Design of an airborne dust control system in ventilated animal housing

C. M. Liao

Department of Agricultural Engineering, National Taiwan University, Taipei, Taiwan, Republic of China

J. J. R. Feddes

Department of Agricultural Engineering, University of Alberta, Edmonton, Alberta, Canada

The dynamics of a lumped-parameter model for describing the behavior of airborne dust in animal housing are used in the development of controllers for an airborne dust control system. Proportional (P) and Proportional-integral (PI) feedback controllers designed from the viewpoint of modern state-variable control theory are used as an airborne dust control system in ventilated animal housing. Linear quadratic regulators (LQRs) with output feedback control of a linear-invariant system are chosen for this study. The plant is represented by a linear dynamic equation that describes the dynamic behavior of airborne dusts undergoing turbulent diffusive deposition and gravitational settling in a ventilated airspace. To illustrate this procedure, the design was applied to control the dust concentration in typical animal housing.

Keywords: lumped-parameter model, airborne dust, linear quadratic regulator, proportional controller, proportional-integral controller, animal housing

Introduction

Conventional and modern control theories have been well developed. Applications of these control theories to human and animal environmental control systems have been documented by various researchers and can be found elsewhere,[1–6] but these are restricted to the heating and air conditioning system control loop. Also, the environment inside an animal housing structure is very complex and cannot be described simply by temperature. However, temperature can be seen as a primary indicator. Relatively few studies have used control theory, especially modern control theory, in the design of controllers for controlling airborne dust in ventilated animal housing. Airborne dust control systems may include fogging, vacuum cleaning, additional ventilation, and electrostatic removal. For instance, fogging systems are currently used for cooling air and lowering airborne dust concentrations in poultry houses. An infrared dust transducer has been developed to operate and control fogging schedules to lower dust levels in turkey grower facilities.[7]

Address reprint requests to Prof. C. M. Liao at the Dept. of Agricultural Engineering, National Taiwan University, Taipei, Taiwan 10617, Republic of China.

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The objective of this paper is to present initial considerations on the use of optimal control theory methods for designing feedback control systems to efficiently control airborne dusts in ventilated animal housing. Control logic developed for airborne dusts will incorporate other control logic algorithms used for temperature and atmospheric contaminants.

The equation used to describe the dynamic behavior of airborne dusts is a linear dynamic equation developed by the authors,[8] which describes the dynamics of airborne dust undergoing turbulent diffusive deposition and gravitational sedimentation at any location within a ventilated airspace. The linear dynamic equation can be represented by the following vector-matrix differential form:[8]

$$\dot{n}(t) = -Bn(t) + V^{-1}G(t), n(0) = n_o \tag{1}$$

where $\mathbf{n(t)}$ = m-dimensional airborne dust concentration vector

B = $m \times m$ nonsingular transport matrix

V^{-1} = $m \times m$ diagonal inverse matrix of air volume

$\mathbf{G(t)}$ = m-dimensional dust generation rate vector

If the outdoor supplied dust concentration vector, $\mathbf{W(t)}$, is included in equation (1), a more general form of the linear dynamic equation can be expressed as:

$$\dot{n}(t) = An(t) + CG(t) + DW(t), n(0) = n_o \tag{2}$$

in which $A = -B, C = V^{-1}$, and $D = V^{-1}Q_s$. Where Q_s is a $m \times m$ diagonal supplied airflow matrix.

By using modern control theory terminology, the following definitions related to equation (2) can be given as:

n(t) = vector of state variables,
G(t) = vector of controllable input variables, and
W(t) = vector of uncontrollable input variables.

Before designing a controller, there are two important presuppositions related to a model and control problem that require mentioning under the modelling and control inseparability principle.[9]

1. A dynamic model is appropriate for a particular controller. Therefore, a model and controller can be compatible.
2. Only "local" properties can be stated concerning the model and the controller. This means that parameters of neither dynamic model nor controller can be taken to infinity or over a wide range.

Optimal P controller design

To derive the optimal feedback control strategy for the system, the linear quadratic regulator (LQR) with state feedback will be considered. The LQR has been well developed for the past two decades. However, it is not possible or economically feasible to measure all state variables (airborne dust concentrations) at all locations within an animal facility. Therefore, the problem of obtaining the optimal or suboptimal output feedback control of a time-invariant system is most suitable for the system introduced.

The LQR, however, has one shortcoming that makes it inapplicable for a number of practical applications, in that only initial condition or impulse type disturbance can be considered.[10] Therefore, the linear dynamic system with an impulse type disturbance will be considered first. To begin the problem formulation, the modification of equation (2) can be written as:

$$\dot{n} = An + CG, n(0) = n_i \tag{3a}$$

When equation (3a) is subjected to impulsive disturbances

$$W_i(t) = w_i\delta(t), i = 1, 2, \ldots, m \tag{3b}$$

and the output relationship becomes:

$$Z(t) = Hn(t) \tag{3c}$$

where w_i = scalar constant for the ith element of W
$\delta(t)$ = unit impulse function
Z(t) = m-dimensional output variables vector
H = $m \times m$ constant matrix of output state vector **Z(t)**

This modified equation can be seen as equivalent to equation (2) with **n(0)** = **0**, and the impulsive disturbance term becomes $DW(t) = n_i\delta(t)$ (i.e., let $D = n_i$, $W(t) = \delta(t)$). Using control theory terminology, equation (3) becomes the plant. The order of the plant is assumed to be equal to the order of the controller.

Thus, for the given plant in equation (3) an optimal control vector $\hat{G}(t)$ is desired that will minimize the following quadratic cost function, commonly referred to as the performance index:[11]

$$J = \frac{1}{2}\int_0^{t_f} [Z^TXZ + G^TYG]\,dt \tag{4}$$

where t_f = any specific time
X = $m \times m$ positive semidefinite output weighting matrix
Y = $m \times m$ positive definite control weighting matrix

Substituting **Z** = H**n** into equation (4):

$$J = \frac{1}{2}\int_0^{t_f} [n^TH^TXHn + G^TYG]\,dt$$

$$= \frac{1}{2}\int_0^{t_f} [n^TMn + G^TYG]\,dt \tag{5}$$

If the linear plant in equation (3) is observable, then $M = H^TXH$ is positive semidefinite when X is positive semidefinite.

Observability and controllability of the plant are guaranteed if and only if the following matrices:

$$\Xi \equiv [H^T|A^TH^T|\ldots|(A^{m-1})^TH^T], \quad \text{and}$$
$$\theta \equiv [C|AC|\ldots|A^{m-1}C]$$

have rank m, respectively.[11] Because J is a scalar, the weighting matrices X and Y must be symmetric; that is, $X^T = X$ and $Y^T = Y$.

The solution of the optimal control vector $\hat{G}$, which minimizes equation (5), can be given by the following well-known expression:[9,11]

$$\hat{G} = -Y^{-1}C^TP\hat{n} = -Y^{-1}C^TPH^{-1}\hat{Z} \tag{6}$$

where $P = P^T$ is the positive definite solution of the Riccati equation:

$$\dot{P} = -PA - A^TP + PCY^{-1}C^TP - M, P(T) = 0 \tag{7}$$

In addition, the minimum value of a quadratic cost function can be given by:[12]

$$J^* = \frac{1}{2}n_i^TPn_i \tag{8}$$

If T approaches infinity, and the system in equation (3) is observable and controllable in the Kalman sense,[13,14] the optimal control policy becomes a suboptimal controller design problem,[15] and the suboptimal control vector in equation (6) can be expressed by:

$$\hat{G} = -Y^{-1}C^TP^*\hat{n} = -Y^{-1}C^TP^*H^{-1}\hat{Z} \tag{9}$$

where $P^* = P^{*T}$ is the unique, positive definite solution of the following algebraic Riccati equation:

$$-P^*A - A^TP^* + P^*CY^{-1}C^TP^* - M = 0 \tag{10}$$

Because J^* in equation (8) is decreased by choice as $\mathbf{n(0)}$ approaches zero (the desired operating condition), and the airborne dust control system in ventilated animal housing is controlled over a semi-infinite period of time, then, for this infinite time integral quadratic cost function, there is no advantage in choosing a nonzero initial condition on the controller. Therefore, the practical choice of $\hat{n}(0)$ before application of disturbance can be zero.[9]

Equation (9) is the desired optimal feedback controller for the output LQR with initial condition. Equation (9) shows that the control vector $\hat{G}(t)$ is proportional to the state vector $\hat{n}(t)$ and therefore, this procedure can be seen as a modern control theory method for designing a proportional feedback controller (P controller).

Optimal PI controller design

If the disturbance $\mathbf{W(t)}$ becomes a steady-state vector ($\mathbf{W(t) = w}$), then, in the presence of a disturbance, the suboptimal control vector in equation (9) would force the output to change in the direction of the desired equilibrium condition, $\mathbf{Z(t) = 0}$, and consequently the control system changes its output proportionately. Eventually, a steady-state condition will be reached. This behavior may be entirely unacceptable in these regulator applications where output state $\mathbf{Z(t)}$ must be constantly maintained near zero when subjected to a stepwise constant disturbance. Therefore, it is necessary to reformulate the optimal LQR so that the resulting optimal feedback controller always brings the output state $\mathbf{Z(t)}$ to a desired equilibrium condition in the presence of any finite constant disturbance.

The analysis will follow that of Johnson[10] and Pereira et al.[3] on the optimal control of the LQR with constant disturbances. Therefore, when considering again the plant in equation (3), a more general form is as follows:

$$\dot{n} = An + CG + DW, n(0) = n_o, G(0) = G_0 \quad (11a)$$

$$Z = Hn \quad (11b)$$

and is subjected to constant disturbances,

$$W_i(t) = w_i, i = 1, 2, \ldots, m \quad (11c)$$

The quadratic cost function to be minimized can be written as:[10]

$$J = \frac{1}{2}\int_0^{t_f} [Z^T XZ + \dot{G}^T Y\dot{G}]\, dt = \frac{1}{2}\int_0^{t_f} [n^T Mn + \dot{G}^T Y\dot{G}]\, dt \quad (12)$$

where $M = H^T XH$ and X are positive semidefinite, and Y is positive definite.

From a design point of view, the cost function of equation (12) differs from the quadratic function in equation (5) in that the rates of change of control variables are penalized such that large values of control are prohibited indirectly rather than the control variables themselves.[10]

The derivative of equation (11) with respect to time, yields:

$$\ddot{n} = A\dot{n} + C\dot{G}, n(0) = n_o, G(0) = G_0, \quad \dot{n}(0) = An_o + CG_o + DW \quad (13a)$$

$$\dot{Z} = H\dot{n} \quad (13b)$$

and defining the following new variables:

$$\omega \equiv \dot{n}, \theta \equiv \dot{G}, \xi \equiv \dot{Z}$$

Therefore, equations (11) and (13) can be reduced to the following pair of vector-matrix differential equations:

$$\dot{n} = \omega, n(0) = n_o \quad (14a)$$

$$\dot{\omega} = A\omega + C\theta, \omega(0) = An_o + CG_o + DW \quad (14b)$$

$$Z = Hn \quad (14c)$$

$$\xi = H\omega \quad (14d)$$

Equation (14) can be compactly expressed as:

$$\dot{\eta} = A_a\eta + C_a\theta, \eta(0) = \eta_i \quad (15a)$$

$$q = H_a\eta \quad (15b)$$

where

$$\eta = \begin{Bmatrix} \mathbf{n} \\ \omega \end{Bmatrix}, \eta_i = \begin{Bmatrix} \mathbf{n}_o \\ \mathbf{An}_o + \mathbf{CG}_o + \mathbf{DW} \end{Bmatrix}$$

$$A_a = \begin{bmatrix} 0 & I \\ 0 & A \end{bmatrix}, C_a = \begin{bmatrix} O \\ C \end{bmatrix},$$

$$H_a = \begin{bmatrix} H & O \\ O & H \end{bmatrix}, q = \begin{Bmatrix} Z \\ \xi \end{Bmatrix}$$

Therefore, equation (12) in terms of the new variables becomes:

$$J = \frac{1}{2}\int_0^{t_f} [\eta^T M_a \eta + \theta^T Y\theta]\, dt \quad (16)$$

where

$$M_a = \begin{bmatrix} M & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} H^T XH & 0 \\ 0 & 0 \end{bmatrix}$$

M_a becomes positive semidefinite since M is positive semidefinite. Thus, the original output LQR in equations (11) and (12) can be restated in equation (16).

An optimal control vector $\hat{\theta}$ that minimizes equation (16) subject to a given linear plant in equation (15) can be found. This alternative problem is recognized as a LQR. The solution of the optimal control vector is given by the well-known expression:

$$\hat{\theta} = -Y^{-1}C_a^T P\hat{\eta} \quad (17)$$

where $P = P^T$ is the positive definite solution of the Riccati equation:

$$\dot{P} = -PA_a - A_a^T P + PC_a Y^{-1}C_a^T P - M_a, \quad P(T) = 0 \quad (18)$$

If the plant in equation (15) is observable and controllable, then as T approaches infinity in equation (16), the LQR becomes a suboptimal controller design, and the suboptimal control vector in equation (17) becomes:

$$\hat{\theta} = -Y^{-1}C_a^T P^* \hat{\eta} = -Y^{-1}C_a^T P^* H_a^{-1}\hat{q} \tag{19}$$

where $P^* = P^{*T}$ is the unique, positive definite solution of the following algebraic Riccati equation:

$$-P^*A_a - A_a^T P^* + P^* C_a Y^{-1} C_a^T P^* - M_a = 0 \tag{20}$$

Integrating equation (19) with respect to time and using the relations of $\mathbf{Z} = H\mathbf{n}$, the equation becomes:

$$\hat{G}(t) = [L_{12} + L_{22}]H\hat{n}(t) + [L_{11} + L_{21}]H\int_0^t \hat{n}(\tau)\,d\tau + \tilde{G}_o \tag{21a}$$

where:

$$\tilde{G}_o = G_o - [L_{12} + L_{22}]Hn_o \tag{21b}$$

The elements L_{ij} in equation (21) are appropriately partitioned submatrices of $[-Y^{-1}C_a^T P^* H_a^{-1}]$.

This is the desired optimal feedback controller to the original LQR with external constant disturbances as defined in equations (11) and (12). The optimal control can be expressed as a combination of a linear function of the state vector and the first time integral of a certain other linear function of the state vector. For a proposed cost function, the optimal control is explicitly independent of the disturbance. Thus, this procedure can be seen as a modern control theory method for designing the proportional plus integral feedback controller (PI controller). A flowchart of the communication process

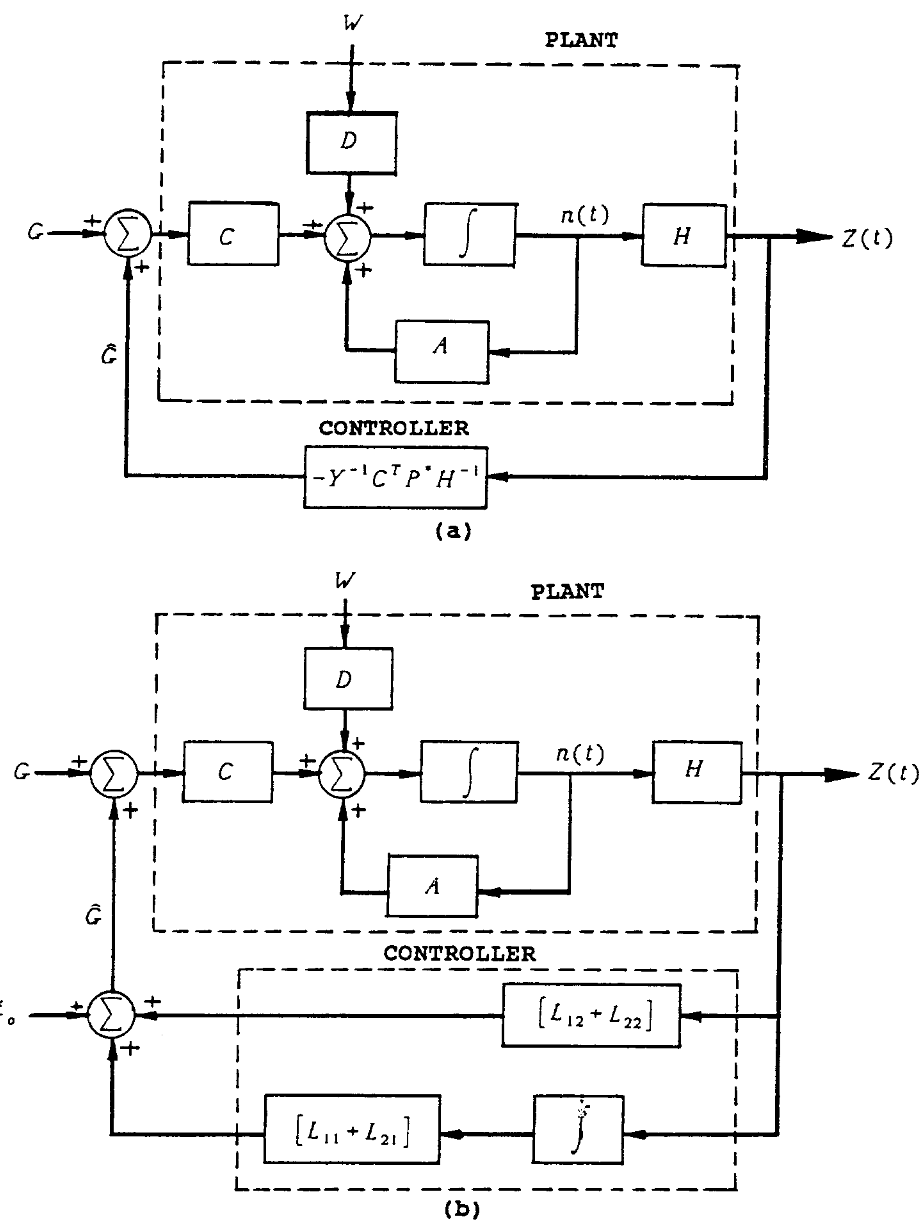

Figure 1. Block diagram of message process and optimal controllers: (a) Optimal P controller and (b) optimal PI controller.

and the optimal P and PI controllers for control system structure is shown in *Figure 1*.

A numerical example

The objective of this section is to evaluate the performance of P and PI feedback controllers in a typical animal housing application. The example will illustrate the procedure and the performance of these controllers compared with each other. For simplicity, a two-lump model of a typical ventilated animal housing unit with a negative pressure ventilation system will be considered. The geometric and system parameters used in this numerical example are listed in *Table 1*.[8]

In a two-lump model, the optimal P controller can be expressed by equation (9):

$$\hat{G} = -Y^{-1}C^TP^*\hat{n} = K\hat{n} \tag{22}$$

where K is a feedback gain matrix.

When carrying out the matrix multiplication the equation can be written as:

$$\begin{bmatrix} \hat{G}_1(t) \\ \hat{G}_2(t) \end{bmatrix} = \begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix} \begin{bmatrix} \hat{n}_1(t) \\ \hat{n}_2(t) \end{bmatrix} \tag{23}$$

The matrix K contains four feedback gains, k_{11}, k_{12}, k_{21}, and k_{22}, which are computed for the optimal P controller.

For the optimal PI controller, equation (21) is appropriate for a two-lump model:

$$\begin{bmatrix} \hat{G}_1(t) \\ \hat{G}_2(t) \end{bmatrix} = \begin{bmatrix} k_{11} & k_{12} & k_{13} & k_{14} \\ k_{21} & k_{22} & k_{23} & k_{24} \end{bmatrix} \begin{bmatrix} \int_0^t \hat{n}_1(\tau)\,d\tau \\ \int_0^t \hat{n}_2(\tau)\,d\tau \\ \hat{n}_1(t) \\ \hat{n}_2(t) \end{bmatrix} + \begin{bmatrix} G_{01} \\ G_{02} \end{bmatrix} - \begin{bmatrix} k_{13} & k_{14} \\ k_{23} & k_{24} \end{bmatrix} \begin{bmatrix} n_{01} \\ n_{02} \end{bmatrix} \tag{24}$$

Thus for the optimal PI controller, there are eight feedback gains, $k_{13}, k_{14}, k_{11}, k_{12}, k_{23}, k_{24}, k_{21}$, and k_{22}, that need to be determined.

Table 1. Input parameters used in the numerical example[8].

Geometric parameters
System volume = 120 m^3 (10 × 6 × 2 m)
System surface = 64 m^2
System height = 2 m
System parameters
Ventilation airflow rate during cold weather = 420 m^3/hr
Entrainment ratio = 5.0 (slot width = 10 cm)
Temperature = 20°C, RH = 30–40% (1 atm)
Average particle radius = 2.5 μm
Reynolds number = 2000–3000
Particle settling velocity = 0.0776 cm/sec
Effective diffusion coefficient = 0.00375 cm^2/sec
Concentration boundary layer thickness = 0.085 cm

The outdoor airborne dust concentration, W_1, is supplied to the upper zone and undergoes a sudden step change. Specifically, W_1 changes from $W_1 = 0$ to $W_1 = 50$ particles/cm^3. It is assumed that an indoor disturbance occurs as a result of animal activity in the building. As a result, the indoor dust source, G_2, undergoes a sudden step change. Specifically, G_2 changes from $G_2 = 0$ to $G_2 = 3 \times 10^8$ particles/min. The above disturbance is simulated under the optimal P and PI regulating actions and presented graphically.

The first step in numerical investigation is to determine matrices A, C, and H. The determinations of A and C are followed by the definitions already developed by the authors.[8] Matrix H in the output relationship, $\mathbf{Z} = H\mathbf{n}$, is selected as a diagonal matrix. The values of h_{11} and h_{22} may be chosen from the results of model verification between model predictions (state variables) and measurements (outputs) for a lumped-parameter model presented by the authors.[16] These values are $h_{11} = 1.1$ and $h_{22} = 1.3$, respectively.

Having defined the matrices A, C, and H, the state controllability and observability of the systems then can be verified. Next, the effect of weighting matrices X and Y in the quadratic cost functions was investigated. Usually X and Y are selected to be diagonal.

The corresponding scalar expressions of the quadratic cost function for a two-lump model in optimal P and PI control systems can be attained by equations (4) and (12):

$$J = \frac{1}{2}\int_0^\infty (x_{11}Z_1^2 + x_{22}Z_2^2 + y_{11}G_1^2 + y_{22}G_2^2)\,dt \tag{25}$$

$$J = \frac{1}{2}\int_0^\infty (x_{11}Z_1^2 + x_{22}Z_2^2 + y_{11}\dot{G}_1^2 + y_{22}\dot{G}_2^2)\,dt \tag{26}$$

Weighting matrices can be chosen in the following way to achieve specified performance bounds:[17]

$$\int_0^\infty Z_i^2(t)\,dt \le \sigma_i^2, \quad \text{and}$$

$$\int_0^\infty G_i^2(t)\,dt \le \mu_i^2, \quad i = 1, 2 \tag{27}$$

The root mean squared (RMS) values of the multiple outputs and inputs can be used to determine the performance bounds:

$$Z_{iRMS} = \left[\int_0^\infty Z_i^2(t)\,dt\right]^{1/2}, \quad \text{and}$$

$$G_{iRMS} = \left[\int_0^\infty G_i^2(t)\,dt\right]^{1/2}, \quad i = 1, 2 \tag{28}$$

In this particular case, it may be required to simultaneously limit the RMS values of output airborne dust concentrations as, $Z_{1RMS} \le 30$ particles/cm^3, $Z_{2RMS} \le$

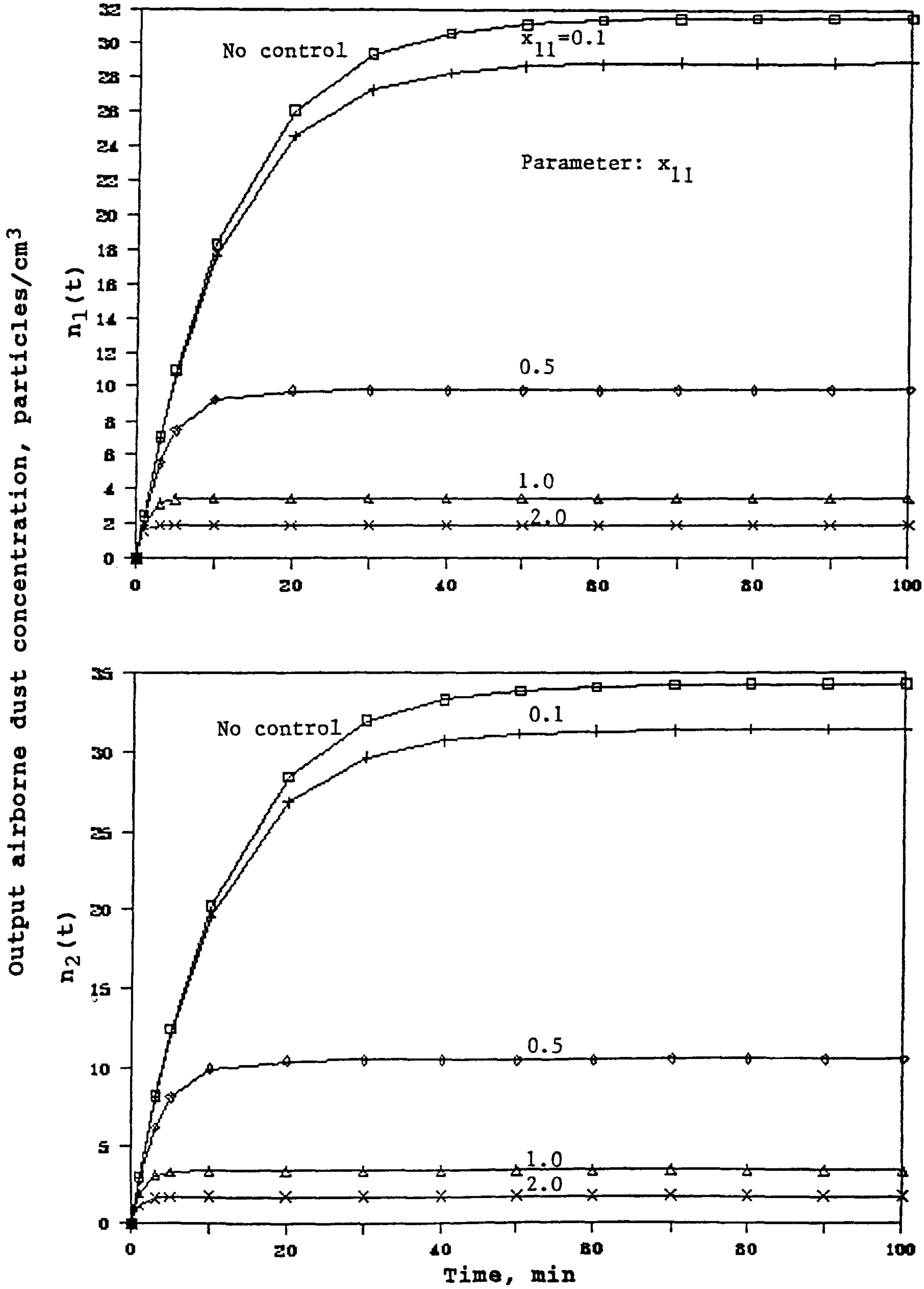

Figure 2. Transient responses of airborne dust concentration in upper ($n_1(t)$) and animal zones ($n_2(t)$) under optimal P control.

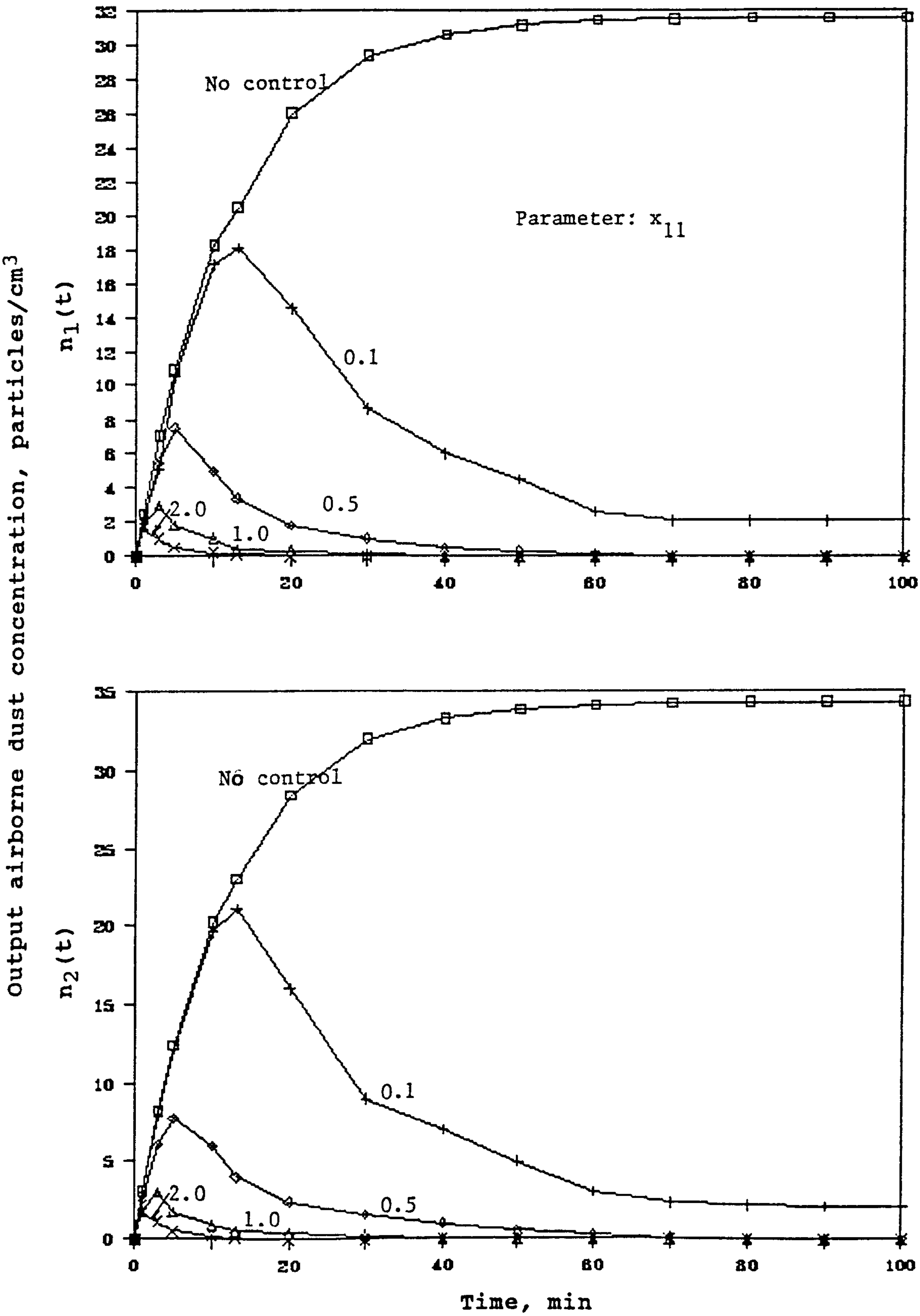

Figure 3. Transient responses of airborne dust concentration in upper ($n_1(t)$) and animal zones ($n_2(t)$) under optimal PI control.

10 particles/cm^3, and the RMS values of input dust generation rate as, $G_{1RMS} \leq 10^8$ particles/min, $G_{2RMS} \leq 10^9$ particles/min. Because no general criterion could be found, it is assumed that $G_{1RMS} = \dot{G}_{1RMS}$, and $G_{2RMS} = \dot{G}_{2RMS}$.[3]

Having determined the values of Z_{1RMS}, G_{1RMS}, Z_{2RMS}, and G_{2RMS}, the elements in the weighting matrices can be calculated as follows by a scaling factor method:[3] In equation (25), let $x_{11}Z_{1RMS}^2 = x_{22}Z_{2RMS}^2$, then $x_{11}/x_{22} = Z_{2RMS}^2/Z_{1RMS}^2 = 0.11$, and therefore, $x_{22} = 9.09x_{11}$; and similarly $y_{22} = 10^{-2}y_{11}$. In this numerical example, y_{11} is kept constant throughout at 1, and only x_{11} is varied. The approach to the numerical solution of the nonlinear algebraic Riccati equation is followed by a simple nonrecursive method,[18] which is applicable to the case of nonsingularity of matrix A in the plant.

Figures 2 and *3* show the transient responses of n_1 and n_2 under the control efforts of the optimal P and PI controllers, respectively. In both figures, the responses were governed by the parameter x_{11}. The success of these manipulations on control efforts can be achieved by adjusting the specified performance bounds for output and input variables to properly select the weighting matrices.

In optimal P control (*Figure 2*), response is governed by an amount proportional to output. Thus there will always be a steady-state offset or overshoot from the desired equilibrium condition. This can be reduced by increasing the values of x_{11}, or feedback gains, but with increasing possibility of instability. Therefore, the optimal P control is designed to have a feedback gain that optimizes the tradeoff between time delay for the system to respond to steady-state offset and system stability.

A better way to eliminate the steady-state offset is to modify the control action by an integral of output, i.e., PI control action (*Figure 3*). *Figure 3* shows that the optimal PI control results from the responses of exhaust airborne dust concentration in a damped form that quickly approaches a desired equilibrium condition with no overshoot. Therefore, when comparing *Figures 2* and *3*, the PI control action is recognized as preferable to that of P control.

Summary and conclusions

In this paper, the dynamics of a lumped-parameter model for describing the behavior of airborne dust in animal housing are used in the development of controllers for an airborne dust control system. The controllers employ microcomputers, not only to perform control calculations but also for other monitoring and recording operations.

Proportional (P) and proportional-integral (PI) feedback controllers have been designed from the viewpoint of a modern state-variable control theory method for an airborne dust control system in ventilated animal housing. The optimization and suboptimization of the linear quadratic regulators (LQRs) with output feedback of a linear-invariant system are defined to determine an output feedback control loop such that the integral quadratic cost function meets its minimum value. Both initial condition and constant external disturbances are formulated, and the optimal P and PI controllers are synthesized. In the numerical example, the optimal P and PI control have been simulated and compared with each other in a typical animal housing application. The result shows that the PI controller is preferable to the P controller.

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