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Prediction of Indoor Climate and Long-Term Air Quality Using the BTA-AQP Model: Part I. BTA Model Development and Evaluation

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Abstract
The objective of this research was to develop a building thermal analysis and air quality predictive (BTA-AQP) model to predict ventilation rate, indoor temperature, and long-term air quality (NH3, H2S, and CO2 concentrations and emissions) for swine deep-pit buildings. This article, part I of II, presents a lumped capacitance model (BTA model) to predict the transient behavior of ventilation rate and indoor air temperature according to the thermo-physical properties of a typical swine building, setpoint temperature scheme, fan staging scheme, transient outside temperature, and the heat fluxes from pigs and supplemental heaters. The obtained ventilation rate and resulting indoor air temperature, combined with animal growth cycle, in-house manure storage level, and typical meteorological year (TMY3) data, were used as inputs to the air quality predictive model (part II) based on the generalized regression neural network (GRNN-AQP model), which was presented in an earlier article. The statistical results indicated that the performance of the BTA model for predicting ventilation rate and indoor air temperature was very good in terms of low mean absolute error, a coefficient of mass residual values equal to 0, an index of agreement value close to 1, and Nash-Sutcliffe model efficiency values higher than 0.65. Graphical presentations of predicted vs. actual ventilation rate and indoor temperature are provided to demonstrate that the BTA model was able to accurately estimate indoor climate and therefore could be used as input for the GRNN-AQP model discussed in part II of this research.

Keywords
Air quality, Building thermal analysis (BTA), Indoor climate, Nash-Sutcliffe model efficiency

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PREDICTION OF INDOOR CLIMATE AND LONG-TERM AIR QUALITY USING THE BTA-AQP MODEL: PART I. BTA MODEL DEVELOPMENT AND EVALUATION

G. Sun, S. J. Hoff

ABSTRACT. *The objective of this research was to develop a building thermal analysis and air quality predictive (BTA-AQP) model to predict ventilation rate, indoor temperature, and long-term air quality (NH_3, H_2S, and CO_2 concentrations and emissions) for swine deep-pit buildings. This article, part I of II, presents a lumped capacitance model (BTA model) to predict the transient behavior of ventilation rate and indoor air temperature according to the thermo-physical properties of a typical swine building, setpoint temperature scheme, fan staging scheme, transient outside temperature, and the heat fluxes from pigs and supplemental heaters. The obtained ventilation rate and resulting indoor air temperature, combined with animal growth cycle, in-house manure storage level, and typical meteorological year (TMY3) data, were used as inputs to the air quality predictive model (part II) based on the generalized regression neural network (GRNN-AQP model), which was presented in an earlier article. The statistical results indicated that the performance of the BTA model for predicting ventilation rate and indoor air temperature was very good in terms of low mean absolute error, a coefficient of mass residual values equal to 0, an index of agreement value close to 1, and Nash-Sutcliffe model efficiency values higher than 0.65. Graphical presentations of predicted vs. actual ventilation rate and indoor temperature are provided to demonstrate that the BTA model was able to accurately estimate indoor climate and therefore could be used as input for the GRNN-AQP model discussed in part II of this research.*

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Due to the absence of a nationwide monitoring network for quantifying long-term air emission inventories of livestock production facilities, state and federal regulatory agencies in the U.S. have identified a need for air quality predictive (AQP) models to assess the impact of annual airborne pollutants on human health, the ecological environment, and global warming. Moreover, with the increasing number of complaints and lawsuits against the livestock industry, state planners, environment scientists, and livestock producers also need AQP models to determine science-based setback distances between animal feeding operations and neighboring residences as well as evaluate relevant emission abatement strategies. Most of the AQP models proposed so far use mass balance equations to describe the mechanisms of gaseous emissions, estimate their characteristic and amount at each transformation stage, and forecast gas release from animal production sites (Aarnink and Elzing, 1998; Ni et al., 2000; Kai et al., 2006). Source odor and gas concentrations and emission rates are very difficult to model because they are highly variable with time of day, season, weather conditions, building characteristics, ventilation rate, animal growth cycle, and manure handling method. Thus, the whole modeling process can be regarded as a complicated dynamic system with many nonlinear governing relationships. In addition, there still exist some circumstances of gaseous emissions that cannot be explained with our current limited scientific understanding. On the contrary, neural network modeling techniques, unlike the traditional methods based on physical principles and detailed prior knowledge of the modeling structure, are able to capture the interactions of numerous multivariate parameters, learn the relationships between input and output variables, and give quite satisfying prediction results. Sun et al. (2008a) developed backpropagation and generalized regression neural network models to predict diurnal and seasonal gas and PM_{10} concentrations and emissions from swine deep-pit finishing buildings. It was found that the obtained forecasting results of the neural network models were in good agreement with actual field measurements, with coefficients of determination between 81.2% and 99.5% and very low values of systemic performance indices. The promising results from this work indicated that artificial neural network technologies were capable of accurately modeling source air quality within and emissions from these livestock production facilities.

Although AQP models can be used to forecast air quality over time periods that are beyond an actual monitoring period, the main input variables for the model must be known, which requires field measurements. These variables include indoor environment (indoor, inlet, and exhaust temperature and relative humidity), outdoor climate conditions (outdoor temperature, relative humidity, wind speed, wind direction, solar energy, and barometric pressure), pig size and density

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(animal units), building ventilation rate, animal activity, overall management practices, and properties of the stored manure, to name a few. Sun et al. (2008b) performed a multivariate statistical analysis and identified four significant contributors to AQP models: outdoor temperature, animal units, total building ventilation rate, and indoor temperature. The purpose of introducing fewer uncorrelated variables to the models is to reduce model complexity, eliminate model overfitting problems, and minimize field monitoring costs without sacrificing model predictive accuracy. Conducting long-term field measurements of the identified four variables using current engineering approaches is still time-consuming and expensive. Therefore, making use of simulation programs is a good alternative to obtain the required significant input variables for AQP models.

Basically, there are three steady-state methods used to calculate indoor climate of livestock buildings, which include heat, moisture, and carbon dioxide balances (Albright, 1990). Pedersen et al. (1998) compared these three balance methods for estimating the ventilation rate in insulated animal buildings. They reported that the three methods could give good prediction results on a 24 h basis when the temperature differences between inside and outside, the absolute humidity, and the CO_2 concentrations were greater than 2°C, 0.5×10^{-3} kg water per kg dry air, and 200 ppm, respectively, for buildings tested in northern Europe. A simple steady-state balance model (Schauberger et al., 1999) was developed for the sensible and latent heat fluxes and CO_2 mass flows resulting in the prediction of inside temperature and ventilation rate of mechanically ventilated livestock buildings. The obtained variables were further applied for diurnal and annual odor emission estimates. Due to the lack of field measurements, the accuracy of the predicted parameters could not be determined. Morsing et al. (2003) released a computer program entitled StaldVent to help design and evaluate heating and ventilation systems in animal houses. They primarily used a steady-state energy balance method to predict the required ventilation rate and heat capacity, room temperature, CO_2 concentration, and expected energy consumption throughout the year.

On the other hand, indoor climate can be predicted by studying thermal transients in buildings. Nannei and Schenone (1999) developed a simplified numerical model for building thermal transient simulation. The model can be applied to compute the room air temperature and the temperature of the inner surface of the walls. The good numerical results compared with the experimental data indicated that this model was useful for the study of unsteady thermal performance. Mendes et al. (2001) presented a dynamic multimodal capacitive nonlinear model to analyze transient indoor air temperature using Matlab/Simulink (Matlab, 1999). This thermal model was improved by introducing internal gains and inter-surface long-wave radiation. However, the predicted results were not experimentally validated. Morini and Piva (2007) investigated the dynamic thermal behavior of residential heating and cooling with control systems during a sinusoidal variation of the outside temperature. The core of their program employed mechanical and thermal energy conservation equations implemented in the Simulink environment. It was found that their transient model outperformed the standard steady-state approach.

The overall objective of this research is to predict indoor climate and long-term air quality (NH_3, H_2S, and CO_2 concentrations and emissions) for swine deep-pit finishing buildings using a transient building thermal analysis and air quality predictive (BTA-AQP) model and a typical meteorological year database. This article is part I and discusses the BTA model development and resulting indoor thermal climate predictions. In part II (Sun and Hoff, 2010), specific air quality predictive results are presented for the complete BTA-AQP model.

Materials and Methods

Description of Typical Deep-Pit Swine Building

A mechanically ventilated deep-pit (2.4 m) swine finishing building, located in central Iowa, was used for this research. As shown in figure 1, this swine building was 60 m long and 13 m wide, designed to house 960 finishing pigs from ~20 to 120 kg. Gas concentrations inside the building, near the sidewall and pit exhaust fans, and at an outside location (background) were monitored using a mobile emission laboratory and accompanying air sampling lines. In addition, pertinent environment parameters (temperature, relative humidity, and static pressure) and total building ventilation rate were simultaneously measured. During cold-to-mild seasons, pit fans 1 and 2, sidewall fan 3, and tunnel fans 4 and 5 (fig. 1) combined with a series of ten rectangular center-ceiling inlets were used to distribute fresh air and remove moisture, odors, and aerosols within the building. During warm and hot weather, all the fans (except sidewall fan 3) and an adjustable curtain at the opposing end wall were used to maintain a suitable indoor environment (i.e., tunnel ventilation). The total ventilation rate was obtained by recording the on/off status of four single-speed tunnel fans (fans 5, 6, 7, and 8) and the on/off status along with fan rpm levels for all variable-speed fans (fans 1, 2, 3, and 4). The ventilation rate of each fan was measured *in situ* using a FANS unit (Gates et al., 2004); calibration equations were developed as a function of static pressure and fan rpm levels for variable-speed fans. Gas emission rates were determined by multiplying fan airflow rate by representative gas concentration differences between inlet and outlet for all fans operating at any given time. Field monitoring was conducted for 15 months between January 2003 and March 2004, with the one-year monitoring in 2003 used in this research for model prediction comparison. Details of the field monitoring and overall procedures used can be found in Heber et al. (2006).

Transient BTA Model Development

A generalized lumped capacitance model was used to predict inside barn temperature changes as a function of outdoor temperature, animal units, supplemental heat, building envelope thermal characteristics, and the ventilation staging system for the monitored barn described above. In general, this model was developed from the following:

$$\frac{dU}{dt} = Energy_{in} - Energy_{out} \tag{1}$$

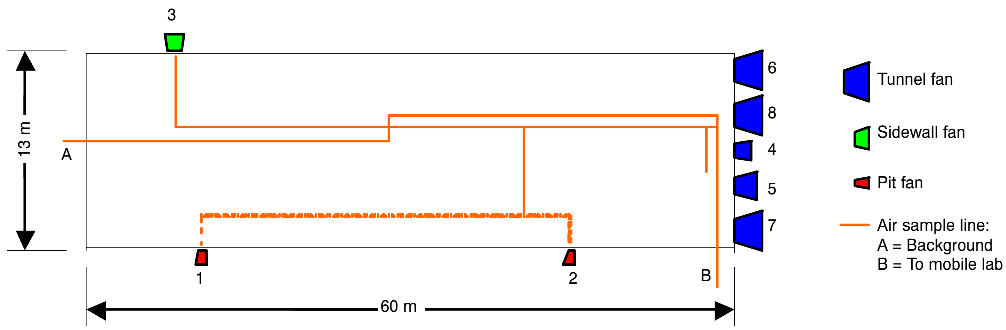

Figure 1. Layout of deep-pit swine finishing building.

where

- U = internal energy of the air mass inside the barn ($= mC_{v,air}\ T_{in,i}$) (J)
- m = mass of air inside barn ($= \rho_{air}\ V$) (kg)
- ρ_{air} = inside air density (an assumed constant of 1.20 kg m^{-3})
- V = volume of airspace in barn (m^3)
- $C_{v,air}$ = specific heat of air at constant volume (an assumed constant of 719 J kg^{-1} °C^{-1}).
- $T_{in,i}$ = predicted inside barn temperature at current time i (°C)
- t = time (s).

Assuming that the mass (m) and specific heat ($C_{v,air}$) are constant results in:

$$\frac{dT_{in,i}}{dt} = \frac{\{Energy_{in} - Energy_{out}\}}{\rho_{air} V C_{v\,air}} \tag{2}$$

The energy inputs ($Energy_{in}$) considered with this BTA model include sensible heat gained from the animals ($q_{animals}$) and any supplemental heat input (q_{heater}) required to maintain a desired setpoint temperature inside the barn. The losses ($Energy_{out}$) considered with this BTA model include net envelope losses [$BHLF(T_{inside} - T_{out})$] and net enthalpy losses from the ventilation air [$VR\rho_{air}\ C_{p,air}(T_{inside} - T_{out})$]. Integrating equation 2 results in the following generalized lumped capacitance BTA model used for this research:

$$\begin{aligned} T_{in,i} = T_{in,i-1} + \{ & q_{animals} + q_{heater} \\ & - \left[VR\rho_{air} C_{p\,air} (T_{in,i-1} - T_{out}) \right. \\ & \left. + BHLF\,(T_{in,i-1} - T_{out}) \right]) \times \Delta t \} \\ & \div \left(\rho_{air} V C_{v\,air} \right) \end{aligned} \tag{3}$$

where

- $T_{in,i-1}$ = predicted inside barn temperature at previous time i-1 ($= t$-Δt) (°C)
- $q_{animals}$ = sensible heat produced by the pigs (J s^{-1})
- q_{heater} = sensible heat produced by supplemental heaters (J s^{-1})
- VR = current ventilation rate (m^3 s^{-1})
- $C_{p,air}$ = specific heat of air at constant pressure (an assumed constant of 1006 J kg^{-1} °C^{-1}).
- T_{out} = outside air temperature (°C)
- $BHLF$ = building heat loss factor (J s^{-1} °C^{-1})
- Δt = time increment used in transient analysis, which was fixed at 36 s (0.01 h).

The lumped capacitance BTA model was able to determine the time dependence of indoor temperature within a mechanically ventilated building and take into account the heat transfer through the components of the building structure and the ventilation system, setpoint temperature, transients of outdoor climate, the presence of different sensible heat sources inside the building, and the inertia of the transient system. To simplify the modeling process, the following assumptions were introduced:

- The thermal stratification of indoor air has been neglected, i.e., the indoor temperature is uniform at any location inside the building.
- Radiation exchange between the pigs and the surroundings is included within the overall pig sensible heat production available from published data.
- Constant thermal properties have been considered.
- The air is incompressible (i.e., constant air density).

Table 1 gives the approximate building heat loss factor (BHLF) for the deep-pit swine building used for the field measurements. Each end wall had one 0.9 × 2.1 m steel insulated door. The lower 0.9 m of the end wall containing fans (fig. 1) was 203 mm thick concrete, with the balance 38 × 90 mm wood stud construction (0.4 m on-center), 19 mm thick plywood interior, steel outer siding, and the cavity filled with fiberglass batt insulation. The lower 0.9 m of the inlet end wall was 203 mm thick concrete with a 1.2 m curtain and a top 0.30 m section of wood/insulation construction. The sidewall containing the pit fans (fig. 1) had a 0.9 m lower portion of 203 mm concrete, a 1.22 m tall curtain used for emergency ventilation, with the balance (0.3 m top section) consisting of wood/insulation construction. The sidewall containing the lone sidewall fan had a 0.9 m lower portion of 203 mm concrete, with the balance (1.5 m) consisting of 38 × 90 mm stud construction (0.4 m on-center) with the cavities filled with fiberglass batt insulation. The interior ceiling was flat consisting of a flexible woven material of inconsequential thickness, rafters spaced 1.22 m on-center, with the balance filled with 254 mm of blown-in cellulose insulation. The top chord of the rafters and gable ends were uninsulated and covered with conventional steel roofing/siding.

As shown in table 1, the total barn BHLF was 965 W °C^{-1}. The ceiling/roof/gable system accounted for 18% of the total, the curtain-containing sidewall accounted for 31%, with the perimeter accounting for 23%. The remaining contributions are shown in table 1.

Table 1. Building heat loss factor for the modeled deep-pit swine building.

Component	L (m)	H or W (m)	Area (m^2)	R Values (°C m^{-2} W^{-1})	BHLF (W $°C^{-1}$)	Component (%)
Ceiling/roof/gable	59.7	12.8	765	4.5	170	17.6
SW1 lower	59.7	0.9	55	0.4	152	15.8
SW1 upper (solid)	59.7	1.5	91.0	3.4	27	2.8
SW2 lower	59.7	0.9	55	0.4	152	15.8
SW2 upper (with curtain)	59.7	1.5	91.0	0.6	148	15.3
EW1 (fan end)	12.8	2.4	29.3	0.8	36	3.7
EW1 door	0.9	2.1	2	2.0	1	0.1
EW2 (with curtain)	12.8	2.4	29.3	0.5	60	6.2
EW2 door	0.9	2.1	2	2.0	1	0.1
Perimeter	145	--	--	1.50[a]	218	22.6
Total barn BHLF					965	100%

[a] Perimeter heat loss factor is expressed in W m^{-1} $°C^{-1}$, estimated using the uninsulated perimeter heat loss factor value suggested by Albright (1990).

The ventilation system consisted of nine stages with eight fans having four different diameters (46, 61, 91, and 122 cm). These fans (table 2) were operated automatically to maintain an operator-desired inside climate according to the difference between indoor air temperature and setpoint temperature (SPT). The airflow rates for each direct-drive fan used in the BTA model were downgraded to 85% of their published maximum free-air capacity to account for in-field fan performance negatively affected by a variety of factors including operating static pressure differences, dust accumulation on fan shutters and blades, and changing power supply to the fans. The airflow rates for the three belt-driven fan (i.e., 122 cm fans 6, 7, and 8) needed to be further corrected because of the influence of high operating static pressures when these belt-driven fans were used and belt-tightening effects. A value of 68% of the reported maximum free-air capacity (10.38 m^3 s^{-1} downgraded to 7.06 m^3 s^{-1}) was used for each of these belt-driven 122 cm fans in the BTA model. For example, fan 7, shown in figure 1, had a maximum reported free-air capacity of 10.38 m^3 s^{-1}. Actual in-field airflow testing using FANS (Heber et al., 2006) indicated an airflow delivery of 7.06 m^3 s^{-1} at an operating static pressure difference of 20 Pa, or a factor of 0.68. Therefore, correction factors of 0.85 for direct-drive fans and 0.68 for belt-driven fans had their basis from in-field FANS testing conducted at this research site (Hoff et al., 2009) and are not considered to be atypical. The rational for adjusting fan delivery rates was that in a generalized procedure, where in-field performance data on fans might not be available, a procedure is needed for modeling fan performance as might be expected in the field. Using published free-stream fan data would certainly overestimate actual in-field fan delivery rates. Anticipating operating static pressures and using published fan delivery rates accordingly would not account for actual in-field performance as well. Therefore, the procedure used here was to model fan delivery based on published free-stream fan performance criteria, using adjustment factors that are based on in-field testing, to be then extrapolated to other fan-ventilated animal housing systems.

Table 2. Fan type and airflow rate used for the swine deep-pit building.

Fan[a]	Fan Diameter (cm)	Rate (m^3 s^{-1})	Modeled Rate (m^3 s^{-1})
PF (1,2)	46	1.06	0.90[b]
SF (3), TF (4)	61	2.83	2.41[b]
TF (5)	91	4.96	4.21[b]
TF (6, 7, 8)	122	10.38	7.06[c]

[a] PF = pit fan; SF = sidewall fan; TF = tunnel fan. Numbers in parentheses indicates the fan numbers shown in figure 1.
[b] Modeled rate at 85% of published free-stream value.
[c] Modeled rate at 68% of published free-stream value.

Table 3 outlines the fan staging scheme for the swine deep-pit building used for field monitoring. Fan stages 0 and 1 consisted of variable-speed fans 1 to 4 (two pit fans, one sidewall fan, and one tunnel fan). These fans operated continuously at stages 0A-0B and 1A-1B when the temperature difference between indoor air temperature and the SPT fell into a range of -0.3°C to 0.6°C and 1.1°C to 1.7°C, respectively, while higher stage fans (single-speed fans) were activated gradually with increasing temperature differences until the maximum fan stage 9 was achieved, e.g., pit fans 1 and 2 and tunnel fans 5 to 7 turned on when the temperature difference reached 6.1°C. The SPT was set at 23.3°C when pigs entered (~20 kg). This SPT was reduced manually by the producer about 0.2°C every Monday until a lower limit of 20°C was reached.

Typically, one complete growth production cycle (~20 to 120 kg) was 140 days, or about 4.5 months. The sensible heat fluxes from the pigs were calculated by multiplying sensible heat production (SHP kg^{-1}) at a specific temperature by the total pig weight (Albright, 1990). Moreover, the swine buildings monitored were equipped with 148 kW of rated supplemental heating for cold weather make-up energy.

Model Performance Evaluation Measures

Statistical measures, such as mean absolute error (MAE), coefficient of mass residual (CMR), index of agreement

Table 3. Fan staging scheme for the swine deep-pit building.

Stage	Fan On[a]	Rate (m^3 s^{-1})	Activation ΔT[b] (°C)
0A	PF 1, 2 at 65% VFC	1.17	-0.3
0B	PF 1, 2 at 100% VFC	1.81	0.6
1A	PF 1, 2; SF 3, TF 4 at 70% VFC	5.17	1.1
1B	PF 1, 2; SF 3, TF 4 at 100% VFC	6.62	1.7
2	PF 1, 2; TF 3, 5	8.42	2.2
3	PF 1, 2; SF 3; TF 4, 5	10.83	3.3
4	PF 1, 2; TF 5,6	13.08	4.4
5	PF 1, 2; TF 5, 6, 7	20.14	6.1
6	PF 1, 2; TF 4, 5, 6, 7, 8	29.60	7.8

[a] VFC = ventilation full capacity.
[b] ΔT is equal to T_{in} - SPT, where T_{in} = indoor temperature.

(IoA), and Nash-Sutcliffe model efficiency (NSEF), can be used to quantify the differences between modeled output and actual measurements, and provide a numerical description of the goodness of the model estimates (Nash and Sutcliffe, 1970; Willmott, 1982; Sousa et al., 2007). The following statistical measures were employed to ensure the quality and reliability of the BTA model predictions:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|P_i - O_i\right| \tag{4}$$

$$\text{CMR} = \frac{\sum_{i=1}^{N} P_i - \sum_{i=1}^{N} O_i}{\sum_{i=1}^{N} O_i} \tag{5}$$

$$\text{IoA} = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}\left(\left|O_i - \overline{O}\right| + \left|P_i - \overline{O}\right|\right)^2} \tag{6}$$

$$\text{NSEF} = \frac{\sum_{i=1}^{N}(O_i - \overline{O})^2 - \sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(O_i - \overline{O})^2} \tag{7}$$

where N is the total number of observations, P_i is the predicted value of the ith observation, O_i is the observed value of the ith observation, and $\overline{O}$ is the mean of the observed values.

The MAE estimates the residual error, expressed in the same unit as the data, which gives a global idea of the difference between the observed and predicted values. The CMR measures the tendency of the model to overestimate or underestimate the measured values. The IoA compares the difference between the mean, the predicted, and the observed values, indicating the degree of error for the predictions. The NSEF evaluates the relative magnitude of the residual variance in comparison with the measurement variance.

In addition to the statistical measures identified above, the predictive accuracy of the model was examined through graphical presentations of the predicted vs. observed ventilation rate and indoor air temperature.

Results and Discussion

Model validation is possibly the most important step in any model development sequence. However, no standard model evaluation guidance has been established to judge model performance and further compare various models that were developed using different modeling approaches. The reason could be due to the fact that model validation guidelines are model and project specific. For this research, the BTA model was evaluated based on two main techniques: graphical presentation and statistical analysis. The graphical presentations provide a visual comparison of the predicted vs. observed values and a first overview of model performance (ASCE, 1993), while the statistical analysis provides a numerical tool to quantify the goodness of model estimates.

Graphical Presentation for Model Evaluation

Based on the monthly averages from the measured 2003 data (calendar year), the central Iowa climate could be separated into three typical global categories that were defined as: warm weather (June, July, Aug.; 20.2°C to 23.5°C), mild weather (Apr., May, Sept., Oct.; 10.0°C to 16.4°C), and cold weather (Jan., Feb., Mar., Nov., Dec.; -7.6°C to 2.6°C). Figures 2 to 7 illustrate the different diurnal and seasonal patterns of the hourly predicted vs. actual ventilation rate and indoor air temperature during these three representative seasons (warm, mild, and cold weather).

Generally, the predicted values were visually in close agreement with actual measurements, as shown in figures 2 to 7. Specifically, in August (warm weather), the mean and standard deviation for the actual and predicted ventilation rate and indoor air temperature were 12.03 ±5.91 m^3 s^{-1} vs. 13.82 ±7.50 m^3 s^{-1} and 27.8 ±2.3°C vs. 26.8 ±2.8°C, respectively. It is obvious in figures 2 and 3 that the diurnal patterns of ventilation rate and indoor temperature were very similar to those of outside temperature, as expected. The predicted ventilation rate was overestimated by an average of 8% when the highest outside temperatures occurred for some

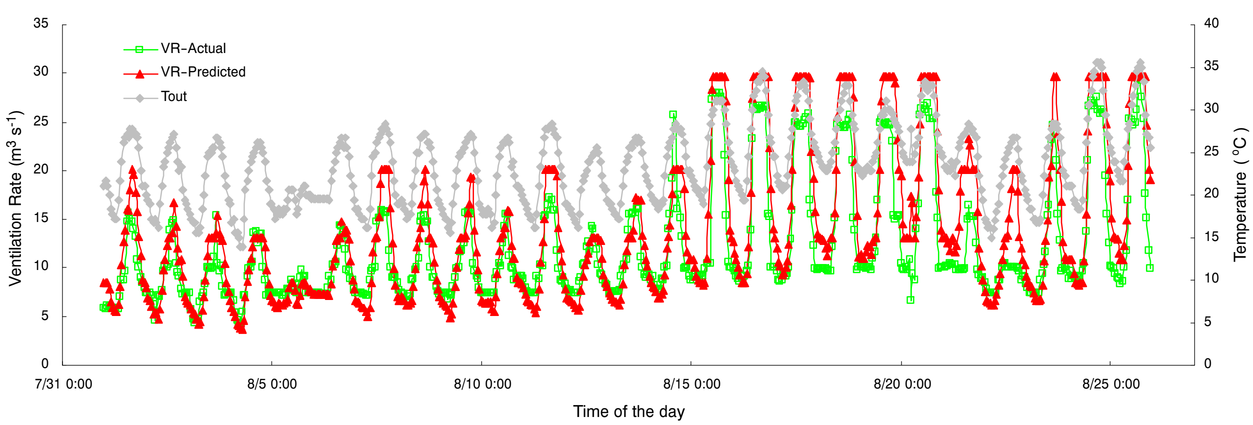

Figure 2. Predicted vs. actual ventilation rate (*VR*) with outside temperature (T_{out}) in August 2003.

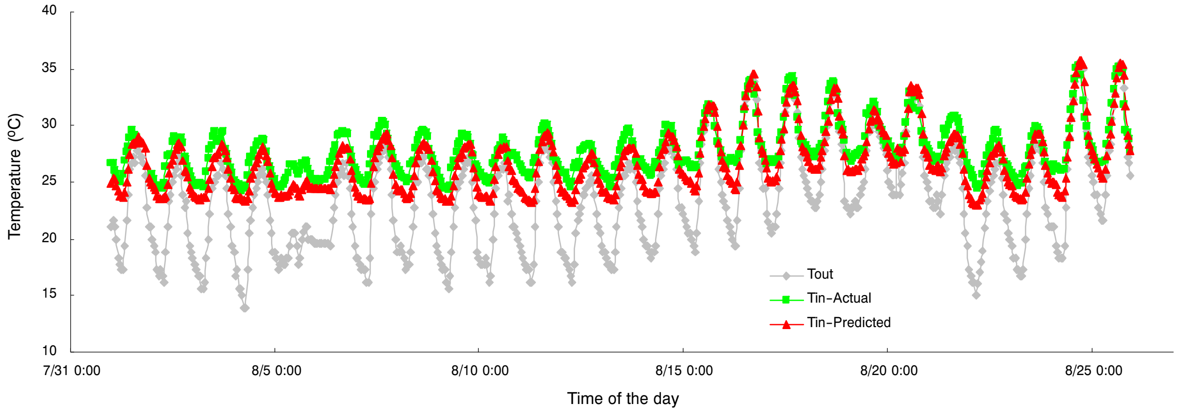

Figure 3. Predicted vs. actual indoor air temperature (T_{in}) with outside temperature in August 2003.

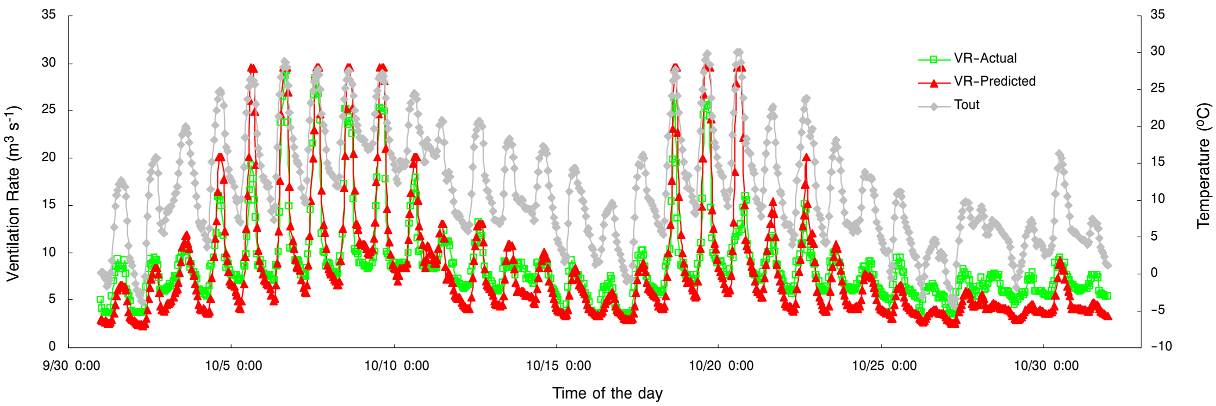

Figure 4. Predicted vs. actual ventilation rate (*VR*) with outside temperature in October 2003.

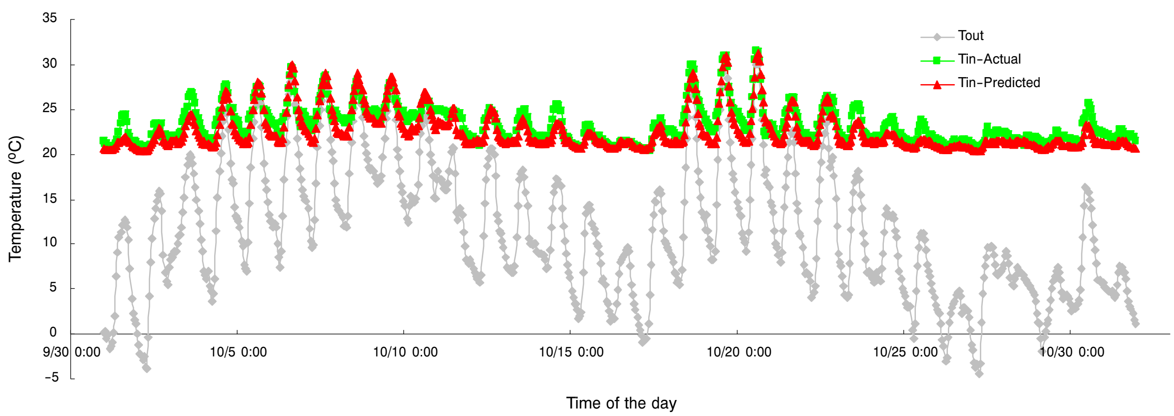

Figure 5. Predicted vs. actual indoor air temperature (T_{in}) with outside temperature in October 2003.

days, whereas the predicted indoor temperature was underestimated by an average of 2% in comparison with the actual measurements.

In October (mild weather), the mean and standard deviation for the actual and predicted ventilation rate and indoor air temperature were 8.61 ±4.40 m^3 s^{-1} vs. 8.17 ±6.14 m^3 s^{-1} and 23.3 ±2.1°C vs. 22.5 ±2.2°C, respectively. It can be seen in figures 4 and 5 that the ventilation rate and indoor air temperature seemed to show much less fluctuation compared with the August patterns, except for a few days with high outside temperature. The ventilation rates were underestimated by the BTA model when the outside temperature dropped below 0°C.

In February (cold weather), the mean and standard deviation for the actual and predicted ventilation rate and indoor air temperature were 1.95 ±0.39 m^3 s^{-1} vs. 1.20 ±0.09 m^3 s^{-1} and 23.4 ±0.9°C vs. 21.6 ±0.5°C. It can be observed in figures 6 and 7 that the ventilation rate and indoor air temperature were fairly constant, since the minimum ventilation rate was being used in the building to maintain the room setpoint temperature during these cold periods. Almost all the predicted ventilation rates and indoor temperatures were slightly lower than corresponding field measurements.

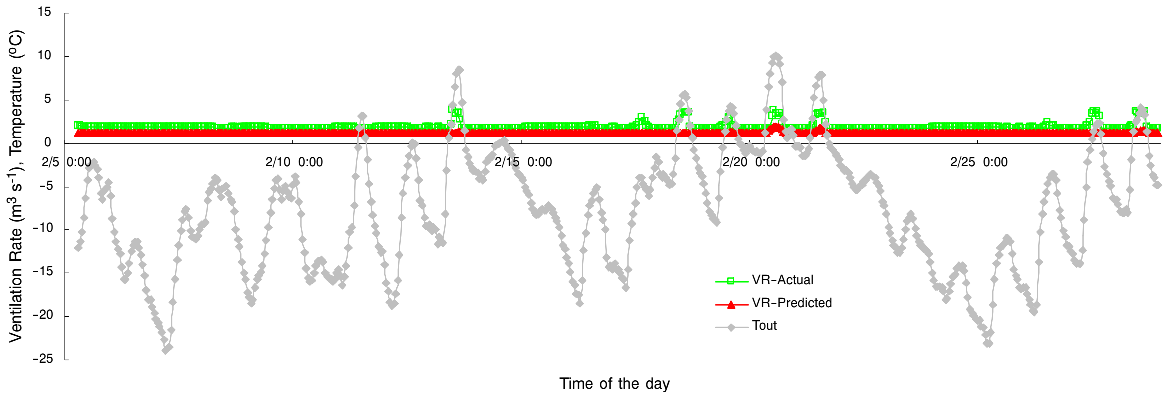

Figure 6. Predicted vs. actual ventilation rate (*VR*) with outside temperature in February 2003.

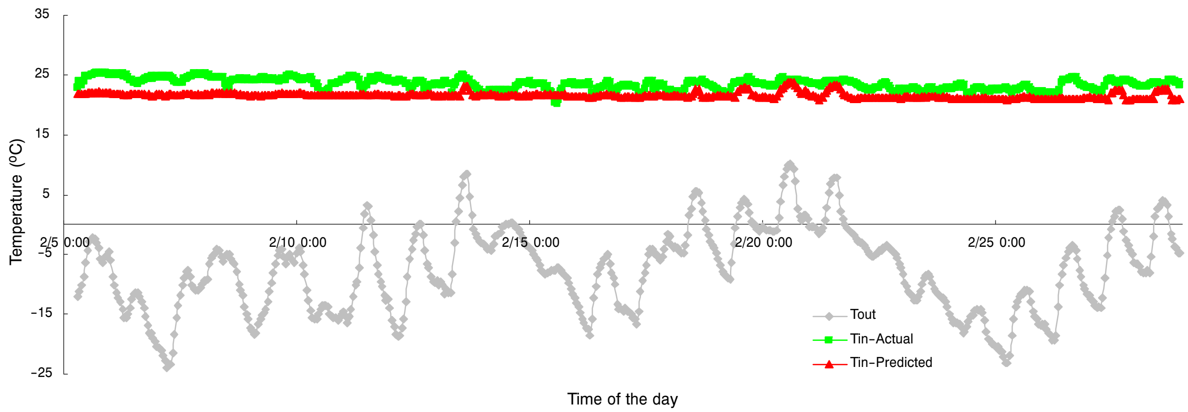

Figure 7. Predicted vs. actual indoor air temperature (T_{in}) with outside temperature in February 2003.

Table 4. Statistical performance of the BTA model.

Variable	Actual Data (mean ±SD)	Predicted Data (mean ±SD)	MAE	CMR	IoA	NSEF
Ventilation rate	7.03 ±5.43 $m^3\ s^{-1}$	6.83 ±6.66 $m^3\ s^{-1}$	1.74 $m^3\ s^{-1}$	-0.03	0.96	0.79
Indoor air temperature	23.8°C ±2.8°C	22.8°C ±2.7°C	1.2°C	-0.04	0.92	0.68

Statistical Analysis for Model Evaluation

Table 4 summarizes the statistical performance of the BTA model to predict the hourly ventilation rate and indoor air temperature in calendar year 2003. The mean absolute error (MAE) tests the accuracy of the model, which is defined as the extent to which predicted values approach a corresponding set of measured values. The MAE values were 1.74 $m^3\ s^{-1}$ and 1.2˚C for the ventilation rate and indoor temperature, respectively. Singh et al. (2004) reported that MAE values less than half the standard deviation (MAE/SD < 0.50) of the measured data can be considered low. In this research, MAE/SD < 0.50 was used as a stringent criterion for evaluating the BTA model. The MAE/SD values for the ventilation rate and indoor air temperature were 0.32 and 0.41, respectively, which indicates that the BTA model performance for the residual variations was very good. The coefficient of mass residual (CMR) expresses the relative size and nature of the error: the closer CMR is to 0, the better the model simulation. A negative value of CMR shows a tendency to underestimation in the model, and positive values indicate a tendency to overestimation. The CMR values for the ventilation rate and indoor temperature were -0.03 and -0.04, respectively, which means that there was no systematic under- or overprediction of the ventilation rate and indoor temperature by the BTA model. The index of agreement (IoA) measures the agreement between predicted and measured data and ranges from 0 (no agreement) to 1 (perfect agreement) (Willmott, 1982). The IoA values for the ventilation rate and indoor air temperature were 0.96 and 0.92, respectively, which indicates that the predicted values had a very good agreement with the field measurements. Nash-Sutcliffe model efficiency (NSEF) evaluates the error relative to the natural variation of the actual measurements and varies from $-\infty$ to 1. NSEF = 1 means a perfect match of predicted data to observed data. NSEF = 0 indicates that the model predictions are as accurate as the mean of the observed data, whereas an NSEF value less than 0 suggests that using the observed mean would be better than the models predictions. Values between $0.5 \leq$ NSEF ≤ 1.0 are considered good (Helweig et al., 2002). The NSEF values for the ventilation rate and indoor air temperature were 0.79 and 0.68, respectively, which fell within the good range.

The graphical data along with the statistical parameters suggest that the performance of the BTA model for predicting ventilation rate and indoor air temperature were very good and could be used to provide predicted climate parameters for the ultimate goal of predicting inside barn concentrations and emissions, as presented in part II of this research (Sun and Hoff, 2010).

SUMMARY AND CONCLUSIONS

Due to the absence of a nationwide monitoring network for quantifying long-term air emission inventories of livestock production facilities, a building thermal analysis and air quality predictive (BTA-AQP) model was developed to forecast indoor climate and long-term air quality (NH_3, H_2S, and CO_2 concentrations and emissions) for swine deep-pit finishing buildings.

In this article, part I of II, a lumped capacitance model (BTA model) was developed to study the transient behavior of indoor air temperature and ventilation rate according to the thermo-physical properties of a typical swine building, the setpoint temperature scheme, fan staging scheme, transient outside temperature, and the heat fluxes from pigs and supplemental heaters. The obtained indoor air temperature and ventilation rate developed from the BTA model could then be combined with animal growth cycle, in-house manure storage level, and typical meteorological year (TMY3) data (NSRDB, 2008) to predict indoor air quality and emissions based on the generalized regression neural network (GRNN-AQP model; Sun and Hoff, 2010). The overall purpose of this article was to acquire accurate estimates of significant input parameters required for the GRNN-AQP model without relying on expensive field measurements.

The performance of the BTA model for predicting ventilation rate and indoor air temperature was very good in terms of the statistical analysis and graphical presentations. The statistical results showed that:

- The mean absolute error values of VR and T_{in} were less than half the standard deviation of the measured data.
- The coefficient of mass residual values for VR and T_{in} were equal to -0.03 and -0.04, respectively.
- The index of agreement values were 0.96 and 0.92 for VR and T_{in}, respectively.
- The Nash-Sutcliffe model efficiency values were all higher than 0.65.

These good results indicated that the BTA model was capable of accurately predicting ventilation rate and indoor air temperature in swine deep-pit buildings.

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