Energy and Buildings 66 (2013) 553–561

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Multi-objective optimization of indoor air quality control and energy consumption minimization in a subway ventilation system

Hongbin Liu [a], SeungChul Lee [a], MinJeong Kim [a], Honglan Shi [a], Jeong Tai Kim [b], Kailas L. Wasewar [a], ChangKyoo Yoo [a,*]

[a] Department of Environmental Science & Engineering, College of Engineering, Kyung Hee University, Yongin, 446-701, Republic of Korea
[b] Department of Architectural Engineering, College of Engineering, Kyung Hee University, Yongin, 446-701, Republic of Korea

ARTICLE INFO

Article history:
Received 21 May 2013
Accepted 26 July 2013

Keywords:
Multi-objective optimization
Energy consumption
Indoor air quality
Model predictive control
Subway system
Ventilation control

ABSTRACT

Ventilation systems in subway stations have been mainly used to control indoor air pollutants. Conventional control systems using manual control or proportional integral derivative (PID) control are widely implemented without considering the energy cost. In this paper, a multi-objective optimization (MOO) which determines optimal set points of model predictive control (MPC) is developed to ensure healthy indoor air quality (IAQ) as well as to minimize energy consumption. First, three first-order plus time delay models are obtained by using the system identification method, which can be used to control the concentration of particulate matter (PM) at the platform. The input variable of the process model is the speed of the fan inverter and the other two disturbances are the train schedule and the concentration of outside PM_{10}. Next, based on the understanding of IAQ dynamics, the MPC controller that provides optimal control actions is then developed in the D-station of the Korean subway. The multi-objective genetic algorithm with Pareto optimal objective is adopted to determine the optimal set points of the MPC. The results indicate that the performance of the proposed multi-objective optimization ventilation control is superior to that of manual control, both in terms of IAQ and energy savings.

1. Introduction

In recent years, the process monitoring and control of subway indoor air quality (IAQ) have become progressively more appealing due to the increasing awareness of environmental protection [1–11]. Several multivariate statistical methods have been applied to monitor the IAQ in subway systems. Principal components analysis (PCA) was employed for validating four types of IAQ sensor failures in a subway station [1]. PCA, together with the multivariate analysis of variance (MANOVA), was carried out to monitor the IAQ conditions of the platform screen door (PSD) system in subway stations [5]. Seasonal air quality-monitoring models, based on external analysis [2] and multiway principal component analysis (MPCA) [3], were proposed to monitor air pollutants by considering the periodic nature of air pollution in subway stations. Apart from the monitoring of IAQ in subway systems, the impact of several faults on the energy consumption and IAQ of an air handling unit (AHU) was quantitatively evaluated [4]. A joint angle plot, to diagnose the sensor faults in a variable air volume (VAV) system, was proposed [8]. An evaluation of the impact of controller design methods on energy consumption and IAQ in a simplified VAV system was conducted [7].

Ventilation systems are an effective means for improving indoor air quality [12–14]. Some ventilation control strategies have been proposed in the field of heating, ventilation, and air-conditioning (HVAC) [15–17]. A dual-mode demand ventilation control strategy was suggested for improving IAQ and energy cost savings. This ventilation control method could save about 8.3–28.3% in electricity usage, compared with the original fixed-rate ventilation control strategy [17]. A model-based optimal control strategy was presented to control the outdoor air flow rate in air-conditioning systems. The optimal control strategy could significantly reduce energy consumption as well as maintain a satisfactory IAQ [15,16].

However, there is little systematic research on the ventilation control of underground spaces, such as those in subway stations. Subways are a major form of public transportation in modern society. More and more people are spending a substantial amount of time in subway stations. Taking the Korean subway system as an example, more than 2.2 million people are using Seoul Metropolitan Subways (SMS) on a daily basis [18,19]. Since most subways are located underground, it is not enough for subways to exchange the polluted indoor air with outdoor fresh air just by virtue of natural ventilation. To improve the underground air quality, Korean subway ventilation systems currently employ a fixed-rate

* Corresponding author. Tel.: +82 31 201 3824; fax: +82 31 202 8854.
E-mail address: ckyoo@khu.ac.kr (C. Yoo).

0378-7788/$ – see front matter © 2013 Published by Elsevier B.V.
http://dx.doi.org/10.1016/j.enbuild.2013.07.066

Nomenclature

ARMAX	autoregressive moving average with exogenous input model
ARX	autoregressive with exogenous input model
BJ	Box–Jenkins model
IAQ	indoor air quality
MIMO	multiple inputs and multiple outputs
MISO	multiple inputs and single output
MOGA	multi-objective genetic algorithm
MOO	multi-objective optimization
MPC	model predictive control
NSGA-II	non-dominated sorting genetic algorithm II
OE	output error model
PCA	principal component analysis
PEM	prediction error model
PM_{10}	particulate matter with diameter of less than 10 μm
RPM	revolutions per minute of a ventilation fan speed
SPE	squared prediction error
TF	transfer function
TMS	telemonitoring system
VEGA	vector-evaluated genetic algorithm
$\hat{B}$	bias term of OE
H_p	prediction horizon
H_u	control horizon
$\mathbf{Q}$	output-weighing matrix
$\mathbf{R}_u$	input-weighing matrix
$\mathbf{R}_{\Delta u}$	input rate-weighing matrix
$\hat{a}_i$	model parameters of OE
$\hat{b}_i$	model parameters of OE
$\hat{d}$	time delay term of OE
n	model order of OE
r	controller set-point
Δt	sampling time of OE
Δu	input rate variable
u	input variable
$\hat{y}$	predicted output variable in MPC algorithm

Greek symbols

α	updating parameter of OE
λ	eigenvalue of the covariance matrix

Superscript and subscript

j	iteration number of OE

control strategy by manually setting the speeds of ventilation fans. Obviously, this simple method of ventilation control could not achieve a satisfactory level of control performance. Therefore, one goal of this research is to design an advanced controller for the ventilation systems in subway stations.

Model predictive control (MPC), as the most successful advanced control strategy, has attained great success in the field of control engineering over the previous decades [20–23]. Recently, there have emerged many applications of MPC related to the advanced control of HVAC and building systems [24–28]. To increase the energy-saving potential in Integrated Room Automation (IRA) buildings, a stochastic model predictive control (SMPC) strategy was suggested, and this SMPC outperforms some other control methods, including the rule-based control and the deterministic MPC [24]. Compared with the conventional MPC formulation for user thermal comfort, the predicted mean vote (PMV)-based MPC could save 10–15% of energy use in a modeled building [25]. Considering the weather conditions and aiming to minimize energy consumption, MPC was implemented in a building heating system [26]. The MPC controller used for a building heating system achieved savings of 17–24% when compared with a weather-compensated controller [27]. A thermal model of a house was obtained through parameter identification for predicting the future trend in MPC [28]. Since the controller set points play an important role for the success of control strategies, some set point decision rules have been proposed. A simple semi-empirical set point decision law was highlighted [29].

Due to its ability to optimize several conflicting objective functions simultaneously, so far the multi-objective optimization (MOO) technique has been applied to many engineering applications [30–32]. The MOO technique, with the two objective functions of minimizing the fan energy use and maximizing the cold air supplied into the building, was investigated in a building free cooling system [30]. However, based on a search of the literature, very little work on MOO for subway systems is available. Hence, in this current work, the application of MPC to the subway ventilation control system has been studied. With the optimal set points obtained from MOO, the integrated scheme could reduce not only the air pollutants level, but also energy consumption in the subway station.

The remainder of this paper is organized as follows. Section 2 covers the main methods used for the ventilation system in the Seoul subway stations. These methods are a simple outlier detection method, the identification method for obtaining good process models, the designed MPC optimization algorithm, and the multi-objective optimization method to allocate the optimal set points for the MPC controller. Section 3 exhibits the control and energy saving performance of the properly tuned MPC controller. Finally, conclusions are drawn in Section 4.

2. Problem description

2.1. System description and outlier detection of subway IAQ

The air pollutants data at a subway platform (Fig. 1(a)) were collected from the telemonitoring system (TMS, Fig. 1(b)) installed at the center of the Seoul D-subway station during the period of November 21 to 25, 2011. Particulate matter with a diameter of less than 10 μm (denoted as PM_{10}) at the platform is the controlled variable. Revolutions per minute of a ventilation fan speed at the platform (denoted as RPM) is the manipulated variable. Outside PM_{10} and the subway train schedule, both of which can directly affect platform PM_{10}, are disturbance variables. The sampling time for both the platform and outside PM_{10} is 3 min, and the sampling time for the train schedule variable is 1 h. Fig. 2 shows the diurnal variations of these variables. The rush hour periods within each day give rise to the peak platform PM_{10} concentrations, shown in Fig. 2(a). For each day, the RPM values are 45 Hz before 6 p.m., and then increase to 60 Hz until 9 p.m., after which they are set to 40 Hz for one hour (Fig. 2(b)). The values in the y-axis of Fig. 2(c) indicate the total number of trains coming arriving and departing from the D-subway station. The random outside PM_{10} concentrations are normally lower than the platform PM_{10} concentrations (Fig. 2(d)).

Fig. 3 presents the related process variables used for model identification in the ventilation control system. The output variable is the platform PM_{10}, which is also the controlled variable in the following step of controller design. The input variables for model identification are the RPM, train schedule, and outside PM_{10}. In the concept of process control, RPM is the manipulated variable used for controlling the platform PM_{10}, and the train schedule and outside PM_{10} are disturbance variables. The identified model, capturing the main process dynamics, plays a critical role for the model-based control methods, such as model-predictive control.

Data quality is important for process identification. Extreme values or outliers can significantly reduce the accuracy of