Real-time modelling of indoor particulate matter concentration in poultry houses using broiler activity and ventilation rate

A. Peña Fernández[1], T. G. M. Demmers[2], Q. Tong[2], A. Youssef[1], T. Norton[1], E. Vranken[1], D. Berckmans[1]

[1] KU Leuven, M3-BIORES, Kasteelpark Arenberg 30, BE-3001 Heverlee, Belgium

[2] The Royal Veterinary College, Hawkshead Lane, North Mymms, Hatfield, AL9 7TA Hertfordshire, United Kingdom

Corresponding author: daniel.berckmans@kuleuven.be

Abstract

Measuring particulate matter concentration in poultry houses remains as a difficult task, primarily because aerosol analysers are expensive, require specialist knowledge to operate and are labour intensive to maintain. However, it is well known that high concentrations of particulate matter causes health and welfare problems with livestock, farm workers and people living in the vicinity of the farm premises. In this work, a data-based mechanistic model is developed to relate broiler activity and ventilation rate with indoor particulate matter concentration. For six complete growing cycles, in a U.K. commercial poultry farm, broiler activity was monitored using a camera-based flock monitoring system (eYeNamic®) and ventilation rate was measured. Indoor particulate matter concentration was continuously monitored by measuring size-segregated mass fraction concentrations with the aerosol analyser DustTrak™. A discrete-time multi-input single-output time-invariant parameters Transfer Function model was developed to determine the particulate dynamics within each day of the growing cycle in the poultry house using broiler activity and ventilation rate as inputs. This model monitored indoor particulate matter concentration with an average accuracy of $R_T^2 = (51 \pm 26)$ %. A dynamic linear regression modelling with time-variant parameters improved average accuracy with $R_T^2 = (97.7 \pm 1.3)$ %. It forecasted one sample-ahead the indoor particulate matter concentration level, using a time window of 14 samples, with a mean relative prediction error, $MRPE = (4.6 \pm 3.2)$ %. Thus, dynamic modelling with time-variant parameters has the potential to be part of a control system to manage in real-time indoor particulate matter concentration in broiler houses.

Keywords: climate control; dust; environmental quality; forecasting; precision livestock farming

1. Introduction

Poultry production is projected to become the biggest source of meat with at 134 million tonnes predicted to be produced worldwide in 2023 (OECD-FAO, 2014). In the UK production currently stands at 1.42 million tonnes per annum (National Statistics, 2016). Poultry production is also one of the largest producers of bio-aerosols (Winkel, Mosquera, Groot Koerkamp, Ogink, & Aarnink, 2015) often associated with negative effects upon the health and welfare of poultry (Cambra-López, Aarnink, Zhao, Calvet, & Torres, 2010; Lai, Nieuwland, Kemp, Aarnink, & Parmentier, 2009) and humans (Basinas et al., 2015; Guillam et al., 2013; Radon et al., 2001). Normally, in air quality terminology, particulate matter (PM) is defined as a complex mixture of fine solid or liquid particles suspended in a gaseous medium. The term dust refers to a mixture of solid matter particles formed often by mechanical fracture of different materials, sedimenting due to gravitational forces

(Zhang, 2004, p.618). Therefore, dust is made up of a number of PM size fractions exhibiting different physical, chemical and biological characteristics, which define its behaviour and impact in the environment or the health. Regarding particle sizes (PM_{size}), they are normally expressed in µm, and their impact on the respiratory system. Inhalable particles, designated PM_{TOTAL} and up to 100 µm in size, are deposited in the upper airways, whereas thoracic dust or PM_{10} particles penetrate to the tracheobronchial region. Respirable dust (PM_{Resp}) penetrates to the alveolar region and has a maximum size of around 4.5 µm. Thus, in the USA, $PM_{2.5}$ is often referred to as the respirable fraction of dust (Cambra-López et al., 2010).

Poultry production contributes about 40-57 % and 45-50 % of the total UK emissions of PM_{10} and $PM_{2.5}$ from housed livestock, respectively (Klimont & Amann, 2002). The most recent emission factors for $PM_{2.5}$ and PM_{10} measured in the UK were 5.1 and 31.6 mg animal^{-1} day^{-1} (Demmers et al., 2010, p.34), well within the published range of values (Oenema, Velthof, Amann, Klimont, & Winiwarter, 2012). However, due to the difficult nature of PM measurement and analysis, and its expense, the amount of data available is low (Cambra-López, Winkel, Mosquera, Ogink, & Aarnink, 2015; Wathes, Holden, Sneath, White, & Phillips, 1997).

Broiler houses indoor PM concentrations regularly exceed the recommended maximum concentrations of 3.4 and 1.7 mg m^{-3} for inhalable and respirable PM, respectively (CIGR, 1994; Takai & Pedersen, 2000). Most UK poultry operations are subject to environmental legislation based on their size and are obliged to demonstrate dust management measures, i.e. simple control-at-source measures such as using pelleted rather than meal feed or simple “end of pipe” control methods. More complex dust abatement systems are rarely used in the UK, but more are used elsewhere in Europe (Environment Agency UK, 2011, pp. 1-13). Therefore, there is a growing need to integrate PM monitoring and management in modern poultry production.

Precision livestock farming (PLF) technology provides continuous measurement of key indicators on livestock farms through image and sound analysis and other key sensors and thus offers the potential to provide on-line control of the underlying process for these key indicators (Wathes, Kristensen, Aerts & Berckmans, 2008). The focus of PLF technology has been on production and welfare indicators, such as animal growth and animal health and behaviour (Aerts, Wathes, & Berckmans, 2003; Kashiha, Pluk, Bahr, Vranken, & Berckmans, 2013; Van Hertem et al., 2014). To date, few applications have focused on environmental related indicators (Rigo Monteiro, Garcia-Launay, Brossard, Wilfart & Dourmad, 2017; Haeussermann et al., 2008).

In this work, it is aimed to determine the transfer function model structure needed to relate indoor PM concentration dynamics with the key indicators animal activity and ventilation rate. Ventilation rate has been proven to play a major role in PM concentration (Calvet, Cambra-López, Blanes-Vidal, Estellés, & Torres, 2010). PM concentration has also been shown to vary with animal activity (Calvet, Van den Weghe, Kosch & Estelles, 2009; Costa & Guarino, 2009; Demmers et al., 2010). Broiler activity can be measured by analysing infra-red images offline using a detailed analysis of the behaviour resulting in an accurate activity level, which provides a direct cause-effect relationship between animal activity and dust concentration (r^2 = 0.89) (Calvet, et al., 2009). Alternatively, online systems comparing subsequent images at pixel level provide a general non-specified activity level. These activity levels were shown to be modified by inducing step changes in the lighting regimes over the day (Demmers, Cao, Parsons, Gauss & Lowe, 2011;

Kristensen, Aerts, Leroy, Wathes & Berckmans, 2006). Thus, potentially, broiler activity data could be used as an estimate of PM concentration and therefore used to guide the climate control systems of buildings to minimise the emissions to the environment. In pigs, a dynamic modelling approach has been tested to model the variation of PM concentration as function of several inputs, such as animal activity and ventilation rate (Aerts, Vranken, Berckmans, & Guarino, 2008). However, in poultry production there is still the need to develop different strategies at all management levels to reduce dust concentration and air emissions (Powers, Angel & Applegate, 2005).

Therefore, the aim of this work was, firstly, to identify which time-invariant parameters transfer function model structure defines the relationship between indoor PM concentration and broiler activity and ventilation rate. It was expected that the impact of broiler activity and ventilation rate on indoor PM concentration would change over time and it would be impacted by other variables, such as indoor temperature and/or relative humidity, not taken into account explicitly in the model. Thus, a time-variant parameters dynamic modelling approach was tested based on the previous transfer function model structure, in order to develop a model that can be used to predict in real-time the indoor PM concentration. Potentially, this model could then be used in a control system in which manipulating the light level and/or ventilation rate and this would allow for reduced PM indoor concentrations and/or emissions.

2. Material and Methods

2.1. Data collection

The experiments were carried out at a commercial broiler farm in a newly build mechanically ventilated broiler house (110 m × 20 m; capacity 50,000 birds). The building was indirectly heated using a central heating system and heat exchangers placed below the ridge line of the building (CUBO, Chore-time Europe B.V., Panningen, The Netherlands). Water was provided using nipple drinkers and dry pelleted feed was supplied to standard poultry feeders using augers. Wood shavings were used as litter. There were no special means to maintain good litter condition, besides the ad-hoc changes in heating and ventilation settings. This worked well from spring to autumn, but during winter results were limited. Following the current legislation, the daily light scheduled consisted in three light periods of 6 h each, together with two dark periods of 2 and 4 h, respectively

PM concentration was measured below two fan shafts (ventilation stage 1 and 2, respectively) using two DustTrak™ DRX 8533 analysers (TSI Ltd., Shoreview, Minnesota, US fitted with a PM_{10} inlet, providing simultaneous data for PM_1, $PM_{2.5}$, PM_{Resp} (~$PM_{4.5}$), PM_{10} and PM_{TOTAL} inhalable dust at 2 min intervals. Due to the variable fan speed, some non-isokinetic sampling was to be expected. The DustTrak™ instruments were factory calibrated to the respirable fraction of standard ISO 12103-1, A1 test dust. The inlet and PM_{10} impactor of the DustTrak™ instruments were serviced and cleaned prior to use in each batch and the instruments returned to the factory for internal cleaning of the optics and calibration after, on average, 1,600 h. The latter was more frequent than the normal maintenance schedule, due to the continuous monitoring. A correction factor of 1.29 for poultry dust was obtained using the internal gravimetric filter of the DustTrak™ as the reference sampler (n = 8). Filters were weighed before and after exposure using an analytical balance in a climate controlled room (T = 20 ± 1 °C; RH = 50 ± 5 %). This factor was lower than the factor obtained against European reference samplers of 1.58 (Winkel et al., 2015). In this study, the concentrations for PM_1, $PM_{2.5}$, PM_{10}, PM_{RESP} and PM_{TOTAL} obtained within the day were used to evaluate the model performance. During the implementation the continuous operation of the DustTraK^{TM} analysers was hampered by frequent failures of the power supply to the instruments. Therefore, more servicing and calibration of the instruments by the manufacturer was required due to contamination of the internal parts and optics of the instruments by excessive exposure to dust.

Ventilation rate was measured using three full size measuring fans (Fancom B.V., Panningen, The Netherlands) fitted below fans of ventilation stage 1, 2 and 3 (out of 6), as well as the runtime monitoring of each fan and ventilation stage. Based on the number of fans and the throughput measured by the measuring fan(s), the total flowrate calculated was therefore based an accurate measurement of the overall ventilation rate.

The eYeNamic® (Fancom BV, Netherlands) is a top view camera system that measures the activity and distribution of animals. It generates a visualisation of the floor area and image analysis software translates the acquired images into indices of activity and distribution of the flock within the in-view floor area. These indices are measures of animal movement and position. Data collection consisted of an activity index per minute. The camera was not equipped with infrared sensors, thus activity measurements could be only collected during the light periods.

Data were collected from 14 growing batches over a period of 2.5 years, but only data from six growing cycles was accurate enough to be used for further analysis because of the aforementioned power failures and instrument problems. All other data were logged using LabVIEW virtual instrument routines (LabVIEW, National Instruments, Austin, Texas, US) running on a local computer. The eYeNamic® data were logged separately from the fourth batch onwards, following a software modification. Data from each individual light period throughout the growth period was used to perform the system identification and time-variant parameters modelling.

2.2 System Identification and modelling

The modelling framework used in this work is defined as data-based mechanistic. In summary, a deterministic model structure is inferred inductively from the data. This mathematical representation can only be accepted if it can be linked, in physically meaningful terms, to the process analysed (Young, 2006). Therefore, a system identification step is firstly used to find which data-based transfer function model structure characterises the indoor PM concentration as a dynamic response to broiler activity and ventilation rate. Then, a multi-input, single-output (MISO) transfer function (TF) modelling approach was evaluated using broiler activity and ventilation rate as inputs and indoor concentration of each PM size individually as output. Once, the structure of the model was set, a time-variant parameters dynamic transfer function, in this case a dynamic linear regression (DLR) approach, was used to evaluate its performance and potential to be used in a control system for monitoring and controlling indoor PM concentration by evaluating its forecasting properties. Concurrently, the time-evolution of the model parameters was linked to the biological process.

This analysis is carried out using MATLAB® (v.2015b, The Mathworks, Inc., Natick, Massachusetts, US) software and the CAPTAIN Toolbox, which is a collection of routines developed to characterize and model non-stationary time-series (Young , Taylor, Tych & Pedregal, 2007). In this work, the routines dedicated to identify a transfer-function (TF) model structure and the execution of dynamic linear regression models were used.

2.2.1 Multi-Input Single-Output (MISO) Transfer Function (TF) model

The relation between broiler activity and ventilation rate as inputs and indoor PM concentration in different batches was studied by using a MISO discrete-time transfer function model. The model had the following general structure (Young, 1984),

$$y(k) = \sum \frac{B_i(z^{-1})}{A(z^{-1})} u_i(k - \delta_i) + \xi(k) \tag{1}$$

where $y(k)$ and $u_i(k)$ are the output, PM concentration, and the inputs of the model, broiler activity and ventilation rate; δ_i is the delay associated with the input i; $\xi(k)$ is additive noise assumed to be zero mean, serially uncorrelated sequence of random variables with variance σ^2, accounting for measurement noise, modelling errors and effects of unmeasured inputs to the process; k is the sample of the measurement; $A(z^{-1})$ and $B_i(z^{-1})$ are two series given by:

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_{n_a} z^{-n_a} \tag{2}$$

$$B_i(z^{-1}) = b_0 + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_{n_b} z^{-n_b} \tag{3}$$

where a_j and b_j are the model parameters to be estimated; z^{-1} is the backward shift operator, $z^{-1}y(k) = y(k-1)$, with y and k defined as in Eq. (1) and n_a and n_{b_i} are the orders of the respective polynomials. The model parameters were estimated using a refined instrumental variable approach (Young, 1984). The model structure is displayed as [n_a $n_{b_1} n_{b_2}$ δ_1 δ_2]. The best model is selected according to the Young identification criterion (YIC) and the coefficient of correlation (R_T^2). The YIC provides a combined measure of fitting agreement and parametric efficiency.

2.2.2 Dynamic Linear Regression (DLR)

The DLR modelling approach was tested in order to check if model accuracy improved by considering within the day variation of broiler activity and ventilation rate to have an impact on indoor PM concentration. The advantage of the DLR model, with respect to the time-invariant parameters models, is that it allows the parameters to vary over time. Hence, it is possible to take into account the impact of the external variables (disturbances) on the output, which are not used explicitly in the model, and the impact of the dynamic changes of the inputs to the output. The DLR is the simplest state-space model using time-variant parameters. Its general expression is given by:

$$y_k = T_k + \sum_{i=1}^{m} c_{i,k} u_{i,k} \quad (4)$$

where y_k is the output (i.e. the relevant indoor PM concentration) or dependent variable; T_k is a trend or low frequency component; $c_{i,k}$ are time-varying parameters over the observational interval which reflect possible changes in the regression relationship; and $u_{i,k}$ are the inputs of the model (broiler activity and ventilation rate), which are assumed to affect the dependent variable y_k

(Taylor, Pedregal, Young & Tych, 2007). In this study, on each discrete time instant k, the time-variant parameters linear relation can be written as:

$$D_k = c_{1,k} + c_{2,k}A_k + c_{3,k}VR_k \tag{5}$$

where D is the measured indoor PM concentration of different PM sizes ($mg\ m^{-3}$) and A and VR are the animal activity (%) and the ventilation rate ($m^3\ h^{-1}$) at time k, respectively. $c_{1,k}$ ($mg\ m^{-3}$), $c_{2,k}$ ($mg\ m^{-3}$), $c_{3,k}$ ($mg\ h\ m^{-6}$) are the time-variant model parameters estimated at time k.

At every discrete time instant k, the parameters $c_{1,k}$, $c_{2,k}$ and $c_{3,k}$ were estimated based solely in PM concentration, broiler activity and ventilation rate measurements during a time window of a previous S samples, as described in Aerts et al., 2003. In the experiments, the time between two subsequent observations lasted 2 min. At each time instant k (min) the parameters of Eq. (50 were estimated based on the measured values of animal activity, ventilation rate and PM concentration in a time window of S samples (from sample $k - S + 1$ until k) and, subsequently, the concentration was predicted F samples ahead ($k + F$) by using Eq. (5) with A_{k+F} and VR_{k+F}. At sample $k + 1$, the procedure was repeated. In this way, the PM concentration was predicted at each time instant based on a small window of current and past data, minimising the effect of obsolete data (Aerts et al., 2003).

In order to investigate the accuracy of the model predictions, as a function of window size S and prediction horizon F, the recursive estimation algorithm was applied to each dataset with a window size ranging from 7 to 18 samples and a prediction horizon ranging from 1 to 7 samples. The goodness of the prediction estimations of the DLR approach were quantified by means of the mean relative prediction error (MRPE), which is defined as:

$$MRPE = \frac{1}{N}\sum_{k=1}^{N}\sqrt{\left(\frac{D_k-\widehat{D_k}}{D_k}\right)^2}\cdot 100 \quad (6)$$

where MRPE is a percentage; N is the number of samples; D_k is the PM concentration measured at time k and $\widehat{D_k}$ is the predicted concentration at time k.

3 Results and Discussion

The dynamics of the two inputs, broiler activity and ventilation rate, and the output, indoor PM concentration were visually inspected throughout a light period. The measured PM concentration for different particle size classes showed a similar instantaneous pattern as broiler activity, as was expected and can be seen in the example displayed in Fig. 1. However, it can be also seen that there is a change in the indoor PM concentration trend with a change in ventilation rate whilst broiler activity remained constant. This indicates that using only one of the two variables, either broiler activity or ventilation rate, as input it would not be possible to characterise all the dynamics present in the time-evolution of indoor PM concentration.

Thus, a system identification process was applied individually to the data of each light period in the growth cycle using a multi-input single-output discrete-time time-invariant parameters transfer function modelling approach. The aim of this system identification process was to establish, using the data collected, a suitable transfer function model structure to characterise the impact of broiler activity and ventilation rate on the indoor PM concentration dynamics. The model order for the models performing best in terms of YIC and R_T^2 grouped per day (approximately 70 % of the days) was found to be [1 2 1 0 0-5]. These results are displayed in Table 1. In Fig. 2, an example of this MISO TF model performance for a light period in a growth cycle is shown.

Table 1. Results from the system identification process to find a suitable MISO TF model to relate the sampled data of broiler activity and ventilation rate with PM_{RESP} indoor concentration. The table shows the model orders n_A, $\boldsymbol{n_{B_1}}$, $\boldsymbol{n_{B_2}}$ for polynomials A, B_1 and B_2, respectively, the delays δ_1 and δ_2, associated to the inputs broiler activity and ventilation rate, respectively, and the fitting agreement (R^2) and Young Identification Criterion (*YIC*) for the most accurate model found during the identification process from the daily average of the analysis of each individual light period in a growth cycle (*Day*).

Day	$\boldsymbol{n_A}$	$\boldsymbol{n_{B_1}}$	$\boldsymbol{n_{B_2}}$	$\boldsymbol{\delta_1}$	$\boldsymbol{\delta_2}$	$\boldsymbol{R^2}$	***YIC***
2	1	2	1	0	4	0.41	-0.21
3	1	2	1	0	0	0.60	-2.82
6	1	2	1	0	4	0.60	-2.05
7	1	2	1	0	4	0.74	-4.51
9	1	2	1	0	0	0.66	-5.21
10	1	2	1	0	3	0.24	-2.67
11	1	2	1	0	3	0.15	-2.44
13	1	2	1	0	0	0.84	-6.46
14	1	2	1	0	0	0.53	-4.49
15	1	2	1	0	0	0.26	-3.03
16	1	2	1	0	0	0.92	-5.94
17	1	2	1	0	0	0.10	5.27
20	1	2	1	0	1	0.57	-3.45
22	1	2	1	0	2	0.09	1.17
24	1	2	1	0	2	0.81	-7.08
25	1	2	1	0	0	0.80	-5.61
26	1	2	1	0	2	0.49	-2.89
28	1	2	1	0	0	0.02	-0.54
30	1	2	1	0	5	0.66	-5.63
31	1	2	1	0	0	0.56	-1.15
33	1	2	1	0	5	0.57	-4.64

The model structure is a first order model with a second order *B*-polynomial multiplying broiler activity, without any delay, and a first order *B*-polynomial with varying delay multiplying ventilation rate. These results may be interpreted as broiler activity accounting for the short term dynamics in PM concentration (two *b*-parameters and no delay) whereas the ventilation rate accounts for the long term, or trend, dynamics exhibit by PM concentration within the light period (one b-parameter and delay). The delay term associated to the ventilation rate represents, mathematically, the physical characteristic for which a change in ventilation rate has a slower diminishing effect on the PM concentration. This is in agreement with what it was deduced by inspecting the dynamics exhibited by the variables in Fig. 1. Therefore, the model term related to broiler activity takes care of the rapid variability in the indoor PM concentration, while the ventilation rate accounts for the general trend changes in the indoor PM concentration level.

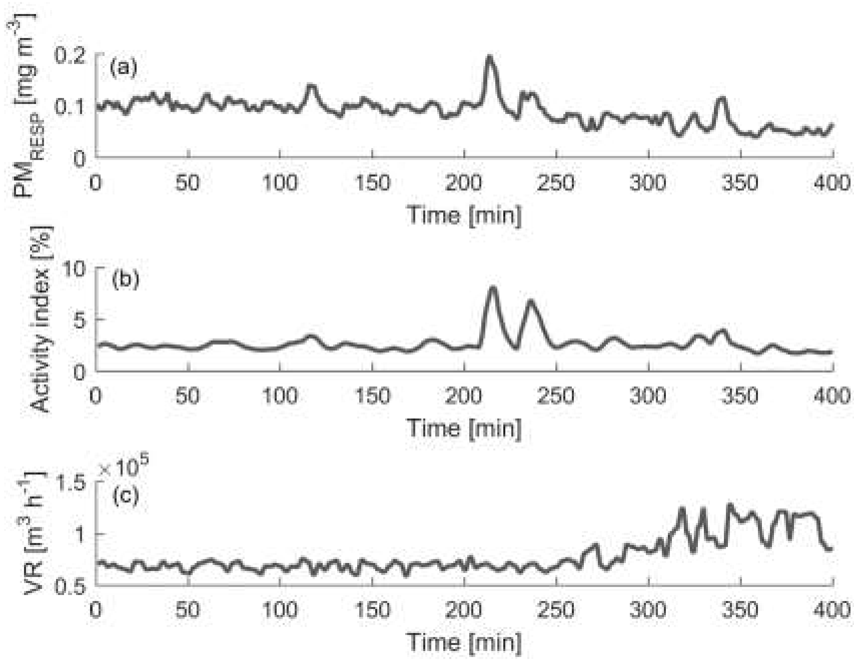

Figure 1. Example of PM$_{RESP}$ indoor concentration (a), broiler activity level (b) and ventilation rate (c) data for a light period on day 10 in the growth cycle.

For 70 % of the days analysed, the model performance was acceptable ($R_T^2 \geq 65\ \%\ and\ YIC\ \leq 5.0$) although, on average, it is showed only a fitting agreement (R_T^2) and YIC values of $R_T^2 = (51 \pm 26)\ \%$ and $YIC = (-3 \pm 2)$, respectively. Fig. 2 shows a descriptive example for a light period, concerning the PM$_{RESP}$ indoor concentration. Similar results were obtained for PM$_1$, PM$_{2.5}$, PM$_{10}$ and PM$_{TOTAL}$ indoor concentrations. Inspecting Fig. 2, the previous performance results discussed can be explained by the inability of the model to capture the fast variability of the indoor PM concentration. The average level and some of the variability was thus captured, but the model consistently missed extreme values from the fast variability. Usually, this indicates that the impact of the input in the output varies throughout the period studied, in this case throughout the light period. Thus, time-variant parameter modelling was considered may be more suitable to characterise the process studied.

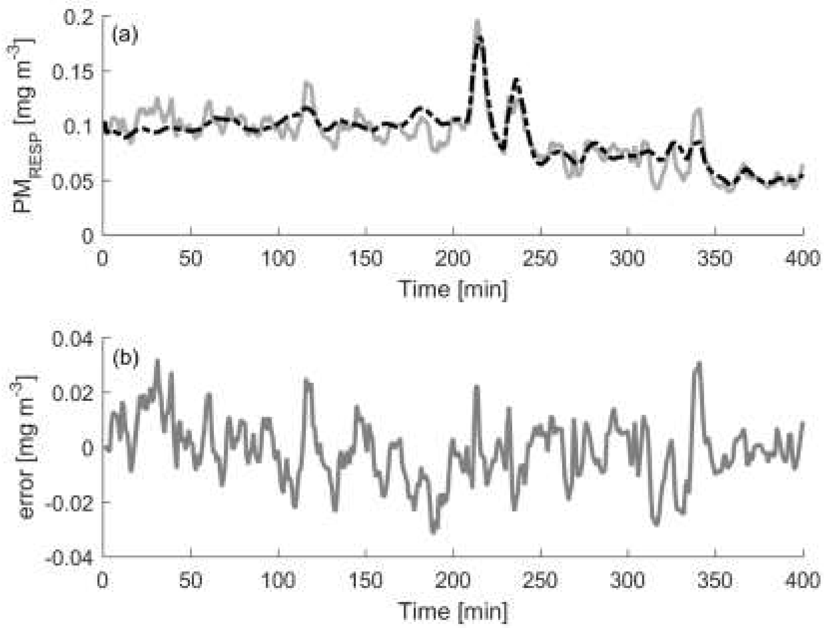

Figure 2. Comparison between the raw PM_{RESP} indoor concentration data (solid line) for one of the monitored light periods and the multi input – single output (MISO) transfer function (TF) model output (dashed line) using broiler activity and ventilation rate as inputs (a). The fitting error is displayed in (b).

In order to explore further the reason why the MISO TF model could not fully describe the indoor PM concentration dynamics, the estimated values of the time-invariant model parameters, summarised per day from the individual light period analysis, were investigated. Fig. 3 shows the daily estimates for the parameters b_{11} and b_{21} associated to broiler activity and ventilation rate, respectively. It is clear that these daily estimates vary throughout the growth cycle. Parameter b_{11} evolution, associated with broiler activity, initially showed low average values and little variability. However, as the growth cycle continued its average value and variability increased. Parameter b_{21} associated with ventilation rate, showed higher average values and variability at the beginning of the growth cycle but as the growth cycle advanced, its average value decreased and it became more stable. The order difference in the values of these parameters is due to the units in which broiler activity and ventilation rate are used in the model.

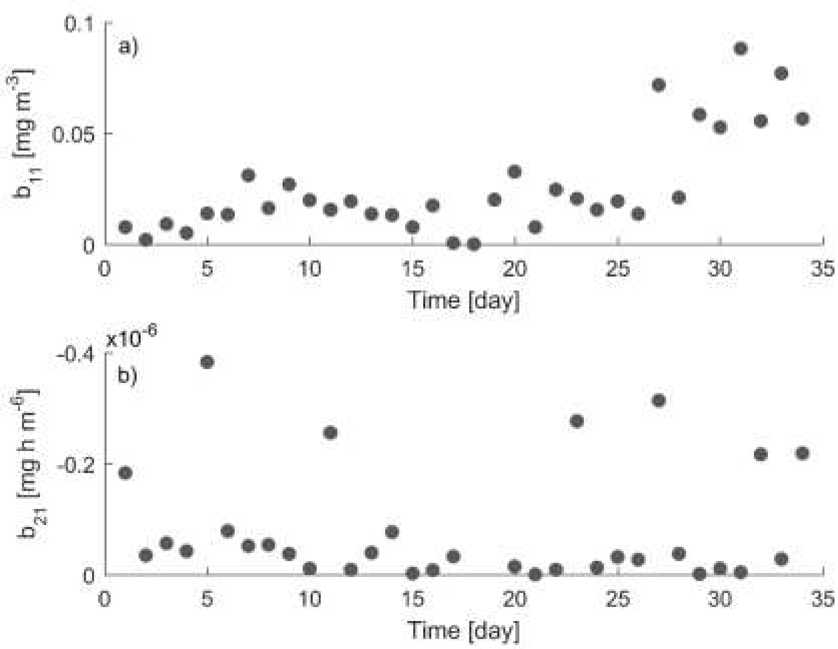

Figure 3. Average daily estimations from the analysis of the individual light periods of the time-invariant parameter b_{11} associated with broiler activity (a) and parameter b_{21} associated with ventilation rate (b).

These parameter evolutions may be related to the poultry production process. At the beginning of the growth cycle, broilers are small and their activity plays a less important role in the generation and dynamics of PM e.g. increase in concentration due to broilers lower than the reduction due to the ventilation rate. It accounts for the sudden variations in the indoor PM concentration level but the overall concentration trend is governed by the ventilation rate. As broilers grow, their activity starts playing a greater role in PM concentration dynamics, while the contribution of ventilation rate diminishes. It can be seen that b_{11} has a positive value, indicating that an increase in broiler activity will induce an increase in indoor PM concentration. Also, b_{22} has negative values, meaning that an increase in ventilation rate will generate a decrease in the indoor PM concentration. This can be also explained in terms of the broiler production process. As broilers increase their movement, they will interact with the dust in their local environment, lifting it up and increasing the overall level of PM concentration. Normally, these events are of short duration and, after some time, these particles sediment due to gravity. Thus, increases in broiler activity induce sudden increases in indoor PM concentrations. This explains the positive value of the b_{11} parameter and the activity being related to the rapidly varying indoor PM concentrations. When ventilation rate increases, it induces it dilutes indoor PM concentration, gradually decreasing its level. This explains the negative b_{22} parameter value and the modelling structure pointing to ventilation rate affecting the trend dynamics of the indoor PM concentration but with a certain time delay. It should also be taken into account that the activity measurements from the eYeNamic® system are less accurate when the floor area is increasingly occupied by birds. It has been shown that once birds reach, on average, 1 kg of bodyweight, the activity index become less reliable as they consistently cover most of the floor area (Peña Fernández et al., 2018). This may contribute to the higher variability exhibited by the model parameter linked to broiler activity towards the end of the growth cycle. Another aspect that can affect the dynamics is the thinning procedure. On day 31, on average, around 10-15 % of the birds are removed. This time evolution for the estimated values of the model parameters is consistent across the different PM sizes analysis, as it can be seen in Fig. 4.

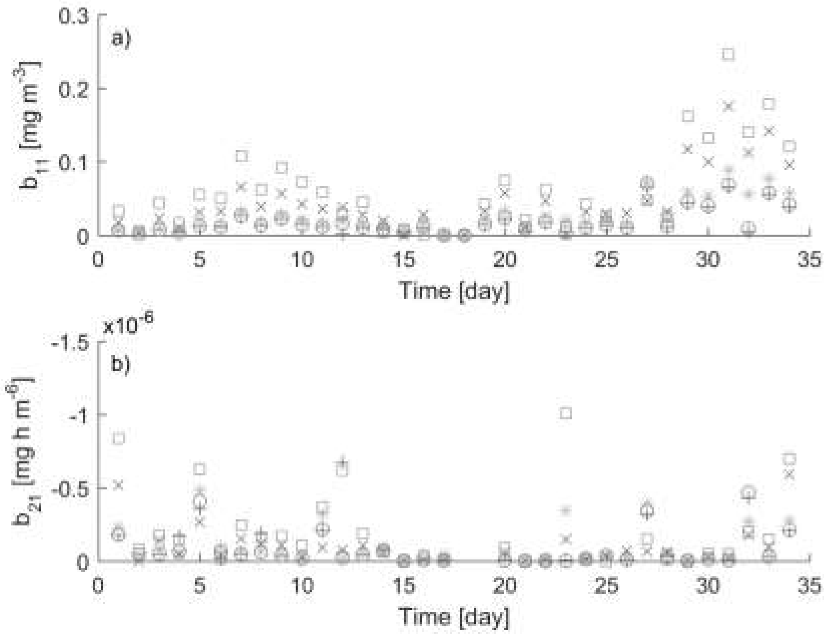

Figure 4. Average daily estimations from the analysis of the individual light periods of the time-invariant parameter b_{11} associated with broiler activity (a) and parameter b_{21} associated with ventilation rate (b) for particle seizes of 1μm (square), 2,5μm (x), 10μm (circle), Respiratory (RESP) size (asterisk) and TOTAL (cross).

Thus, from the previous analysis, it seems that a discrete-time MISO time-invariant parameters TF model with a [1 2 1 0 0-5] structure is capable of estimating the indoor PM concentration level in a broiler house. This model structure seems to be aligned with the expected impact of the inputs, broiler activity and ventilation rate, in the output, indoor PM concentration, according to the broiler rearing process. However, its performance is hampered by its inability to capture all the extremal values exhibited by the indoor PM concentration within the daily dynamics. Estimates of the model parameters show an evolution along the growth cycle, indicating that the impact of broiler activity and ventilation rate on indoor PM concentration changes, not only changes throughout the growth cycle, but also between the consecutive light periods monitored. Consequently, if a discrete-time MISO time-invariant parameters TF model was be built using an average value of the model parameters, the issue of coping with the maximum and minimum variability of the PM concentration would become acute, lowering even more the fitting agreement ($\boldsymbol{R_T^2}$). Thus, it would not be possible to just develop a unique model to simulate dust concentration with a given or fixed set of parameter values that could be used to develop a control system.

Due to this inability to model indoor PM concentration variability over a light period with a time-invariant parameter transfer function model, a time-variant approach was tested. It was expected that these time-varying parameters modelling approach would closely follow the evolution of the indoor PM concentration throughout the light period and the growth cycle. Furthermore, the model forecasting properties were evaluated in order to test the model's capabilities to be used as the core of a control system to actively manage in real-time the indoor PM concentration in broiler houses.

In Fig. 5, a descriptive example for a light period of the DLR one-sample ahead model forecasting performance for PM_{RESP} indoor concentration is shown. Different time window and prediction horizon sizes were evaluated in order to check the potential of the model to estimate the different PM sizes concentration variability exhibited throughout a light period of the growth cycle. By averaging the time-variant parameters model forecasting performances from each individual light period over all the growth cycles monitored, it was discovered that using a window size of 14 samples it was possible to predict one sample-ahead the dust concentration value with an average MRPE of (4.6 ± 3.2) %. This means that after gathering 28 min of data from the inputs and output, it is possible to start forecasting the indoor PM concentration with an average prediction error of 4.6 % of the measured value.

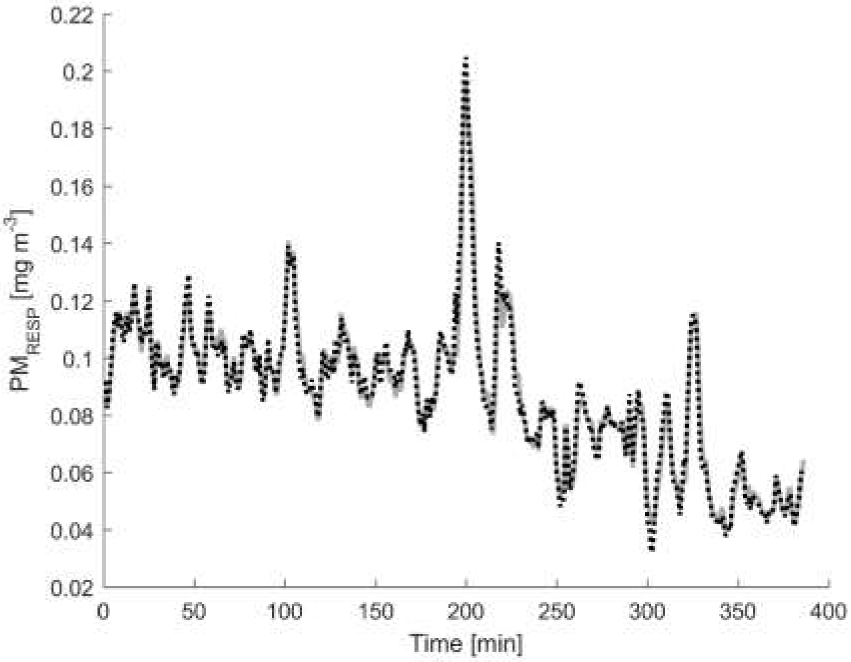

Figure 5. Example of the DLR model one sample ahead forecasting output for the PM_{RESP} indoor concentration (dashed line) against the sampled PM_{RESP} indoor concentration (solid line), using broiler activity and ventilation rate sampled data as inputs for an individual light period.

Fig. 6 shows the average MRPE for different combinations of time window and prediction horizon when modelling PM_{RESP} indoor concentration. These results confirm the hypothesis regarding that the time-invariant behaviour of the model parameters in the discrete-time MISO TF model hampered its ability to describe all the dynamics present in the indoor PM concentration dynamics throughout a light period. Therefore, a DLR model, in which these model parameters are able to vary over time, is able to capture accurately, $R_T^2 = (97.7 \pm 1.3)$ %, the light period dynamics present in the indoor PM concentration

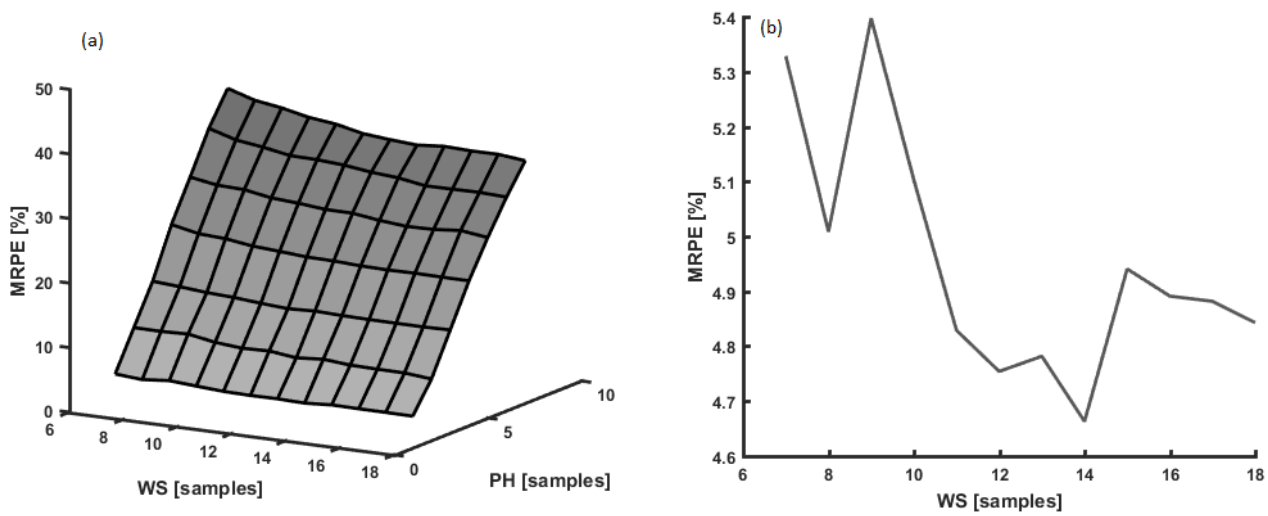

Figure 6. Average mean relative prediction error (MRPE), in percentage, of the forecasts accuracy using the dynamic linear regression (DLR) modelling approach with a historical window size (WS) ranging from 7 to 18 samples and a prediction horizon (PH) ranging from 1 to 7 samples for PM_{RESP} indoor concentration form the individual light period analysis for all growth cycles monitored (a). Insight of the mean relative prediction error (MRPE) for the different window sizes (WS) tested for one sample ahead prediction horizon (b).

A check was required to see if the link between the mathematical model and the biological process is preserved when time variation in the parameters is allowed and model complexity is reduced. As expected, the model parameters exhibit variability, not only along the growing cycle but also within the light period, as it can be seen in the descriptive example shown in Fig. 7.

These dynamics indicate that the impact of broiler activity and ventilation rate changes throughout the light period, and the subsequent parameter behaviour, may be induced by several reasons. The impact of these inputs may be influenced by external variables playing a role in the process, such as temperature or humidity. This could generate extra contributions to the dynamics of indoor PM concentration but there could be external processes contributing to these dynamics such as particle resuspension. Resuspension is a process in which particles initially on a surface, join a stream of fluid. It is influenced, among other factors, by fluid velocity, turbulence, climatic conditions and particle density (Mukai, Siegel, & Novoselac, 2009; Qian & Ferro, 2008). Thus, it is a process that can be generated inside the house by both broiler activity and ventilation rate. It could therefore interfere with the dynamic evolution of the indoor PM concentration and, therefore, contribute to the time-variant parameter behaviour captured by the DLR model. These external contributions do not strongly induce non-linear contributions to the indoor PM concentration dynamics and they can be characterised by assuming general random-walk evolutions for these model parameters. Further studies are needed to characterise fully which external processes contribute to the evolution of these time-variant parameters.

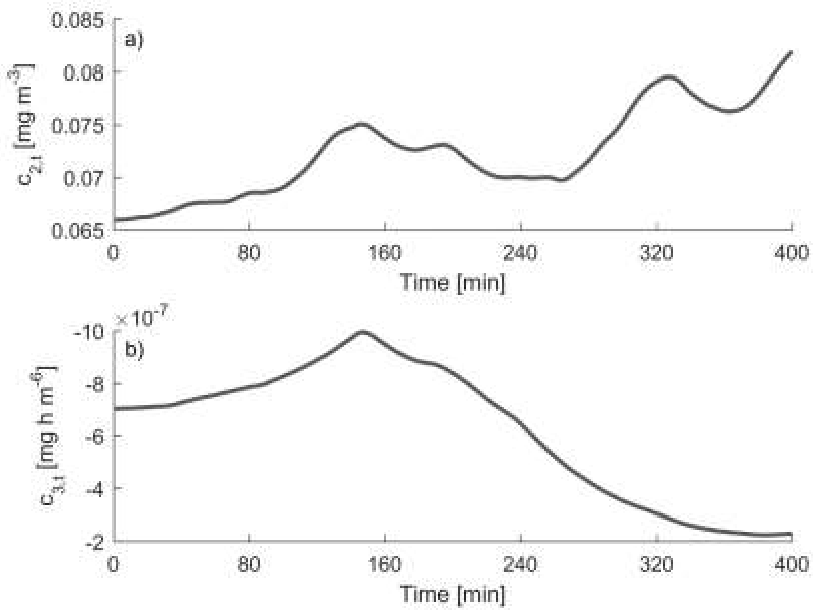

Figure 7. Example of the evolution of the $c_{2,t}$ time-varying parameter from the DLR model, which is associated to broiler activity (a) and evolution of the $c_{3,t}$ time-varying parameter from the DLR model, which is associated to ventilation, rate (b) throughout a light period when modelling PM_{RESP} indoor concentration

Furthermore, the DLR model time-variant parameters dynamics during the growth cycle were evaluated, grouping the outcome from the analysis of each individual light period analysis per day. As before, these parameters exhibit a time evolution during the growth cycle. In Fig. 8, a descriptive example of the time-variant DLR model parameters dynamics during the growth cycle is shown.

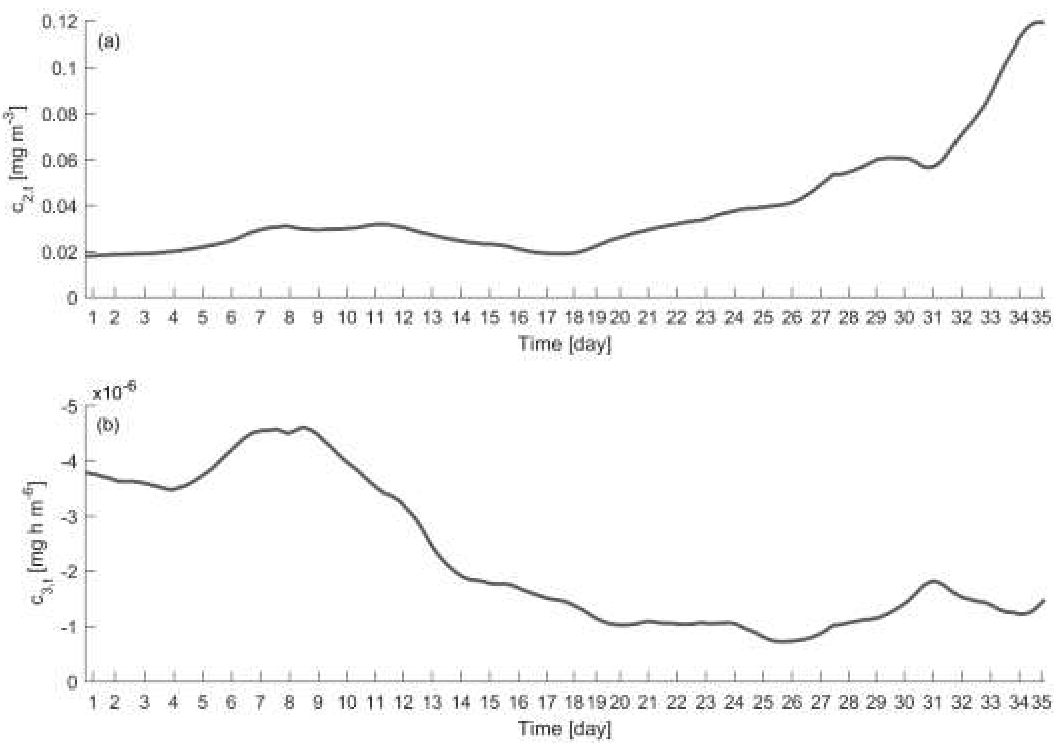

Figure 8. Average daily evolution from the analysis of each individual light period for a complete growth cycle of the $c_{2,t}$ time-varying parameter from the DLR model, which is associated to broiler activity (a) and evolution of the $c_{3,t}$ time-varying parameter from the DLR model, which is associated to ventilation rate (b) for PM_{RESP} indoor concentration.

As well in the results from the time-invariant parameter MISO TF modelling approach, the parameter linked to broiler activity, $c_{2,t}$ in the DLR model, gained importance as the growth cycle evolved as the size of the broilers increased. The parameter linked to ventilation rate, $c_{3,t}$, was more important at the beginning of the growing cycle. Also, certain variability was observed in the time evolution of the parameters, which was also probably induced by the inner variability these parameters exhibit during every light period. It also appeared that there was little change in the dynamics around day 31 when the thinning process which removed 10-15 % of the birds from the broiler house, occurred. Thus, it can be seen that the dynamics of these time-variant parameters are consistent with the time-evolution was inferred from comparing the daily estimates of the time-invariant parameters. The time-variant nature of the parameters in the DLR model allowed these dynamics to be captured in a more consistent and reliable manner. Therefore, it appears that the logical relationship between the model characteristics and what it is expected from the broiler production process is maintained and is clarified by using the DLR model.

Therefore, it appears there are several advantages in using a time-variant DLR model over the discrete-time MISO time-invariant model. By allowing the parameters to vary over time, it is possible to account for the effect on the output of external variables, which are not used explicitly in the model. The averaged coefficient of determination reached by the DLR model, $R_T^2 = (97.7 \pm 1.3)$ %, appears to indicate that some of these external contributions may induce slightly non-linear contributions to these dynamics, but model accuracy seems to be sufficient to characterise the general time-evolution of indoor PM by means of just broiler activity and ventilation rate. Also, model complexity has been reduced. Additionally, the DLR model forecasting error achieved, $MRPE = (4.6 \pm 3.2)$ %, appears to indicate that after around half an hour of data has been gathered for both inputs (broiler activity and ventilation rate) and output (indoor PM concentration), it is possible to make accurate predictions of the changes in indoor PM concentration level induce by changes in broiler activity and ventilation rate.

4 Current limitations and future perspectives

The time-variant parameters model developed in this study shows promising properties to monitor the indoor PM concentration using broiler activity and ventilation rate as inputs. However, there are certain limitations to its application that require discussion and need further research to be addressed.

Firstly, due to the experiments being in a commercial setting, there are certain disadvantages, which should be noted. The system identification and model evaluation were performed during a “light period”. Due to current legislation, the light schedule was fixed. Every day there were 3 light periods of approximately 6 h and two dark periods of approximately 4 and 2 h. Also, the camera included in the eYeNamic® system do not have infrared capabilities, thus it was not possible to collect activity measurements during dark periods with the current technology used on n the farm. Therefore, only data from the light periods have been used to develop and test the model. Moreover, trying to combine the different light periods for a day in a single dataset may induce sudden changes at the end and start of consecutive light periods, introducing artefacts for the model identification and evaluation. In future, if broiler activity data is available during dark periods, the model could be tested and adapted and if required continuously analysing the complete day. However, working only during a light period does not result in a limitation. The aim of the model is to be part of a predictive controller to be used in a commercial farm. The results show that once around half an hour of data is collected under typical commercial conditions, the model provides accurate predictions of indoor PM concentrations. Thus, it is feasible to develop a controller based on the DLR model, which would operate during the light period in the broiler house.

Regarding model performance, there are certain aspects, which should also be discussed. The model may show limitations due to the characteristics of the building; the systems therein, such as lighting or ventilation; the legal regulations required to ensure animal welfare or the type and management of litter. Other external factors which are not explicitly taken into account in the model, such as temperature or humidity, are expected to have an impact in the indoor PM dynamics and thus on model performance. Two aspects should be taken into account regarding these issues.

Due to the adaptive properties of the modelling framework, it is expected that the impact of external factors not taken explicitly into account in the model would be captured by the time evolution of the parameters. This is feasible, since the impact of these factors does not induce a heavy non-linear behaviour during evolution of the model parameters, nor does it change the relationship between model variables thereby impacting on the model order needed to describe the process. Thus, the impact of these external factors does not alter the model structure since the adaptive characteristics of the model can cope with them. Adaptive characteristics should be understood as the model parameters will be estimated using data from that specific farm and will be updated through time according to the past and current conditions of the inputs and output. On the other hand, these different factors will limit the possible values of activity and ventilation rate in the farm. These aspects, rather than affecting the model itself, would affect and limit the development of a future model predictive controller. In principle, these limitations could be included as a constraint for the cost function of the controller. Thus, the action advised by the controller would be limited by these boundaries. Then, if constraints imposed by building characteristics and regulations were too strict, the capabilities of the controller to suggest alternatives to diminish the indoor PM concentration levels would be limited too. However, these limitations also pose an opportunity to develop further the process knowledge. It is expected that the time-evolution of the parameters throughout a rearing period would be the combination of the intrinsic time evolution behaviour of the variables considered in the model and the contribution of these external factors. This would help towards developing mechanistic expressions to establish the relation between the external variables, starting from a data-based approach, which can be used for both, gaining process knowledge and expand the current time-variant parameters model.

In addition, regarding the time evolution of the parameters a trade-off between efficiency and accuracy was needed. As in the commercial conditions tested, light periods will last 6 h, on average, the time window size of 14 samples, or 28 min, selected as optimal to initialise the model, seems acceptable. From the mean relative prediction error analysis, it seems possible to use an even smaller time window size and still achieve low MRPE values. However, it can be also seen that depending on the prediction horizon desired, the optimal time window size varies too. This is due to the process dynamics needed to be captured in order to describe accurately the process. A time window size too small will allow capturing sudden changes more accurately. However, the dynamics involved in the general trend exhibited by the indoor PM concentration will be lost, leading to a poorer overall performance as shown in the results. In contrast, a large time window size will lose the capability to capture sudden changes. Therefore, as the objective was to find a model, which can describe the dynamics of both light periods and growth cycles accurately, the time window size, which minimises the average performance, was selected. It is also expected that during a light period sudden peaks in PM concentration may emerge. Such a situation will have a negative impact in the time-variant parameters model forecasting performance. It is expected that if a particularly sudden increase is generated directly by a sudden change in one of the inputs in the current model (e.g. broiler activity or ventilation rate), the model will be able to capture it to a certain extent because sudden non-linear behaviours cannot be capture fully by the model developed in this study. However, if the sudden change in indoor PM concentration is due to a change in external factors, then the model will need some time to adapt to the new conditions, increasing the prediction error for the immediate forecasted samples. Therefore, an error analysis, focus on evaluating the maximal individual prediction error in each light period was performed. On average, from all of the available dataset, the maximum individual relative prediction error is

(45 ± 23) %. This result demonstrates the existence of high punctual deviations in the model predictions. Therefore, the impact of such errors on model performance was explored. The average mean relative prediction error was one order of magnitude lower than the relative maximum error (4.6 %). This already provides a first indication that in terms of the average performance the impact of these events is not highly relevant. It appears that the adaptive properties of the model allow it to quickly address these situations. An analysis was carried out of individual prediction errors in these situations. It was found that relative individual prediction errors were equal or greater than 20, 30 or 50 % representing only 3.24, 1.15 and 0.23 % of all prediction errors. Thus, a sudden peak in the PM concentration will have an impact on model performance, increasing the prediction error. However, the adaptive capabilities of the time-variant model allowed this sudden change to be quickly addressed, adapting the model parameters to resemble again the conditions governing the indoor PM dynamics. Although the impact of these situations, at least in the datasets analysed in this study, on the overall performance of the algorithm is not highly significant, this aspect needs to be considered when developing a model predictive control system. The data-based mechanistic modelling framework used in this work, allows some possibilities to address this issue. Currently, the weight assigned to the previous measurements is the same. It has utilised a rectangular and not an exponential window. This was because the focus of this study was on the average performance. However, for short predictions may be interesting to assign more relevance to recent measurements. This might be also achieved by selecting shorter time window sizes, although this would indirectly assign more relevance to the impact of broiler activity than to ventilation rate, as this contribution exhibits a delay for indoor PM dynamics. Therefore, further work needs to be done to evaluate, over a longer term, the impact of these situations in the model and model predictive controller. Linking the time evolution of the model parameters in such situations to the

external variables, it is expected to develop expressions for this relation, which in the future may be included in the current model.

Overall, these limitations point out again the need for a dynamic modelling approach, such as the one developed in this work, to manage indoor PM concentration dynamics. These models allow can adapt their structure according to the needs pursued to develop compact model predictive controllers and also provide insights into the biological and physical processes involved. The DLR model shows potential to be part of the design of a control system to actively control indoor PM concentration variability and, ideally, be extended to manage emissions to the surroundings as well. A scheme describing such a control system is shown in Fig. 9.

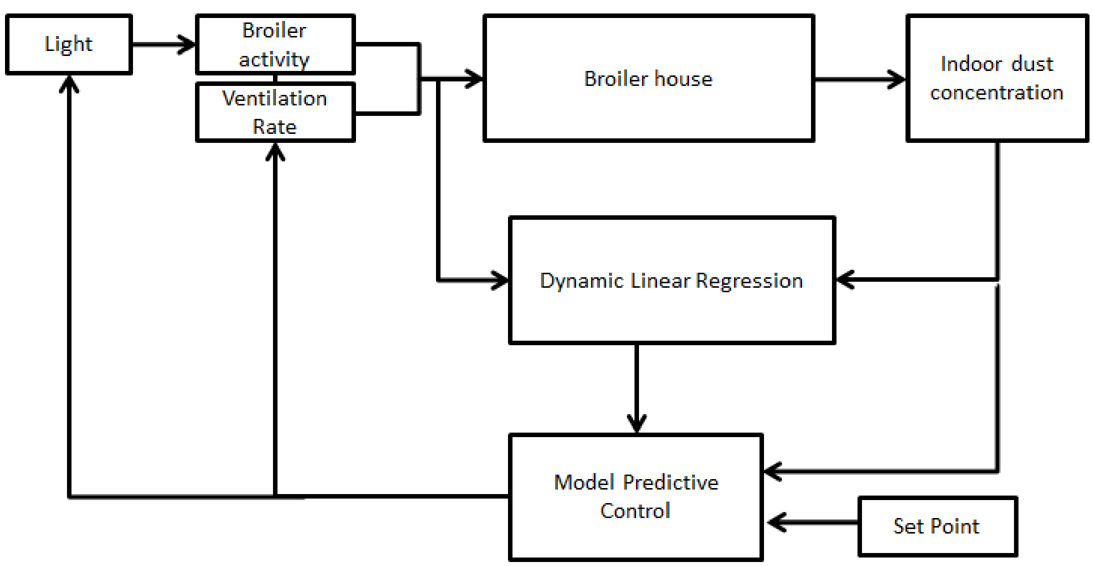

Figure 9. Scheme describing a potential control system to manage and actively control the indoor particulate matter concentration in the broiler house using a dynamic linear regression model as core of the process. Broiler activity, managed by using light schedule and intensity as actuators, and ventilation rate are used as input for the model, which allows forecasting the indoor particulate matter according to changes on these inputs. The model predictive control will advise which broiler activity and ventilation rate levels are needed to achieve the desire set point of indoor particulate matter concentration.

This is the representation of a model predictive control, using the DLR model developed in this work as core of it, to advise broiler activity, whose actuator is the light level in the building, and ventilation rate levels, leading the indoor PM concentration to the desire level, introduced as set point. Moreover, as indoor PM concentration is monitored as part of the model, it can be the first actuator to decide when there is a need for the control system to operate. Once indoor PM concentration exceeds the desired or imposed limit due to, for instance legislation, then the model predictive controller will take action. In the livestock sector, there are already some proposals for the control of integrated management systems in pig and poultry, especially related to their growth process (Frost et al., 1997). In poultry, the development of integrated or control systems has been focussed on broiler growth. There are examples based either on semi-mechanistic models (Stacey et al., 2004) or data-based mechanistic models (Aerts et al., 2003), as applied in this work, to develop control systems to manage broiler growth in real-time. Similarly, there are examples in pig rearing to attempt to estimate the daily nutrient requirements of animals in order to manage their growth and its impact in nitrogen excretion (Andretta, Pomar, Rivest, Pomar, & Radünz, 2016; Hauschild, Lovatto, Pomar, & Pomar, 2012). To the best of our knowledge, there has not being any attempt of developing a data-based mechanistic model to manage and control the indoor dust concentration in a broiler house. Therefore, the data-based DLR model developed in this work has the potential to become the core of a control system to manage in real-time the indoor PM concentration in broiler houses. To date, few of these integrated applications has been either developed or adopted in commercial livestock production. However, it is expected that the combination of the advances in hardware and software, such as an active-control system as used in this example, together with an appreciation of the added value and benefit of these technologies, will stimulate the uptake of precision livestock farming techniques by farmers (Berckmans, 2013, pp. 276-277).

5 Conclusions

The aim of this study was to test the ability to develop a model, which describes the relation between broiler activity and ventilation rate to PM concentration inside the broiler house. This relation was studied in order to develop a real-time model to monitor and forecast the impact of changes in broiler activity and/or ventilation rate in PM concentration within the day variability indoors the broiler house.

A first order discrete-time multi-input single-output time-invariant parameters transfer function (MISO TF) model allowed monitoring the daily variability of PM with an average coefficient of determination $R_T^2 = (51 \pm 26)$ %. Broiler activity accounted for the fast dynamics exhibit by the indoor PM concentration, while ventilation rate accounted for its slow trend or general dynamic evolution within the day. The use of time-invariant parameters in these models hampered its capability of capturing all the dynamics present in the indoor PM concentration.

Furthermore, a DLR model allows monitoring the current PM daily variability accurately and allows PM concentrations to be forecast as functions of broiler activity and ventilation rate accounting for the within the day time-evolution of the model parameters. An MRPE of 4.6 ± 3.2 % was found for prediction of one sample-ahead indoor PM concentration values in this work when using a time window of 14 samples. Thus, the DLR model exhibits excellent properties to be the core of a model predictive control system to actively manage in real-time indoor PM concentration variability along the day in the broiler house as function of broiler activity and ventilation rate.

6 Acknowledgements

This project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement n° 311825.

DISCLAIMER: The views expressed in this publication are the sole responsibility of the author(s) and do not necessarily reflect the views of the European Commission. Neither the European Commission nor any person acting on behalf of the Commission is responsible for potential uses of this information. The information in this document is provided with no guarantee or warranty that the information is fit for any particular purpose. The user thereof uses the information at his or her sole risk and liability.

7 References

Aerts, J. M., Vranken, E., Berckmans, D., & Guarino, M. (2008). Modelling Dust Emission from Fattening Pig Houses. *Automatika*, *49*(3–4), 119–125.

Aerts, J. M., Wathes, C. M., & Berckmans, D. (2003). Dynamic data-based modelling of heat production and growth of broiler chickens: Development of an integrated management system. *Biosystems Engineering*, *84*(3), 257–266. https://doi.org/10.1016/S1537-5110(02)00285-4

Andretta, I., Pomar, C., Rivest, J., Pomar, J., & Radünz, J. (2016). Precision feeding can significantly reduce lysine intake and nitrogen excretion without compromising the performance of growing pigs. *Animal*, 1–11. https://doi.org/10.1017/S1751731115003067

Basinas, I., Sigsgaard, T., Kromhout, H., Heederik, D., Wouters, I. M., & Schlü Nssen, V. (2015). A comprehensive review of levels and determinants of personal exposure to dust and endotoxin in livestock farming. *Journal of Exposure Science and Environmental Epidemiology*, *2583*(10), 123–137. https://doi.org/10.1038/jes.2013.83

Berckmans, D. 2013. Smart Farming for Europe; Value creation through Precision Livestock Farming Pan European Networks: Science & Technology. pp 276-277. EC, Brussel.

Calvet, S., Cambra-López, M., Blanes-Vidal, V., Estellés, F., & Torres, A. G. (2010). Ventilation rates in mechanically-ventilated commercial poultry buildings in Southern Europe: Measurement system development and uncertainty analysis. *Biosystems Engineering*, *106*(4), 423–432. https://doi.org/10.1016/j.biosystemseng.2010.05.006

Calvet, S., Van den Weghe, H., Kosch, R., & Estelles, F. (2009). The influence of the lighting program on broiler activity and dust production. *Poultry Science*, *88*(12), 2504–2511. https://doi.org/10.3382/ps.2009-00255

Cambra-López, M., Aarnink, A. J. A., Zhao, Y., Calvet, S., & Torres, A. G. (2010). Airborne particulate matter from livestock production systems: A review of an air pollution problem. *Environmental Pollution*, *158*(1), 1–17. https://doi.org/10.1016/j.envpol.2009.07.011

Cambra-López, M., Winkel, A., Mosquera, J., Ogink, N. W. M., & Aarnink, A. J. A. (2015). Comparison between light scattering and gravimetric samplers for PM10 mass concentration in poultry and pig houses. *Atmospheric Environment*, *111*, 20–27. https://doi.org/10.1016/j.atmosenv.2015.03.051

CIGR. 1994. Aerial environment in animal housing: Concentrations in and emissions from farm buildings. Report of working group No 13: Climatization and environmental control in animal housing. Commission International du Genie Rural, Ghent, Belgium.

Costa, A., & Guarino, M. (2009). Definition of yearly emission factor of dust and greenhouse gases through continuous measurements in swine husbandry. *Atmospheric Environment*, *43*(8), 1548–

1556. https://doi.org/10.1016/j.atmosenv.2008.11.009

Demmers, T. G. M**.,** Saponja, A., Thomas, R., Phillips, G., Mcdonald, A., Stagg, S., Bowry, A. & Nemitz, E. (2010). Dust and ammonia emissions from UK poultry houses. CIGR XVIIth World Congress No. CSBE10942. p 10, Québec City, Canada.

Demmers, T. G. M**.,** Cao, Y., Parsons, D. J., Gauss, S., Lowe, J. C. & M., W. C. (2011). Modelling and control of broiler activity. In: J. Kofer and H. Schobesberger (eds.) XVth ISAH Congress No. III. p 243-246. Tribun EU s.r.o., Viena.

Environment Agency UK, 2011. 'How to comply with your environmental permit for intensive farming Appendix 11 Assessing dust control measures on intensive poultry installations. Appendix 13: Assessing dust control measures on intensive poultry installations, (2011), EPR 6.09 Sector Guidance Note, pp. 1–13.

Frost, A. R., Schofield, C. P., Beaulah, S. A., Mottram, T. T., Lines, J. A., & Wathes, C. M. (1997). A review of livestock monitoring and the need for integrated systems. *Computers and Electronics in Agriculture*, *17*(2), 139–159. https://doi.org/10.1016/S0168-1699(96)01301-4

Guillam, M. T., Pédrono, G., Le Bouquin, S., Huneau, A., Gaudon, J., Leborgne, R., … Ségala, C. (2013). Chronic respiratory symptoms of poultry farmers and model-based estimates of long-term dust exposure. *Annals of Agricultural and Environmental Medicine*, *20*(2), 307–311.

Haeussermann, A., Costa, A., Aerts, J. M., Hartung, E., Jungbluth, T., Guarino, M., & Berckmans, D. (2008). Development of a dynamic model to predict PM_{10} emissions from swine houses. *Journal of Environmental Quality*, *37*(2), 557–564. https://doi.org/10.2134/jeq2006.0416

Hauschild, L., Lovatto, P. A., Pomar, J., & Pomar, C. (2012). Development of sustainable precision farming systems for swine : Estimating real- time individual amino acid requirements in growing- fi nishing pigs. *Journal of Animal Science*, 2255–2263. https://doi.org/10.2527/jas2011-4252

Kashiha, M., Pluk, A., Bahr, C., Vranken, E., & Berckmans, D. (2013). Development of an early warning system forabroiler house using computer vision. *Biosystems Engineering*, *116*(1), 36–45. https://doi.org/10.1016/j.biosystemseng.2013.06.004

Klimont, Z., & Amann, M. (2002). European control strategy for fine particles: the potential role of agriculture. Landbauforschung Völkenrode Special issue 235: 29-35.

Kristensen, H. H., Aerts, J. M., Leroy, T., Wathes, C. M., & Berckmans, D. (2006). Modelling the dynamic activity of broiler chickens in response to step-wise changes in light intensity. *Applied Animal Behaviour Science*, *101*(1–2), 125–143. https://doi.org/10.1016/j.applanim.2006.01.007

Lai, H. T. L., Nieuwland, M. G. B., Kemp, B., Aarnink, A. J. A., & Parmentier, H. K. (2009). Effects of dust and airborne dust components on antibody responses, body weight gain, and heart morphology of broilers. *Poultry Science*, *88*(9), 1838–1849. https://doi.org/10.3382/ps.2009-00129

Rigo Monteiro, A., Garcia-Launay, F., Brossard, L., Wilfart, A., Dourmad J-Y. (2017). Effect of precision feeding on environmental impact of fattening pig production. 8. European Conference on Precision Livestock Farming (ECPLF), Sep 2017, Nantes, France. 2017.

Mukai, C., Siegel, J. A. and Novoselac, A. (2009). Impact of airflow characteristics on particle resuspension from indoor surfaces. *Aerosol Science and Technology*, 43(10), 1022–1032. doi: 10.1080/02786820903131073.

National Statistics. 2016. UK poultry slaughterings, weight and poultry meat production - montlhy dataset.

OECD-FAO. 2014. OECD-FAO Agricultural Outlook 2014. OECD Publishing, Paris.

Oenema, O., Velthof, G., Amann, M., Klimont, Z., & Winiwarter, W. (2012). Emissions from agriculture and their control potentials. *TSAP Report #3, Version 1.0, DG-Environment of the European Commission*, (June), 34. Retrieved from http://webarchive.iiasa.ac.at/Admin/PUB/Documents/XO-12-013.pdf

Peña Fernández, A., Tullo, E., van Hertem, T., Youssef, A., Exadaktylos, V., Vranken, E., Guarino, M. & Berckmans, D. (2018). Real-time monitoring of broiler flock's welfare status using camera-based technology. *Biosystems Engineering*, *173*, 103–114. https://doi.org/10.1016/J.BIOSYSTEMSENG.2018.05.008

Powers, W. J., Angel, C. R., & Applegate, T. J. (2005). Air emissions in poultry production: current challenges and future directions. *Journal for Applied Poultry Research*, *14*, 613–621.

Qian, J., & Ferro, A. R. (2008). Resuspension of dust particles in a chamber and associated environmental factors. *Aerosol Science and Technology*, *42*(7), 566–578. https://doi.org/10.1080/02786820802220274

Radon, K., Weber, C., Iversen, M., Danuser, B., Pedersen, S., Nowak, D., … Nowak, D. (2001). Exposure assessment and lung function in pig and poultry farmers Exposure assessment and lung function in pig and poultry farmers. *Occupational and Environmental Medicine*, *58*, 405–410.

Rigo Monteiro, A., Garcia-Launay, F., Brossard, L., Wilfart, A., & Dourmad, J.-Y. (2017). Effect of precision feeding on environmental impact of fattening pig production. 8. In European Conference on Precision Livestock Farming (ECPLF), Sep 2017, Nantes, France. 2017.https://doi.org/10.1136/oem.58.6.405

Stacey, K. F., Parsons, D. J., Frost, A. R., Fisher, C., Filmer, D., & Fothergill, A. (2004). An Automatic Growth and Nutrition Control System for Broiler Production, *89*, 363–371. https://doi.org/10.1016/j.biosystemseng.2004.07.006

Takai, H., & Pedersen, S. (2000). A comparison study of different dust control methods in pig buildings. *Applied Engineering in Agriculture*, *16*(3), 269–277.

Taylor, C. J., Pedregal, D. J., Young, P. C., & Tych, W. (2007). Environmental time series analysis and forecasting with the Captain toolbox. Environmental Modelling and Software, 22(6), 797-814. https://doi.org/10.1016/j.envsoft.2006.03.002.

Van Hertem, T., Viazzi, S., Steensels, M., Maltz, E., Antler, A., Alchanatis, V., … Halachmi, I. (2014). Automatic lameness detection based on consecutive 3D-video recordings. *Biosystems Engineering*, *119*, 108–116. https://doi.org/10.1016/j.biosystemseng.2014.01.009

Wathes, C. M., Holden, M. R., Sneath, R. W., White, R. P., & Phillips, V. R. (1997). Concentrations and emission rates of aerial ammonia, nitrous oxide, methane, carbon dioxide, dust and endotoxin in UK broiler and layer houses. *British Poultry Science*, *38*(1), 14–28. https://doi.org/10.1080/00071669708417936

Wathes, C. M., Kristensen, H. H., Aerts, J. M., & Berckmans, D. (2008). Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? *Computers and Electronics in Agriculture*, *64*(1), 2–10. https://doi.org/10.1016/j.compag.2008.05.005

Winkel, A., Mosquera, J., Groot Koerkamp, P. W. G., Ogink, N. W. M., & Aarnink, A. J. A. (2015). Emissions of particulate matter from animal houses in the Netherlands. *Atmospheric Environment*, *111*, 202–212. https://doi.org/10.1016/j.atmosenv.2015.03.047

Young P. C. (1984). Recursive Estimation and Time-series Analysis. Springer-Verlag, Berlin.

Young, P. C. (2006). The data-based mechanistic approach to the modelling, forecasting and control of environmental systems. *Annual Reviews in Control*, *30*(2), 169–182. https://doi.org/10.1016/j.arcontrol.2006.05.002

Young, P. C., Taylor, C. J., Tych, W., & Pedregal, D. J. (2007). The Captain Toolbox. UK: Centre for Research on Environmental Systems and Statistics, Lancaster University. Internet: www. es.lancs.ac.uk/cres/captain.

Zhang, Y. (2004). Indoor Air Quality Engineering. CRC Press, Boca raton, Florida 618 pp.