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RUB IN MACHINE LEARNING SYSTEMS TO MINE VENTILATION CONTROL SCHEMES

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ABSTRACT

The purpose of the research is determination of mine ventilation system regulators positions providing required airflow on ventilated directions. Currently regulators positions are set iteratively that causes hunting. It is proposed to use historical data of the system for defining regulators functional dependencies on required airflow values with consideration of temporal variability of a ventilation network. The problem is solved by a regression model based on neural networks. Consequently, a set of model parameters is defined and the control algorithm of the system is modified for using a historical data set. Many studies have proven that the building sector can significantly benefit from replacing the current practice rule-based controllers (RBC) by more advanced control strategies like model predictive control (MPC). However, the optimization-based control algorithms, like MPC, impose increasing hardware and software requirements, together with more complicated error handling capabilities required from the commissioning staff. In recent years, several studies introduced promising remedy for these problems by using machine learning algorithms. The idea is based on devising simplified control laws learned from MPC. The main advantage of the proposed methods stems from their easy implementation even on low-level hardware.

INTRODUCTION

Heating, ventilation, and air conditioning (HVAC) systems provide a suitable living environment with thermal comfort and air quality. These mechanic–electrical systems include several types, such as air conditioners, heat pumps, furnaces, boilers, chillers, and packaged systems. In most of the countries, the building sector accounts for nearly 40% of the total consumed energy. For every building type, HVAC and lighting systems occupy more than half of the energy consumption. A large fraction of the increasing energy expenditure for the buildings was because of the extending HVAC installations for better thermal comfort and air quality. Therefore, the HVAC system plays an important role in the energy efficiency of buildings. Improving the control of HVAC operations and the efficiency of the HVAC system can save significant energy, increase thermal comfort, and contribute to improved indoor environmental quality (IEQ). Artificial intelligence (AI) was founded as an academic discipline in 1956. In contrast to human intelligence, AI demonstrates machine intelligence and imitates human behaviors through mathematical coding and mechanical works. In 1997, an AI program known as Deep Blue defeated the reigning world chess champion, Garry Kasparov.

It was the first time that the chess-playing computer performed better than a human. That moment was a turning point in

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the development of AI that enabled AI to be utilized more in a wider range of applications.

Even though the development of AI tools for HVAC systems is more than two decades old, the performance of HVAC systems controlled by AI tools has been unsatisfactory overall. Their energy savings, energy consumption, precision of heating and cooling based on load forecasting, and the predictive ability of the predictive controls, will be discussed in Section 4. From 1976 to 2014, the average energy savings of HVAC systems by applying the scheduling control technique reached 14.07%. The maximum energy savings of HVAC systems was 46.9% after applying smart sensors for smart air conditioners in 2014. However, from 1997 to 2018, the average energy savings of HVAC systems using AI tools reached 14.02%. The maximum energy savings when applying case-based reasoning (CBR) controlling tools for the HVAC systems in an office building was only 41% in 2014. Therefore, the energy savings of HVAC systems after applying AI tools was less than that of traditional energy management system (EMS) controlling techniques.

Data mining is the process of discovering patterns in large data sets involving methods at the intersection of machine learning, statistics, and database systems. Data mining is an interdisciplinary subfield of computer science and statistics with an overall goal to extract information (with intelligent methods) from a data set and transform the information into a comprehensible structure for further use. Data mining is the analysis step of the "knowledge discovery in databases" process or KDD. Aside from the raw analysis step, it also involves database and data management aspects, data pre-processing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating.

The term "data mining" is a misnomer, because the goal is the extraction of patterns and knowledge from large amounts of data, not the extraction (mining) of data itself. It also is a buzzword and is frequently applied to any form of large-scale data or information processing (collection, extraction, warehousing, analysis, and statistics) as well as any application of computer decision support system, including artificial intelligence (e.g., machine learning) and business intelligence. The book Data mining: Practical machine learning tools and techniques with Java (which covers mostly machine learning material) was originally to be named just Practical machine learning, and the term data mining was only added for marketing reasons. Often the more general terms (large scale) data analysis and analytics – or, when referring to actual methods, artificial intelligence and machine learning – are more appropriate.

The actual data mining task is the semi-automatic or automatic analysis of large quantities of data to extract previously unknown, interesting patterns such as groups of data records (cluster analysis), unusual records (anomaly detection), and dependencies (association rule mining, sequential pattern mining). This usually involves using database techniques such as spatial indices. These patterns can then be seen as a kind of summary of the input data, and may be used in further analysis or, for example, in machine learning and predictive analytics. For example, the data mining step might identify multiple groups in the data, which can then be used to obtain more accurate prediction results by a decision support system. Neither the data collection, data preparation, nor result interpretation and reporting is part of the data mining step, but do belong to the overall KDD process as additional steps.

The difference between data analysis and data mining is that data analysis is used to test models and hypotheses on the dataset, e.g., analyzing the effectiveness of a marketing campaign, regardless of the amount of data; in contrast, data mining uses machine learning and statistical models to uncover clandestine or hidden patterns in a large volume of data.

Mine Environment Index (MEI)

Various indices, such as the air quality index (AQI) [37], air pollution index (API) [38], and indoor air quality index (IAIQ) [39] have been introduced as key tools for easy and quick assessment of air quality in various environments and to predict pollutant concentrations. Among these indices, AQI, introduced by United Stated Environmental Protection Agency (US-EPA), is the most widely adopted index for the representation of open air environments. The constitutive components of this index are CO, SO2, PM10, O3, and NO2, which are commonly present in open air. As people spend 90% of their time in indoor environments [40], therefore, some researchers have also introduced indoor air quality indices. Compared to open air and indoor ambience, the environment in underground coal mines is relatively harsh, confined, and toxic because of the presence of gases such as CO, CO2, CH4, SO2, NO2, and H2S, which are emitted from coal beds during excavation. Thus, the indices defined for open or indoor air quality are insufficient to fully represent underground mine air quality. There should be an index available that gives a true representation of the mine environment and can readily assesses mine air quality.

However, despite extensive research on ventilation systems for underground mines, the mining industry and underground structures still lack such an index for the true representation of air quality. Therefore, for quick assessment and easy interpretation of mine air quality, this study introduces the mine environment index (MEI). This index is coined from two individual indices: the mine air quality index (MAQI) and the thermal comfort index (TCI). MAQI relies on the concentration of air pollutants, while TCI is mainly concerned with comfortable working conditions, such as temperature and humidity. MAQI has been assigned a weighting of 0.7 because of its major contribution to the mine environment, and a weighting of 0.3 has been given to TCI. Thus,

$$\text{MEI} = 0.7(\text{MAQI}) + 0.3(\text{TCI})$$

MAQI has been defined in a similar manner as to AQI, but it has different variables. Its representative equation is the same as that of AQI for open-air and is given as

$$\text{MAQI}_p = \frac{(\text{MAQI}_{\text{Hi}} - \text{MAQI}_{\text{Lo}})}{(\text{BP}_{\text{Hi}} - \text{BP}_{\text{Lo}})} \times (\text{C}_p - \text{BP}_{\text{Lo}}) + \text{I}_{\text{Lo}}$$

where, MAQIP is the index value for pollutant p, CP is the input concentration of a given pollutant p, BPHi is the higher breakpoint that is ≥CP, BPLo is the lower breakpoint that is ≤CP, MAQIHi is the index breakpoint value corresponding to BPHi, and MAQILo is the index breakpoint value corresponding to BPLo. The MAQI values have been categorized into five status categories: very good, good, moderate, poor, and very poor.

LITERATURE REVIEW

In recent decades, various scientific studies have used multivariate statistical

2581-4575

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approaches, such as cluster analysis (CA), PCA, factor analysis (FA), and discriminant analysis for solving environmental and air quality issues. However, based on the eigenvalues solution, PCA is the most prevailing and simplest technique. Specifically, in air quality problems, it has been used alone or in combination with other approaches. For instance, used PCA and CA to figure out the seasonal variations and spatial distribution of PM_{10} and O_3 in the open air. Similarly, Juneng et al. analyzed PM_{10} concentrations all over Malaysia using rotated PCA. Moreover, PCA, in combination with an enrichment factor, has successfully been implemented in the assessment of the air quality of an indoor charcoal cooking restaurant; it identified the particle fraction of $PM_{2.5}$ as a possible source of pollution. Therefore, in the present study, PCA is used to identify major pollutant sources present in the mine environment.

Recently, ANN has shown great potential in the fields of engineering, industrial process control, medicines, computing, risk management, and marketing. Several air quality studies have utilized ANN to simulate PM_{10} concentrations, air quality prediction, and other environmental issues. These applications clearly indicate the high capability of ANN to accurately predict in complex environments. Cigzoglu and Kisi accurately predicted air pollution in Istanbul, Turkey using feedforward backpropagation combined with a radial basis function algorithm. In regard to the mining engineering, ANN is not a new concept. An initial example for the adoption of ANN in the mining industry is the real-time control of mineral processing plants. Edwards et al. collected data from a smoke sensor installed in a mine to accurately identify the combustibles present in the mine environment. Similarly, Karacan conducted a series of modelling, simulation, and real experiments using a neural network to accurately predict the methane gas concentration and automatically control mine ventilation. For air quality in mines, Dixon et al. applied ANN to the gas monitoring data and forecasted the concentration of methane gas inside the mine environment. Similarly, Park et al. simulated ANN for the prediction of the PM_{10} concentration in metropolitan subway stations in Seoul. They found the prediction accuracy of ANN to be between 60–80% relative to measured values. They also described the effect of the architecture and depth of subway stations on the ANN results. Conclusively, ANN is a valuable technique for enhancing safety in mines through its ability to predict air quality and allow the automatic control of mine ventilation. A member from the family of ANN is multi-layered perception (MLP); this has proved its ability for prediction using time series. It enables easy extraction of precise information from complicated databases. MLP has shown great potential for solving complex environmental problems. For instance, Ramedani et al. used relative humidity, temperature, sunshine duration, and amount of precipitation as input variables of MLP-ANN for predicting global solar radiations. Thus, it can be expected that ANN, including MLP, will be able to provide accurate prediction of air quality in the complex environment of UCMs.

ALGORITHM

While modifying the control algorithm using revealed dependencies expressed in neural network models it should be considered that there is a chance to overestimate the required airflow (that means inefficient ventilation) or underestimate the required value (that means

2581-4575
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safety violation). While the first case is undesirable, the second one is unacceptable. According to this point, the control algorithm of the automatic ventilation system should be expressed as follows:

For each required airflow req Q_i^{req}

Repeat Calculate and set α_i ;

Get fact Qi ;

Correct weights in neural networks

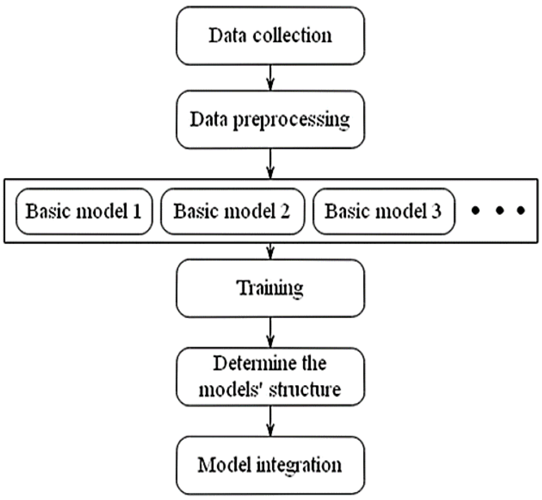
$$\left\langle \left\langle Q_i^{fact}, Q_{all}^{fact}, p_i \right\rangle, \alpha_i \right\rangle$$

for each i.

Unitl : req fact i i ∃ − ≤δ iQ Q ,

where δ stands for acceptable tolerance

An additional temporal parameter p enables decreasing number of network correction iterations and thus reduce duration of possible regulator fluctuations.



METHODOLOGY

The optimum number of hidden neurons were determined with a hit and trail approach. The output values determined in the forward phase were transmitted back from the hidden layer, and the weights of each node adjusted themselves accordingly to minimize error, relative to original values. The performance of MLP-ANN was monitored using MAE, root mean square error (RMSE), relative absolute error (RAE), relative square error (RSE), and coefficient of determination (R^2).

$$\mathrm{MAE} = \frac{\sum_{i=1}^{N} |y_{exp} - y_{cal}|}{n}$$

$$\mathrm{RMSE} = \left(\frac{1}{N}\sum_{i=1}^{N} (y_{exp} - y_{cal})^2\right)^{0.5}$$

$$\mathrm{RAE} = \frac{\sum_{i=1}^{n} |y_{exp} - y_{cal}|}{\sum_{i=1}^{n} |\bar{y} - y_{cal}|}$$

$$\mathrm{RSE} = \frac{\sum_{i=1}^{n} (y_{exp} - y_{cal})^2}{\sum_{i=1}^{n} (\bar{y} - y_{cal})^2}$$

$$R^2 = \frac{\sum_{i=1}^{n} (y_{pi} - y_{om})^2}{\sum_{i=1}^{n} (y_{pi} - y_{om})^2 + \sum_{i=1}^{n} (y_{oi} - y_{pi})^2}$$

RESULTS

The main results of the current research are as follows:

- A neural network model is designed to predict angles of regulator leafs depending on required airflow.
- An additional temporal parameter for a network input layer calculated on a preceding system state enables adjusting the described neural network for long-term prediction.
- The developed control algorithm for automatic ventilation systems meets efficiency and safety requirements.

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