The role of information and communication technology in poultry broiler production process control: a review

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Abstract: Broiler production is arguably one of the most challenging food supply industries in the world due to the large number of animals that are reared on a given site, and the competitive nature of the sector. These factors taken together mean that every opportunity to optimise the production process must be considered to boost bird weight gain while at the same time reducing resource investment and risk of major incidents. Because of this, the last decade has seen the introduction of Precision Livestock Farming techniques to the broiler production industry. In this paper, we review the emergence and trends in Precision Livestock Farming in the broiler production industry by examining both in-market and laboratory based advances for this sector. The review spans three tiers of Information and Communication Technology (ICT) that together form the basis for an integrated precision farming solution for poultry. These three tiers are Sensor Technology, Data Collection and Integration Frameworks, and Data Analysis and Processing. These tiers are reviewed in the context of intensive poultry farming. In addition to examining, the trends seen in the broiler production industry a number of prominent directions in related agri-food domains are also examined to gain a better insight into where Precision Farming for broiler production industry can be expected to move over the next decade.

Keywords: poultry production, broiler, automatic process control, sensor technology, data analysis, machine learning.

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1 Introduction

The poultry industry is a fast growing and hugely competitive industry with global production of approximately 110,000 metric tonnes of broiler meat in 2015; that figure is projected to breach 130,000 metric tonnes by 2025 (The Poultry Hub, 2017), though typical profit margins for producers can be very small. Hence, producers need to avail of every opportunity to add efficiencies into their production systems. Furthermore, there is a continuing and growing burden of legislative and regulatory compliance at both national and international level (Stevenson et al., 2014) which requires continuous and comprehensive spatial and temporal monitoring of the production process by the farmer. Thus, the traditional approach of using many years of experience and intuition to make process control decisions is increasingly unviable. This has led the poultry sector along with other similar farming sectors to move towards a Precision Livestock Farming approach to farm management (Jackman et al., 2015; Corkery et al., 2013).

The drive towards the adoption of Precision Farming methods has been facilitated by great improvements in Information & Communication Technology (ICT) sectors including the so-called Internet of Things (Oppitz and Tomsu, 2018) and Data Analytics (Beer, 2018) domains. Improvements in these domains have led to low-cost and, in some cases real-time

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reporting systems that aim to relieve or at least substantially reduce the process control burden placed on the farmers. Farmers generally welcome such developments as it is commonly expected that these developments will make the farmer's workload more manageable (Jackman et al. 2015).

This drive towards Precision Farming methods for production systems in poultry production has been considered previously, e.g., (Corkery et al., 2013). Based on that analysis and our own review of the domain, we identify three tiers of precision farming technology for the poultry sectors, i.e., Sensor Technology; Data Collection and Integration Frameworks; and Data Analysis and Processing. Sensor Technology refers to the development and deployment of sensors that allow us to acquire robust and accurate characterisations of animal and environment state. Data Collection & Integration refers to the processes that build on wired and wireless networks to collate and consolidate raw sensor signals into spatially and temporally rich data repositories (Jackman et al., 2013, 2015). Finally, Data Analysis and Processing is the mostly machine learning based set of methods that map from curated input data to meaningful target variables such as descriptors of animal behaviour. These are three tiers of complexity rather than pillars or unrelated groups of functionalities since the Sensor Technology tier provides a basis on which the Data Collection and Integration tier is based. Similarly, this middle tier underpins a higher level Data Analysis and Processing tier.

Beyond raw technological issues, there are other factors that influence trends and uptake of precision farming in the poultry space that are worthy of a detailed review. For example, socio-economic factors motivate the development and deployment of precision farming methods in general (Hostiou et al., 2017). Here the issues are not only related to the individual farmers economic drivers, but also national and international trends such as sustainability of food supply, policy on antibiotic and anti-microbial treatments, and animal welfare requirements. Generally, we see that these factors affect the entirety of the precision farming movement, and as such, we do not cover them specifically here. However, these issues and more have been covered well elsewhere.

Given the above, the structuring of this paper will be based around the three technological tiers already identified. Each tier will be examined firstly in the terms of the raw technological trends that underlie that tier. We believe this content will be useful for the casual reader but may be skipped by the technologically experienced reader. We will then focus on the specific deployments for that tier into the poultry industry. The trend in recent years has been to bring hardware and sensor networks up to commercial level via commercially targeted research and full-scale commercialisations such as the SYield system developed by Syngenta for Sclerotinia detection (Derbyshire and Denton-Giles, 2016). As such our review will not focus exclusively on the laboratory based academic findings, but will also include references to existing commercial systems – though obviously the lack of peer review of claims associated with commercial systems means that the relative strength of performance metrics in commercial systems remain open to verification. The review was conducted using searches on the website 'Science Direct' (www.sciencedirect.com).

Following the review of each of the three tiers, we also provide an analysis that examines external trends and speculates on future directions for precision farming in poultry based on such external trends. This analysis is based on developments seen both outside the poultry industry specifically but also outside precision farming in general. Finally, we draw a set of conclusions and highlight the key trends and open trends revealed by our analysis.

2 Sensor Technology for Precision Poultry Farming

The collection of such high-quality raw data is essential to supply downstream processing with the predictive information from which a reliable model can be built and applied. Even the best data processing algorithms cannot be expected to perform well with poor data. Hence well-designed sensors must be used that have a clearly understood calibration curve, a detection limit below the expected lowest exposure and clean contact interfaces. With these criteria, highly precise and accurate data can be captured.

Raw sensors and their associated hardware provide the Sensor Technology tier of Precision Poultry Farming. Being more precise, sensors here refer to the situated devices that collect data of different types that define animal or house state. Associated hardware refers to the support devices that commonly integrate with sensors. These include environmental control units and other electronic components that integrate sensors into a smart environment. In the following, we firstly give an overview of sensor technology types for the casual reader and then focus on the specific deployments that have been seen in Precision Poultry Farming.

2.1 Sensors for biological monitoring

A sensor can be defined as any device that can be used to collect information about the physical environment, or any object in the physical environment – including the state of individual animals. As such, there literally exists many thousands of different types of sensors that are developed across fields ranging from electronic and photonic engineering through to pharmacology laboratories. Given the wide variety of sensors in the literature, we will not attempt to cover all types of sensors here. Instead, the interested reader is directed to Kyung et al. (2015) for a useful introduction to sensor technology.

Regardless of the application domain, a given sensor usually targets a single property, i.e., the measurement type. Examples of properties include specific chemicals, e.g., oxygen, a biological substance, e.g., salmonella, a physical property, e.g., acceleration, or even a process. Independently of the quality being targeted, a sensor can usually be classified into three categories: (a) chemical sensors, (b) physical state sensors, and (c) remote sensors. It should be noted that sensors from different classes can be used to sense the same quality; for example, carbon dioxide sensors can be based on either chemical sensor or remote sensor technology with the performance and reliability of the sensor different across the underlying technology (Neethirajan et al., 2009). Similarly, it should be noted that some sensors often use a hybrid combination of different underlying technologies. A biomimetic carbon monoxide sensor for example combines a substrate that undergoes a chemical reaction with CO with a Light Emitting Diode-photodiode pair that observes the reaction (Lin et al., 2018).

While the lines between different sensor types is a blurred one, we believe the distinction between chemical, physical state, and remote sensing is a useful categorisation for more detailed discussion.

2.1.1 Chemical sensors

Chemical sensors are the broadest class of sensors developed in research labs and that are available in the marketplace. These sensors attempt to determine the level of certain target chemicals in the environment. Chemical sensors that are deployed in precision farming type environments are typically designed to measure either gaseous or liquid properties. The most common gas state sensors are carbon dioxide (Neethirajan et al., 2009) and carbon monoxide sensors (Aroutiounian, 2007) but wide varieties of sensors of various costs and sizes exist for chemicals including ammonia (Timmer et al., 2005), methane (Shemstad et al., 2012), and alcohol vapour (Manera et al., 2004).

Most chemical sensors are reliant on an underlying chemical reaction that results in either a directly observable physical change in a substrate or the change of a chemical potential. For example, a Ph meter is a potentiometric device that measures the difference in electrical potential between a reference electrode and a Ph electrode. Potentiometric and other direct electric sensors are useful since they can be directly integrated into a complete sensor rich application. Chemical sensors based on the visual change of properties in substrates are generally more problematic and hence more expensive, as they generally require the integration of some remote sensing equipment such as a photodiode to report on a change in state.

The use of chemical sensors in precision farming scenarios are now widespread. Chemical sensors can give early indicators of environmental problems such as methane build-ups (Patel, 2017), biological contaminate presence in water (Hou et al., 2013), or even the nutrient quality of food stuffs (Miyamoto et al., 2013). A broader overview of the state of the art in chemical sensing is provided by Kassal et al. (2018) and Kaisti (2017). A summary of chemical based sensors in in Table 1.

2.1.2 Physical state sensors

Physical state sensors are used to measure physical properties such as temperature, acceleration, or location. Physical sensors are a relatively small class of sensors but are arguably the most widely applied class of sensor type historically. For example, both the classical thermistor and thermocouple device have been used extensively in electrical devices ranging from water kettles to engines for many decades. Acceleration sensors meanwhile are now pervasive in domestic electronics devices ranging from smartphones to games console controllers. Location and proximity sensors meanwhile are more recent developments as their widespread introduction will have begun in the mid-1990s.

Within the precision farming domain, physical state sensors are still at an early state of deployment but are now well recognized as providing benefit.

Table 1 Summary of chemical based sensors

Author	Sensor Target	Capacity/Detection Limit
Neethirajan et al. (2009)	Carbon dioxide	Up to 6000 ppm
Aroutiounian (2007)	Carbon monoxide	Up to 10,000 ppm
Timmer et al., (2005)	Ammonia	50 ppb
Shemshad et al. (2012)	Methane	5 ppb to 7600 ppm
Manera et al. (2004)	Alcohol vapour	15,000 ppm
Patel (2017)	Methane	5 ppm
Hou et al. (2013)	Ferrous contaminants	<1 mg L^{-1}
Miyamoto et al. (2013)	Nutrients	<150 mmol

The ICE Robotics ICE Tag for example is one example of a physical state sensor that can provide information on the state of bovine livestock (Munksgaard et al., 2007). The ICE Tag like other physical state monitors does not necessarily provide information that is directly interesting. Instead, the acceleration information provided by a device such as the ICE Tag becomes useful when it is fed into higher-levels of analysis that provides insight on an animal's behaviour. However, applying such sensors to large flocks of birds, where there may be 25,000 - 50,000 in a crop, is a lot less clear as it will be infeasible to track every bird and furthermore birds grow rapidly. This will be an interesting area of research in the coming years as the cost of wearable sensors comes down. One study that did attempt to capture these types of measurement was performed by Stadig et al. (2018). However, it was observed that for a week, the birds' normal behaviours were disturbed thus illustrating the challenge of designing truly passive tags. Table 2 provides a summary below.

Table 2 Summary of physical state sensors

Author	Sensor Target	Capacity/Detection Limit
Munksgaard et al (2007)	Position and motion	High correct classification
Stadig et al. (2018)	Track bird location	No detriment to tagged birds

2.1.3 Remote sensors

The class of remote sensors are different from the others in that the technologies they employ are inherently based on the observation of the target substance to measure properties of that substance. The most commonly understood example of a remote sensor is the common digital camera or RGB (Red Green Brown) visual sensor. The class of remote sensors is however much broader than the common camera. Near Infrared (NIR) sensors for example look at a different spectral range than RGB sensors by collecting information on the amount of near infrared light that is absorbed, emitted or transmitted by a given substance. This can give valuable information such as thermal profiles and averages of the birds in the crop (McCafferty, 2013). The cost of all types of camera devices has fallen heavily in recent years making them a viable economic choice of sensor.

Acoustics are another form of remote sensing whereby soundwaves emanating from the object of interest are captured and recorded for further analysis. For centuries, farmers and animal handlers have listened to their animals for clues as to their wellbeing (Gerhardt, 1998). The enclosed nature of broiler growing houses makes acoustic analysis a strong candidate for remote sensing, however coping with interference from echoes, reverberations etc. makes this a very difficult challenge (Fontana et al., 2017). Table 3 provides a summary below.

Table 3 Summary of remote sensors

Author	Sensor Target	Capacity/Detection Limit
McCafferty. (2013)	Thermal patterns	Pattern extraction possible
Gerhardt et al. (1998)	Acoustic patterns	Animal communication detected
Fontana et al. (2017)	Acoustic patterns	96% correlation with weight

2.2 Sensor application for Precision Poultry Farming

A wide variety of environmental sensing hardware already exists for the majority of poultry house environmental features that includes temperature, humidity, carbon dioxide and ammonia (Corkery et al., 2013). In particular, for temperature and humidity there exists an abundance of low cost, robust, high precision and high accuracy sensors. These sensors break down into three main types: thermocouples, thermistors and resistance temperature detectors devices. Similarly, for humidity sensors, an abundance of options exist which consist of approximately five main types: dielectric polymers, ionically conducting polymers, aluminium oxide, phosphorous pentoxide and chilled mirror hygrometers.

For the measurement of carbon dioxide, non-Dispersive Infrared or 'NDIR' sensors have emerged as the industry standard (Hodgkinson et al., 2013). The principal choice how much cost is the user willing to bear in return for more accurate, greater operating range and faster response as these sensors can cost many hundreds of US Dollars each. For Ammonia, the challenge to find an economic and ergonomic detector remains a very difficult one and each type of ammonia sensor has major drawbacks as discussed in depth by Timmer et al. (2005). Thus, cost effective, reliable and rapid ammonia measurement are remained as substantial challenges.

There is also an abundance of hardware commercially available to capture non-point sensor datasets that are of importance to the assessments of conditions within the poultry house (Jackman et al., 2015). In particular, video and still image datasets allow a farmer to remotely monitor the crop as it grows and identify any malfunction or performance deficiencies according to his or her knowledge and experience. This can lead to time saving as the farmer no longer needs to be physically present at the house. This has been implemented by Naas et al. (2017), Zhuang et al. (2018), Aydin (2017a, 2017b), Bergmann et al. (2017), Pereira et al. (2013), Gates and Xin (2008) and Neves et al. (2015) for monitoring bird performance and by Amraei et al. (2017), De Wet et al. (2003), Mollah et al. (2010) and Mortensen et al. (2016) for estimating average bird weight. An alternative application of video data was devised by Racicot et al. (2011a, 2011b) for monitoring the biosecurity of personnel entering and exiting poultry houses and a similar approach was taken by Schroeder et al. (2016) in monitoring biosecurity of personnel in processing houses.

Acoustics are another data type that can give that a highly experienced farmer an overview of the wellbeing of their crop. The common subtle variations in the bird's cooing can be detected by the ear to brain function as can the characteristic sound of equipment that is performing as expected. Acoustic data is long established as a measure of animal welfare (Manteuffel et al., 2004) so there is a solid theoretical as well as empirical basis for this. Furthermore, recent research has used analysis of broiler bird acoustic patterns to predict the presence of important diseases such as Newcastle, Bronchitis and Influenza (Banakar et al., 2016). Acoustic data is also proven to have predictive value on broiler bird weight (Fontana et al., 2015, 2017) which is the ultimate measurement of farm productivity. A particularly novel application of this fact was by Aydin et al. (2014) who used the sound of 'pecking' to determine whether normal eating patterns were occurring at the automatic feeding stations within the house. This all means that strategically placed microphones can capture useful data that can be sent to a remote farmer. It is also worth noting a review by Sassi et al. (2016) into the application of modern technology in poultry welfare discussed the power of acoustic datasets in considerable detail.

With the advancement of imaging hardware, the utility of non-visible thermal image datasets has been comprehensively investigated by the University of Kentucky (2014) which outlines the benefits of thermal imaging in finding defects in the house structure that are causing heat leaks. They also identified a fringe benefit of allowing emerging electrical faults due to the additional heat generated at the locus of the fault. A more short term benefit is the ability of thermal imaging to monitor heat stress in the broiler birds; in hot countries like Brazil this is a very serious problem and thermal image data was used by Nascimento et al. (2011) to provide an estimate of mean surface temperature of the birds and hence their comfort in a poultry house. A broader study into the potential of modern technology to maximise bird welfare was undertaken by Sassi (2016) and this examined the potential of thermal imaging to monitor heat stress and off the shelf hardware is commercially available.

Key biohazards in poultry houses such as Campylobacter, E-Coli and Salmonella are difficult to measure directly as direct confirmation via functional microbiology takes the order of days and is very costly (McDowell et al., 2008). Alternatively, the outbreak risk could be inferred from other data or the farmers experience but this is also very difficult and particularly so for Campylobacter. Thus, a rapidly reporting sensor that directly senses the ambient airborne concentration would be of great values. The advancement in recent years of nanotechnologies could offer a route to the manufacture of such as sensor as Nano sensors can be stimulated in solid phase (Rajkumar et al., 2017; Derisevic et al., 2015) and liquid phase (Gheorghe et al., 2017; El-Moghazy et al., 2016), however airborne bacteria and molecules would be more difficult to detect.

The use of biosensors in plant analysis has attracted considerable interest in recent years as detailed by (Uslu and Grossman, 2016) and biosensors would have great utility in remote and real time or rapid monitoring of crops where early detection of biohazards would be extremely valuable. This was researched intensely in the early years of this decade (Derbyshire and Denton-Giles, 2016). Further evidence of this drive to remotely monitor pathogens in foodstuffs with biosensors is discussed by (Fronczek and Yoon, 2016) with an important example of how the critical problem of mycotoxins can be addressed with biosensors given by Atar et al. (2015).

Poultry house monitoring biosensors need to be sensitive to the main threats of Campylobacter, Salmonella and E-coli as well as other important threats such as Avian Tuberculosis and Influenza. For example, the need for direct Campylobacter sensors in modern food production is discussed in great depth by Yang et al. (2013). These developments need to be monitored closely for possible translation into feasible poultry house biohazard detectors.

Importantly, biosensors do not always need to depend upon a biological or chemical reaction to generate a response as it can be possible to capture passive measurements such as amperometeric (Pérez, 2013) and fluorescence (Xu et al., 2017). This would be hugely advantageous as passive measurements would avoid the problems of biosensors being clogged up by reaction residue or accumulated molecules. The utility of single use biosensors for monitoring poultry houses for biohazards would not be a good option as it would involve frequent labour commitments that would not be acceptable to time poor farmers and hence research needs to be directed towards automatic variants. Table 4 provides a summary below.

Table 4 Summary of precision poultry farming sensors and candidate sensors

Author	Sensor Target	Capacity/Detection Limit
Corkery et al. (2013)	Environmental features	Prototype devised
Timmer et al. (2005)	Ammonia	50 ppb
Naas et al (2017)	Gait score	80% Correct classification
Zhuang et al. (2018)	Bird sickness	99.5% Correct classification
Aydin (2017a)	Gait score	99% Model accuracy
Aydin (2017b)	Lying down patterns	93% Correct classification
Bergmann et al. (2017)	Bird welfare patterns	Increased bird activity detected
Pereira et al. (2013)	Bird body shape	70% Behaviour correct classification
Gates and Xin (2008)	Timeseries weights	<2% Error of feeding time
Neves et al. (2015)	Flock distributions	Feeder Design can impact feeding rates
Amraei et al. (2017)	Bird dimensions	98% accurate weight predictions
deWet et al. (2003)	Bird dimensions	Low as 10% prediction error
Mollah et al. (2010)	Bird dimensions	99% accurate weight predictions
Mortensen et al. (2016)	Bird dimensions	7.8% error in weight prediction
Racicot et al. (2011b)	Biosecurity errors	Identified needs for staff training
Racicot et al. (2011a)	Biosecurity errors	Identified non-compliance patterns
Schroeder et al. (2016)	Biosecurity errors	Measured effect of workplace signs
Banakar et al. (2016)	Bird vocalisation	91% Correct disease identification
Fontana et al. (2017)	Acoustic patterns	96% correlation with weight
Fontana et al. (2015)	Acoustic frequency	80% Correlation with weight
Aydin et al. (2014)	Pecking frequency	99% Model accuracy for feed intake
Nascimento et al. (2011)	Thermal profiles	Mean bird temperature predicted
Rajkumar et al. (2017)	Biocontaminants	Relating electric signals to presence
Derisevic et al. (2015)	Xanthine molecules	Biofilm pH and temp to presence
El-Moghazy et al. (2016)	Olive oil contaminants	Biofilm current related to concentration
Atar et al. (2015)	Citrinin	Infections detectable in red yeast rice
Pérez et al. (2013)	Histamine	Concentration in fish detected linearly
Xu et al. (2017)	Multiple pathogens	Lettuce, shrimp and beef infection detected

3 Data collection & integration frameworks

While delivering high quality and low-cost sensors is a significant challenge, the collection and integration of data in itself presents both technological and semantic difficulties. In the context of real-world deployments, hardware is required to network together usually multiple sensors with control units, user interfaces and the like. Semantic integration frameworks meanwhile are needed whenever data from multiple sensor types are to be integrated into a coherent data processing application. In this section, we consider these joint challenges for data collection and integration frameworks in precision poultry farming.

3.1 Hardware integration

Assuming sensors connected have sufficient power to operate, and the question has become the biggest to gather the data together. In recent years, the trend in agricultural production environments is to have a local central hub (the aforementioned electronic control unit) that collects real-time data from a network of sensors placed in the production environment and firstly reports that data back to the manager or farmer and secondly can make recommendations to the farmer or manager via embedded software algorithms. Conversely, this central hub can use manual instructions or software algorithms to issue instructions to hardware in the production environment such as the venting boards or diesel burners. Such ECU's are available from many manufacturers such as Rotem (Munters, Tobo, Sweden), Fancom (Panningen, Netherlands) and Agrologic (Tel-Aviv, Israel).

There are a number of options to integrate this hardware, and the most stable and secure is a direct connection by Ethernet cable as modern Power by Ethernet or 'PoE' allows both Direct Current (DC) electric power and data to be carried over many metres (IEEE, 2005). A very strong advantage is that the power can be boosted with injections points called 'switches' that are connected to the mains electricity supply; furthermore these 'switches' can act as hubs and dividers to direct power and data in many directions. This greatly increases the lengths of connections possible. There is a multitude of suppliers of these 'switches' such as Netgear (San Jose, CA, United States). The current control systems would lean towards this direct or 'hard' connection for its robustness. A direct DC power connection without PoE is also a stable and secure option to power and automatically trigger hardware. A limitation of this direct connection is that only the central computer can connect to the internet; however, this adds a layer of data security as long as a robust firewall is in place on the central hub or if the farmer chooses not to connect the hub to the internet. A further downside is that direct connection adds 'moving parts' to the network that will need periodic maintenance and updating.

A modern trend is to avail of the emergence of greater computing power and enhanced mobile telecommunications technology to allow for sensors to operate truly remotely with only a wireless or 'soft' connections to the central hub and their own capacity to make independent external connections to the internet. A recent network devised by Jackman et al. (2015) sought to use the mobile telecommunications network to allow sensors to communicate with a cloud server in real time. The advantages of this approach are that data from many sensors and production sites can be synergised in real time and the cloud server can run in real time a broad algorithm that can communicate down to the farmers, local central hubs or even directly to the process control hardware. The network has much fewer 'moving parts' as mentioned previously but is dependent upon the strength of the mobile telecommunications network to function and in some rural areas signal strength can be poor. A further disadvantage is that moving image data through domestic internet connections will consume data allowances quickly and thus images or large convoluted datasets would need to be processed locally and their summary features transmitted. Robust data encryption is essential for this approach as the data streams are vulnerable to unauthorised access. There is again a multitude of suppliers of mobile transmitters suitable for this task as a basic 'dongle' and 'router' are freely available from any mobile phone or cell phone store.

These two examples give a strong insight into the choices facing optimal hardware integration. The emergence of low-cost motherboards in recent years has made it possible to turn sensors and production hardware into local data and process control hubs and thus relieving pressure on the local central hub allowing for simpler central hubs that can be a simple desktop computer rather than a highly specialised and expensive control box. Some leading brands of these low-cost motherboards are “Raspberry Pi’s” (Raspberry Pi Foundation, Caldecote, United Kingdom) and “BeagleBones” (Texas Instruments, Dallas, TX, United States). Pressure can be relieved by performing local data processing so only summary features need to be transmitted and performed local predictive analytics. Ultimately, a classic intelligent control box with dumb sensors and production hardware could be used but this will be a more expensive choice and a much less efficient choice.

The choice of wired or wireless or ‘hard’ or ‘soft’ will often be forced upon the design engineer as while intensive animal production environments will have the luxury of access to mains electric power many other scenarios will not. In some scenarios the sensors will have to be placed in remote and inhospitable environments such as crop fields (Jackman et al., 2013). Similarly, the limited dimensions of intensive growth houses are within the maximum length of Ethernet cable that can support a stable signal. Where a wireless network proves necessary or desirable in the event of strong and stable mobile internet coverage established protocols such as the Zigbee standard (Zhang and Chen, 2010) or Wi-Fi alternatives can provide a framework for data transfer.

The next most pressing choice will be to what extent the power of Cloud Computing will be utilised. The advancement of cloud computing has meant that the central computer can actually be a remote server accessible by the internet and all the advantages mentioned previously can be realised. Having a single point of contact will make for more secure data as only that single point of contact has to be policed for malicious actions. However, having multiple points of contact allows for much more efficient data transfer with the cloud server although each of these points of contact need to be diligently policed. Fully secure systems that are not connected to the internet are also a possibility if required. Table 5 provides a summary below.

Table 5 Summary of hardware integration

Author	Sensor Type	Sensor Target
Jackman et al. (2015)	Environmental Point	Bird Environmental Conditions
Jackman et al. (2013)	Bio and Environmental	Sclerotinia Spores and Environment

3.2 Semantic integration

When there is a large set of data that can complement each other and need to be properly synchronised, a strategy for placing the data into a common framework has to be established so that the merged datasets can be sensibly interpreted and applied. This will involve for example converting all data points into S.I. Units. Furthermore, this strategy must avoid accidentally misaligning data that should be co-ordinated and reconciled, typically this means ensuring that data points are put into the correct spatial and temporal co-ordinates. Thus, a data ontology should be prepared before any data analysis occurs.

The modern prevalence of rapid reporting sensor hardware has led to the availability of effectively continuous data streams that can provide useful information on events occurring within the poultry house. Thus there is a need to capture and integrate multiple data streams so the useful information within those streams can be synergised and the consolidated data streams can be used to inform process control decisions both as recommendations to the farmer and as triggers for automatic control systems such as the aforementioned ‘Environmental Control Units ‘or ECU’s.

There are numerous commercial ECU systems available and these ECU’s will have defined protocols for correctly interpreting the sensor data. However, these units are limited to conventional point sensor datasets that while containing useful information are not setup to synergise a whole variety of potentially useful datasets including bespoke biosensors, video and image datasets, acoustic datasets and other historical, structural and background datasets. Merging multiple and diverse datasets is a far more difficult challenge than might be expected and requires a complete ‘ontology’ (Effingham, 2013), so each data point can be safely converted into S.I. Units (NIST, 2017) and archived correctly spatially and temporally.

Without a complete ontology, data points could be misinterpreted and thus they would subsequently misinform any future data analysis and thus may lead to sub-optimal process control decisions. A complete Ontology for sensor networks was devised by the W3C Semantic Sensor Network Incubator Group (Compton, 2012) to ensure the safe handling of data. This Ontology was adapted for a specific purpose, i.e., a bespoke remote point sensor network in Oilseed Rape Fields (Jackman et al., 2013) and an internal wireless point sensor network in Poultry houses (Jackman et al., 2015).

A drive to include non-point sensor data will greatly complicate the sensor definitions and thus a far more detailed ontology will be required as there are far more opportunities for the data points to be misinterpreted. The question of how to correctly define video data for analysis was investigated by Bai et al. (2007) and the same question of how to correctly define audio data for analysis was investigated by Gorrepati et al. (2013). Other supporting sensor data are available in most modern poultry houses such as the water flowmeters, feed line flowmeters and the level sensors on the feed vats. Additionally, there is typically persistent data regarding the poultry-growing house such as its infection history, infrastructure, maintenance record and management personnel that are all factors that could influence outcomes. Integration of multiple and diverse data sources will create a highly robust and comprehensive model even if data streams become interrupted (Aziz and Reddy, 2010) and thus it is by synergising all of the available datasets that the best models can be created. Table 6 provides a summary below.

Table 6 Summary of semantic integration

Author	Data Type	Sensor Target
Compton et al. (2012)	General Purpose	General Purpose
Jackman et al. (2013)	Environmental	Local Air Features
Jackman et al. (2015)	Environmental	Indoor Air Features
Bai et al. (2007)	Video Image	General Purpose
Gorrepati et al., (2013)	Audio Stream	Bird Calling
Aziz and Reddy (2010)	General Purpose	General Purpose

4 Data analysis for precision poultry farming

Once the data has been safely transported to the central server and correctly interpreted according to the ontology then the process of data analysis can begin.

While classical machine learning and data analytics have been broadly successful in a variety of precision farming tasks, the most exciting opportunities lie in the state of the art in machine learning that has been made possible by the recent expansion of computing power. The power of these algorithms to extract useful information from previously impenetrable datasets offers the possibility of large improvements in the utility of predictive models.

Of particular interest is how the latest methodologies in data processing are making the creation of better predictive models possible that can provide better advice to farmers or even lead to better automatic control responses in the broiler bird production field. While classical data processing has led to some notable and tangible successes, it is the emergence of very powerful new machine learning and data analysis tools such as Deep Learning Neural Networks (Goodfellow et al., 2016), Convolutional Neural Networks (Lu et al., 2017) and Recurrent Neural Networks (Graves, 2012) which make it possible to cope with very opaque and nuanced data that offer the most exciting potential for problem solving in this field.

Data analysis can consist of an expert review of the causal factors such as temperature etc. to formulate a decision. However, the true power in data analysis is when real time or close to real time causal datasets are analysed to give a real time or close to real time prediction of the most important performance metrics so that remedial actions can be taken quickly.

For growing broiler birds in a poultry house, the performance metrics we are concerned with include average bird weight, weight gain versus weight of feed consumed a.k.a. 'Feed Conversion Ratio' or 'FCR', percentage mortality, percentage 'Foot Pad Dermatitis' and percentage 'Hock Burn' (The Poultry Site, 2017). These performance metrics can all be given an economic value leading to an overall return on investment for the farmer when collated with costs such as electricity, maintenance, depreciation, labour costs etc. Average bird weight can be automatically measured in real time with commercially available hanging balances that the birds jump onto at random; feed and water consumption can also be measured by commercially available flowmeters and deadweight silo sensors. Bird foot ailments and mortality does however still need to be observed and recorded manually and economic datasets are usually generated from other sources. Once armed with these performance metrics, a predictive model can be built from the causal datasets that can be calibrated, validated and tested to ensure its reliability

4.1 Machine learning and data analysis methods for poultry systems

The implementation of data analysis to deliver a decision support system or preferably automatic process control relies upon the generation of a reliable algorithm that can be encoded into an automatic control system. Up until very recently this has been some form of regression model (Jackman et al., 2015; Mollah et al., 2010; Aydin, 2014; Nascimento, 2011) such as Partial Least Squares Regression (PLSR) with time shifted datasets and simple multilinear regressions or some kind of classic standard neural network such as a conventional Neural Network with a variety of stopping criteria and a Bayesian Artificial Neural Network (Mortensen et al., 2016).

Variations on commonly applied statistical methods include Generalised Linear Modelling with Procrustes analysis (Fontana, 2015) or pure General Linear Modelling (Neves et al., 2015) a Classification Tree using both set training and cross validation (Pereira, 2013), bespoke algorithms for high frequency and low frequency data (Gates and Xin, 2008) these algorithms combined simple thresholds, event identification and feeding classification steps. A Support Vector Machines approach was used by Banakar (2016) which integrated data mining and the Dempster-Shafer evidence theory to find more models that are accurate.

A notable move towards the state of the art machine learning was the use of differential recurrent neural networks (DRNN) by Demmers et al. (2010) to find non-linear trends in time series data and capture the underlying growth mechanisms and reduce prediction error to less than 2%. This offers the opportunity to create models that are totally driven by the data and not by fixed assumptions and suggests that this advanced neural network is the way to cope with relationships between variables that are difficult or infeasible to explicitly express. The 'Deep Learning' concept described above is an ideal candidate for this challenge.

A highly promising machine learning method based around random forest algorithms was developed by Diez-Olivan et al. (2018) for broiler farm management that is especially pertinent. This approach predicted growth, welfare and mortality with high accuracy across a diverse range of flocks. A further promising method based around complex Neural Networks was developed by Ribiero et al. (2018) for real time adjustment of control parameters and is of great interest to our own challenges. Table 7 provides a summary below.

Table 7 Summary of precision poultry data analytics

Author	Analysis Type	Analysis Target
Jackman et al. (2015)	Classic	Bird Weight
Mollah et al. (2010)	Classic	Bird Weight
Aydin et al. (2014)	Classic	Bird Feed Intake
Nascimento et al. (2011)	Classic	Bird Surface Temperature
Mortensen et al. (2016)	Classic	Bird Weight
Fontana et al. (2015)	Modified Classic	Bird Weight
Neves et al. (2015)	Modified Classic	Bird Motion
Pereira et al. (2013).	Modified Classic	Bird Motion
Gates and Xin (2008)	Modified Classic	Bird Behaviour
Banakar et al. (2016)	Modified Classic	Bird Disease Estimation
Demmers et al. (2010)	Recurrent Neural Network	Bird Growth
Diez-Olivan et al. (2018)	Random Forests	Bird Growth, Welfare & Mortality
Ribiero et al. (2018)	Deep Neural Network	Automatic Environmental Control

4.2 Machine learning and data analysis methods in similar agricultural challenges

There are similar process control challenges in other agricultural production scenarios; in particular in pig production that also involves growing animals in intensive indoor conditions. Other agricultural scenarios that require close monitoring of environmental conditions would be for housing cattle. Thus, any successful applications of machine learning controlled environments for these other domains need to be examined for suitability in controlling poultry environments.

For image processing-based solutions, the Vector Quantised Temporal Associative Memory (VQTAM) based learning algorithm of Wongsriworaphon (2015) is very relevant as it is designed to estimate average animal weight that is an identical problem for growing broiler birds. The approach is to use the average dimension and the perimeter of the pig silhouette as the two predictors of weight and then a VQTAM model supplemented by Autoregressive (AR) and Local Linear Embedding (LLE) predicts the bodyweight. High classification accuracies of up to 97% proved possible.

For bovine disease surveillance, an ensemble classifier was used by Yazdanbakhsh (2017) that combined the benefits of logistic regression and radial basis function neural networks; this reduced the need for manual checks of the animals that was also the case in broiler production. Another ensemble classifier was used by Dutta et al. (2015) which combined a variety of learning algorithms to create multi-faceted classifiers for real time surveillance of cattle. More general surveillance of pig production was simulated with a C4.5 decision tree algorithm by Kirchner et al. (2004). These approaches should be attempted during the data analysis and predictive modelling phases of any real time modelling of growing broiler birds.

A particularly promising method was proposed by Ter-Sarkisov et al. (2017) for using realistic and challenging video image data to track individual cows in a working cowshed. A bespoke random forest algorithm that chose a subset of features of interest was used to successfully track the cow of interest in a cow shed with a variety of 'Deep Learning' neural networks such as Conditional Random Field Recurrent Neural Network (CRF as RNN) applied to the raw datasets for the crucial image segmentation step. This algorithm can be investigated for the potential to track individual birds in a poultry shed. Table 8 provides a summary below.

Table 8 Summary of other agricultural data analytics

Author	Analysis Type	Analysis Target
Wongsriworaphon. (2015)	Associative Memory	Pig Weight
Yazdanbakhsh et al. (2017)	Ensemble Classifier	Cattle Disease
Dutta et al. (2015)	Ensemble Classifier	Cattle Motion Patterns
Kirchner et al. (2004).	Decision Tree	Sow Replacement Threshold
Ter-Sarkisov et al. (2017)	Deep Learning	Cow Tracking and Motion

4.3 Machine learning and data analysis methods in non-agricultural challenges

The question of automatic process control and decision support is far from limited to poultry house environment or intensive agricultural production. This question crosses almost every aspect of engineering and production sciences and thus lessons can be learned

from any pertinent process control challenge whereby real time sensor datasets are used in concert with persistent datasets to formulate a recommendation or an automatically implemented decision. These control systems will have relied upon a machine-learning algorithm to devise said decisions. Thus, the latest algorithms used can provide some insights into how state of the art machine learning might transfer into poultry house control.

A strongly related challenge can be found in environmental control in Greenhouses whereby a tightly controlled environment must be supplied to the crops to ensure maximal growth and minimisation of biohazards. A fuzzy logic-based controller was proposed by Cañadas et al. (2017) to maintain optimal conditions within the greenhouse. A similar challenge is the question of optimising energy usage in a confined building and this was investigated by Google (Gao, 2014) where they used deep neural networks to cope with the highly complex non-linear interdependencies between the input data. This method mimics the problem of poultry house process control where such highly complex and non-linear interdependencies exist. Thus, approaches such as these should be regarded with great interest. Further studies in deep learning came in the optimisation of crude oil production (Shang et al., 2014) where sensor datasets are used to feed the model. The power of recurrent neural networks (RNN) in process control was explored by Lu and Tsai (2007) where it was used to optimise the performance of an oil-cooling machine; the power of RNN to cope with time delays and time shifts makes them a particularly attractive option in process control. Another approach of considerable interest is the use of 'Self Organising Maps' (Choung et al., 2017) to optimise the manufacture of electronic components. This is a process in which there could be many non-linear interdependencies and variables are not time invariant. Table 9 provides a summary below.

Table 9 Summary of non-agricultural data analytics

Author	Analysis Type	Analysis Target
Cañadas et al. (2017)	Fuzzy Inference	Greenhouse Automatic Controls
Gao (2014)	Deep Neural Networks	Building Environmental Controls
Shang et al. (2014)	Deep Neural Networks	Crude Oil Distillation Threshold
Lu and Tsai (2007)	Recurrent Fuzzy Network	Liquid Level Controls
Choung et al. (2017)	Self-Organising Map	Electronic Component Production

5 Conclusions

The continual advancement of ICT is constantly providing new opportunities to automate and increase objectivity in process control challenges. This will relieve the burden on expert human operators and managers by performing comprehensive calculations based upon reliable predictive models fed with data from reliable sensors and other data sources. The technology exists to capture a huge variety of reliable real time or close to real time data for almost all pertinent data sources. With a rising global population and a rising demand for meat products in developing countries optimal decision making during intensive agricultural production will only become more urgent if food supplies are to meet demand. Advancing food safety and animal welfare regulations will similarly increase the urgency to accurately detect biohazards so the use of anti-biotics and other medicines that can enter the food chain is minimised without compromising protection. That trend should be continued into direct detection of biohazards via real time or close to real time biosensors as real time biohazard detectors are the principal missing piece of the 'jigsaw'. Any future real time biohazard sensors need to be continuous or quasi-continuous; this will be very difficult for any sensor that depends upon a contact based biological reaction to generate a reading, thus biohazard sensors need to use some kind of passive measurement.

The second research opportunity lies in integrating the state of the art in machine learning into the process control and decision support algorithms. There has been moved towards recurrent neural networks to cope with datasets involving unknown time shifts and time delays in other scientific areas and these are needed to be explored for their suitability for transposition. Similarly, the advancement of convolutional neural networks for image-based datasets are very promising and are being used for novel automatic control systems in driverless cars for example. Deep Learning neural networks are also emerging as feasible means of coping with the complex non-linear inter-dependencies between the variables with predictive power; as computing capacity continues to expand to allow network training in a reasonable time. Additional neural network types and artificial intelligence methods such as fuzzy inference should be also continued to be appraised. A synergy of many machine-learning methods into ensemble models may also hold the key to the optimum algorithms. In the last year, there has been some rapid developments on this front so there are indications that the potential of machine learning may be crystallising. As this machine learning software becomes mainstream through research and development it can be tailored for real scale intensive agricultural production.

Thirdly, there are some important telecommunications questions that can be investigated to maximise the potential of ICT in Agricultural production, so it can realise its full potential. Can Ethernet cables be designed to carry a signal over distances of hundreds of metres so networks that would previously have been forced to be wireless can have option of being wired? Can mobile telecommunications systems be designed to allow large volumes of raw images to be transmitted rapidly to a cloud server to abate the need for local processing? Can mobile telecommunications coverage be extended to all or almost all rural areas, the midlands of Ireland are a particularly challenging case in this regard. Can microcomputers and motherboards be improved to allow greater local data processing where that is desired and support more complex sensor hardware or local process control hardware? With these challenges addressed the next generation of sensor networks for poultry growing houses and many other agricultural production environments can be developed.

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