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Moving Horizon Control and Estimation of
Livestock Ventilation Systems and Indoor Climate ⋆

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Abstract: In this paper, a new control strategy involves exploiting actuator redundancy in a multi-variable system is developed for rejecting the covariance of the fast frequency disturbances and pursuing optimum energy solution. This strategy enhances the resilience of the control system to disturbances beyond its bandwidth and reduce energy consumption through on-line optimization computation. The moving horizon estimation and control (also called predictive control) technology is applied and simulated. The design is based on a coupled mathematical model which combines the hybrid ventilation system and the associated indoor climate for poultry in barns. The comparative simulation results illustrate the significant potential and advancement of the moving horizon methodologies in estimation and control for nonlinear Multiple Input and Multiple Output system with unknown noise covariance and actuator saturation.

1. INTRODUCTION

The objective of this work is to design a control strategy to improve the performance of a hybrid ventilation system and associated indoor environment for livestock barns, where hybrid ventilation systems combine the natural ventilation and mechanical ventilation (Heiselberg [2004]). As shown in Fig. 1, the full scale livestock ventilation system consists of evenly distributed exhaust units mounted in the ridge of the roof and fresh air inlet openings installed on the side walls. From the view of direction A and B, Fig. 1(a) and 1(b) provide a description of the dominant air flow map of the building including the airflow interaction between each conceptual zone.
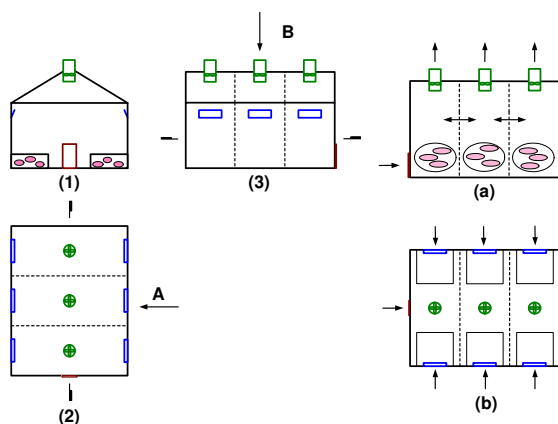

Fig. 1. Synoptic of Full-scale Livestock Barn

Traditionally, the livestock ventilation system has been controlled using classical SISO controllers through single zone analysis. The challenge of this work is to introduce a more efficient and comprehensive multi-variable control scheme to allow a better trade off between the optimum performances of indoor climate and energy consumption saving. The controller mainly focuses on minimizing the variation of the indoor temperature and concentration level, keeping both variables within the Thermal Neutral Zone (TNZ) (der Hel et al. [1986] and Geers et al. [1991]) in the presence of actuator saturation, random noise, and disturbances at different frequencies.

Dynamic optimization implemented in moving horizon estimation and control has successfully been applied to a number of industrial processes in order to realize the ambitions of lowering production costs, increasing asset utilization, and improving product quality by reducing the variability of key process quality indicators (Jorgensen [2005]). The applications are mainly for the economically important, large-scale, multi-variable processes, and the rationale is that this optimization formulated control algorithm can deal with strong non-linearities, handle constraints and modeling errors, fulfill offset-free tracking, and is easy to tune and implement (Maciejowski [2002], Rossiter [2003], Qin and Badgwell [2003] and Pannocchia et al. [2005]).

An actuator redundancy is exploited to accommodate the limitation of the bandwidth of the closed-loop system as well as pursuit of an optimum energy solution through on-line optimization computation. By assigning different weights in the objective function which is based on energy consumption considerations, according to the covariance of the fast frequency disturbances, the modified optimal control command are reassigned to the actuators.

The comparative simulation results derived from the control system with dynamic optimization of moving horizon imple-

mentation with the nominal control method are illustrated. Most importantly, the output performances with and without actuator redundancy in the presence of disturbances are demonstrated. The proposed methods in this paper proved to be fruitful for its high potential and advanced advantages.

2. PROCESS DYNAMIC MODEL

Based on the so called conceptual multi-zone method, the livestock building is divided into several macroscopic homogeneous conceptual zones horizontally so that the nonlinear differential equations governing the thermal comfort and indoor air quality can be derived based on the energy balance equation for each zone. The inlet system provides variable airflow directions and controls the amount of incoming fresh air by adjusting the bottom hanged flaps. In the exhaust unit, the airflow capacity is controlled by adjusting the r.p.m. of the fan impeller and by means of the swivel shutter. Basically, the zone division is according to the number of the operating exhaust fans. For a detailed description for developing, simplifying and coupling of the models and significant dynamic parameters estimation, we refer to Wu et al. [2005], Wu et al. [2007] and Wu et al. [2008].

We regard the livestock ventilation system as consisting of two parts by noting that the overall system consists of a static air distribution system (inlet-exhaust air flow system) and a dynamic environmental system (thermal comfort and indoor air quality). The two parts are interconnected through air flow rate. This strongly coupled Multiple Input and Multiple Output (MIMO) dynamic nonlinear system is expressed as an LTI state space model around the equilibrium point

$$x(k+1) = A \cdot x(k) + B \cdot u(k) + B_d \cdot \begin{bmatrix} d_{umd}(k) \\ d_{md}(k) \end{bmatrix}, \quad (1a)$$

$$y(k) = C \cdot x(k) + D \cdot u(k) + D_d \cdot \begin{bmatrix} d_{umd}(k) \\ d_{md}(k) \end{bmatrix}, \quad (1b)$$

where, $A \in \mathbb{R}^{6\times6}$, $B \in \mathbb{R}^{6\times9}$, $C \in \mathbb{R}^{6\times6}$, $D \in \mathbb{R}^{6\times9}$, $B_d \in \mathbb{R}^{6\times12}$, $D_d \in \mathbb{R}^{6\times12}$ are the coefficient matrices. The disturbance transient matrices B_d and D_d are formulated as (2) corresponding to the unmeasured and measured disturbances.

$$B_d = [B_{dumd} \ B_{dmd}], D_d = [D_{dumd} \ D_{dmd}]. \quad (2)$$

x, y, u, d_{umd}, d_{md} denote the sequences of vectors representing the deviation variable values of the process state of zonal temperature x_T and carbon dioxide concentration x_C, the controlled output, the manipulated input which consists of the valve openings and voltage supplied to the fans, the unmeasurable disturbances of animal heat and carbon dioxide generation, the measurable disturbances as the wind speed, wind direction, ambient temperature and concentration level. The representation of these vectors is shown in (3)

$$x = \begin{bmatrix} \bar{T}_1 & \bar{T}_2 & \bar{T}_3 & \bar{C}_{r,1} & \bar{C}_{r,2} & \bar{C}_{r,3} \end{bmatrix}^T_{6\times1}, \quad (3a)$$

$$u = \begin{bmatrix} \bar{A}_{in,i=1...6} & \bar{V}_{volt,j=1...3} & \bar{\theta}_{shutter,j=1...3} \end{bmatrix}^T_{12\times1}, \quad (3b)$$

$$d_{umd} = \begin{bmatrix} \bar{Q}_1 & \bar{Q}_2 & \bar{Q}_3 & \bar{G}_1 & \bar{G}_2 & \bar{G}_3 \end{bmatrix}^T_{6\times1}, \quad (3c)$$

$$d_{md} = \begin{bmatrix} \bar{V}_{ref} & \bar{c}_{P,w} & \bar{c}_{P,l} & \bar{c}_{P,r} & \bar{T}_o & \bar{C}_{r,o} \end{bmatrix}^T_{6\times1}. \quad (3d)$$

Concluded from systematical analysis for the developed process model, the pair (A,B) is controllable, (C,A) is observable, and the plant is stable.

3. MODEL PREDICTIVE CONTROL

Moving horizon estimation and control is implemented through dynamic optimization calculations. These calculations are repeated and conducted on-line each time when new information such as process measurements become available, the horizon of the estimator and the regulator are shifted one sample forward. At each time, the dynamic optimization considers a fixed window of past measurements to estimate the current state of the system. This estimated state is used along with the model to forecast the process behavior for a fixed time-window into the future. The dynamic optimization computes the optimal sequence of manipulable variables so that the predicted process behavior is as desirable as possible subject to the physical and operational constraints of the system. Only the first element in the sequence of optimal manipulable variables is implemented on the process.

3.1 Target Calculation

As discussed in Rao and Rawlings [1999] and Rawlings [2000], the target tracking optimization could be formulated as a least-square objective function (4), subjected to the constraints in (5), in which the steady state target of input and state vector u_s and x_s can be determined from the solution of the following computation when tracking a nonzero target vector z_t. The objective of the target calculation is to find the feasible triple (z_s, x_s, u_s) such that z_s and u_s are as close as possible to z_t and u_t, where u_t is the desired value of the input vector at steady state, and, $z_s = Cx_s$.

$$\min_{[x_s,u_s]^T} \Psi = (u_s - u_t)^T R_s (u_s - u_t) \quad (4)$$

$$s.t. \begin{cases} \begin{bmatrix} I-A & -B \\ C & 0 \end{bmatrix} \begin{bmatrix} x_s \\ u_s \end{bmatrix} = \begin{bmatrix} 0 \\ z_t \end{bmatrix} \\ u_{\min} \leq u_s \leq u_{\max} \end{cases} \quad (5)$$

In this quadratic program, R_s is a positive definite weighting matrix for the deviation of the input vector from u_t. The equality constraints in (5) guarantee a steady-state solution and offset free tracking of the target vector. In order to guarantee the uniqueness of the solution, the system must be detectable. A detectable system also guarantees the nominal stability of the regulator (Rao and Rawlings [1999]). The methods for checking detectability are provided in Muske and Badgwell [2002] and Pannocchia and Rawlings [2003].

3.2 Moving Horizon Control

Constrained Optimization   In Muske and Rawlings [1993b], the moving horizon control by a quadratic cost function (6) on finite horizon, subjected to the linear equality and inequalities (7) formed by the system dynamics (1) and constraints are proposed. The following optimization problem with the exact soft constraints is proposed in Scokaert and Rawlings [1999].

$$\min_{u^N} \Phi_k^N = \sum_{j=1}^N \frac{1}{2} \|z_{k+j} - r_{k+j}\|_{Q_z}^2 + \frac{1}{2} \|\eta_k\|_{S_\eta}^2 + s_\eta' \eta_k$$
$$+ \frac{1}{2} \sum_{j=0}^{N-1} \|\Delta u_{k+j}\|_S^2 + \|u_{k+j} - u_s\|_R^2, \quad (6)$$

$$s.t. \begin{cases} x_{k+j+1} = Ax_{k+j} + Bu_{k+j} + B_d d_{k+j} \\ z_{k+j} = Cx_{k+j} \\ z_{\min} \le z_{k+j} \le z_{\max}, j = 1, 2, \cdots N \\ u_{\min} \le u_{k+j} \le u_{\max}, j = 0, 1, \cdots N-1 \\ \Delta u_{\min} \le \Delta u_{k+j} \le \Delta u_{\max}, j = 0, 1, \cdots N-1 \end{cases} \quad (7)$$

where, Φ is the performance index to be minimized by penalizing the deviations of the output $\hat{z}_{k+j}$ from the reference r_{k+j}, the slew rate of actuator Δu_{k+j} and the control input u_{k+j} from the desired steady states u_s at time j. The steady state input vector u_s can be determined from the solution of target calculation. $Q_z \in \mathbb{R}^{6 \times 6}$ and $S \in \mathbb{R}^{9 \times 9}$ are symmetric positive semi-definite penalty matrices for process states and rate of input change, $R \in \mathbb{R}^{9 \times 9}$ is a symmetric positive definite penalty matrix. η_k is a slack variable introduced in both the quadratic and linear terms with coefficient S_η and s_η to relax output constraints and avoid infeasible mathematical programs. The vector u^N contains the N future open-loop control moves as shown below

$$u^N = \begin{bmatrix} u_k \\ u_{k+1} \\ \vdots \\ u_{k+N-1} \end{bmatrix}. \quad (8)$$

At time $k+N$, the input vector u_{k+j} is set to zero and kept at this value for all $j \ge N$ in the optimization calculation. Since the plant is stable, according to the parametrization method proposed in Muske and Rawlings [1993b], the end prediction $z_{k+1} = CAx_k$, implies $z_k = CA^{k-N}x_N$ for $k \ge N$ such that

$$\sum_{k=N}^{\infty} z_k^T Q z_k = x_N^T \left(\sum_{k=N}^{\infty} \left(CA^{k-N} \right)^T QCA^{k-N} \right) x_N = x_N^T Q_N x_N, \quad (9)$$

in which, Q_N may be computed from the Lyapunov equation

$$Q_N = \sum_{k=N}^{\infty} \left(CA^{k-N} \right)^T QCA^{k-N} = \sum_{j=0}^{\infty} \left(CA^j \right)^T QCA^j \quad (10)$$
$$= C^T QC + A^T Q_N A.$$

It proved to be clear that the solution generated from the finite horizon optimization formulation with a terminal equality constraint is the approximate solution to the infinite horizon linear quadratic optimal control problem for stable systems. The selection of horizon N has been subject of extensive research (Muske and Rawlings [1993a], Rawlings and Muske [1993], Scokaert and Rawlings [1998], and Mayne et al. [2000]).

Unconstrained Optimization The feedback gain of moving horizon control derived from the unconstrained linear quadratic optimization, together with the estimator gain derived from Kalman Filter provide the framework for analyzing properties such as the stability and bandwidth of the system in frequency domain. The formulation of finite horizon quadratic programming without constraint has been discussed in Rawlings and Muske [1993] for stability analysis.

$$\min_{u^N} \Phi_k^N = \frac{1}{2} u^{N\prime} H u^N + g' u^N \quad (11)$$

in which, $H = \Gamma^T Q_z \Gamma + H_S$ is the hessian matrix, $g = M_{x_0} x_0 + M_R R + M_{u_{-1}} u_{-1} + M_D D$, $M_{x_0} = \Gamma^T Q_z \Phi$, $M_R = -\Gamma^T Q_z$, $M_D = \Gamma^T Q_z \Gamma_D$

$$\Phi = \begin{bmatrix} C_z A \\ C_z A^2 \\ \vdots \\ C_z A^N \end{bmatrix}, \Gamma = \begin{bmatrix} H_1 & 0 & 0 & \cdots & 0 \\ H_2 & H_1 & 0 & \cdots & 0 \\ H_3 & H_2 & H_1 & & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ H_N & H_{N-1} & H_{N-2} & \cdots & H_1 \end{bmatrix}$$

$$\Gamma_D = \begin{bmatrix} H_{1,d} & 0 & 0 & \cdots & 0 \\ H_{2,d} & H_{1,d} & 0 & \cdots & 0 \\ H_{3,d} & H_{2,d} & H_{1,d} & & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ H_{N,d} & H_{N-1,d} & H_{N-2,d} & \cdots & H_{1,d} \end{bmatrix}, \quad (12)$$

$$H_S = \begin{bmatrix} 2S & -S & \cdots & 0 \\ -S & 2S & -S & \cdots & \vdots \\ & & \ddots & & \\ \vdots & \cdots & -S & 2S & -S \\ 0 & \cdots & & -S & S \end{bmatrix}, M_{u_{-1}} = - \begin{bmatrix} S \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

where, $H_i = CA^{i-1}B, H_{i,d} = CA^{i-1}B_d$, for $1 \le i \le N$. The optimal u^N could be found by taking gradient of Φ_k and set it to zero. The first control move u_k at current time k will be applied to the plant.

$$u_k = K_{MPC} \cdot \begin{bmatrix} x_0 \\ R \\ u_{-1} \\ D_d \end{bmatrix} \quad (13)$$

where, S_H is the square root of the hessian matrix $H = S_H^T S_H$

$$S_H^T S_H K_{x0} = -M_{x0} \quad (14a)$$
$$S_H^T S_H K_R = -M_R \quad (14b)$$
$$S_H^T S_H K_{u-1} = -M_{u-1} \quad (14c)$$
$$S_H^T S_H K_D = -M_D \quad (14d)$$

therefore,

$$K_{full} = [K_{x0} \ K_R \ K_{u-1} \ K_D] \quad (15)$$

and,

$$K_{MPC} = K_{full}(1 : \ell, :) \quad (16)$$

Figure 2 demonstrates the structure of the entire feedback control system with estimator and the control law described in 13 with derived feedback gain 15.
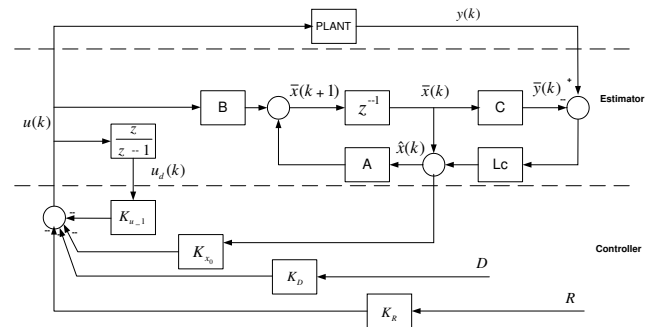

Fig. 2. Structure of the Feedback Control System

3.3 Moving Horizon Estimation

The linear Moving Horizon Estimation (MHE) solves the constrained linear least square problem is expressed as the constrained linear quadratic optimization (17) and (18). This for-

mulation of MHE was first proposed by Muske et al. [1993] and Robertson et al. [1996].

$$\min_{\left[\hat{x}_{k-N/k},\hat{w}^N\right]} \Psi_k^N = \frac{1}{2}\left\|\hat{x}_{k-N/k}-\bar{x}_{k-N/k-N-1}\right\|_{P_{k-N}^{-1}}^2$$

$$+\frac{1}{2}\sum_{j=k-N}^{k-1}\left\|w_{j/k}\right\|_{Q_w^{-1}}^2+\left\|v_{j/k}\right\|_{R_v^{-1}}^2 \tag{17}$$

$$s.t. \begin{cases} x_{k+j+1}=Ax_{k+j}+Bu_{k+j}+B_d d_{k+j}+Gw_{k+j} \\ z_{k+j}=Cx_{k+j}+v_{k+j} \\ x_{\min}\le\hat{x}_{k-N/k}\le x_{\max} \\ w_{\min}\le\hat{w}_k\le w_{\max} \\ z_{\min}\le z_k\le z_{\max} \end{cases} \tag{18}$$

The estimator selects the state $x_{(k-N/k)}$, a sequence of process noise $\left\{w_{j/k}\right\}_{j=k-N}^k$ and a sequence of measurement noise $\left\{v_{j/k}\right\}_{j=k-N}^k$ such that the agreement with the measurement $\left\{y_{j/k}\right\}_{j=k-N}^k$ is as good as possible while still respecting the process dynamics, the output relation, and the constraints.

$$\begin{bmatrix} w \\ v \end{bmatrix}\sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix},\begin{bmatrix} Q_w & 0 \\ 0 & R_v \end{bmatrix}\right) \tag{19}$$

$$x_{k-N/k-N-1}\sim N\left(\bar{x}_{k-N/k-N-1},\,P_{k-N/k-N-1}\right) \tag{20}$$

As described in Rao and Rawlings [2000], Rao [2000], Tenny and Rawlings [2002], and Rao and Rawlings [2002], the covariance P_{k-N} is derived by the solution of the Lyapunov Equation $P_{k-N}=\bar{A}^T P_{k-N}\bar{A}+\bar{G}^T\bar{Q}\bar{G}$, in which,

$$\bar{A}=[A-ALC],\bar{G}=[G\ -AL],\bar{Q}=\begin{bmatrix} Q_w & 0 \\ 0 & R_v \end{bmatrix}. \tag{21}$$

To achieve offset-free control of the output to their desired targets at steady state, in the presence of plant/model mismatch and/or unmeasured disturbances, the system model expressed in (1) is augmented with an integrated disturbance model as proposed in Muske and Badgwell [2002] and Pannocchia and Rawlings [2003] to form an augmented moving horizon estimator. The dynamics of the disturbance model will be the stochastic generation process of animal heat and contaminant gas. The resulting augmented system with process noise n_w and measurement noise n_v is

$$\tilde{x}(k+1)=\tilde{A}\tilde{x}(k)+\tilde{B}u(k)+\tilde{G}n_w(k), \tag{22a}$$

$$y(k)=\tilde{C}\tilde{x}(k)+n_v(k), \tag{22b}$$

$$n_w(k)\sim N(0,Q_w(k)), \tag{22c}$$

$$n_v(k)\sim N(0,R_v(k)), \tag{22d}$$

in which the augmented state and system matrices are defined as follows,

$$\tilde{x}(k)=\begin{bmatrix} x(k) \\ x_{umd}(k) \end{bmatrix}_{12\times1},\tilde{A}=\begin{bmatrix} A & B_{dumd}C_{dumd} \\ 0 & A_{dumd} \end{bmatrix}_{12\times12},$$

$$\tilde{B}=\begin{bmatrix} B \\ 0 \end{bmatrix}_{12\times12},\tilde{C}=[C\ 0]_{6\times12},\tilde{G}=\begin{bmatrix} B_{dmd} & 0 \\ 0 & B_{dumd} \end{bmatrix}_{12\times12}. \tag{23}$$

In this model, the original process state $x\in\mathbb{R}^6$ is augmented with the integrated unmeasurable disturbance state $x_{umd}\in\mathbb{R}^6$. The process and measurement noise n_w and n_v are assumed to be uncorrelated zero-mean Gaussian noise sequences with covariance Q_w and R_v. Q_w, R_v and $P_{k-N/k}$ are assumed to be symmetric and positive definite. The measurable deterministic disturbance $d_{md}\in\mathbb{R}^{12}$ is assumed to remain unchanged within the prediction horizon and equal to the constant at the last measured value, namely $d_{dmd}(k)=d_{dmd}(k+1/k)=\cdots=d_{dmd}(k+$

$N-1/k)$. A new Autocovariance Least Square method is applied to recover the covariances of unknown noises, and adaptively determine the penalty in the moving horizon estimation objective function. Rajamani and Rawlings [2007] presented the necessary and sufficient conditions for the uniqueness of the covariance estimates, and formulated the optimal weighting.

4. ACTUATOR REDUNDANCY

Based on the energy consumption consideration, a constrained nonlinear optimization is formulated, in which the stage cost (24) is the quadratic function with quadratic terms and the equality constraints is the nonlinear algebraic equation of the exhaust fan (25).

$$\min_{[V,\theta]^T} E_k=\|V_k\|_{Q_V}^2+\|\theta_k\|_{\sigma\cdot R_\theta}^2 \tag{24}$$

$$s.t. \begin{cases} \Delta P=(b_0+b_1\theta+b_2\theta^2)q^2+a_0V^2+a_1qV+a_2q^2 \\ V_{\min}\le V\le V_{\max} \\ \theta_{\min}\le\theta\le\theta_{\max} \end{cases} \tag{25}$$

where, Q_V and R_θ are symmetric positive definite matrices. σ is the variance of the covariance of the fast frequency wind speed signal which is processed through digital filters. σ is the adjusting factor for assigning different penalties on the energy associated decision variable supplied voltage V_k and the swivel shutter opening angle R_θ to attenuate the wind gusts. The convex cost function and the nonlinear characteristic curve of the constraints for the exhaust fan unit are demonstrated in Fig. 3.
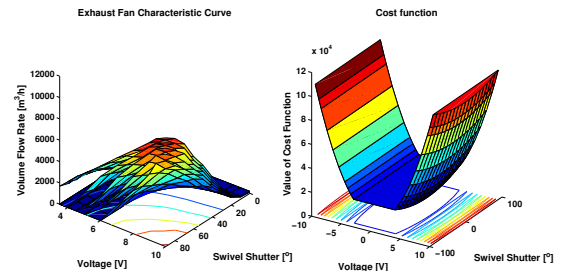

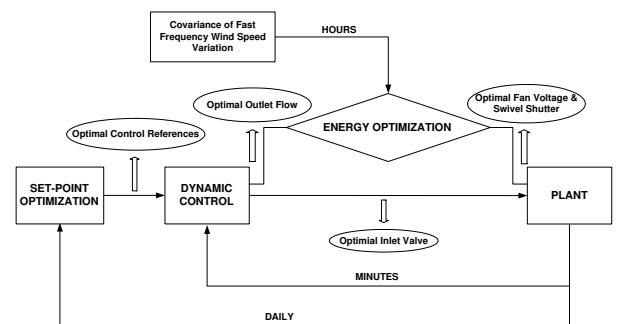Fig. 3. Nonlinear Equality Constraints and Cost Function

Fig. 4. Structure of the Entire Control System with Moving Horizon Control and Actuator Redundancy

From the overview of the control structure for the entire system as shown in Fig. 4, obviously, the introduced actuator redundancy will not affect the plant output which is mainly controlled by a dynamic controller through the fast dynamic inner loop system, and a set-point controller through the low dynamic

outer loop system. The dynamic controller is implemented with moving horizon estimation and control.

Through exploring the nonlinearities of the passive disturbance attenuation on the shutter angles, this strategy enhances the resilience of the control system to disturbances beyond its bandwidth and reduces energy consumption through on-line optimization computation.

5. SIMULATION RESULTS

The nonlinear developed plant model is used for simulation. The hard constraints on the inlet opening is $0(m^2)$-$0.6(m^2)$, on the supplied fan voltage is $0(V)$-$10(V)$ and on the swivel shutter is $0(^o)$-$90(^o)$. The entire volume of the stable is around 2500 (m^3). The weights Q on the tracking errors are different according to different requirement of the control objective. For animal thermal comfort, the indoor temperature is limited around the reference value $21(^oC)$ within the TNZ. For indoor air quality, the indoor air concentration level should be maintained below $700(ppm)$. The sampling time step is defined to be 2 (min), the prediction horizon is $N = 20$. For the following simulation scenarios, we assume that the constraint stability of the control system is guaranteed in the infinite horizon when the feasibility of the input constraints is satisfied within the finite horizon.

5.1 Off-set free tracking

In order to demonstrate the benefits of moving horizon estimation and control in handling constraints and fulfill off-set free tracking for multi-variable system, the system performances for indoor zonal temperature and concentration level are presented. As shown in Fig. 5, the simulation results are derived in the presence of a big step change of mean value of external temperature, large covariances of wind speed variation and different zonal heat production. Fig. 6 shows the corresponding actuator behaviors.
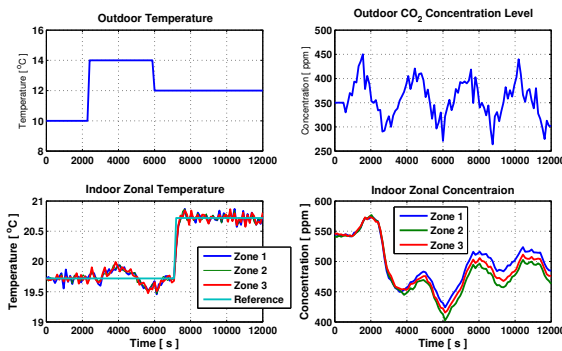

Fig. 5. Reference Tracking and Rejection of Deterministic Disturbance. Dynamic Performances of Zonal Temperature and Concentration

With a step change of the reference value for comfortable temperature, the indoor zonal temperatures keep tracking the reference with slight variations, the zonal concentration level vary with the change of the actuators and stay below the limitation. Viewed from Fig. 6, the voltage and swivel shutter in the exhaust unit rise and fall in response to the onset and cease of the disturbances from external weather condition. The inlet vents openings on the windward and leeward side are adjusted differently according to the horizontal variations. The
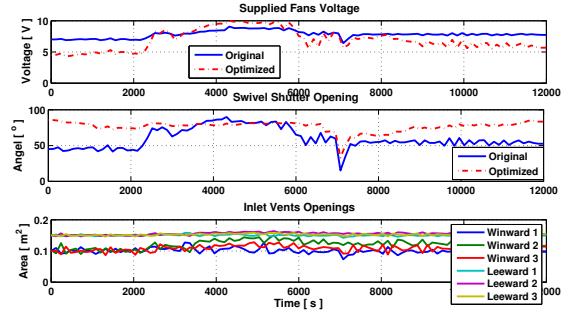

Fig. 6. Optimal Control Signals. Solid line (Dynamic Control without Actuator Redundancy); Dashed dot line (with Actuator Redundancy)

actuator behavior of exhaust unit in each zone is similar, thus only one them is picked up for demonstration. The comparison of the control signals for exhaust unit manifests the further exploitation and improvement space in applying constrained optimization on pursuing optimum energy consumption and attenuation of fast frequency wind variation.

5.2 Exhaust System Energy Optimization

Fig. 7 shows the wind speed disturbances and its low and fast frequency component. Fig. 8 compares the effect of the exhaust unit control signals with and without the actuator redundancy.
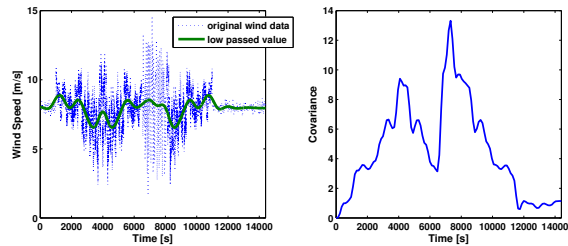

Fig. 7. Wind Speed Disturbance and the Amplitude of its High Frequency Components (covariance)
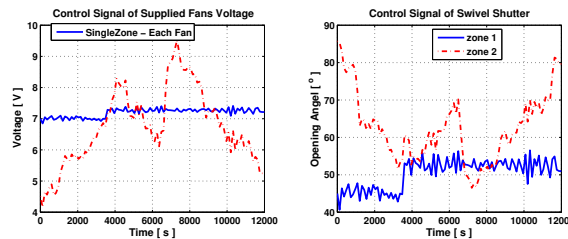

Fig. 8. Comparison of the Control Signal of Exhaust Fan System

5.3 Comparison of Kalman Filter and MHE

As shown in Fig. 9, the simulation results have convincingly proved the advantages of applying moving horizon method for estimation and control compared with the controller using a nominal Kalman Filter in rejecting the unmeasured disturbances and lowering the output variation.

Through demonstration and comparison both for output performances and actuators behaviors so far, we could recognize that
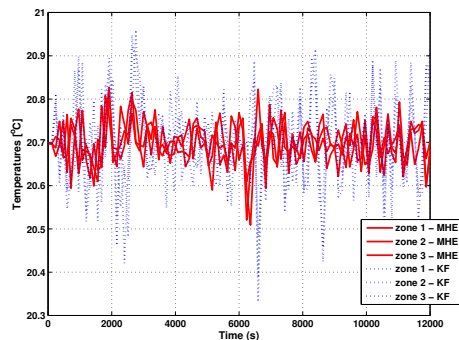
Fig. 9. Comparison of the System Performances with MHE technique vs. Nominal Kalman Filter Method

with the application of dynamic optimization in a moving horizon matter, the system behavior has been profoundly modified, and the variance of the output has been reduced considerably. The controlling consumed energy is also optimized by adding an actuator redundancy into the entire control system.

6. CONCLUSIONS

Aiming at improvement of performances and optimization of energy, the main achievement of this work is the efficient application of moving horizon estimation and control for indoor thermal comfort and air quality. The offset-free control is achieved and the optimum energy consumption solution is derived through exploiting actuator redundancy.

7. ACKNOWLEDGEMENT

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