertain to the same data fields as discussed above. The general architecture of these solutions is built around the possibility to input data into the either mobile or web-type applications in order to generate reports later. The limitation of commercially available systems lies in rigidity, i.e., the inability to adjust and/or extend the said system functionally (i.e., with real-time analysis and decision support systems). Requirements of EU Directives mostly concern the general chicken welfare aspects – by stating the maximal mortality rate, minimal size, and density requirements for housing and environmental parameters. The strictest EU regulation defines egg grades and requirements for packaging.

Business related data concern the investments, i.e., amount of feed, maintenance and logistics expenses, and returns – amount of broiler meat, eggs, or hens produced. Business related data is associated with farm monitoring data that should be gathered on a daily basis. In addition, in-depth analytical indices [24] may be applied, for example, Net Feed Efficiency Index or Egg to Feed price ratio.

Future prospects relate to any additional data that has not yet been regulated by any EU directive and is not a priority for business optimization. However, this data can affect both previously mentioned data groups. For example, by monitoring an individual chicken's temperature the prediction of a potential harmful state can be made, thus reducing the total mortality rate [25].

There are multiple ways to implement IoT into poultry farms, however, most often [1, 26] multiple sensors are used in a different location. Often sensors are installed in pairs where each sensor is responsible for particular data (i.e., one sensor for CO_2, another one for NH_3). These sensors can be either grouped by measurement type, for example, temperature, NH_3, and CO_2, or be redundantly placed in order to provide data for aggregation. In cases where multiple sensors are used for the same measurement multi-sensor data fusion can be applied to ensure accuracy and consistency [27, 28].

2.2. Concept of the model

The concept has been developed with consideration of multiple independent poultry farms managed by a single processor, see Fig. 2. Therefore, despite the Industry 4.0 goals to alleviate the need of centralization, the main processing is designated to one main data centre that is responsible for providing management software access to all farms.

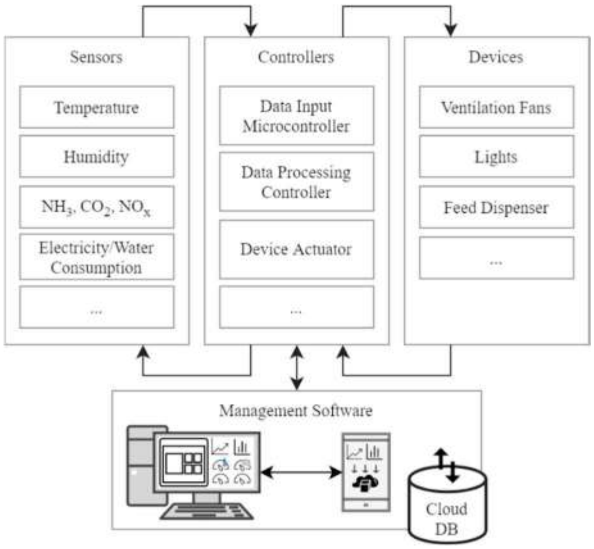

Fig. 2. Concept of Cyber-Physical Model.

Each poultry farm of the same kind would be equipped with appropriate sensors to take measurements controllers that define when and how to take these measurements, and interactive devices which can be manipulated based on the processed measurements. Currently, the following sensors have been considered: NH_3 concentration, CO_2 concentration, NO_x concentration, temperature, humidity, electricity and water consumption. Controllable devices are selected following EU directives, for instance, to regulate indoor temperature, humidity and to control lightning intensity. The management itself is considered to be a part of a Smart Poultry farm and will be available for each farm owner and/or manager. The software will allow to monitor real-time data, provide support for decision making and allow manual data input.

3. Data base design

The Data base (DB) design is based on the premise that poultry farm can be used for multiple goals – egg production, the broiler meat production and hen raising. In order to achieve these goals appropriate data must be gathered. However, environmental variables, standard value, feeding data and housing data are static; therefore, the design can leverage the possibility to create a universal framework that would cover around 90% of DB architecture. It is also important to mention, that the proposed data base design should be used as core for development of farm-specific management system, where any additional functionality/data types must be added either as separate module or a combination of data tables. The proposed architecture, however, is already usable for basic needs of any poultry farm, whereas the described later use case is focused on egg production.

The proposed poultry management system aims to quantitatively and qualitatively track egg or meat production in relation to the feeding provided to available chickens. Depending on the poultry farm the data may be collected in various intervals, typically [29] every 1 h or 2 h. The objectives of the proposed data structure are 1) to store data of the identified groups, 2) to provide aggregation of particular sensor data and store it separately, and 3) to give users the data required for analyses and reports. In the case of poultry related data, the data structure must consider the size of dimension tables and possible normalization levels. In order to simplify DB design, single central register was used, whereas other tables are satellites. The satellite tables can be connected to each other, can be dependent on one another's data, or be completely independent, see Fig. 3. The main data of a poultry management system is either egg production data or meat production data; however, these data encapsulate a lot of parameters that contribute to the final result.

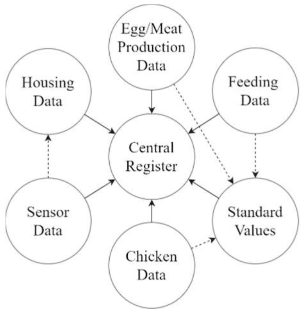

Fig. 3. The interrelationship of data.

3.1. Main log and chicken data

The most common data in any poultry management system are the chicken data [30]. These data include information about breed, type, current parameters such as weight, age and total count. The term "chicken" refers to bird species as a whole; this includes *hen* as a term for egg laying chicken, *pullet* as pre-laying chicken and *rooster* as meat production chicken. There are also statistical and logistics data, such as *chicken import/export*, *total count of deaths,* etc. The centralized fact table in DB structure (see Fig. 4) is table [productionLog].

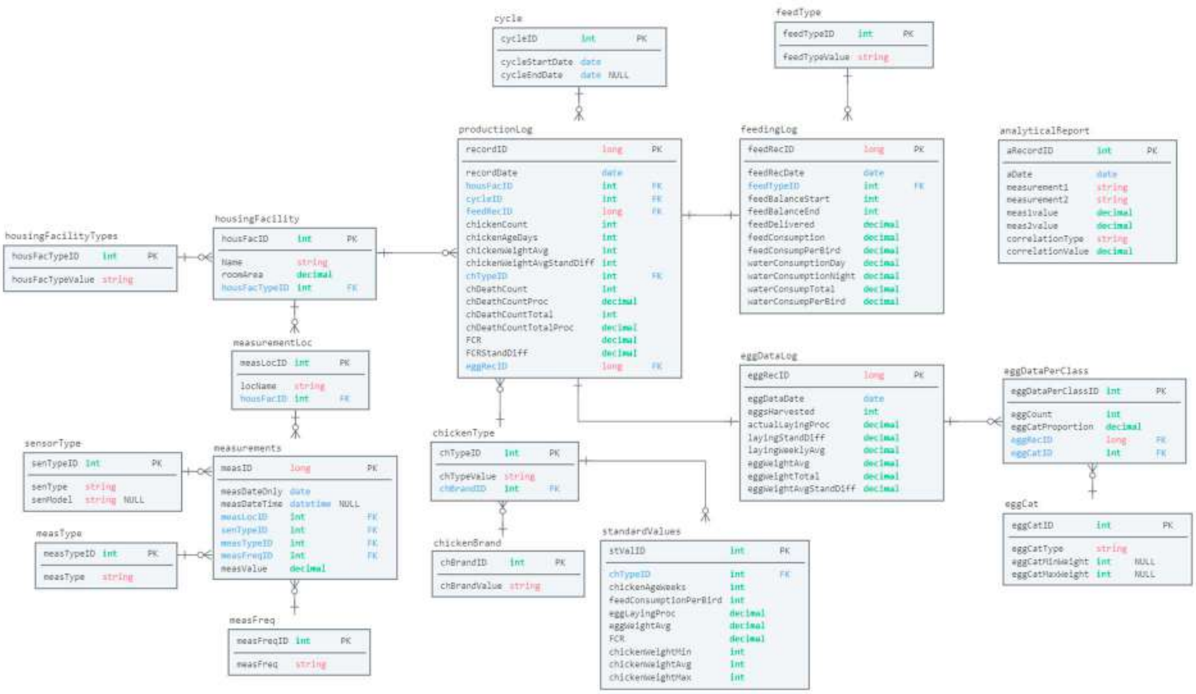

Fig. 4. The centralized fact table in database structure.

This table joins dimension tables that store sensor data, feeding data, and egg production data; it is also used to store chicken-related data. The related data is associated with using such fields as [productionLog].housFacID, housing facility's identification number, [productionLog].cycleID, particular production's cycle, and [productionLog].recordID as a main key to join feeding and egg production data.

Joined dimension tables relate to housing facility, production cycle, feeding log's records, and egg production log's records. In addition, all records include either calculated values, for example, the chicken death toll in percentage, or depict the difference from a standard value, such as feed consumption rate and chicken average weight. The standard values are stored in the table [standardValues] that include standardized weekly plan's values according to particular chicken's breed like Lohmann Brown [31] and are joined using the rounded value of [productionLog].chickenAgeDays/7 and [standardValues].chickenAgeWeeks. The standard values must be kept for every parameter that should be optimized. In the case of egg production, this table must also include standard values for laid eggs and average egg weight.

The [productionLog] table contains raw or aggregated daily values, such as chicken age, chicken average weight, current chicken count, and death toll. It is common for larger poultry farms to operate with multiple chicken types, for example, chicks in the early weeks and hens later; nonetheless, it is also a common practice to import layers. The number of breeds chosen depends on the size of the farm, and availability to different breeds as each breed has its own standardized stack of parameters. The use of only one breed allows to precisely monitor production data related to standardized values.

A production log is required to determine the relative quality and productivity of applied feeding protocols that result in particular quality and quantity of egg or meat production. The DB structure addresses only egg production; however, in the case of meat production, an additional snowflake path can be added, for example, table [meatDataLog] with corresponding fields and lower-level dimension tables. One of the main qualities and productivity parameters is feed consumption rate or FCR, which is the ratio of feed consumed to the egg mass or the number of eggs produced.

3.2. Egg production data

Technically, all statistical data referring to egg count, egg weight, egg distribution per category and size. This also includes deviation from standardized values, depicted in brand specifications. The following tables belong to this data group: [eggDataLog], [eggDataPerClass], [eggCat]. The general data stored in table [eggDataLog] are a number of eggs harvested, egg-laying performance, average and total weight of eggs harvested. Additionally, there are two lower dimension tables related to egg data.

Table [eggDataPerClass] contains data about different categories or classes of eggs gathered. There are three main categories for egg production – category A, category B, category C. Category A is then divided into multiple subcategories, defined by the size of an egg. The category A subcategories are XL (extra-large), L (large), M (medium) and S (small) eggs. The data regarding egg categories are stored in dimension table [eggCat] depicting minimal and maximal egg weight in the case of category A subclasses.

3.3. Feeding data

The type of food, its composition of macronutrients, determines the welfare of birds and the cost/production curve or egg/meat production [32]. The food given to birds differs depending on their age and breed, so an appropriate type and the amount must be reserved. The following tables are in this data group: [feedingLog], [feedType].

Feeding-related data is kept in the separate dimension table [feedingLog] in order to ease the analysis of applied feeding protocols. Each record corresponds to a particular feed type, i.e., particular name, formula or composition of major nutrients. The table keeps track of feed amount at the start and the end of each day, including the amount of feed delivered to the poultry farm and the amount of feed consumed by birds in total and per bird. This log also includes water consumption parameters such as water consumption during a day and a night, amount of water consumed by birds in total, and per bird.

3.4. Sensor data

The intelligent management system is not complete without the implementation of sensors and sensory data. Most of the sensors are aimed to optimize environmental and welfare quality. Environmental inputs include temperature, air velocity, ventilation rate, litter quality, humidity, and gas concentrations, including carbon dioxide and ammonia [1]. It is assumed that sensory data is gathered automatically and is sent to the warehouse periodically, while also, although rarely, can be inputted manually. The following tables are in this data group: [housingFacility], [housingFacilityTypes], [measurements], [measurementLoc], [sensorType].

Poultry management systems use sensor data to monitor environmental parameters that have a direct effect on the quality of production and/or quantity. Sensor data come from sensors installed in poultry farms that are different in terms of size and housing types; therefore, each sensor must relate to a particular sensor location, whereas location must relate to a particular housing facility. The housing itself plays an important role in the success of egg production. There are European standards regarding types and according to sizes for poultry farm housing [33, 34, 35] depending on the bird type. Housing data addresses the facility that is used as the main building to keep birds. The following facility types can be defined – cages, aviaries, barns, free ranges, and organic systems. The location of a particular facility determines the requirements for temperature and ventilation management, as the optimal range of indoor temperature, humidity, and O_2 richness is narrow [36].

The information about the housing facility is stored in table [housingFacility], where [housingFacility]. Name is facility's name and [housingFacility].roomArea is the area of the facility in square meters. For normalization purposes, facility types are stored separately, in table [housingFacilityTypes]. The following facility types are considered: cages, aviary, barn, free-range, and organic system. Technically, these tables should also contain private information like facility's owner name, surname, etc.; however, this data is absent as the connection between the farm owner and a particular facility is stated in the contract. DB structure also considers different sources, frequency, and input types of sensor data. Typically, such data is raw measurement data from temperature, moisture, and CO_2 sensors. Alternatively, measurements can be entered manually by poultry farm personal, for instance, the average temperature of the entire facility in a particular moment or an outside temperature taken from a stationary thermometer. In order to store aggregated data for fast access, additional measurement parameters are defined. Sensor data is stored in the table [measurements], where each record corresponds to one measurement [measurement].measValue. Each record relates to particular sensor location, stored as [measurementsLoc].locName and particular sensor type, stored as [sensorType].senType and [sensorType].senModel.

To address the issue of data being entered automatically and/or manually in different frequencies, two date fields are included – [measurements].measDateOnly and [measurements].measDateTime. In case database implementation allows usage of only one type for two of these values, one of the fields must be removed. Measurement type, e.g. raw, aggregated or manual input, is stored in table [measType].measType, whereas frequency, for instance, hourly, daily or weekly, is stored in [measFreq].measFreq.

3.5. Application of the proposed data set in Baltic poultry farm

The proposed data set was implemented into the existing infrastructure of a Baltic poultry farm, that consists of two types of poultry houses – enriched cages and barn system. The finalised implemented solution is built with 28 data tables and uses Microsoft Azure Cloud as the main processor. Complete implementation (at two Baltic farms) includes installation of 6 pairs of sensors, analyser, and system of microcontrollers, where installation period was between October 13, 2020 and January 21, 2021. For instance, the first poultry farm consists of several barns divided into cage free and caged egg laying system. Henhouse A (see Fig. 5b), where two pairs (1 pair = 1 CO_2 + 1 NH_3 sensor) of sensors are placed on each floor, birds can move freely, while at henhouse B (see Fig. 5a), where one pair of sensors have been located, belongs to the second type, i.e., caged. NH_3 sensors (Membrapor NH3 / MR-100) at house are located at a height of 2,5 meters on each floor, at the henhouse B at a height of 5 meters. CO_2 (GDS CO2 sensor IR-2) sensors are located at a height of 0,4 meters at each henhouse. Sensors are connected with a central data accumulation analyser (Combi 64, GDS Technologies, Garforth, UK) which is connected with a switchboard which sequentially is embedded with a Z-logger gateway device or MQTT broker. MQTT broker converts the signal (RTU – short distance communication protocol) of communicator into the Azure intelligible MQTT network protocol. The

MQTT connection is protected by a username and password. The MQTT broker processes only incoming and outgoing requests made by an authorized user to create an encrypted connection. After data processing in MQTT broker, emission measurements are accessible in the new section of the system - Sensor Measurements form to be exported in .csv and .xlsx format. The solution was developed on centralized cloud-based data processing system. The main advantages of practical application lie in automatic data gathering and automatic data processing. Additionally, the system provides the possibility to manually input measurements and import historical data from excel spreadsheets. The mobile application provides a modern and handy approach in entering measurements from devices and the number of fallen birds right from the poultry houses. The processed data is used by the decision support system to define optimal feeding and housing.

a) Enriched cages b) Barn system

Fig. 5. Examples of installed CO_2 and NH_3 sensors in (a) enriched cages and (b) barn system poultry houses.

There are currently ongoing debates [37, 38] on how to increase the involvement of IoT in the precision poultry farming sector. Some authors [39] propose to implement solutions of individual monitoring already actively used in other sectors like precision livestock farming and precision pig farming. To name a few, such solutions are RFID sensors, internal sensors for temperature monitoring, behaviour monitoring, and control. There are multiple researchers working towards sound [40, 41] and video [42] analysis in the poultry sector. Future technology also tends to develop towards prediction [43, 44] rather than reactive response., this mostly includes health status and respiratory problems.

4. Conclusions

Depending on the company size and available resources, each poultry company has an individual approach for data collection for further analysis. The smart poultry management system is a crucial component of a modern poultry farm, but the majority manage the data using outdated technologies and platforms instead of modern IT solutions. Small enterprises still rely on manual processes and only the most advanced and large enterprises use smart IT solutions that allow practicing advanced management. Currently, the regulations of the poultry sector on the governmental level do not offer an exact prescription to data processing. The farm owners thus tend to interpret these regulations to their advantage, and instead of increasing the welfare of poultry they aim to meet the minimal requirements. IT engineers, on the other hand, aim to provide a full IoT package – from the sensors to in-depth analysis with easy-to-use client-side mobile applications.

The proposed concept of database design can be implemented in real solutions of sophisticated Smart Poultry Management systems. It has been successfully used in the development of Baltic poultry farm IoT solutions within ongoing research. It was concluded that the well-performing and beneficial IT system for the poultry industry must be cloud-based (also deployable on-premise servers) which allows having little IT investments to be made on the enterprise-level while using a sophisticated IT system and data centre which ensures better and safer data retention and an eco-friendlier approach. The daily data input is a challenge for each poultry industry company depending on the tools that are used for data gathering and related processes. The mobile application allows entering data immediately from the henhouses, where user can enter the information of dead birds as well as measurements data from various measuring devices directly from the henhouse.

Validation of hypothesis of broilers productivity based on real-time production data for outside temperature, lighting, flock density and ventilation capacity for broiler with different feeding will be made, using analysed data provided by manufacturers. Validation of hypothesis of the causes of emissions, based on real-time production data for ventilation efficiency and rate, the stocking density, poultry house cleaning frequency, and house cleaning methods will be made, using data transferred by sensors.

Acknowledgements

The research leading to these results has received funding from the Specific Objective 1.1.1 "Improve research and innovation capacity and the ability of Latvian research institutions to attract external funding, by investing in human capital and infrastructure" 1.1.1.1. measure “Support for applied research” project No. 1.1.1.1/19/A/145 “HENCO2: Cloud based IT platform designed to improve poultry productivity and reduce greenhouse gas emissions”.

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