An Internet of Things (IoT) Solution to Optimise the Livestock Feed Supply Chain

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Abstract

The animal feed supply chain to farm, mainly represented by the feed suppliers and livestock farmers, currently faces great inefficiencies due to outdated supply chain management. Stakeholders struggle with the timing and quantity evaluation when restocking their feed bins, significantly affecting cost and labour efficiency. However, the lack of accurate and cost-effective sensors to measure stock levels of solid materials stored in containers and open piles is preventing the implementation of these strategies in a large number of industrial sectors. In these cases, traditional technologies cannot offer a convenient solution due to an inevitable trade-off between accuracy and cost. This work develops an integral feedstock management system to optimise the entire supply chain. A new monitoring system based on an RGB-D sensor is presented as well as the data processing pipeline from raw depth measurements to bin specific daily consumption rates.

Keywords

Inventory management, Vendor Managed Inventories, Internet of Things.

1. Introduction

As the global human population grows and logistics improve, livestock production (pig meat, poultry, beef, cattle, etc.) is forecast to grow further. However, satisfying increasing and changing demands for animal-source foods requires a further shift from extensive to intensive-scale operations. This intensification means a progressive introduction of industrially manufactured compound feeds for the livestock sector. Commercial animal feed companies are best placed to provide such formulated feeds, but there is a strong pressure to optimize the use of resources while providing the lowest cost of production to the farmer. Compound feed production is a global growing industry with a one billion tones produced yearly worth of $400 billion. The EU28 is the third largest feed producer in the world (16% share), along with USA (17%) and China (18%). By 2030, feed production is predicted to double due to the increase mechanization and meat consumption in emerging economies [1, 2].

The animal feed supply chain to farm, mainly represented by feed suppliers and livestock farmers, suffer from great inefficiencies for both stakeholders. These inefficiencies are due to a very traditional and inefficient supply chain management, more precisely: a) Bad estimations of feedstocks by the farmer, b) Uncertainty of feed demand and c) Obsolete bin monitoring and restocking methods [3]. The compound feed industry is also competitive
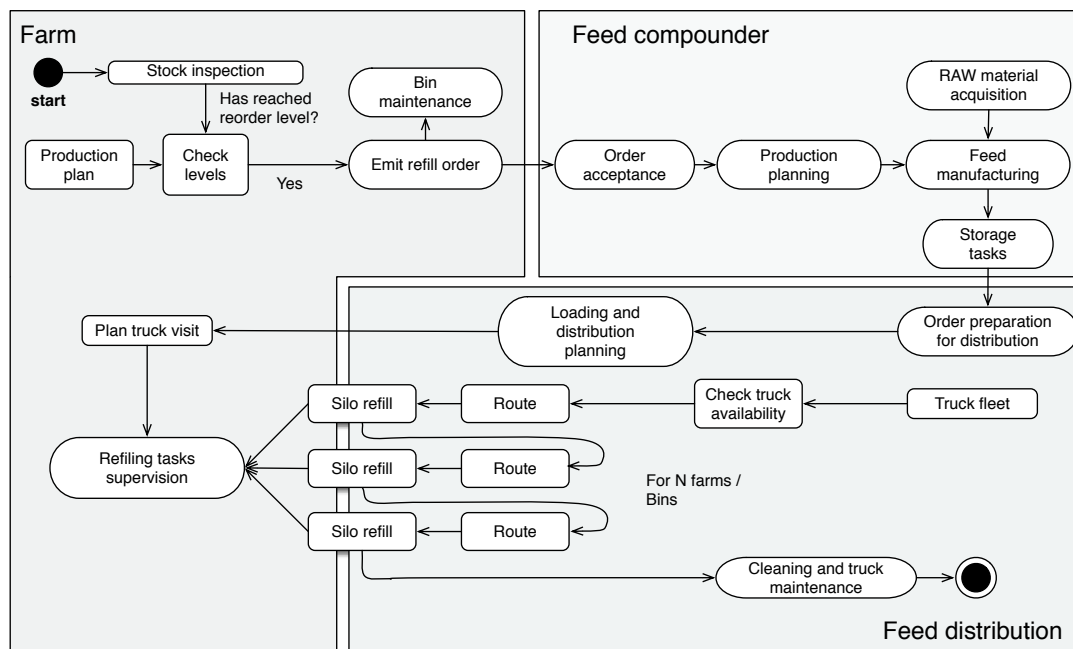
Figure 1: Activity diagram of an animal-feed delivery supply chain.

in that it works in a market which has essentially achieved maturity. Following the intensification trend, they have been progressively merged into large companies that perform under the integrated production system, where they aim to control the whole or partial process of animal-source food production. Although feed management is primarily the responsibility of the farmer, most of the big players (Cargill, Nutreco, ForFarmers, Vall Companys, El Pozo, etc.) of this 'livestock intensification' are adopting precision feeding schemes from farrowing to fattening farms which can be a highly effective tool in enabling a reduction of feed intake per animal while also maximizing individual growth rates [4]. It enables the provision of the right amount of feed, in the right nutrient composition, at the right time. However, main efforts to connect on-farm feeding activities logistics of getting feed to farm have hitherto been unsuccessful due to the difficulties to accurately measure animal farm feed-stocks. Nowadays, big corporations are investing to narrow this gap as they recognize that it is essential to plan the logistics of feed movements from the factory to the farm site to protect the feed as much as possible as well as seek for increased efficiency for supply chain players, boosting business profitability.

This work presents a new bin measurement system and supporting data processing methods to better estimate the volume and weight of stored compound feed in livestock farms. Additionally, this work aims to set the basis to optimize the animal feed supply chain (Figure 1) for global leaders and farmers by developing a feedstock remote monitoring system, validate different business processes, as well as the scalability of the hardware solution.

The remainder of this paper is structured as follows: related work and details on the case study and the problem considered in this paper are provided in Section Related Work; Section Materials and Methods outlines the proposed solution; in Section Results case studies are described and results are analyzed; Afterwards, in Section Technology Adoption results are discussed along with other insights of the work; Finally, Section Conclusions and Future Research highlights the main contributions of this work.

2. RELATED WORK

There are few kinds of solutions in the market that have attempted to provide a solution to remotely monitor feedstocks in livestock farms bins. They either measure bin's weight or measure the feed level inside the bin. The first approach (weight) uses "load cells", which are installed in the bin's support structure. The second approach (level) uses level sensors usually based on cable, radar, ultrasonic or guided wave technology. Additionally, it exists similar products to our proposal present on the market (e.g., 3DLevelScanner Non-Contact Sensor by BinMaster [5]). These sensors make use of a complex radar system to measure a 3D feed surface as our proposal. Even though these sensors are completely out of scope for our environment due to: a) their high cost, what makes large deployments not affordable and b) the physical principle they rely on, that do not allow them to provide accurate and reliable data in small bins like the ones our environment present (fibber manufactured bins with a cylinder diameter of up to 3 meters).To access the data remotely, they often use standard data loggers and GPRS modems with private protocols. Measuring stock level within the bin is difficult since the feed surface is uneven (the difference between the lowest and the highest points can easily reach 2 meters). Since level sensors only measure the distance between the device and a single point in the feed's surface, measures have a lack of accuracy [6]. The only solution in the market able to provide accurate measures are the load cells. However, their installation costs are extremely high (€3,000/bin including installation) for the market niche this work targets. Moreover, devices with the lowest price – ultrasonic and guided wave radars – cost per bin €1, 200 plus €150 to €300 for annual maintenance and communication services. In addition, the functionality obtained by suppliers' standard software is limited to a daily record of the levels in the bins. If the customer requires a higher level of integration (which is the most common situation, since a single feed supplier manages several farms), the customization will raise even more the final price. With regards sensor network deployment and operations scalability, most of the solutions which are already in the market must be mains powered, raises the installation costs. Additionally, some farms have electricity generators which are only active for certain hours per week, failing to supply all day-round power to the devices and making them non-operable most of the time. Besides, the smart services offered by these devices do not go beyond checking the bin's feed level from the online platform and receiving an alert if they are low. They do not combine and analyse the data gathered from different devices, so they cannot forecast the feed demand and optimize inventories, production batches, delivery routes and raw materials purchases. Most of these devices suffer of the same pain, uncertain profitability, that avoids them to obtain a successful market uptake. Of course, several sensors are present in the literature that try to address similar problems in the smart city environment like the waste collection [7, 8, 9]. Even though, non of them reach the required accuracy to measure bulk solids stored into farm bins.

The availability of this remote monitoring systems will enables the use of smarter feed logistics platforms (SFLP). With gathered real-time feedstock data, and production data of both stakeholders (farmers & suppliers) taken mainly from suppliers' Information Management Systems (IMS). The SFLP would work in three areas: a) Feed demand forecast to predict the feed demand and the future stock levels in the farms, based on current stock levels and production data shared by farmers, b) Automatic restocking process that automatically would generate the restocking orders based on the selected restocking policies. Farmers would receive alerts and would be able to confirm the restocking orders with a simple click and c) Feed suppliers can take full responsibility of the feedstocks (Vendor Managed Inventory, VMI) and process the restocking orders automatically, taking into account current stock levels, feed demand forecast, production data, and cost functions defined by the supplier. The SFLP will provide a solution to mitigate the uncertainty of

demand, help smooth the peaks of production allowing smaller buffers of inventory and reduce transport costs optimizing the shipping routes. SFLP will allow the feed plant to improve several business processes such as feed orders processing, ingredient purchasing, feed production, product storage, and delivery schedules. Research on collaborative supply chain strategies constitutes promising concepts in the establishment of sustainable freight transportation systems [10]. Even though, the literature on this specific vertical of the well known VMI applied to livestock feed to farm is really scarce. There is an interesting work, CHAINFEED [11], where the authors introduced this new strategy for the feed producers to improve their supply chain performance. After modelling statistically the feed supply chain and simulating distinct replenishment scenarios, they highlighted the importance of having updated stock information to reduce model's uncertainty.

3. Materials and Methods

This work is part of the IoFEED project (`https://www.iof2020.eu`), that aims to monitor approximately 325 bins and validate two distinct business processes carried out between farmers and feed manufacturers. Initially, two test-beds have been set in two distinct countries, the United Kingdom (UK) and Spain (ES). The UK has two distinct partners (UK1 and UK2) and 25 bins each, and Spain has a single partner (ES1) with 50 devices. After this initial phase, the number of monitored bins will increase up to 175 more for the Spanish pilot. Two business processes will be put to test in this project proving cost-benefit and cost-effectiveness: *(i)* business process 1 (BP1), focused on farmers; and *(ii)* business process 2 (BP2), focused on helping to feed manufacturers. BP1 aims to provide the best solution for farmers to achieve a seamless procedure to measure bins' stock, and provide the best and accurate real-time information for daily tracking of feed consume in the farm to assess feeding costs and help the farmer to increase his feed conversion rate, and a reduction in stock ruptures. Additionally to BP1 benefits, BP2 aims on changing the business strategy moving the workload balance of maintaining the feedstock to the feed supplier, so they can handle and manage the correct and exact amount of feed for each bin that covers their client needs (the farmer) while, at the same time, optimizing the supply chain cost (production, own stocks, product shipping / distribution, etc.).

3.1. Remote monitoring system

The key enabling technology consists of a camera with a commodity RGB-D sensor that captures colour images along with dense pixel-wise depth information in real-time. With an embedded computer vision algorithm, it provides much more accuracy (error $< 3\%$) than traditional single-point level sensors (error $= 15 - 20\%$). Instead of using a single point measure like lasers or ultrasound, a matrix of $320x240$ readings over the feed's surface is taken. This device has been designed for providing up to 24 readings per day. It is battery powered with an integrated solar panel for recharging the battery pack. Each device mounts with a M2M module (GPRS/3G) that allows the use of the cellular network when available. Electronics, batteries and energy harvesting have been configured to lower the energy consumption an enable a live-span of one month without solar contribution.

This device has been designed to provide an easy installation. Figure 3 shows how in four steps the sensor is placed by drilling a hole in the top cone, attaching an adapter ring and screwing the sensor. In case a sensor has to be removed, a metal cap is also provided. It does not require any cleaning or maintenance after installation since batteries must not be substituted and it has a self-cleaning system against dust and condensation (Figure 2). As it is shown in Figure 4, the sensor measures distance from the camera (placed in the top of the bin) to the feed surface. Using this depth map ($320x240$ distances), the
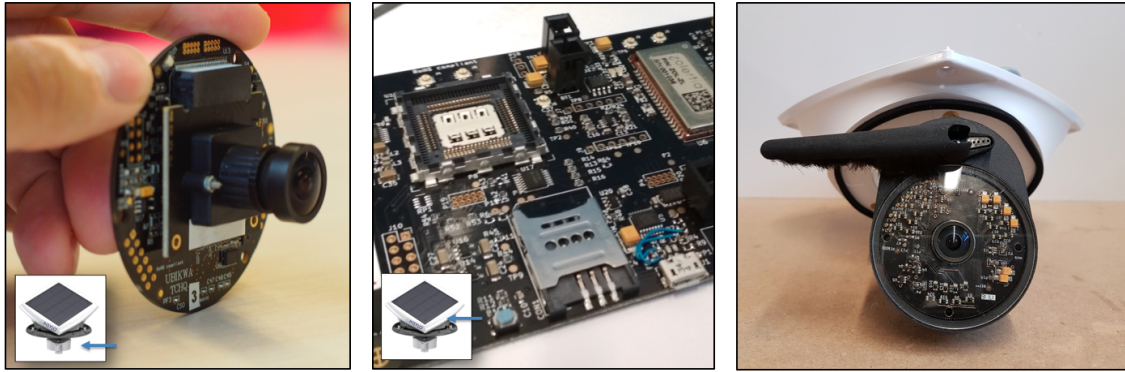
Figure 2: From left to right, the 3d sensor, communication electronics, and self-cleaning system.

sensor: *(i)* performs a 3D reconstruction of the feed surface; *(ii)* intersects this surface with the user-defined bin geometry; and *(iii)* estimates the remaining volume. In the following subsection, it is described the data processing applied from depth map to volume estimation.
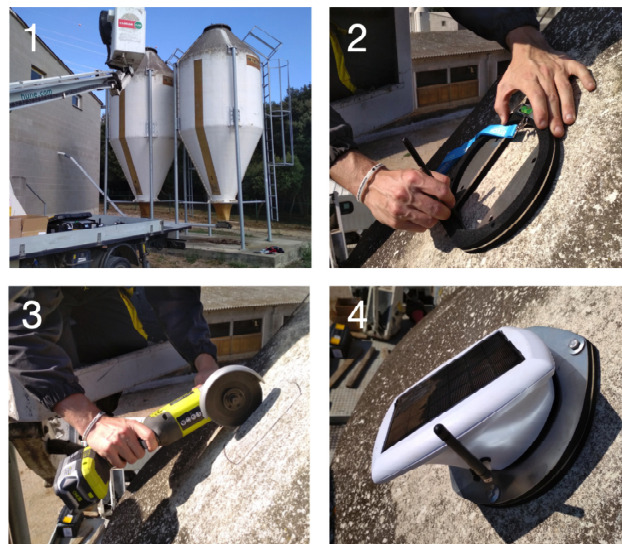

Figure 3: Four steps of the sensor installation procedure with (1) cherry picker placement, (2) hole marking and (3) drilling, (4) adapter ring placement and sensor fixation.

The FIWARE IoT stack has been used as an Open Initiative for this project [12] to develop cloud systems. FIWARE architecture has been demonstrated as a powerful and reliable solution for the implementation of IoT based applications. One of the key aspects of this architecture is the adoption of the OMA NGSI Context Management standard to manage and exchange context information about context Entities [13]. I that sense, the Orion Context Broker has been used to model data. The Orion Context Broker is an implementation of the Publish/Subscribe Context Broker Generic Enabler. It decouples the consumers of data, like end users and M2M applications, from the devices, objects and resources that produce the data. The Context Broker provides an API that implements the NGSI-9 and NGSI-10 Context APIs [14]. It enables the interoperability of the systems with other use cases of the IOF2020 programme.
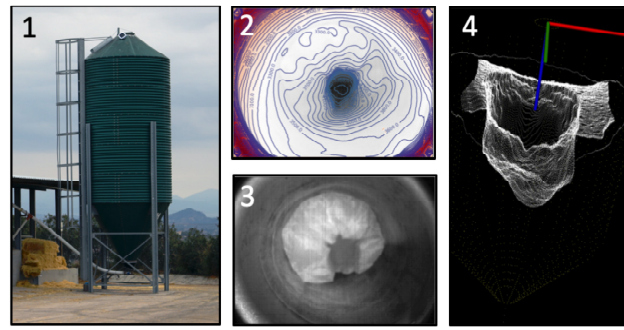
Figure 4: Illustrative example of feed bin (a), single shoot measured disparity maps (b top) and IR channel (b bottom) and feed surface reconstruction in distinct time steps (c-f) while feed is consumed.
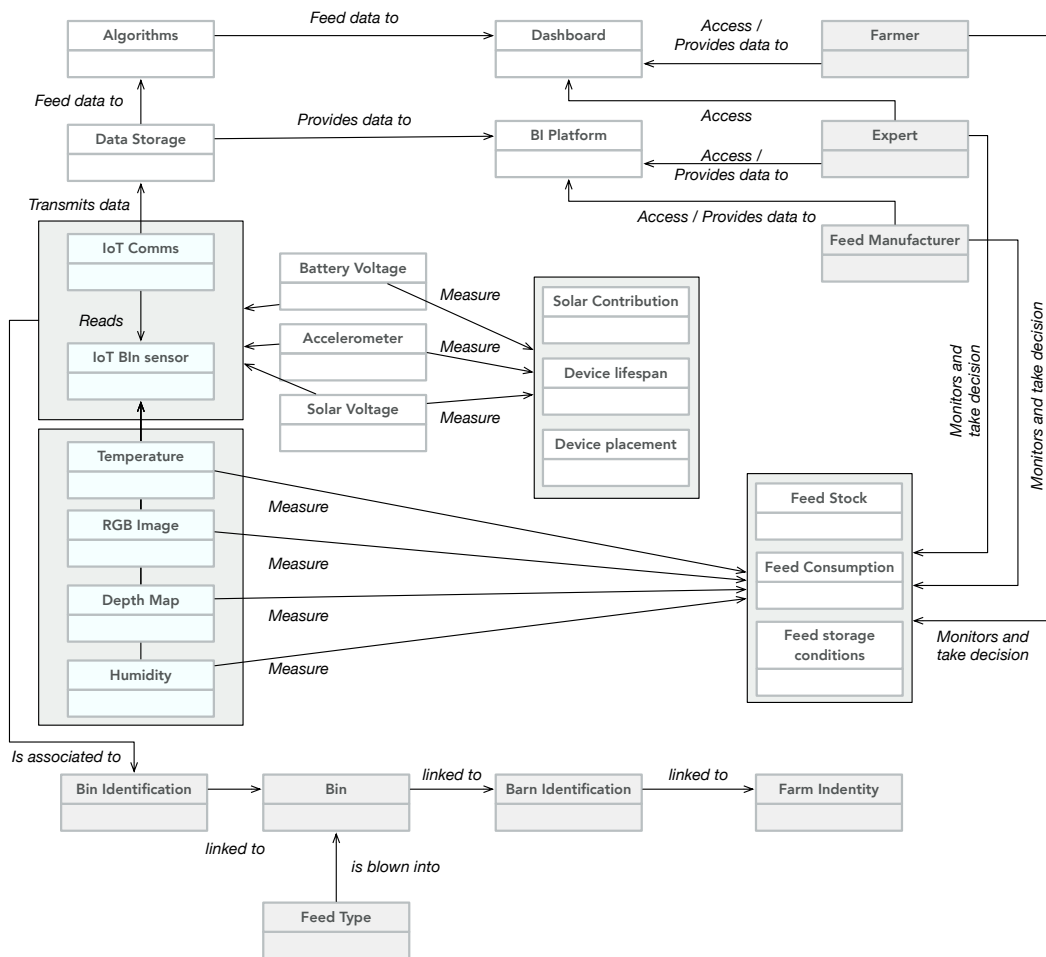

Figure 5: Domain model for the livestock feed remote monitoring system.

Figure 5 shows how is organized and structured the knowledge of our problem. Distinct actors are contributing to the system. Apart from the Farmer and the Feed manufacturer, also technical experts are informing the system with data related to the specific feed diets delivered to farms. After data gathering, raw data is sent to the cloud systems to be processed.

3.1.1. From Depth Map to Volume

Although the process applied to convert the raw depth map into the scalar volume has been designed specifically for our data pipeline, it is commonly known in the literature [15, 16]. A free-space approach is applied to estimate the bin's current stock. Hence, this free-space based method allows calculating the remaining empty volume of a bin by using the measured depth map from the inner bin and the measured or informed bin diameter. It is important to point out that the described method supports the free placement of the sensor on any top cone position. Hence, if the camera is not centred and perpendicular to the surface, it is required to geometrically transform the inferred inner surface. The geometric transformation values can be introduced manually given the camera pose and location or automatically extracted using the bin walls (if they are presents in the depth map).
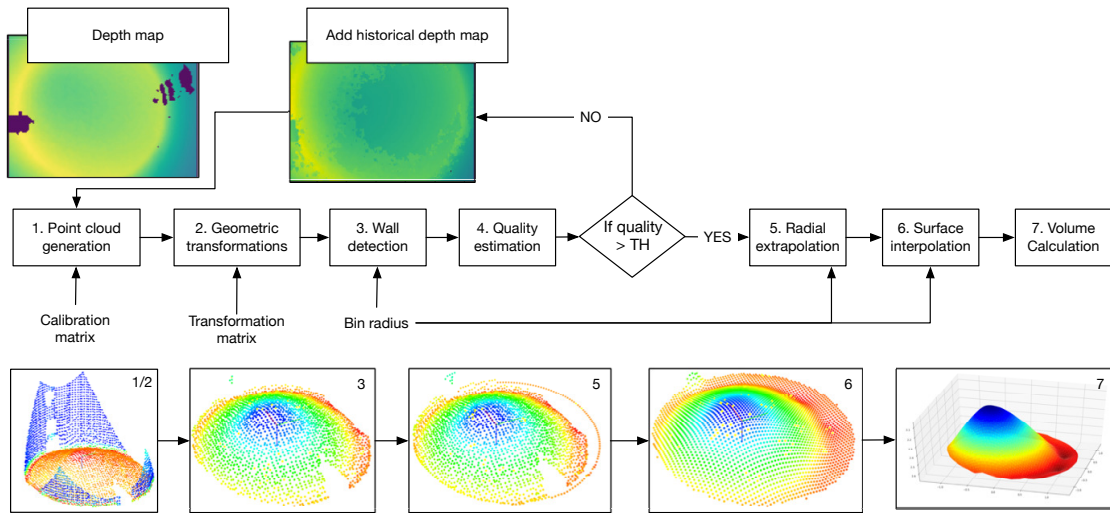

Figure 6: Flow chart of procedure used to determine the volume.

Figure 6 shows the pipeline applied to estimate remaining volume for each bin. First, the point cloud generation (step 1), in this phase we translate each single pixel value from the depth map to a real-world coordinate using the calibration matrix. Next step implies geometrically transform the obtained mesh to get it aligned with the origin of coordinates (step 2), in our case, the central axis of the bin at its maximum high. Bin walls are removed from 3D mesh by filtering via face normal filtering (step 3). This procedure enables us to effectively remove points that do not belong to the feed surface. Afterwards, the point cloud is decimated by removing outliers within a predefined neighbourhood in a fixed radius. A quality check is performed to assess how reliable is the information available (step 4). A threshold (TH) is set experimentally, to decide including previously capture depth maps into the current measurement to fill the gaps by overlapping two or more historical depth maps. We also exclude the points that do not belong to the theoretical geometry of the bin. The surface sampling rate is quantified by comparing the theoretical maximum bin area that can be measured and the relative area described by each depth map. Hence, only feed surface points score to this ratio. The remaining surface is approximated by a combination of multi quadratic radial basis functions (RBF [17]). RBF allows us to create a clean and smooth point grid (step 5) to recover missing zones produced by sunlight, temperature or other external factors as will be discussed on Section Results. Finally, the interpolated surface is triangulated using the Delaunay algorithm [18] on the projected points in the x, y plane (step 6). Then the surface of each triangle is multiplied by its

mean depth (z) value to obtain the total empty volume. We infer the remaining volume by subtracting the calculated empty volume to the total bin volume (step 7). All this pipeline is currently executed on our cloud systems. Even though, each device performs an image acquisition process to ensure data quality before sending raw depth map and RGB images to the cloud.

3.1.2. Measure of a Known Weight

One of the main drawbacks of measuring inner volume to estimate the weight is the assumption that the bulk density of the stored product remains constant throughout the entire bin. This might be true for smaller bins but in modern commercial-size bins, bulk density of feed compounds substantially increases due to compressive and hoop stresses [19]. In our experiments feed density is modelled as a constant value, but an additional packing factor is considered. While the objective of this research was to determine the field pack factors and bin capacities for on-farm and commercial bins used to store corn in the U.S. [20], we manually adjust packing factor for every bin based on a known feed load and the provided density by the feed manufacturer. Hence, our weight estimation is calculated by multiplying the remaining volume estimation and the given density.

3.2. Planning the Feed Delivery

As it has been briefly explained in Section Introduction, feed market is divided into two main segments. First, there is a *free market*, where farmers are free to buy to any feed supplier and buying decisions based on best price and service, and second, there is another *captive market* that operates in a highly integrated model where farmers and feed suppliers are owned by the same agribusiness corporate or where farmers have long term contracts with feed suppliers. From the feed manufacturer perspective, one of the main pains is the uncertain demand forecast. *Captive market* is normally more predictable, but it is still highly depended on observed production plan done by the farmer to generate new feed orders. On *free market*, the need for an accurate demand forecast is a must. Modelling the feed consumption is one most wanted tools a demand planner could ask for, because a) it would be really appreciated to have a projection of feed intake and b) it enables them to detect abnormal patterns on animal feed consumption.

Feed efficiency (FE) is an important production trait as feed accounts for 60–70% of the costs for layer production systems [21]. Although we cannot measure the feed conversion ratio (FCR) efficiency between individual animals, an initial estimation to be measured is the daily consumption rate (DCR) for a given bin. There are two main sources of information. First, the feedstock measured by using remote monitoring sensors and second, fattening schemes designed by livestock managers. This work focuses on the first source of information to estimate DCR from hourly measured stocks. Algorithm 1 explains the procedure followed to compute DCR by using two or three days of hourly based estimations.

This algorithm to compute DCR and the remaining days of stock estimation (ETA) makes use of W, a date ascent ordered time series with estimated weights including the last available reading where $|W| \geq 48$. It samples a period of three days since the current time; $minLoad$ as the minimum load detected in Kg. Any increase in weight below this value is filtered; $order$ that defines the order of the used low-pass filter used; f_{cut} as its cutoff frequency in Hz; and $w_{current}$ as the current stock in Kg.

Input:
    W, $minLoad$, $order$, f_{cut}, $w_{current}$

Output:
    DCR, ETA

    Preserve peaks from being filtered :

1: Compute differences $W_{diff} \leftarrow |W_{i+1} - W_i|$
2: Get the peaks $W_{peaks} \leftarrow W_{diff} \geq minLoad$
3: Remove the peaks $W_{nopeaks} \leftarrow W - W_{peaks}$
    Apply a Lowpass Butterworth filter (LBF) :
4: $W_f \leftarrow LBF(W_{nopeaks}, order, f_{cut})$
    Group W_f by date :
5: $W_{agg}(date) \leftarrow max(W_f(date))$
6: Compute DCR value $DCR \leftarrow Average(W_{agg})$
    Compute ETA value :
7: $ETA \leftarrow Average(W_{agg})\ w_{current}$
8: **return** DCR, ETA

Algorithm 1: Using weight timeseries to compute Daily Consumption Rate (DCR) and estimate remaining days of stock (ETA)

4. RESULTS

4.1. Remote monitoring system

In order to validate the sensor's accuracy, some reference bins have been upgraded with weighting cells. Hence, for those bins, the real weight is collected along with the new sensor-based estimation.

4.1.1. Accuracy and Repeatably

A bin has been placed on a weighting bay to validate the accuracy and repeatability of our sensor. Having installed a device on this bin, we proceed to fill the bin with materials until its maximum capacity ($TotalCapacity$). A discharging process is carried out while measuring. The sensor has been configured to work in continuous mode. Hence, the device is connected to the main power to be capable of sending data every 15 minutes. This test has been done with the collaboration of an independent company. They have provided us a bin as well as materials used to perform the tests on their facilities. This test has been repeated for five times. An external team have been operating on the bin and collecting information about the whole process of draining the bin. We have collected the amount of Kg that they removed from the bin and also the remaining material (W_{ref}). Data is collected and processed during the discharge operation to estimate the remaining stock (W_{est}). Figure 7 shows data collected from the five runs performed and relative error (Eq. 1) obtained compared with the reference weight given by load cells.

$$e_{rel} = \frac{|W_{ref} - W_{est}|}{TotalCapacity} \tag{1}$$

Overall, results shows an average deviation between our estimations and the weighing system used is about 1.15% with a maximum deviation of 4.15% in one of the points. It is important to point out that, when materials are very close to the sensor (sensor measures distances from 60 cm to 8.5 m) it is observed that sensor has some inaccuracies, data provided on this point is an estimation based on the maximum bin capacity. It is planed
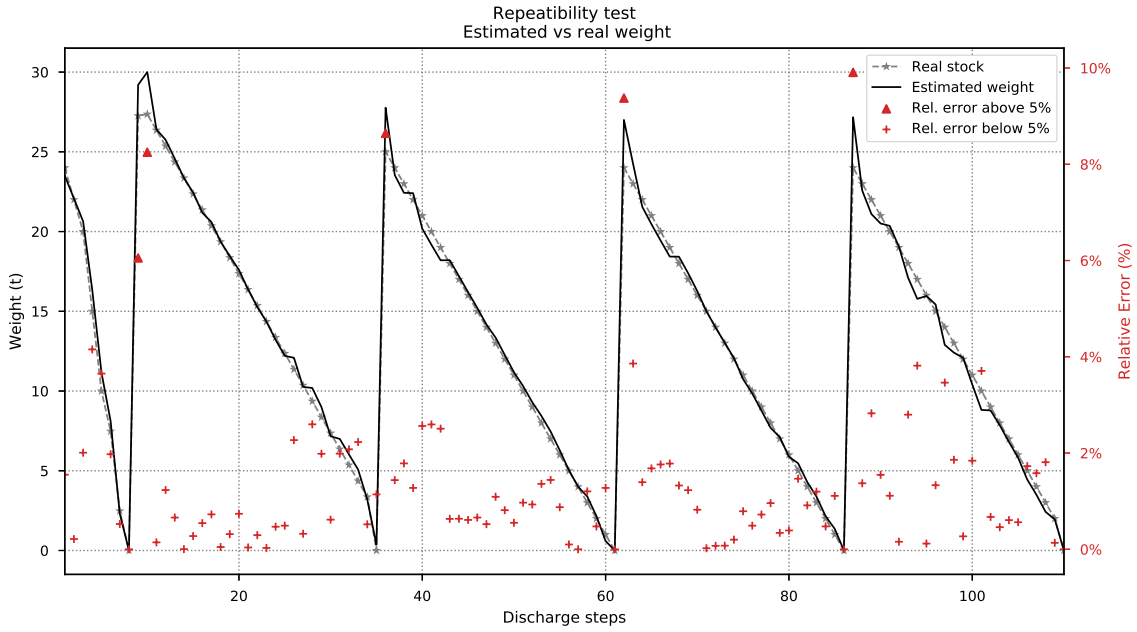
Figure 7: Weight estimations compared with weight reference (load cell) for the five runs with relative error to $TotalCapacity$.

to add a short range sensor to overcome this drawback. This reality is observed on initial measurement with full bin for every run. We do not take into account error introduced in this extreme range where estimated error may exceed 6% of the bin's maximum capacity. So far, only four bins are tested in field conditions, where load cells and our sensor have been installed for each bin. Results achieved are similar to the ones observed in laboratory conditions. It is important to notice that load cells typically have impressive worst-case specifications, and their actual performance is usually better than the specification. As a general rule, they operate with a 0.01% percent of span, which is really accurate. Meanwhile, other single-point-based sensors (ultrasound, laser, contact sensors, etc.) highly depend on how uneven is the feed surface.

4.1.2. Reliability

Considering this sensor aims to work on outdoor conditions, an important point to validate consists of verifying that the depth measurement is stable to environmental conditions. electronic sensors, signal conditioning circuits are sensitive to temperature, that often causes output drifts on range measurements regardless of the used technology. Reflective surfaces also affect RGB-D cameras, but considering the analyses done by other works [22], it can be deduced that the color and the material of a target influence the depth measurement. The reflectivity of the surface indicates the quantity of light that bounces back to the sensor, as well as external light sources add noise to the camera. Even though surface reflectivity, sunlight, temperature affect the available signal-to-noise ratio on captured images by reducing the depth map quality.

We have defined a *Quality Index* (Eq. 2 where $0 \leq Qi \leq 1$), to rank acquired depth maps according to the results obtained. In other words, how far a measured depth map (D) is from the perfect acquisition, being 1 the perfect depth map, and 0 not having available any data point. Eq. 3 defines $f(D, x, y)$ that determines if a depth reading is available or
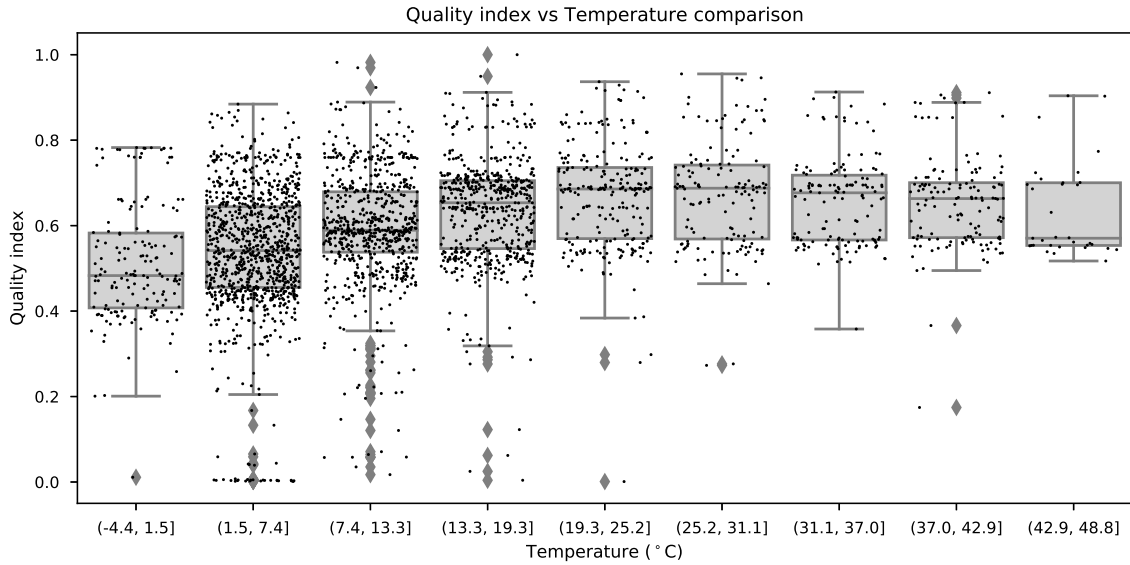
Quality index vs Temperature comparison

Figure 8: Two months of readings from 6 random bins: Quality Index vs temperature at acquisition time.

not.

$$Q_i(D, n, m) = \frac{\sum_{n=0}^{N} \sum_{m=0}^{M} f(D, n, m)}{n * m} \tag{2}$$

$$f(D, x, y) = \begin{cases} 1, & \text{if } D[x, y] \geq 1 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Figure 8 shows how *Quality Index* varies with temperature measured by our sensor. It shows a decline in *Quality Index* below $10\,°\text{C}$. Most of this temperature effect has been corrected by setting up an appropriate warm-up time to the device and reached accuracy level is not affected.

4.1.3. Limitations

The system has been designed to work under appropriate conditions, but it is with limitations. Some preventive actions has been taken to ensure these conditions: First, a cleaning system has been included (essentially a wiper) to maximise the likelihood to have a clean reading, removing sticked feed. Even though, dust suspended in the air in the headspace between the sensor and the feed surface reduces the depth map quality or even a blind reading when bins were measured shortly after or while filling. The sensor should be able to measure the entire bin wall/feed surface interface. Sometimes, when bins are very full and the surcharge cone of grain exceeded the eave height of the bin, or simply the system's field of view is obstructed, our estimation algorithm takes some assumptions and extrapolate readings to fill the gaps. This may lead us to introduce some error in our estimations.

4.2. Planning the Feed Delivery

Regarding to DCR and ETA estimations, filter parameters have been set for the experiments with $f_{cut} \leftarrow 2/24$ and $order \leftarrow 4$. Figure 9 gives an example of daily stock, daily

consumption rate (DCR) and ETA values for every day. This is the main information provided to farmers along with other gathered data (ie. temperature, humidity and visual image of the inner bin, etc.). Additionally to BP1 benefits, BP2 aims on changing the business strategy moving the workload balance of maintaining the feedstock to the feed supplier, so they can handle and manage the correct and exact amount of feed for each bin that covers their client needs (the farmer) while, at the same time, optimising the supply and logistics chain costs (production, own stocks, product shipping/distribution, etc.). Figure 10 depicts the global information available to feed manufacturers to plan according to feed types, consumption rates, and simple demand forecast (ETA).

Days of stock according to daily consumption
Farm XX::3a::BIN2AEEE978

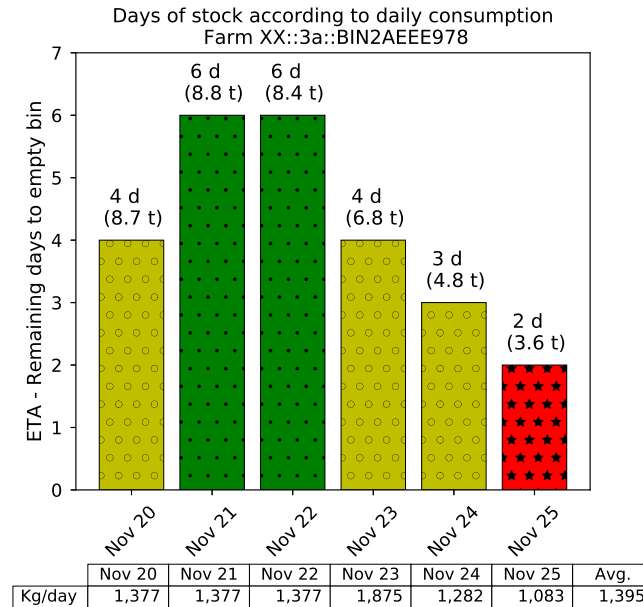|	Nov 20	Nov 21	Nov 22	Nov 23	Nov 24	Nov 25	Avg.
Kg/day	1,377	1,377	1,377	1,875	1,282	1,083	1,395

Figure 9: Sample location, remaining stock estimation based on daily consumption. Coloring is based on a traffic light schema where color gets red when stock live-span reaches two days of stock.

4.3. Technology Adoption

This project has provided a collaborative framework through this we have been able to deploy a significant amount of devices. Besides, distinct countries have shown different business models between farmers and feed manufacturers. After several improvements on algorithmic and electronic design, a set of 50 devices are installed across farms to validate device accuracy, durability and weather conditions resilience. Since the installation done across distinct farms, they have been collecting data for a working period of 10 months. We have assessed a good functionality of the sensor, not only in terms of data accuracy and repeatability but in terms of usability and deployability. It takes 20 minutes to install and configure in a bin without ladder, lesser if truck mounted crane is not needed (ladder availability). Apart from the observed limitations (Section Limitations), it is interesting to point out that during these pilots we have experienced some implementation barriers with farmers. They typically focus mainly on their core business and have little or no interest in data gathering. Moreover, it is required a reliable technological basis to encourage farmers into low-risk implementations, even in the scenarios where they are not the facility owners. Although it is commonly accepted that smart farming requires information sharing across supply chains, farmers are still and often not willing to provide access to their data in the
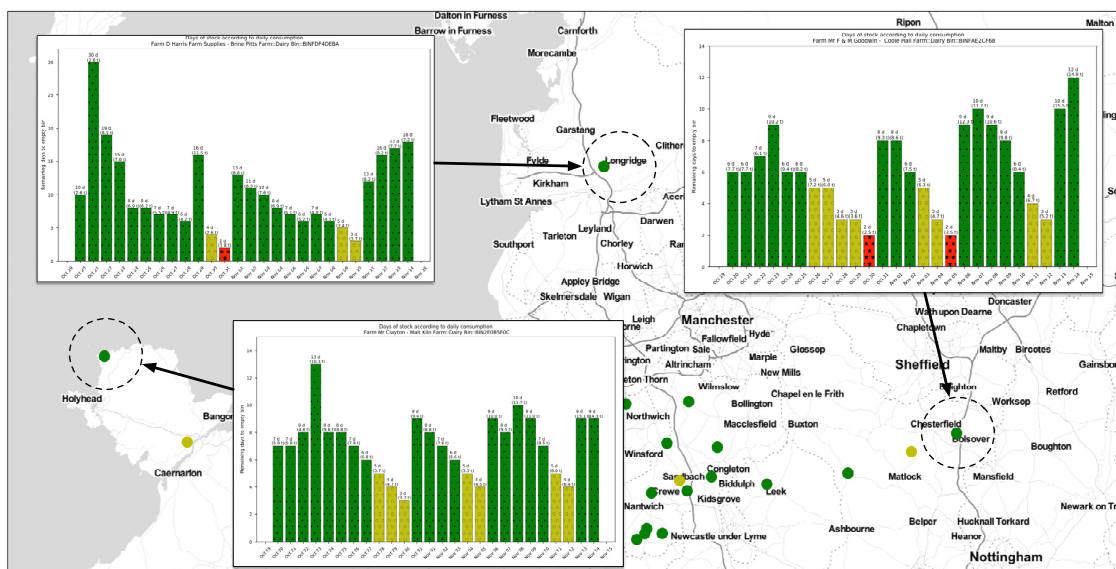
Figure 10: Case study UK1 pilot with 20 locations and 27 sensor mounted bins.

light of uncertainties about ownership and security of their data. While these concerns tend to dilute when they are not the real owners of the facility, it will be required the implementation of policies to give farmers ownership of their data. All the actors of the value chain seek for proven results of direct impact and improvement potential on individual farm and supply chain levels.

5. Conclusions and Future Research

This work presents a new monitoring system for animal feed storage bins that gives volume estimations with errors below 5% in all cases. According to the results obtained, the average deviation between our estimations and the used weighing system can achieve up to 1.15% relative full scale error. This system is designed to enable large deployments. It is battery powered with solar charging. Its installation is done in lesser that 20 minutes each bin without maintenance required. Additionally, a data processing pipeline is presented to generate business insights to help decision takers, either farmers or feed manufacturers. The main problem of this work aims to address originates from a practical application of feed compounder delivery to animal farms, where the main objective is to satisfy all the farm demands at a minimal cost. In the same vein, this work enables a closed-loop system where periodical measures gathered from the field will be used by heuristics to dynamically optimise inventories and routes. Thus, this updated information from real inventories will reduce the uncertainty with which heuristics has to deal. Several future research lines are possible. This work needs to boost the collaboration with partners or consultants to overcome investment hesitance by providing enough business cases. Rich and extensive analysis on costs and pay-offs as well as implementation support will be of utmost importance before proceeding to larger deployments. A good starting point would be proposing the integration of the proposed solution in other sectors (for example, by fostering the collaboration with other use cases within the EU-IoF2020 project).

6. Acknowledgment

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