Application of wireless technologies to forward predict crop yields in the poultry production chain

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Abstract: Average bird weight is the primary measure of crop yield and is the basis for calculating payment for the grower by the wholesaler. Furthermore the profit per bird is very small. Thus very tight control of growing process that is essential to ensure average bird weight is maximised. The important factors (air temperature, air humidity, carbon dioxide concentration and ammonia concentration) that affect the intake of feed and water must be kept at their optimum during the progress of the growing cycle. These factors can be influenced by activating burners and opening the vents on walls of the growing house. It then follows that the burning and venting strategy will be influential on the average bird weight of the crop.

Currently the burning and venting strategy is based on notional ideal levels and data from wall mounted sensors. This suffers from two fundamental problems: firstly the strategy is determined by ideals that may not be suitable for all growing houses and secondly the data are not measured from the chickens own airspace. Thus the management strategy is based on a model that may not reflect reality and on data that may not reflect reality

The "BOSCA" project addresses these problems by placing wireless environmental sensors into the chickens own airspace. This provides for direct measurement of the air experienced by the chickens and reports the recorded data in near real-time to a cloud based data management system. The sensor data are merged with the data from the growing house weighing scales in the cloud repository so a predictive model of average bird weight from the measured environmental data can be calibrated and validated. Furthermore, a time shift can be applied to the environmental data during model calibration and validation so the average bird weight can be forward predicted by 72 h(R2up to 0.89 with neural networks). This gives the grower advance notice of a deviation from ideal feeding and watering conditions and the likely consequences of failing to take remedial action such as turning on the burners or venting the house.

Keywords: environmental control, productivity, average bird weight, wireless agricultural sensors, cloud computing

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1 Introduction

It is anticipated that there will be very strong growth in the global poultry market into the next decade (Mulder, 2012), thus it is essential that anyone wishing to maintain or grow their market share will have adopt the best standards and practices. Specifically it will be necessary for producers to maximise their average bird weights by maintaining high feed and water conversion efficiencies throughout the production cycle (Van Horne and Bondt, 2013).It should be noted that in a typical production cycle (five to six week period) average bird weights can increase from 50 g to 2.2 kg(Hall and Sandilands, 2007).

The comfort and the contentment of the broiler chickens depend on the control of the house environment. More specifically this means that the air temperature, humidity, carbon dioxide (CO_2) and ammonia (NH_3) must be within acceptable parameters (Aviagen, 2009). These parameters can be maintained by an in-house environmental control system (Rotem, 2014) which adjusts the internal house environmental profile by

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controlling the use of heaters, air conditioning and external vents and other environmental manipulation devices. However, burners that use gas or liquid diesel fuel to generate additional heat at the cost of also introducing additional CO_2 into the house environment. The gas concentrations and importantly the house temperature and humidity can be lowered by opening vents on the walls of the house to allow fresh air to enter the house and stale air to escape (Aviagen, 2009). However, venting due to excessive gas concentrations or humidity may mean that the heaters need to be activated to maintain temperature.

In addition to the economic requirements for close control of poultry house environments there is a legal requirement in respect of animal welfare and workers healthcare (Corkery et al., 2013) and it is insufficient to merely reduce flock density to guarantee animal welfare (Jones et al., 2005) so additional welfare supports arerequired. The trend in regulation is towards progressively stricter limits on the house environment but equally the grower does not want use the environmental manipulation mechanisms as they are costly to use (Jones-Hamilton, 2014). Thus, the solution is the optimum use of the environmental manipulation mechanisms, which is a type of Precision Livestock Farming (PLF), towards a reduction in production losses (Mollo et al., 2009) leading to better incomes, reduced environmental impact, increased product quality, earlier diagnosis of health risks and improved waste management (Hocquette and Chatellier, 2011). The principal characteristics of good PLF systems are continuous adequate sensing, dynamic mathematical models, target values for outputs and model based predictive controllers (Wathes et al., 2008).

To implement a PLF solution, poultry growers typically install an automatic environmental control system which uses standard curves and the growers' inputs to make process decisions. However, these systems suffer from a number of shortcomings in that they use mounted sensors and thus they are not in direct contact with the chickens own airspace. Hence, the environmental control algorithms must make their decisions based on data that may be unrepresentative. Similarly the decision making algorithms are generic may not be appropriate to the unique characteristics of the particular growing house.Another weakness is that there is no cloud sharing of data meaning the data is only available locally.

Thus, there is an industry gap for a new PLF solution for poultry houses that can avail of data directly measured from the chickens own airspace so decisions can be made based on truly representative data. There is a further gap in using decision algorithms that are tailored to the uniqueness of the growing house in question that can be quickly calibrated and validated from a small number of training crops.

In particular what be of great value would be a predictive facility that could estimate the likely impact of a loss of environmental control or a failure to maintain optimum environmental conditions. This would be an advance on the traditional predictive models of bird weight that estimate future weights based on past weights during that crop cycle. Thus such an environmental model could be optimised on a house by house basis after a period of training and testing. The traditional bird weight gain models do not have this capacity for optimisation nor do they have the ability to incorporate environmental data into their predictions.

The decision making algorithms must have a substantial forward prediction capability so there is enough time to take remedial action before the problem becomes irrecoverable. Furthermore the longer the forward prediction period the better as there is more time for a manual intervention by the grower if required. The sharing of all of this data on a cloud platform will greatly enhance its usefulness as all interested parties will be able to benefit including the wholesaler, the retailer and the consumer.

2 Materials and methods

2.1 BOSCA design

Bespoke environmental sensing boxes suitable for use in poultry houses (each known as a "BOSCA") were constructed by Shimmer Sensing (Dublin, Ireland); these consisted of a robust box design, sensors, a sensor board, a Raspberry Pi and a 3G communication device. The BOSCAs were programmed with appropriate firmware and software to record readings as comma separated values and to allow transmission over the 3G network. The environmental sensors chosen for suitability for the task were: a Sensirion (London, United Kingdom) SHT21 temperature and humidity sensor, an Elektronik (Bremen, Germany) EE891 carbon dioxide sensor and a Winsensor (Zhengzhou, China) MQ137 ammonia sensor. Two variants of the sensor boxes were constructed; a "BOSCA-MOR" or big box which contains all the elements described and a "BOSCA-BEAG" or small box which does not contain gas sensors and a 3G communication device. The BOSCA-BEAGs communicated their data to any BOSCA-MORs within range.

Calibration experiments were performed to verify the calibration curves that were embedded in the BOSCA firmware. The sensor boxes were placed into a culture cabinet (Binder, Tuttlingen, Germany) where temperature, humidity and gas concentrations could be manipulated. Inside the cabinet were a Davis Vantage Pro2 weather station (Davis, Hayward, California, USA) and a Geotech G100 CO_2 gas detector (Geotech, Leamington Spa, United Kingdom). Special NH_3 rich air was supplied by BOC gases (Dublin, Ireland) at 25mg/kg and 50 mg/kg. As a result some adjustments to the BOSCA firmware were required to edit the calibration polynomials.

2.2 BOSCA deployments

The BOSCAs were deployed in a growing house in County Monaghan, Ireland for two crop cycles. The schematics are shown in Figures 1 and 2. Each BOSCA was placed in this location for the full cycle. The data recorded were condensed into comma separated values (.csv) every 1 min for the BOSCA-MORs and every 10 min for the BOSCA-BEAGs. The .csv files were immediately uploaded to a cloud server via the 3G connection using a standard file transfer protocol (ftp) process. A local copy of the sensor data repository was made on a Linux server in University College Dublin where the .csv were parsed by bespoke Python and Bash scripts to facilitate their entry onto a PostgreSQL database suitable for forensic queries and web portal interface.

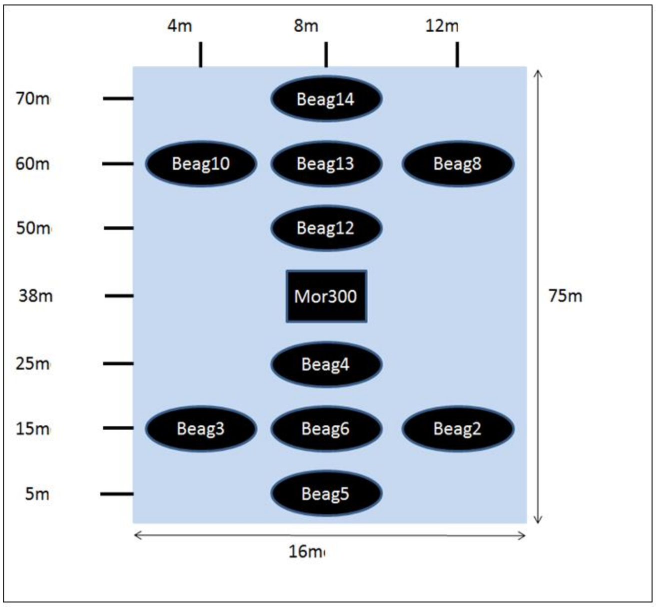

Figure 1Planar schematic of placement of sensor boxes in the growing house for the first crop cycle

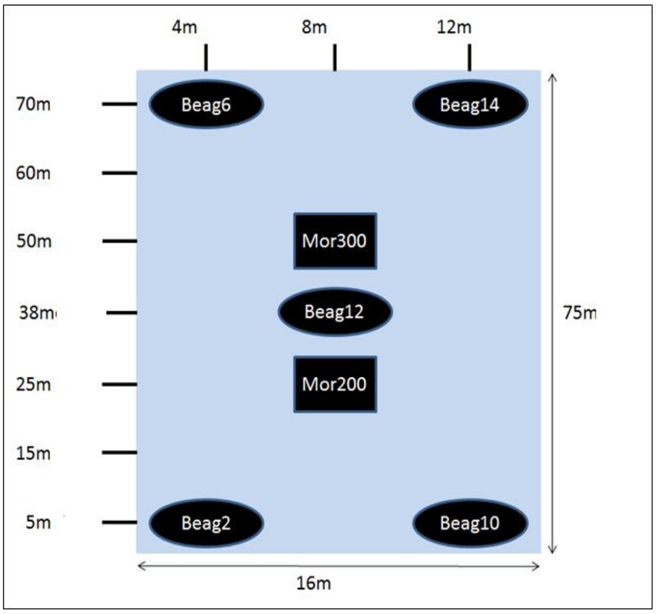

Figure 2 Planar schematic of placement of sensor boxes in the growing house for the second crop cycle

2.3 Data processing

Time series data for each BOSCA and each sensor within the BOSCAs were extracted from the PostgreSQL database with standard SQL queries (e.g. SELECT VALUE from READINGS where SENSOR_ID = …) with a Python for Linux interface. The time series data were saved as an excel spreadsheet where it was joined with the daily average bird weight data provided by the chicken grower. To make the data comparable all of the time series were grid interpolated into hourly readings. The hourly readings were copied into the statistical software MINITAB (Minitab Inc, Cologne, Germany) for analysis by partial least squares regression (PLSR) and by neural networks (NN) in Matlab (The Mathworks, Natick, Massachusetts, United States of America). Sensor redundancy analysis was performed and both internal comparison and cross comparison predictive models of average bird weight in 72 hours' time were generated.

3 Results and discussion

3.1 Sensor spatial redundancy

A vital question for sensor deployment is the spatial density required to capture trends and patterns within the area of interest. Deploying too high a density is a waste of resources and could also add error to the data stream, conversely too low a density will cause potentially important variability in the area to be missed and consequently important process control decisions to be distorted. Redundancy in the time series data can be estimated by a correlation matrix and by extracting the eigenvalues from a principal component analysis of the time series matrix. This was performed for both crops 1 and 2 and the results are shown in Tables 1 and 2. The correlation matrix shows the linear correlation between any pair of sensors for temperature and humidity, it also shows the average cross correlation for each sensor. The eigenvalues for each matrix is shown alongside the correlation matrix, this shows how much variance is explained by each successive principal component. It is important to note that BOSCA-BEAG8 in crop 1 and BOSCA-MOR200 in crop 2 only performed intermittently and their data were thus excluded from calculations.

Table 1Temperature and humidity correlation matrices and eigenvalues for the first crop

Temperaturecorrelation matrix	Mor300	Beag2	Beag3	Beag4	Beag5	Beag6	Beag10	Beag12	Beag13	Beag14		Eigenvalues,%
Mor300												93.0
Beag2	0.905										0.905	3.4
Beag3	0.936	0.96									1.896	1.1
Beag4	0.93	0.929	0.954								2.813	0.8
Beag5	0.882	0.941	0.944	0.905							3.672	0.5
Beag6	0.926	0.975	0.975	0.968	0.957						4.801	0.5
Beag10	0.921	0.906	0.936	0.917	0.862	0.923					5.465	0.3
Beag12	0.941	0.934	0.962	0.959	0.897	0.955	0.948				6.596	0.2
Beag13	0.932	0.882	0.921	0.955	0.844	0.925	0.953	0.962			7.374	0.1
Beag14	0.851	0.884	0.865	0.885	0.804	0.892	0.905	0.9	0.907		7.893	0.1
	8.224	7.411	6.557	5.589	4.364	3.695	2.806	1.862	0.907			

Humiditycorrelation matrix	Mor300	Beag2	Beag3	Beag4	Beag5	Beag6	Beag10	Beag12	Beag13	Beag14		Eigenvalues,%
Mor300												93.4
Beag2	0.937										0.937	2.5
Beag3	0.894	0.945									1.839	1.2
Beag4	0.934	0.964	0.907								2.805	0.8
Beag5	0.899	0.943	0.973	0.901							3.716	0.6
Beag6	0.897	0.944	0.973	0.907	0.98						4.701	0.5
Beag10	0.938	0.95	0.952	0.94	0.947	0.946					5.673	0.3
Beag12	0.924	0.942	0.944	0.957	0.943	0.952	0.962				6.624	0.2
Beag13	0.948	0.952	0.937	0.942	0.939	0.939	0.976	0.957			7.59	0.2
Beag14	0.859	0.869	0.909	0.845	0.92	0.941	0.908	0.909	0.915		8.075	0.1
	8.23	7.509	6.595	5.492	4.729	3.778	2.846	1.866	0.915			

Table 2Temperature and humidity correlation matrices and eigenvalues forthe second crop

Temperaturecorrelation matrix	Mor300	Beag2	Beag6	Beag10	Beag12	Beag14		Eigenvalues,%
Mor300								73.2
Beag2	0.79						0.79	9.3
Beag6	0.617	0.601					1.218	6.5
Beag10	0.69	0.63	0.598				1.918	5.4
Beag12	0.863	0.738	0.667	0.719			2.987	3.8
Beag14	0.712	0.572	0.526	0.701	0.709		3.22	1.8
	3.672	2.541	1.791	1.42	0.709	0		

Humiditycorrelation matrix	Mor300	Beag2	Beag6	Beag10	Beag12	Beag14		Eigenvalues,%
Mor300								59.0
Beag2	0.392						0.392	23.3
Beag6	0.314	0.66					0.974	6.7
Beag10	0.605	0.183	0.135				0.923	5.7
Beag12	0.839	0.347	0.264	0.687			2.137	2.9
Beag14	0.841	0.299	0.237	0.562	0.82		2.759	2.3
	2.991	1.489	0.636	1.249	0.82	0		

3.2 Sensor type redundancy

The inclusion of an ammonia sensor comes at significant financial cost and thus if it was possible to estimate ammonia by other means the financial cost of the BOSCA-MORs could be substantially reduced. Experience of the industry is that ammonia levels track humidity levels as the crop progresses. To test this hypothesis a PLSR model was built using humidity, temperature and time elapsed as predictors of humidity. To account for possible non-linearity squared, cubic and interaction terms were included. The PLSR model was validated by 10-fold cross validation. In parallel a NN was developed using humidity, temperature and time elapsed as a predictor of ammonia. The NN was validated and tested with a 70-15-15 split of the data. The results of the PLSR predictive models are shown in Figure 3. The corresponding NN model could on average predict ammonia with an $R^2$of 0.94.

Similarly the inclusion of a carbon dioxide sensor also comes at noticeable financial cost although less than for an ammonia sensor and thus its elimination would reduce the overall costs. As with ammonia, experience within the industry is that there is a substantial tracking of humidity levels as the crop progresses. Identical PLSR models and NN were thus developed to test for redundancy of the carbon dioxide sensor. The results of the PLSR predictive models are shown in Figure 4. The corresponding NN model could on average predict carbon dioxide with an $R^2$of 0.84.

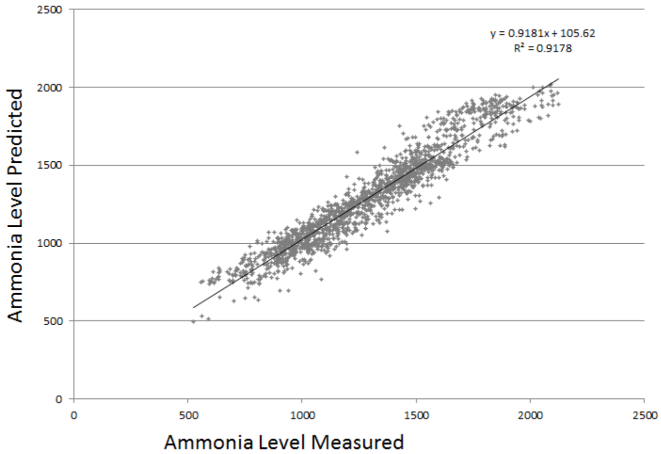

Figure 3 Results of a PLSR model of ammonia level in mg/kgfrom linear, squared, cubic and interaction terms of humidity, temperature and time elapsed

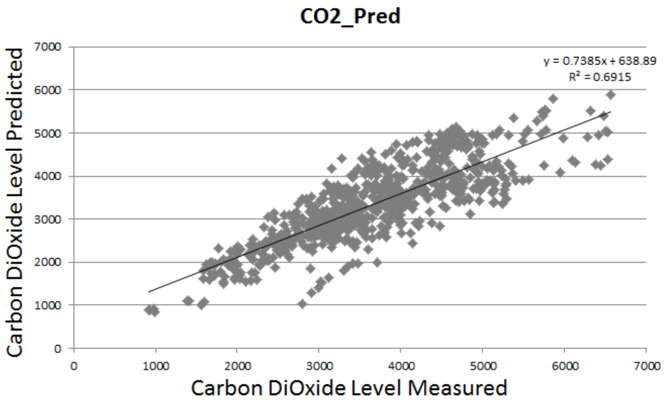

Figure 4 Results of a PLSR model of carbon dioxide level in mg/kgfrom linear, squared, cubic and interaction terms of humidity, temperature and time elapsed

3.3 Forward predictions of average bird weight

The most useful outcome for a big data would be to provide an alert system for potential deviations from weight gain targets for the crop based on parameters that can be adjusted by the grower. The further into the future this model could predict the better but industry experience is that a few days would be adequate. Thus a 72 h time shift was applied to the average bird weight data so sensor readings were matched to average bird weight 72 h into the future. The time series were then used for PLSR and NN modelling in two contexts. The first was where the data from both crops was merged to form a single dataset; this would produce a growing house specific model that may not generalise well in other growing houses. The second was where a model calibrated from one dataset was applied on the other and vice versa, this would produce more conservative results but would generalise better. The PLSR models were validated by 10-fold cross validation. The PLSR results are shown in Figures 5, 6and 7. The corresponding NN models were again validated and tested with a 70-15-15 split of the data. The NN model predictions were R^2 = 0.89 for the combined crop dataset, R^2 = 0.89 for forward predicting the crop 2 average bird weight from a model developed from the crop 1 data and finally R^2 = 0.79 for forward predicting the crop 1 average bird

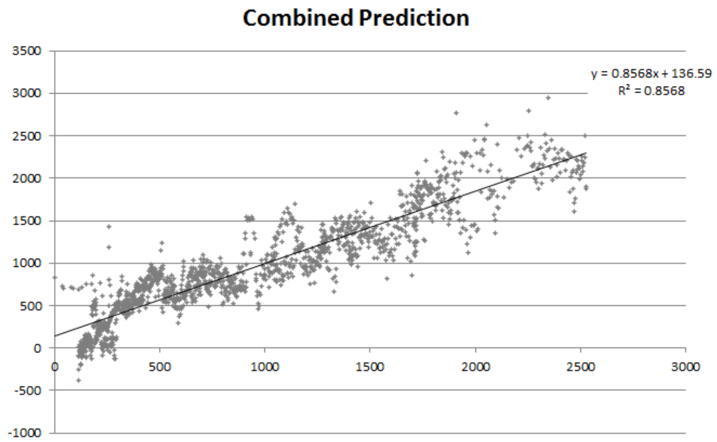

Figure 5Results of a PLSR model forward predicting average bird weight in grams from environmental parameters over all the collected crop data

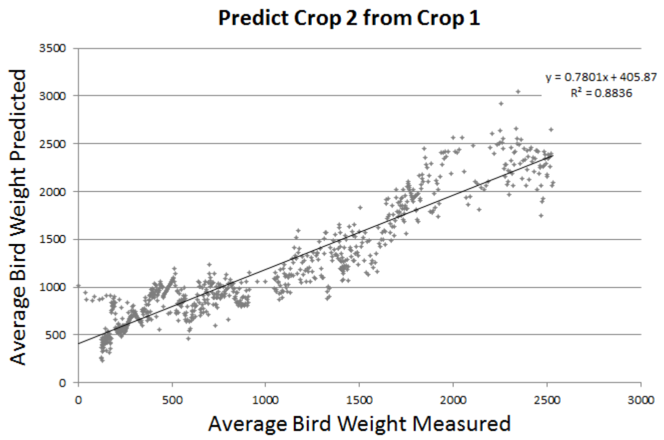

Figure 6Results of a PLSR model forward predicting average bird weight in grams in crop 2 from environmental parameters over crop 1

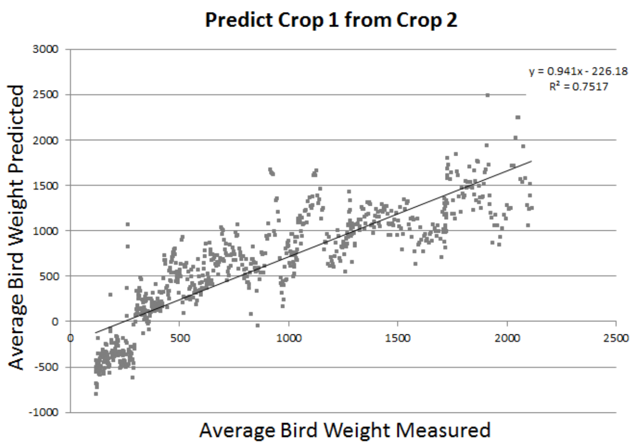

Figure 7Results of a PLSR model forward predicting average bird weight in grams from crop 1 from model parameters calculated over crop 2 weight from a model developed from the crop 2 data.

3.4 Discussion

The key question of sensor spatial redundancy has been investigated in detail. The spatial arrangement in the first crop places all BOSCAs in areas that have good air circulation and are free from major obstructions. Thus it is no surprise that there is a very strong intra sensor correlation and very high proportions of variance are expressed in the first few eigenvalues. This would support the view that where air can move freely a very low density of BOSCAs will be adequate to capture the trends and patterns of air temperature and humidity.

The spatial arrangement in the second crop places some BOSCAs in the corners of the house where there would be less free circulation of air and some large obstructions are present. In this case the intra sensor correlations were much weaker except for the BOSCAs in the centre of the house. Similarly the proportion of variance expressed in the first few eigenvalues is much smaller. This would support the view that it is essential to have sensors deployed in the corners of the house to fully characterise the trends and patterns in the house.

The results for predicting ammonia from the other environmental parameters and other crop data are adequate to replace the ammonia sensor in the BOSCA-MORs and to estimate the ammonia levels in the BOSCA-BEAGs. Additional gas calibration experiments to take place in the laboratories of University College Dublin can further refine the signal produced by the ammonia sensor to increase the robustness of the prediction equations.

The results for predicting carbon dioxide from the other environmental parameters and other crop data would not be adequate to replace the carbon dioxide sensor for two main reasons. Firstly the carbon dioxide sensor will be substantially cheaper than an ammonia sensor and secondly poultry farmers and poultry house managers in Ireland place a very high importance on direct carbon dioxide readings in their experience when determining the correct moment to open the house vents, thus any predictive model of carbon dioxide would need to be extremely accurate to warrant replacement of a direct carbon dioxide measurement.

The ability to forward predict by 72 hthe average bird weight based on current environmental data has ranged from good to excellent. Where the data from both crops were envisaged as a single dataset an excellent correlation with measured average bird weight was found. This would suggest that it is realistic to attempt to build house specific models of crop progression, these would not be expected to generalise well and it would be necessary to carry out similar experiments in each new house.

Where the data from the crops were treated as distinct the results were mixed, an excellent prediction of the progression of crop 2 was possible based on a model developed with the crop 1 data, however the converse was not the case and it was more difficult to predict the progression of crop 1 based on a model developed with the crop 2 data. These models would be more likely to generalise as they have had to deal with fully external test data. The mixed results would suggest that it may be too ambitious to produce generalised models of crop progression based on environmental data as the differences between houses may be too difficult to capture without a vast program of experiments and the inclusion of house infrastructural features into the predictive models.

The benefits of artificial intelligence based modelling approaches are marginal as the NN model prediction statistics are only a few percent at best beyond the classical multivariate statistical model predictions. As such it is recommended to use explicit methods that can be more clearly understood rather than opaque artificial intelligence methods.

Further experimental data arebeing collected in the same chicken growing house and in other chicken growing houses in Ireland. This will add to the supply of data which can enhance and refine the results found in this series of experiments. Similarly additional calibration experiments are being carried out with ammonia rich gas mixtures to further refine the ammonia sensor signal.

4 Conclusions

A comprehensive series of experimental work has been carried out to collect environmental data from a typical chicken growing house in Ireland. Key questions of sensor spatial deployment and which sensors are necessary to characterise the trends and patterns in the house that lead to weight gain in the crop have been substantially addressed. Important questions of how current environmental data can be used to forward predict crop weight gain have been explored and it has been proven possible to build a house specific predictive model that can forecast a few days into the future giving the grower enough time to take mitigating action.

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