2950 Niles Road, St. Joseph, MI 49085-9659, USA
269.429.0300 fax 269.429.3852 hq@asabe.org www.asabe.org

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Prediction of Indoor Climate and Long-term Air Quality Using a Building Thermal Transient model, Artificial Neural Networks and Typical Meteorological Year

Gang Sun, Steven J. Hoff

Department of Agricultural and Biosystems Engineering, Iowa State University, Ames, Iowa

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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 indoor climate and long-term air quality (NH_3, H_2S and CO_2 concentrations and emissions) for swine deep-pit buildings. The paper presents the development of the BTA-AQP model using a building thermal transient model, artificial neural networks, and typical meteorological year (TMY3) data in predicting long-term air quality trends. The good model performance ratings (MSE/S.D.<0.5, CRM≈0; IoA≈1; and Nash-Sutcliffe EF > 0.5 for all the predicted parameters) and the graphical presentations reveal that the BTA-AQP model was able to accurately forecast indoor climate and gas concentrations and emissions for swine deep-pit buildings. By comparing the air quality results simulated by the BTA-AQP model using the TMY3 data set with those from a five-year local weather data set, it was found that the TMY3-based predictions followed the long-term mean patterns well, which indicates that the TMY3 data could be used to represent the long-term expectations of source air quality. Future work is needed to improve the accuracy of the BTA-AQP model in terms of four main sources of error: (1) Uncertainties in air quality data; (2) Prediction errors of the BTA model; (3) Prediction errors of the AQP model, and (4) Bias errors of the TMY3 and its limited application.*

Keywords. *Air quality, Typical meteorological year, Modeling, Long-term mean.*

Introduction

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 United States 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 et al., 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. Also, 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 coefficient of determination values 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 as a useful tool to forecast air quality over a time period 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 (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 the 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 structure complexity, eliminate model over-fitting 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 are 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.

The 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 data base.

Materials and Methods

Long-term Air Quality Prediction Method

Long-term air quality predictions can be separated into three components as shown in Figure 1: the building thermal analysis (BTA) model, the air quality predictive (AQP) model, and a typical meteorological year (TMY3) database (NSRDB, 2008). Specifically, a lumped capacitance model was developed to study the transient behavior of indoor air temperature and ventilation rate according to the thermo-physical properties of a typical Iowa swine building, a typical set-point temperature scheme, a typical fan staging scheme, transient outside temperature, and the heat fluxes from pigs and supplemental heaters. The obtained indoor room temperature and ventilation rate combined with animal growth cycle, in-house manure storage level, and typical meteorological year (TMY3) data were fed into the generalized regression neural network (GRNN) air quality predictive model to calculate average yearly ammonia, hydrogen sulfide and carbon dioxide concentrations and emission rates. The TMY3 data used for this research project consists of representative hourly solar radiation and meteorological values for a 1-year period in Des Moines, Iowa, about 100 kilometers away from the swine deep-pit finishing facility where field data was collected (calendar year 2003 data collection). Animal growth cycle includes pig number and average pig weight in the room, which were used to estimate total animal units (AU). The total AU was obtained by dividing the total pig weight by 500 kg animal live weight. In-house manure storage level was considered as an additional input variable representing a deep-pit system for the AQP model.

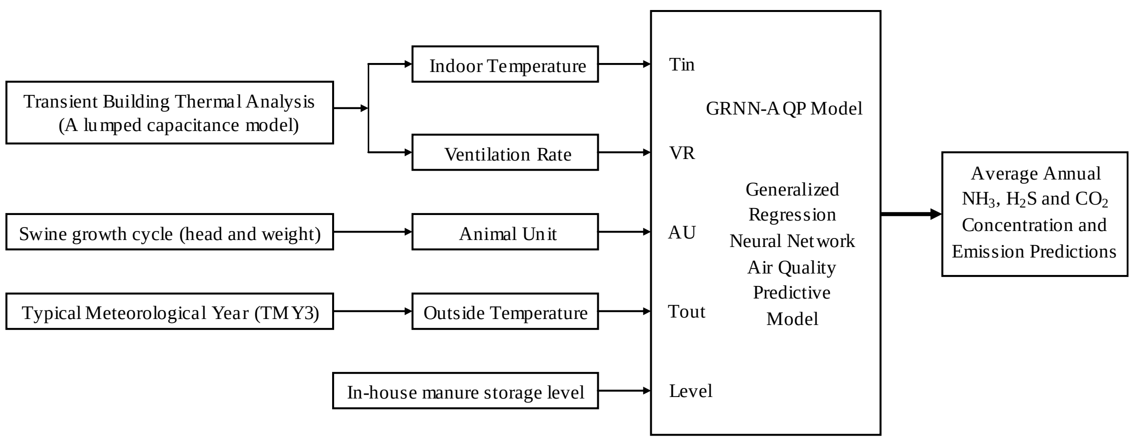


Figure 1. Scheme of the BTA-GRNN-AQP model (Tin: indoor temperature (^oC); VR: ventilation rate (m^3s^{-1}); AU: animal unit; Tout: outside temperature (^oC), Level: in-house manure storage level (m)).

Description of field measurements

Two identical deep-pit swine finishing buildings located in central Iowa were monitored for a 15-month sampling period in order to obtain long-term gas concentrations and emissions (Jan 2003 – March 2004). Each building was 60 m long and 13 m wide, which can house 960 finishing pigs from ~20 to 120kg. Slurry was collected in a 2.4-m-deep pit below a fully slatted floor and was stored for one year. Once a year in the fall, the under-floor deep pit was emptied and the slurry was injected to nearby cropland as a fertilizer source.

The real-time gas concentrations and emission rates, environmental data, and building ventilation rate were measured by a mobile emission laboratory (MEL) that included a gas sampling system

(GSS), a computer-based data acquisition system, gas analyzers, environmental instrumentation, standard gas calibration cylinders, and other supplies. Gas concentrations from multiple sampling locations within the swine building were quantified with a chemiluminescence NH_3 analyzer (Model 17C, Thermal Environment Instruments, Franklin, MA), a pulsed fluorescence SO_2 detector (Model 45C, Thermal Environment Instruments, Franklin, MA), and two photoacoustic infrared CO_2 analyzers in the range from 0 to 2,000 and 10,000 ppm (Model 3600, Mine Safety Appliances CO., Pittsburg, PA). A three-way solenoid system was used to automatically switch between 12 measuring locations with 10-min sampling intervals and sequentially delivered gas from each location to the gas analyzers. Therefore, gas samples were taken during twelve, 120-min measurement cycles per day. Details of the monitoring method and QA/QC can be found in Heber et al. (2006). Climate parameters (temperature, relative humidity, and static pressure) and total building ventilation rate were also simultaneously monitored. The total ventilation rate was measured by recording the on/off status of four single-speed tunnel fans and the on/off status along with fan rpm levels for all variable speed fans. The ventilation rate of each fan was obtained in situ using a FANS unit where 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.

Transient BTA model development

A generalized lumped-capacity model (Sun and Hoff, 2009) was used to predict inside barn temperature changes as a function of outdoor temperature, animal unit, supplemental heat, the building envelope thermal characteristics, and the ventilation staging system for the monitored barn described above. In general, this model was developed from the following;

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

where

U = internal energy of the air mass inside the barn, J.

$= m\, C_{p,air}\, T_{in,i}$

m= mass of air inside barn, kg.

$= \rho_{air} V$

ρ_{air}= inside air density (an assumed constant of 1.20 kg/m^3).

V= volume of airspace in barn, m^3.

$C_{p,air}$= specific heat of air (an assumed constant of 1006 J/kg-^{o}C).

$T_{in,i}$= predicted inside barn temperature at current time i, ^{o}C.

t= time, s.

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

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

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 set-point 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-capacity BTA model used for this research;

$$T_{in,i} = T_{in,i-1} + \frac{\{q_{animals} + q_{heater} - [VR\rho_{air}C_{p_{air}}(T_{in,i-1} - T_{out}) + BHLF(T_{in,i-1} - T_{out})\ ]\ \}* \Delta t}{\rho_{air}VC_{p_{air}}\beta} \tag{3}$$

where;

$T_{in,i-1}$= predicted inside barn temperature at previous time i-1 (=t-Δt), ^{o}C.

$q_{animals}$= sensible heat produced by the pigs, J/s.

q_{heater}= sensible heat produced by supplemental heaters, J/s.

VR= current ventilation rate, m^3/s.

T_{out}= outside air temperature, ^{o}C.

$BHLF$= building heat loss factor, J/s-^{o}C.

Δt= time increment used in transient analysis, s, which was fixed at 360 s.

β= a building dampening factor (dimensionless).

The building dampening factor β was required to dampen erratic and unrealistic changes between inside barn temperature predictions with adjacent time steps. After several iterations by trial and error, a dampening factor of β=5 was chosen for this project. Other barn styles that differ in overall heat capacity would be expected to have a different dampening factor although in general most animal production housing systems have similar thermal properties.

The lumped capacitance BTA model was able to determine the time dependence of indoor temperature within a negative-pressure, mechanically ventilated building and take into account the heat transfer through the components of the building structure and the ventilation system, set point temperature, transients of outdoor climate, the presence of different sensible heat sources inside the building, and the inertia of the transient system. To simply 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.
- The heat fluxes across the structure have been considered unidirectional.
- Constant thermal properties have been considered.
- The heating medium is not compressible.

Table 1 gives the approximate building heat loss factor (BHLF) for the deep-pit swine building used for the field measurements. Each end wall has one 0.9x2.1 m steel insulated door. The lower 0.9 m wall consists of 203 mm thick concrete with the balance 38x90 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. Each sidewall has 0.9 m lower portion of 203 mm concrete and 38x90 mm stud construction 406 mm on-center with a 1.5 m tall two-layer curtain. 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 was covered with conventional steel roofing.

As shown in table 1, the total barn BHLF was 965.1 W/^{o}C with the ceiling, curtains and building length perimeter accounting for the majority. The maximum heat loss component (17.9% of the overall BHLF) was the curtain component of the side walls, followed by the building length perimeter (16.1 %) and ceiling (15.0%).

Table 1. Building heat loss factor for a typical deep-pit swine building.

Component	L (m)	H or W (m)	Area (m^2)	R-Values (^{o}C-m^2/W)	BHLF (W/ ^{o}C)	Component (%)
Ceiling	59.7	12.8	764.8	5.28	144.8	15.0
SW1 lower	59.7	0.9	54.6	1.41	38.8	4.0
SW1 upper	59.7	1.5	91.0	0.53	172.3	17.9
SW2 lower	59.7	0.9	54.6	1.41	38.8	4.0
SW2 upper	59.7	1.5	91.0	0.53	172.3	17.9
EW1	12.8	2.4	30.1	3.52	8.6	0.9
EW1 door	0.0	1.2 x0.9	1.1	0.53	2.1	0.2
EW2	12.8	2.4	30.1	3.52	8.6	0.9
EW2 door	0.0	1.2 x0.9	1.1	0.53	2.1	0.2
Perimeter 1	59.7			2.60 [a]	155.2	16.1
Perimeter 2	12.8			2.60	33.3	3.4
Perimeter 3	59.7			2.60	155.2	16.1
Perimeter 4	12.8			2.60	33.3	3.4
Total Barn BHLF					965.1	

[a] The unit for the perimeter heat loss factor is W/m-C.

The ventilation system of the monitored building 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 set point temperature (SPT). The ventilation rates for each fan used in the BTA model were downgraded to 85% of their published capacity due to the fact that fan field performance can be negatively affected by a variety of factors including dust accumulation on fan shutters and blades, loose fan belts, and changing power supply to the fans. Also, the airflow rate capacity for each of the three 122 cm fans (fans 6, 7, and 8) needed to be further corrected because of the influence of high operating static pressures when these fans were used. A value of 80% of the "free-air condition" value (8.82 m^3/s) for each 122 cm fan was used in the BTA model.

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

Fan	Fan Diameter (cm)	Rate (m^3/s)	85% of Rate (m^3/s)	122cm Fan added (m^3/s)
PF (1,2) [b]	46	1.06	0.90	-
SF (3), TF (4)	61	2.83	2.41	-
TF (5)	91	4.96	4.21	-
TF (6, 7, 8)	122	10.38	8.82	7.06

[a] PF: Pit Fan; SF: Side Wall Fan; TF: Tunnel Fan.

[b] Number in parenthesis indicates the number of the fans used.

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 side wall 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 to 0.6 $°C$ and 1.1 to 1.7 $°C$, respectively; while higher stage fans (single-speed fans) were activated gradually with increased temperature differences until the maximum fan stage 9 was achieved, e.g., the pit fans 1 and 2 and tunnel fans 5 to 7 turned on when the temperature difference reached 6.1 $°C$.

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

Stage	Fan ON	Rate (m^3/s)	Activation Delta T (°C)
0A	PFs-1,2 at 65% VFC	1.17	-0.3
0B	PFs-1,2 at 100% VFC	1.81	0.6
1A	PFs-1,2; SF-3, TF-4 at 70% VFC	5.17	1.1
1B	PFs-1,2; SF-3, TF-4 at 100% VFC	6.62	1.7
2	PFs-1,2; TF-3,5	8.42	2.2
3	PFs-1,2; SF-3; TF-4, 5	10.83	3.3
4	PFs-1,2; TF-5,6	13.08	4.4
5	PFs-1,2; TF-5, 6, 7	20.14	6.1
6	PFs-1,2; TF-4,5,6,7,8	29.60	7.8

[a] Delta T is equal to Tin-SPT. Tin: indoor temperature. VFC: ventilation full capacity.

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) at a specific temperature by the total pig weight (Albright 1990). Moreover, the swine buildings monitored were equipped with a 14.7 kW supplemental heating system for cold weather make-up energy.

Neural Network Air quality model

Modeling source air quality in a swine deep-pit building is a complicated dynamic system with many nonlinear governing relationships. Moreover, there still exist some circumstances of gaseous emissions that cannot be explained with our current limited scientific understanding. Therefore, a black-box modeling approach using artificial neural networks (ANN) would be a potential method for handling air quality predictions. Black-box models do not need detailed prior knowledge of the structure and different interactions that exist between important variables. Meanwhile, their learning abilities make the models adaptive to system changes. Recently, there has been an increasing amount of applications of ANN models in the field of atmospheric pollution forecasting (Hooybergs et al., 2005; Grivas et al., 2006; Sousa et al., 2007; Sun et al., 2008a). The results show that ANN black-box models are able to learn nonlinear relationships with limited knowledge about the process structure.

Sun et al. (2008a) employed backpropagation neural network (BPNN) and generalized regression neural network (GRNN) techniques to model gas and PM_{10} concentrations and emissions generated and emitted from a swine deep-pit finishing building. The obtained BPNN and GRNN predictions were in good agreement with field measurements, with coefficient of determination (R^2) values between 81.2% and 99.5% and very low values of systemic performance indexes. The good results indicated that ANN technologies were capable of accurately modeling source air quality within and from these livestock production facilities. Furthermore, it was found that the process of constructing, training, and simulating the BP network models was very complicated. The effective way of obtaining good BP modeling results was to use some trial-and-error methods and thoroughly understand the theory of backpropagation. Conversely, for the GRNN models, there was only one parameter (the smoothing factor) that needed to be adjusted experimentally. Additionally, the GRNN performance was not sensitive to randomly assigned initial values and the GRNN approach did not require an iterative training procedure as in the backpropagation method. Other significant characteristics of the GRNN in comparison to the BPNN were the excellent approximation ability, fast training time, and exceptional stability during the prediction stage. Thus, it was recommended in Sun et al. (2008a) that a GRNN be used for source air quality modeling.

In this current research, a GRNN model was developed to explore the complex and highly nonlinear relationships between air pollutants and many input variables on the diurnal and seasonal NH_3, H_2S, and CO_2 levels and emissions. This developed air quality model was then used to forecast long-term gas concentrations and emissions from a typical swine deep-pit building associated with five significant input elements: outdoor temperature obtained from a specific year or the TMY3 data; a typical swine growth cycle; and ventilation rate and indoor air temperature predicted by the transient BTA model (Sun and Hoff, 2009). It is noted that in the midwestern United States, it is common practice to store manure in deep holding concrete pits for one calendar year. This year-long slurry storage system is also a concentrated source for gas concentrations and emissions (Hoff et al., 2006). Therefore, in-house manure storage level was considered as an additional factor representing the deep-pit system for the AQP model. The manure depth changes with swine production time, from 0.3 m (empty pit) to 2.1 m (full pit) throughout the year. The full and empty events generally occur before and after slurry removal which is typically conducted once per year in the fall after harvest (i.e. October).

Typical meteorological year

Selecting appropriate representative meteorological data is vitally important to accurately predict indoor climate and long-term air quality levels. Normally, a representative meteorological data consists of a multi-year and long-term average measured data series which would represent a year of prevailing weather conditions for a specific location. It is noted that the use of typical climatic parameters instead of multiple-year data can reduce a great deal of time and computation in computer simulation and facilitate performance comparisons of different system types, configurations, and locations. Therefore, typical weather data has been extensively used for building energy simulation and solar energy analysis to assess the expected heating and cooling costs for the design of industrial and residential buildings. Currently, the most prevalent weather representations are test reference year (TRY), typical meteorological year (TMY3), and weather year for energy calculations (WYEC2). These data sets are used for different simulation purposes (Pedersen, 2007): TRY is suited to short-term energy predictions due to the representation of weather characteristics; while TMY3 and WYEC2 are most suitable for long-term energy estimations because the data represents long-term weather features; TRY can be used for short-term and long-term predictions. Yang et al. (2007) investigated the energy simulation results for office buildings in the five main climate zones of China and compared the results using TMY2 with those using multi-year data (1971-2000). It was found that the TMY2 was able to predict monthly load and energy use within 5.4% of the long-term mean. Based on these results, it was concluded that the TMY3 data was an acceptable meteorological data set to be used for this current study.

TMY3 is composed of typical hourly meteorological values at a specific location over a long period of time (30 years). For each TMY3 dataset, 12 typical months are selected using statistics (Sandia method; NSRDB, 2008) determined by five important parameters: global radiation on a horizontal surface, direct normal radiation, dry bulb and dew point temperatures, and wind speed (NSRDB, 2008). These important parameters were chosen because solar radiation determines the heat gain; dry bulb temperature and wind speed determine heat loss by convection; and dew point temperature is an absolute measure of humidity, which determines latent energy. The 12 judged most typical months were picked by the Sandia approach to form a complete year. Due to adjacent TMY3 months from different years, linear interpolation was performed to smooth the gap for 6 hours on each side of adjacent months. In each TMY3 month, mean values of the TMY3 elements are the closest to the averages of the elements for multiple years. Thus, the TMY3 can represent long-term average climatic conditions.

Model performance evaluation measures

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

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

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

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

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

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 CRM 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 model outputs were examined through graphical presentations of the predicted vs. observed values.

Results and Discussion

In this section, a comparison was made between the predicted and actual gas concentrations and emissions in 2003 to evaluate the accuracy of the BTA-AQP model estimates. In addition, the simulated results using the TMY3 data set and a five-year mean weather data set were compared to validate the assumption that the TMY3 could accurately represent long-term source air quality levels. Finally, overall prediction errors of the BTA-AQP model were analyzed and future work is identified for improving the model.

BAT-AQP Model Evaluation

The monthly average predicted vs. field collected NH_3 concentrations and emissions in 2003 are shown in figure 2. The absolute error (AE) was used to quantify the difference between the monthly predicted and field collected values. It was observed that AE ranged from 0.3% underestimation in October to 16.0% overestimation in December with an overall average value of 4.3 % for NH_3 concentration. The 16% absolute error in December was probably due to two growth cycles appearing in the same month, i.e., mature pigs (120 kg) were gradually shipped to market in early December and smaller pigs (~20kg) entered at the end of December. During these times, air quality levels and indoor climate were highly influenced by the management of the swine barn and workers' involvement, which were not considered as a factor in the development of the BTA-AQP model. It can be further seen in figure 2 that the AE varied from 0.4% overestimation in August to 23% underestimation in April with an overall average value of 8.3% for NH_3 emission. The big difference between the predicted and actual NH_3 emission in April may be attributed to a lower ventilation rate predicted by the BTA model as compared with actual values (mean predicted vs. field measured ventilation rate was 2.67 vs. 3.40 m^{-3} s^{-1}) and lower estimations of NH_3 concentration.

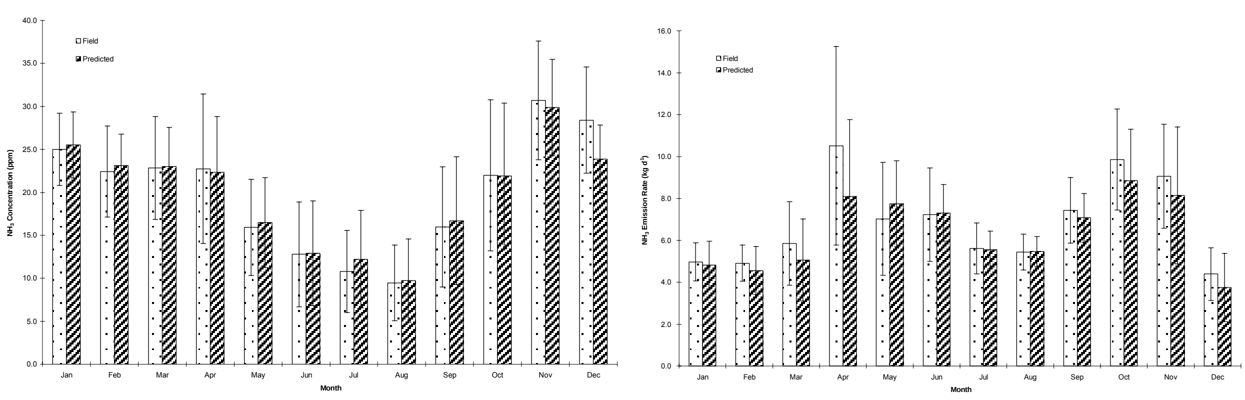


Figure 2. Predicted vs. field NH_3 concentrations and emissions in 2003.

The monthly average predicted vs. field collected H_2S concentrations and emissions in 2003 are shown in figure 3. The absolute error ranged from 2% underestimation in September to 37% overestimation in July with an overall average value of 10.5 % for H_2S concentration. The 37% overestimation in July could be explained by the fact that some important variables were excluded in the H_2S predictive model, such as manure characteristics and surface temperature. The manure temperature may be an important variable affecting H_2S release in hot weather. Moreover, in early

July, some underestimated ventilation rates were observed at the beginning of a new swine growth cycle resulting in a corresponding higher predicted H_2S concentration. For H_2S emissions, the absolute error varied from 1% underestimation in January to 27% underestimation in December with an overall average value of 11.1 %. Again, the poor forecasting performance that occurred in December were mainly due to the model's inability in estimating gas concentrations resulting from barn management and pig activity. Furthermore, it was found that the BTA-AQP model with an additional variable, in-house manure level, could largely improve H_2S prediction accuracy. When in-house manure level was incorporated into the model, the overall average AE dropped to 11% from an original 24% without manure depth considered.

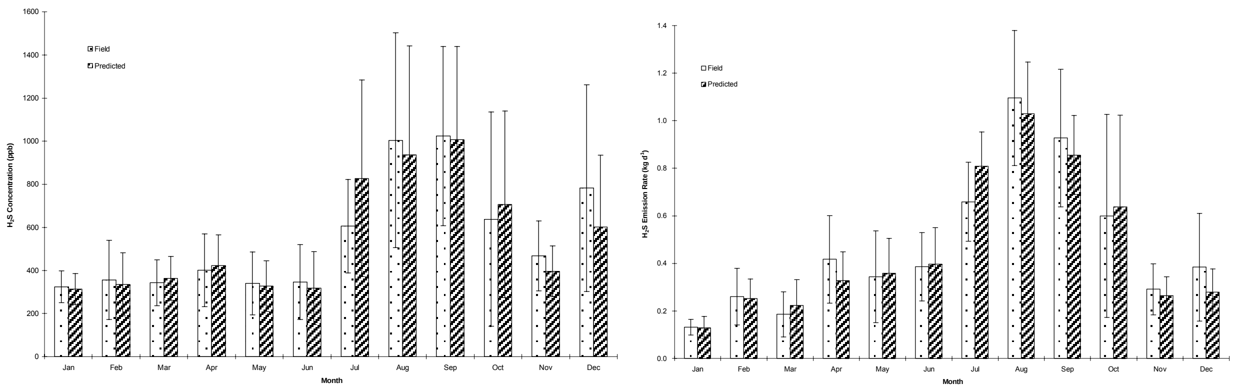


Figure 3. Predicted vs. field H_2S concentrations and emissions in 2003.

The monthly average predicted vs. field collected CO_2 concentrations and emissions in 2003 are illustrated in figure 4. The absolute error ranged from 0.3% overestimation in February to 10.9% overestimation in July with an overall average value of 2.8 % for CO_2 concentration. For CO_2 emissions, the AE varied from 1.6% underestimation in September to 28.3% underestimation in April with an overall average value of 7.7 %. The relatively inaccurate ventilation rate predictions, in comparison to other monthly fitted values, led to greater absolute error in CO_2 emission calculation in April.

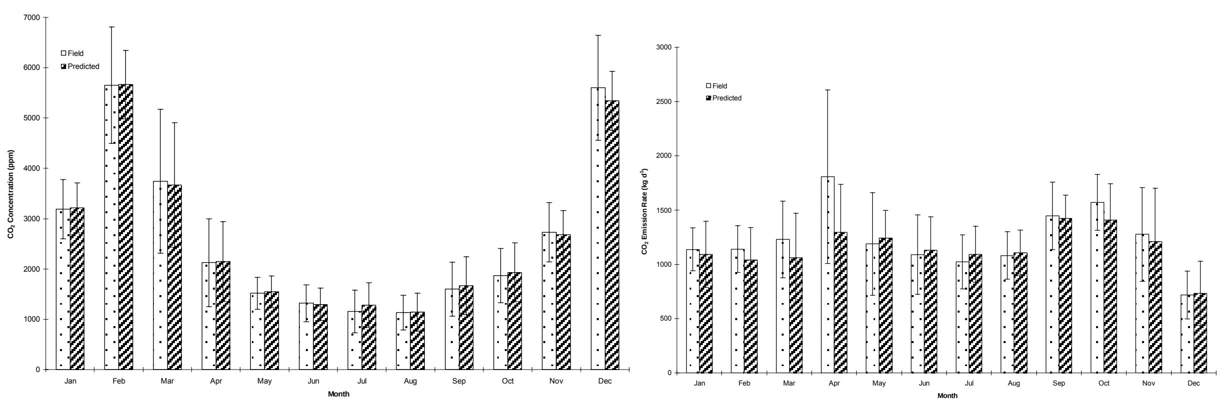


Figure 4. Predicted vs. field CO_2 concentrations and emissions in 2003.

Table 4 summarizes the statistical performance of the BTA-AQP model for predicting monthly average gas concentrations and emissions in 2003. The annual predicted averages and standard deviations (S.D.) of gas concentrations and emissions were in very good agreement with the actual measurements. For all the parameters, the MAE/S.D. (S.D. is the standard deviation of the measured data) ratios were less than 0.5, indicating that the BTA-AQP models' performance for the residual variations were very good. The CRM values approximated to 0, meaning that there was no systematic under- or over- prediction by the BTA-AQP model. The IoA values were close to 1, implying excellent agreement between the observed and predicted values. The Nash-Sutcliffe EF values were greater than 0.5, indicating that the simulated data matched the measured data very well. Therefore, the BTA-AQP model was able to accurately predict indoor climate and gas concentrations and emissions from the monitored swine deep-pit building.

Table 4. Statistical performance of the BTA-AQP models.[a]

Parameter	Actual ± S.D.	Predicted ± S.D.	MAE	CRM	IoA	EF
NH_3Con (ppm)	19.9 ± 6.8	19.8 ± 6.1	0.9	-0.005	0.99	0.95
NH_3ER (kg d^{-1})	6.86 ± 2.04	6.37 ± 1.69	0.63	-0.071	0.94	0.79
H_2SCon (ppb)	553 ± 260	546 ± 260	62	-0.011	0.97	0.87
H_2SER (kg d^{-1})	0.473 ± 0.295	0.463 ± 0.293	0.052	-0.021	0.99	0.94
CO_2Con (ppm)	2636 ± 1618	2633 ± 1556	64	-0.001	0.99	0.99
CO_2ER (kg d^{-1})	1226 ± 280	1153 ± 185	107	-0.059	0.85	0.60

[a] Con and ER indicate the concentrations and emissions, respectively.

Long-term NH_3, H_2S, and CO_2 concentrations and emissions

A comparison was made between the TMY3 data set and the long-term mean weather data and the corresponding air quality predicted by the BTA-AQP model in order to investigate how the air quality values using a TMY3 data set followed actual long-term means. The long-term period of time used in this study was selected from 2004 to 2008 due to the availability of a complete online weather data set in the region near the monitored swine facility. The Des Moines International Airport was chosen as the TMY3 site, which is about 100 kilometers away from the swine facility used for field data collection, since it is the closest Class I site in the Iowa TMY3 data set. Class I stations are those with the lowest uncertainty in weather information. Figure 5 illustrates the relationship between the long-term mean (i.e. on-site 5-year average data) and the TMY3 generated values for outside temperature. The minimum and maximum dashed lines represent the minimum and maximum ranges of the outside temperature during the selected 5-year period (2004-2008). It was observed that the TMY3 data fell within the min-max range but some noticeable differences between the TMY3 and the long-term means were evident especially in February, May, August, and December. The overall absolute error between data sets was 16.3% throughout the year.

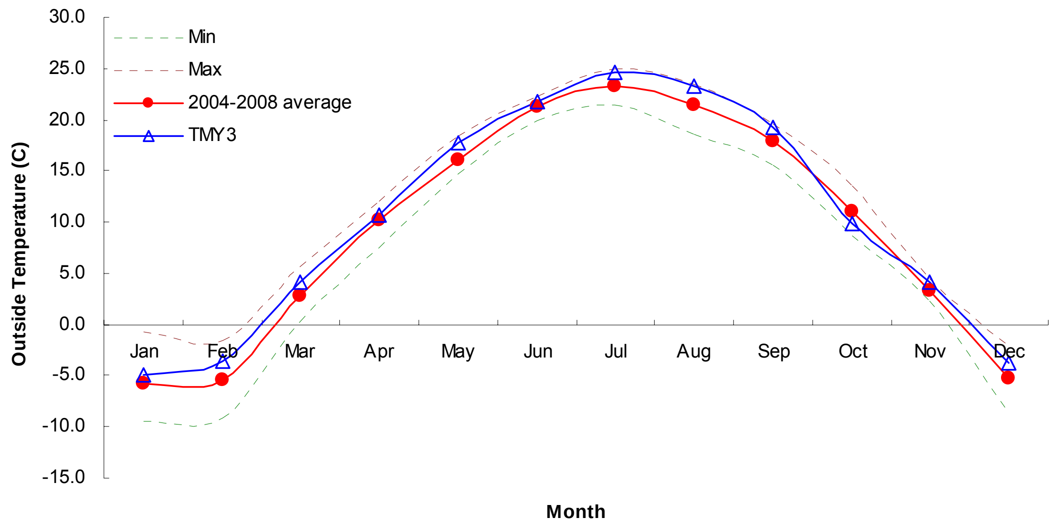


Figure 5. TMY3 vs. long-term mean for the outside temperature.

Figures 6 and 7 summarize monthly ventilation rate and indoor temperature estimated by the BTA model using the TMY3 data set and the on-site 2004-2008 weather data, respectively. The monthly ventilation rate predictions were higher than the long-term means during warm weather but closely matched the long-term means during cold weather conditions (figure 5). This probably was caused by the discrepancy in outdoor temperature between the TMY3 data set and the 2004-2008 weather data, i.e., relatively higher outdoor temperature using the TMY3 in the summer resulted in a higher estimated ventilation rate. Conversely, the predicted indoor temperatures were in good agreement with the long-term means (figure 7). The overall absolute error was less than 2.0%.

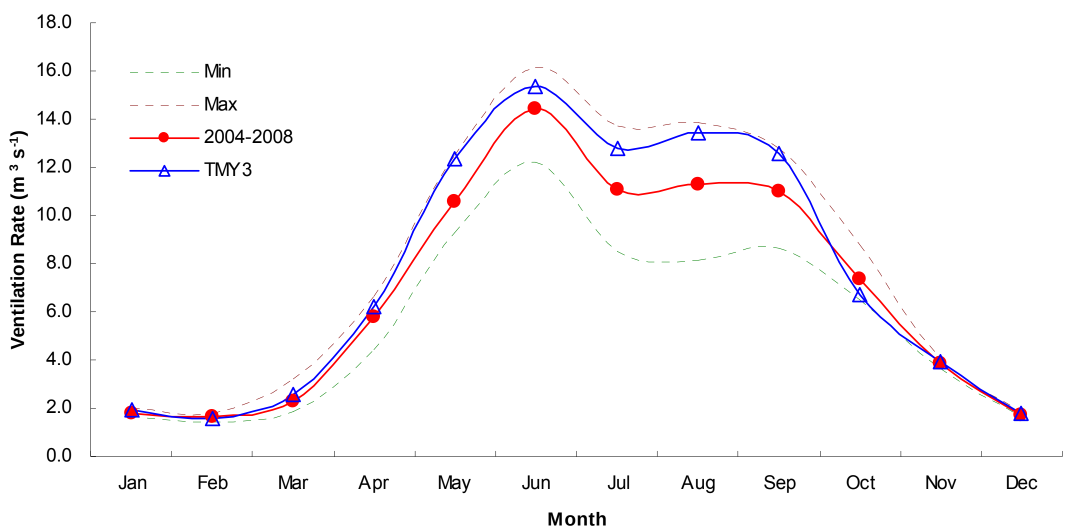


Figure 6. TMY3 vs. long-term mean for the estimated ventilation rate.

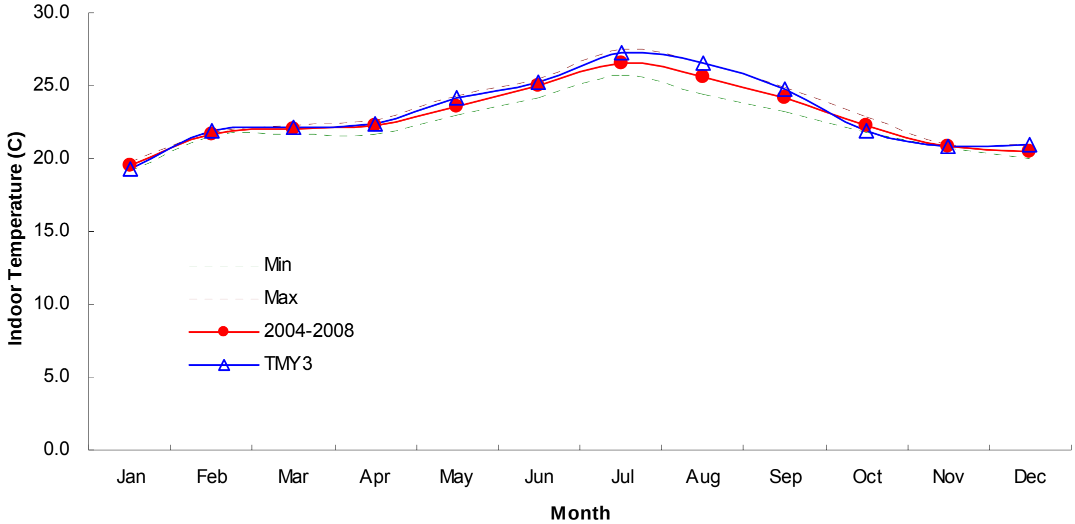
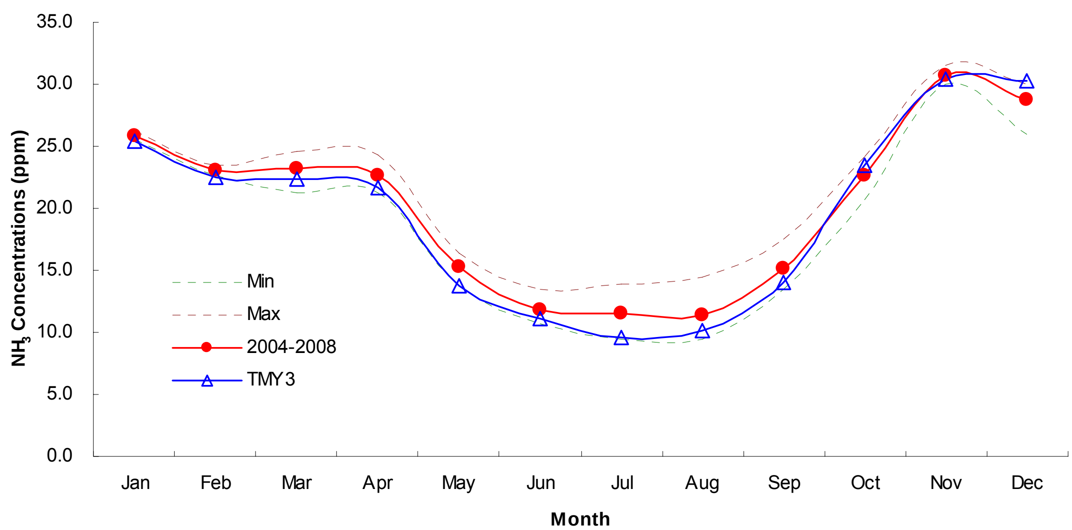
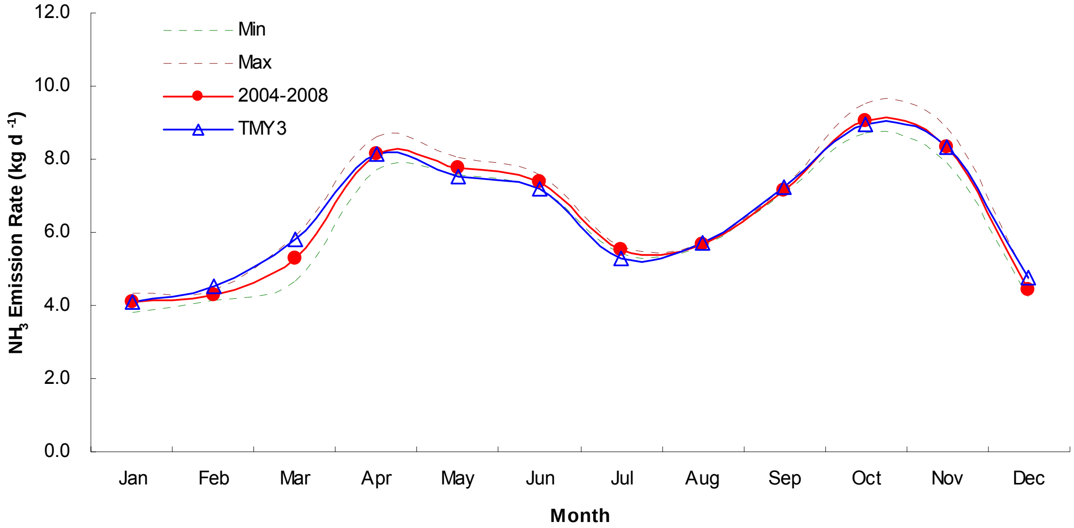


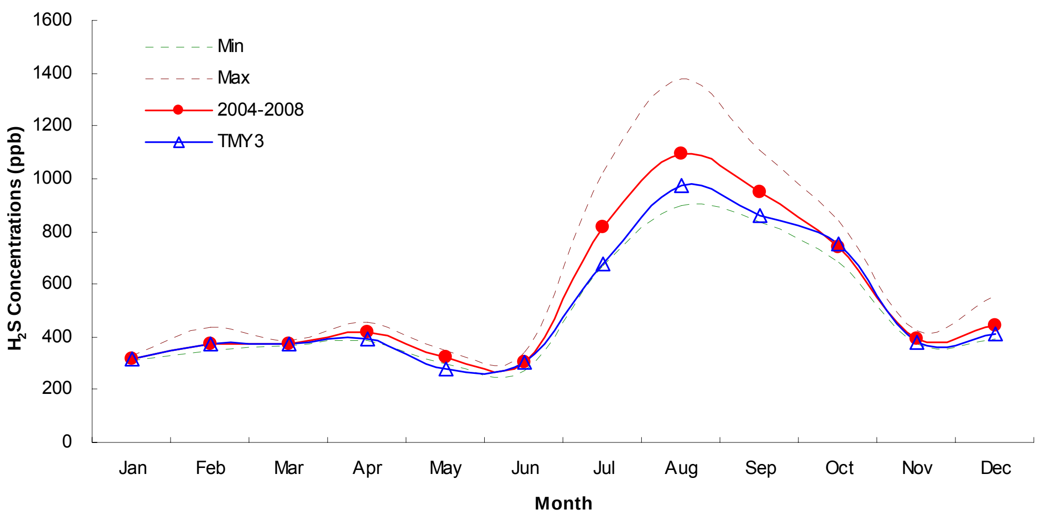
Figure 7. TMY3 vs. long-term mean for the estimated indoor temperature.

The monthly air quality predictions for the TMY3 were compared with the averaged results of the 5-year period and these are shown in figure 8. It was found that the NH_3, H_2S, and CO_2 concentrations and emissions obtained by the TMY3 data set and the long-term air quality means were between the minimum and maximum values of the five individual year simulations, and the TMY3 predictions followed the long-term means well. It can be further seen that the TMY3 values were within 6.1%, 6.1%, and 5.0% of the mean weather year annual total for the NH_3, H_2S, and CO_2 concentrations respectively and 3.0%, 2.7%, and 2.5% of the mean weather year annual total for the NH_3, H_2S, and CO_2 emissions respectively. These good agreements between the TMY3 data set predictions and the long-term means indicate that TMY3 data can be used in performing accurate long-term simulations of source air quality.

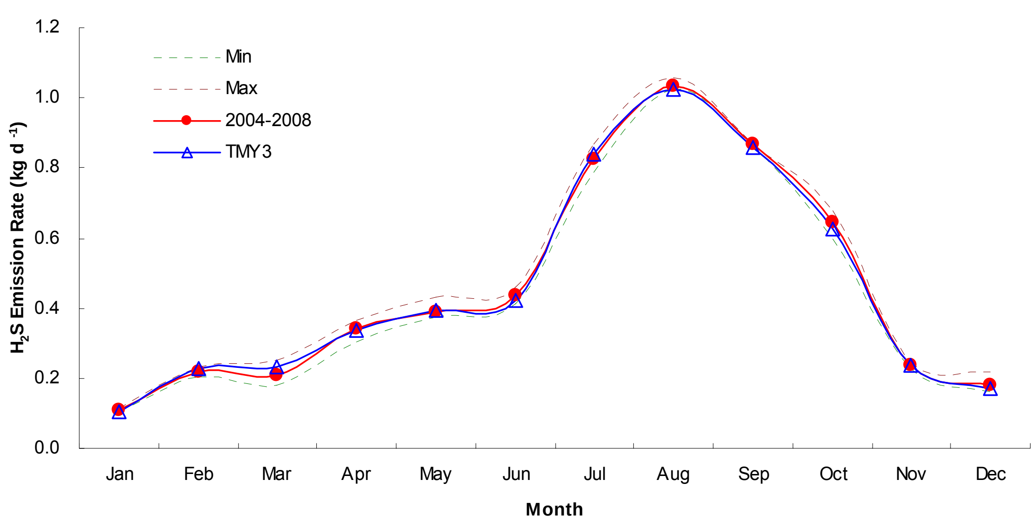




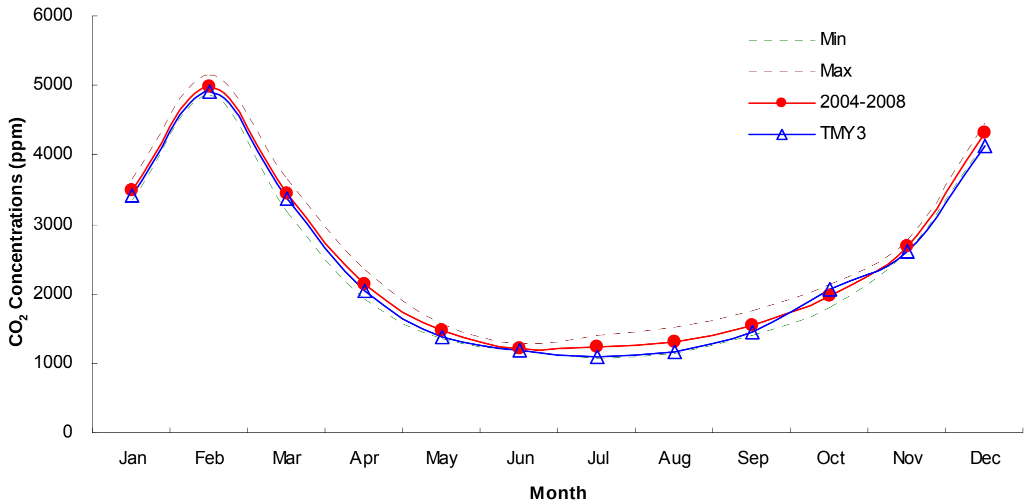
Min
Max
2004-2008
TMY3
NH_3 Emission Rate (kg d^{-1})
12.0
10.0
8.0
6.0
4.0
2.0
0.0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month



Min
Max
2004-2008
TMY3
H_2S Concentrations (ppb)
1600
1400
1200
1000
800
600
400
200
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month



Min
Max
2004-2008
TMY3
H_2S Emission Rate (kg d^{-1})
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month



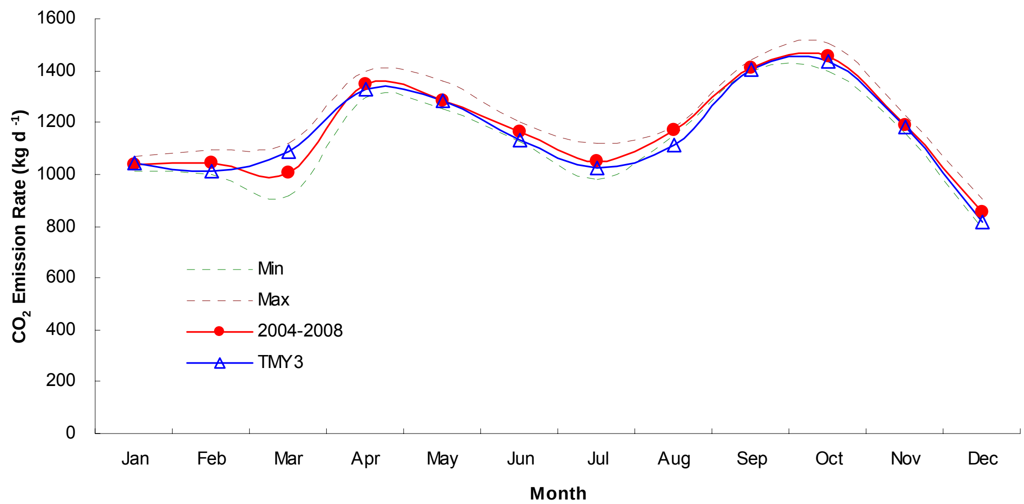


Figure 8. TMY3 vs. long-term mean for the monthly air quality values (NH_3, H_2S and CO_2 concentrations and emissions).

Table 5 gives the absolute errors for comparing predicted annual gas concentrations and emissions using the TMY3 and a single year weather data. No major differences were observed between annual TMY3 and any one single year in terms of air quality values. The minimum AE (2.4%) occurred with CO_2 emissions in 2007 while the maximum AE (10.2%) appeared in H_2S concentration in 2004, which suggests that annual gas concentrations and emissions can be obtained by a TMY3 data set instead of an individual year weather data without resulting in large errors. These results show that a Class I TMY3 data set can be used to evaluate annual air quality levels within an acceptable accuracy, especially for the livestock producers and environment researchers who might not be able to acquire complete and Class I level local weather information near a particular animal facility. However, it should be noted that TMY3 data is not appropriate to estimate peak values for a particulate period of time. Also, it cannot be used for real-time air quality predictions.

Table 5. Comparison of predicted air quality using the TMY3 and a single year.[a]

Year	NH_3Con	NH_3ER	H_2SCon	H_2SER	CO_2Con	CO_2ER
2004	8.4%	2.7%	10.2%	2.7%	6.5%	3.6%
2005	6.1%	4.9%	7.1%	3.3%	5.4%	3.3%
2006	4.9%	4.7%	6.3%	6.8%	4.1%	3.7%
2007	5.3%	3.2%	6.7%	4.3%	5.7%	2.4%
2008	8.6%	4.9%	8.1%	6.6%	7.7%	4.7%

[a] Con and ER indicate concentrations and emissions, respectively.

Overall model error analysis and future work

The developed BTA-AQP model and TMY3 data can be used for accurately predicting indoor climate and long-term gas concentrations and emissions, but improvement in its accuracy should be made according to the following sources of error:

(1) Uncertainties in source air quality data. Since the source air quality data is important to develop the BTA-AQP model and evaluate the model predictive performance, more efforts should be made to maximize confidence, credibility, and consistency of the measured data;

(2) Prediction errors of the BTA model. As the number of assumptions in a model increases, the accuracy and relevance of the model diminishes. For example, the simulated supplemental heaters turning on and off during cold weather resulted in spikes of the predicted ventilation rate and corresponding low indoor temperature. These predictions largely differed from the actual hourly measurements. Thus, more attention should be given to the supplemental heater simulation in future work. The swine heat production data used in this research was from ASABE standards established decades ago. With improved genetics and feed management and diets, swine heat production (HP) has been changed in recent years. Brown-Brandl el al. (2004) reported that the lean percent increase of 1.55% in the last 10 years has caused an increase in HP by approximately 15%. Future work is needed to collect new swine HP data from the latest literature;

(3) Prediction errors of the AQP model. The accuracy of the artificial neural network AQP model depends on the completeness of the data set and availability of various model input factors that significantly affect source air quality. The complete emission profiles should cover all possible swine production stages for a long period of time. In this study, one-year source air quality data was used that might not capture all of the relationships between gaseous concentrations and emissions and theses input factors. More gas measurements are needed to expand the size of the data set. For the model input parameters, more important factors beyond indoor and outdoor temperatures, ventilation rate, swine growth cycle, and in-house manure storage level, should be considered and incorporated in the model. Added variables such as feed nutrient content, management practices, and manure temperature might prove to be important input variables. When pigs grow, the amount and composition of the feed intake change, as do the amount and composition of the manure. Thus, the amount of gas generation tends to increase. However, sharp decreases in the amount of daily nitrogen excretion were found when diet formulation changes were implemented. This adjustment process alleviates the amount of nitrogen in the manure converted to ammonia and other gases. Swine management practices are also vital factors to determine air quality levels. Good management practices can maintain proper environment requirements for the animals and decrease daily air emissions. Manure temperature might be a factor that may directly influence H_2S release; and,

(4) Bias error of the TMY3 and its limited application. Uncertainty values exist in the meteorological elements of the TMY3 data set (NSRDB, 2008). Additionally, TMY3 data is suitable for simulating solar energy conversion systems and building systems since each TMY3 month was selected according to five elements (global horizontal radiation, direct normal radiation, dry bulb and dew point temperatures, and wind speed) which are the most important for solar energy and building systems. No literature has shown that the TMY3 data is suited to air quality predictions as well. Therefore, further research may focus on the development of new TMY data that is determined to be more appropriate for air quality simulations.

Summary and Conclusions

The over-arching goal of this study was to develop a building thermal analysis and air quality predictive (BTA-AQP) model to quantify indoor climate and long-term air quality (ammonia, hydrogen sulfide and carbon dioxide concentrations and emissions) from swine deep-pit buildings.

A comparison was made between the predicted and actual gas concentrations and emissions collected in 2003 in order to evaluate the accuracy of the BTA-AQP model estimates. It was found that the mean absolute errors between the monthly predicted and field collected values were 4.3%, 10.5%, and 2.8% for the NH_3, H_2S, and CO_2 concentrations respectively and 8.3%, 11.1%, and 7.7% for the NH_3, H_2S, and CO_2 emissions respectively. For all the predicted parameters, the MAE/S.D. (S.D. is the standard deviation of the measured data) ratios were less than 0.5; the CRM values approximated to 0; the IoA values were close to 1; and the Nash-Sutcliffe EF values were greater than 0.5. These good model performance ratings indicated that the BTA-AQP model was able to accurately predict indoor climate and gas concentrations and emissions from swine deep-pit buildings.

The monthly air quality values estimated by the BTA-AQP model using TMY3 data were compared with those using 5-year averaged on-site weather data. It was observed that the predictions using TMY3 data followed the long-term mean patterns very well, which suggests that TMY3 data can be used in performing accurate long-term simulations of source air quality. In addition, annual gas concentrations and emissions can be obtained using TMY3 data instead of an individual year weather data without resulting in large errors. These results demonstrate that a convenient approach to evaluate annual air quality levels within an acceptable accuracy is possible without long-term expensive on-site measurements. However, it should be noted that the TMY3 data is not appropriate to estimate peak values for a particulate period of time or for real-time estimates.

Improvement in the BTA-AQP model accuracy should be made according to four main sources of error: Uncertainties in air quality data; Prediction errors of the BTA model; Prediction errors of the AQP model, and Bias errors of the TMY3 data and its limited application.

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