Sense, Model and Identify the Load Signatures of HVAC Systems in Metro Stations

Yongcai Wang
Institute for Interdisciplinary Information Sciences (IIIS) Tsinghua University,
Beijing, P. R. China, 100084
wangyc@tsinghua.edu.cn

Haoran Feng
National Engineering Research Center of Software Engineering, Peking University,
Beijing, P. R. China, 100084
haoran@pku.edu.cn

Xiangyu Xi
Department of Automation
Tsinghua University
Beijing, P. R. China, 100084
xixy10@gmail.com

***Abstract*—The Heating Ventilation and Air Conditioning (HVAC) systems in subway stations are energy consuming giants, each of which may consume over 10, 000 Kilowatts per day for cooling and ventilation. To save energy for the HVAC systems, it is critically important to firstly know the "load signatures" of the HVAC system, i.e., the quantity of heat imported from the outdoor environments and by the passengers respectively as a function of time, which will significantly benefit the control policies. In this paper, we present a novel sensing and learning approach to identify the load signature of the HVAC system in the subway stations. In particular, sensors and smart meters were deployed to monitor the indoor, outdoor temperatures, and the energy consumptions of the HVAC system in real-time. The number of passengers was counted by the ticket checking system. At the same time, the cooling supply provided by the HVAC system was inferred via the energy consumption logs of the HVAC system. Since the indoor temperature variations are driven by the difference of the *loads* and the *cooling supply*, linear regression model was proposed for the load signature, whose coefficients are derived via a proposed algorithm . We collected real sensing data and energy log data from HaiDianHuangZhuang Subway station from the duration of July. 2012 to Sept. 2012. The data was used to evaluate the coefficients of the regression model. The experiment validated the presented load signature, which may provide important contexts for smart control policies.**

I. Introduction

Being backbone of transportation network, the subways are also major energy consumers. As stated in a site survey conducted in [1][2], a subway line (for example the line 1 in Beijing) can consume nearly 500 thousands $kW \cdot H$ power per day in the summer season, among which, more than 30% of energy was consumed by the Heating Ventilation and Air Conditioning (HVAC) subsystems for cooling and ventilation. If it is possible to save the energy consumption of the HVAC system a few percents, for example 10%, dramatical energy (nearly 20 thousands $kW \cdot H$ per line, per day) can be saved.

A major way to save energy for the HVAC systems in established subways is to design optimal control strategies to minimize the overall energy consumption while still maintaining the satisfying indoor thermal comfort and healthy environment[3]. To optimize the design and operation of HVAC, understanding the signature of the heating or cooling load is the first critical step, which is to estimate the quantity of heat (or cold) imported from the environments or passengers in different time of a day. By learning the knowledge of the load signature, the HVAC system can be optimally controlled to supply only necessary cooling (or heating) efforts to meet the predicted demands, which on one hand maintains the indoor comfort, on the other hand optimizes the energy consumption.

However, because the outdoor environments and the passenger flows are highly dynamic, the heating (cooling) loads are diverse and hard to estimate. Some existing load estimation methods for buildings use the construction details and material features to construct empirical models of heat conduction, radiation and convection [4]. However these models cannot capture the special features of the subway station: i) the impacts of passenger flows; ii) the piston wind pushed by trains in tunnels ; iii) the complex materials and underground construction structures. Lacking effective methods to predict the load in the subways, current HVAC systems generally controlled by simple time-driven policies, or in passive responding mode. As a result, the mismatching of load and supply is the main reason for energy waste in current subway HVAC systems.

To characterize the load signature of HVAC system in metro stations, in this paper, we exploit sensing and learning technologies. In a subway station, i.e., HaiDianHuangZhuang station of line 4 of Beijing subway, we deployed different kinds of environment sensors to monitor the indoor/outdoor temperatures, humidity and CO2 moisture in realtime. The passenger flow is recorded by the ticket checking system, and the energy consumptions of the refrigerators, ventilators and cooling towers of the HVAC system are monitored by the deployed smart meters. By thermal principles, since the indoor temperature variations are driven by the difference of load and cooling supply, linear regression model was set up to relate the heating load and the cooling supply. We further proposed a search algorithm to minimize the difference between integrated load and supply to estimate the load signature robustly by dealing with the noises of sensor measurements. We show by the identified load signatures the joint impacts by the outdoor temperature and the passenger flow, both of which can be predicted in working days and weekends. The derived load signature provides hints for predictive control strategies.

The rest of this paper is organized as follows. Related work is introduced in Section II. Sensor deployments and the field study in HaiDianHuangZhuang station are introduced in Section III. We propose load and supply models in Section IV. Solution method, experimental results and verification of load signatures are introduced in Section V. Conclusion and further works are discussed in Section VI.

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II. Related Work

The autonomous, optimal control for HVAC systems has attracted much research attention in the studies of smart and sustainable buildings [5], which is to determine the optimal solutions (operation mode and setpoints) that minimize overall energy consumption or operating cost while still maintaining the satisfying indoor thermal comfort and healthy environment [3].

This goal is the same in the subway HVAC control systems. Because the HVAC systems contain different types of subsystems, such as gas-side and water-side subsystems, the optimal control problems of HVAC are extremely difficult. One of the difficulties is the lack of an exact model to describe the internal relationships among different components. A dynamic model of an HVAC system for control analysis was presented in [6]. The authors proposed to use Ziegler-Nichols rule to tune the parameters to optimize PID controller. A metaheuristic simulation (evolutionary programming) coupling approach was developed in [7], which proposed evolutionary programming to handle the discrete, non-linear and highly constrained optimization problems. Multi agent-based simulation models were studied in [8] to investigate the performance of HVAC system when occupants are participating. In [9], swarm intelligence was utilized to determine the control policy of each equipment in the HVAC system.

One of the most closely related work is the SEAM4US (Sustainable Energy mAnageMent for Underground Stations) project established in 2011 in Europe[10]. It studies the metro station energy saving mainly from the modeling and controlling aspect. Multi-agent and hybrid models were proposed to model the complex interactions of energy consumption in the underground subways[11], [12]. Adaptive and predictive control schemes were also proposed for controlling ventilation subsystems to save energy [13].

Another related work reported the factors affecting the range of heat transfer in subways [14]. They show by numerical analysis that how the heat is transferred in tunnels and stations. Reference [15] studied the environmental characters in the subway metro stations in Cairo, Egypt, which showed the different environment characters in the tunnel and on the surface. The most related work is [2], which surveyed the energy consumption of Beijing subway lines in 2008.

Different from these existing work, we deployed sensors and presented models to study the load signatures and distinct features of energy consumption of HVAC systems.

III. Monitor the Thermal Dynamics

We firstly define notations listed in Table I, which will be used in the load and supply models.

TABLE I. Notations defined for the load and supply models

Notations	Definitions
$L(t)$	the quantity of thermal imported from outside to inside at t.
$T(t)$	the indoor temperature at t.
$T_o(t)$	the outdoor temperature at t
R_{eq}	heat transferring resistance from outside to inside.
M_{air}	the volume of outdoor air input into the subway station
c	the heat capacity of per cube air.
T_p	the body temperature of people.
$n(t)$	the the number of passengers at time t.
M_{mix}	volume of mixed air
M_{new}	volume of new air
M_{ac}	volume of cooling air
α	the proportion of new air in the mixed air.
T_{ac}	temperature of cooling air at the outlet of refrigerator.
T_{mix}	temperature of the mixed air.
e_{ac}	efficiency of of the cooling air transportation.
M_z	the volume of air inside the subway station.

A. Sensor Deployment

A way to capture the thermal and environment dynamics in the subway station is to deploy sensors to measure the indoor, outdoor temperatures, passenger flows and power consumptions of the HVAC systems in real-time. In HaiDian-HuangZhuang, which is a transferring station between line 10 and line 4 in Beijing subway, we deployed different kinds of sensors and smart meters to measure these information. The sensors were mainly deployed in the section of line 4, which is operated by Hongkong MTR.

We installed temperature sensors at four points inside the subway station and two points outside the subway to monitor the indoor and outdoor temperatures $T(t)$ and $T_o(t)$ respectively. Note that $T(t)$ is calculated by the average of indoor temperature sensors, so as $T_o(t)$. CO2 sensors are installed inside the subway to measure the indoor air quality. The passenger flow is recorded by the ticket checking system, which is denoted by $n(t)$. Note that $n(t)$ is calculated by the sum of the checked-in and checked-out passengers from $t-1$ to t.

To monitor the working state of the HVAC system, temperature sensors were installed at both the inlets and the outlets of the refrigerators to measure the temperature of the return air $T(t)$ and the cooling air $T_{ac}(t)$. Temperature sensors are also installed at the new air pipes and mixed air pipes of the ventilator to measure the temperatures of new air $T_o(t)$ and mixed air $T_{mix}(t)$. Note that the mixed air is the mixture of return air and new air. The energy consumptions of different components of the HVAC system, i.e, refrigerator, ventilator, water tower, pumps, fans etc are measured in real-time by the embedded power meters of the HVAC system.

B. Observed Passenger Flow Pattern

From the data of ticket checking system, which gathered real-time information about passengers flow. Fig. 1 shows the variation of passenger flow as a function of time during a week from Sep. 15 to Sep. 21. The passenger flow shows different structures in working days and weekends. In working days there are two obvious peaks in the rush hours in the morning and evening. In weekends, the passenger flow was almost uniformly distributed from 8:00 AM to 8:00 PM.

C. Observed Load Signatures

The indoor thermal condition is mainly affected by three factors: i) the outdoor temperature; ii) the passenger flow; iii) the working state of the HVAC system. To investigate how these factors affect the indoor temperature, for a particular day, Sept. 4, February, a sunny day in 2012, we monitored the variations of outdoor temperature, indoor CO2 density and indoor temperature and plotted the results in Fig. 2. It intuitively shows how the outdoor temperatures and passenger flows affect the variation of the indoor temperature. Note that during the monitoring, the HVAC system was working.

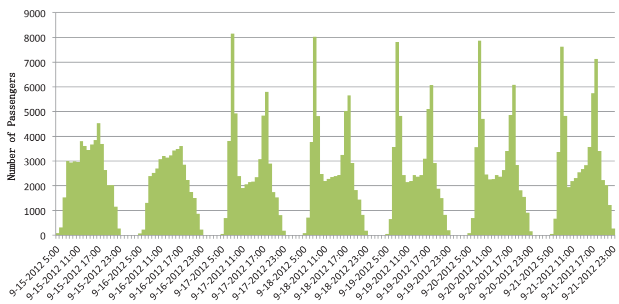


Fig. 1. Pattern of passenger flow over a week.

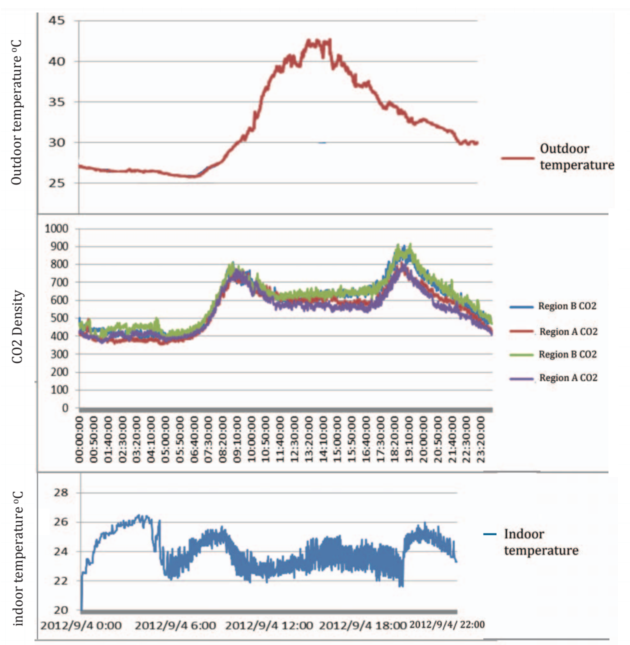


Fig. 2. How the indoor temperature was affected by the outdoor temperature and passenger flow when the HVAC system was running.

Fig. 2(a) shows the outdoor temperature change during that day. Fig. 2(b) shows the CO2 density which is used to infer the traffic flow in the subway station. Fig. 2(c) shows the variation process of the indoor temperature. The comparison of these figures shows that: i) the indoor temperature is jointly impacted by the outdoor environments, the passenger flows and the HVAC system; ii) there are four peaks in the indoor temperature curve, which are attributed to the following reasons:

- The first peak is at 4:00 AM, which is because the HVAC system was off in the morning, so the indoor temperature increases slowly.
- The second peak is at 8:00 AM, the rush hour in the morning. It is because the quantity of heat brought in by the passengers was more than the cooling effects of the HVAC system.
- The third peak is at 2:00 PM, which is the hottest time in the day. This peak is not obvious, because the outdoor temperature increases slowly, so that the HVAC system had enough time to cool down the indoor environment.
- The last peak is at 18:00 PM, the rush hour in the evening.

These measurements show intuitively the impacts of outdoor environments and passengers on the indoor temperature. However a quantitative model to characterize these impacts is still lacked. We call it the load signature, which will be modeled and learned in the next section.

IV. Model and Identify the Load Signatures

A critical problem is that we are still not clear either the environment or the passenger flow's influence is more significant to the indoor temperature. In this section, we present linear regression model to identify the load signature.

Definition 1 (load model): We define the quantity of heat imported from outdoor environments and the passengers into the subway station in a time unit as the *load* of the HVAC system in the subway station.

$$L\left(t\right)=\frac{T_{o}(t)–T(t)}{R_{eq}}+n(t)\left(T_{p}–T\left(t\right)\right)+cM_{air}\left(T_{o}(t)–T(t)\right) \tag{1}$$

$L(t)$ contains three parts: 1) the heat imported from outdoor environments by heat conduction through walls, roofs etc, i.e., $\frac{T_o(t)-T(t)}{R_{eq}}$; 2) the heat imported by passengers, i.e, $n(t)\left(T_p-T(t)\right)$; 3) the heat imported via outdoor air, i.e., $cM_{air}\left(T_o(t)-T(t)\right)$ which is due to piston wind or wind entered through doors. We can rewrite the equation (1) as:

$$\begin{aligned} &L\left(t\right)=c_{p}n(t)\left(T_{p}-T\left(t\right)\right)+\left(cM_{air}+\tfrac{1}{R_{eq}}\right)\left(T_{o}(t)-T(t)\right)\\ &=L_{p}(t)+L_{a}(t) \end{aligned} \tag{2}$$

where $L_p(t)=c_pn(t)\left(T_p-T\left(t\right)\right)$ is only related to the passengers, called the *passenger introduced load (PIL)*; $L_e(t)=\left(cM_{air}+\frac{1}{R_{eq}}\right)\left(T_o(t)-T(t)\right)$ is caused by the indoor-outdoor temperature difference, which is called *Environment Introduced Loads (EIL)*. Note that in (2), $T_o(t), T(t), n(t)$ are measured in realtime; T_p, c are known constants; only $\{c_p, M_{air}, R_{eq}\}$ are unknown variables.

Definition 2 (supply model): We define the quantity of heat cooled down by the HVAC system in a unit time as the *supply* of the HVAC system, which is defined based on different working modes of the HVAC system:

$$\begin{aligned} &S(t)=\\ &\begin{cases} cM_{new}\left(T(t)-T_o(t)\right), & \text{New air mode}\\ \left(T^w_{in}(t)-T^w_{out}(t)\right)V^w_{cool}\beta_{ac}, & \text{Refrigerator mode}\\ cM_{new}\left(T(t)–T_o(t)\right)+\left(T^w_{in}(t)–T^w_{out}(t)\right)V^w_{cool}\beta_{ac}, & \text{Mixed} \end{cases} \end{aligned} \tag{3}$$

The HVAC system in subway station has three working modes:

1) *New air mode:*, used when the outdoor temperature is lower than the indoor temperature. In this mode, the refrigerator is off; The new air is the source to cool the indoor air.
2) *Refrigerator mode:* used when the outdoor temperature is higher than the indoor temperature, during

which the new air intaking is closed and the refrigerators are working to cool the indoor air.

3) *Mixed mode:* used when the new air's capacity is not enough to cool the indoor temperature, so both the new air ventilator and a part of the refrigerator are working.

Note that in (3), M_{new} is the volume of new air blowed into the subway station by the new air ventilator. $T^w_{in}(t) - T^w_{in}(t)$ is the temperature difference of input and output water at the refrigerator; V^w_{cool} is the volume of the cooling water; $\beta_{ac} = c^w_{cool} e_{ac}$, where c^w_{cool} is the heat capacity of the cooling water and e_{ac} is the heat transportation efficiency of the refrigerator. So that $(T^w_{in}(t) - T^w_{out}(t))\, V^w_{cool}\beta_{ac}$ measures the cooling supply provided by the refrigerator and $cM_{new}(T(t) - T_o(t))$ measures the cooling supply of the new air.

Note that $T_o(t), T(t), T^w_{in}(t), T^w_{out}(t)$, and V^w_{cool} are measured in real time by the deployed sensors. c is a known constant. Only M_{new} and β_{ac} are unknown. But the volume of air blowed by the ventilator in a time unit can be further inferred by the power meter readings of the ventilators. From the fan affinity laws[16], ventilators operates under a predictable law that the air volume delivered by a ventilator is in the one-third order of its operating power.

$$M_v = \beta_v E_v^{\frac{1}{3}} \tag{4}$$

So that, the supply model of the HVAC system in the subway station can be rewritten into:

$$S(t) = \begin{cases} cE_v^{\frac{1}{3}}\beta_v\left(T(t) - T_o(t)\right), & \text{New air mode} \\ \left(T^w_{in}(t) - T^w_{out}(t)\right) V^w_{cool}\beta_{ac}, & \text{Refrigerator mode} \\ cE_v^{\frac{1}{3}}\beta_v\left(T(t) - T_o(t)\right) + \left(T^w_{in}(t) - T^w_{out}(t)\right) V^w_{cool}\beta_{ac}, & \text{Mixed} \end{cases} \tag{5}$$

A. Identify Load Signature by Linear Regression

The HVAC system runs adaptively to response the dynamics of the loads to control the indoor temperature at desired temperature. Assuming the indoor air is fully mixed, the variation of indoor temperature is mainly caused by the thermal difference of the load and the supply:

$$L(t) - S(t) = cM_z\Delta(t) \tag{6}$$

where M_z is the volume of air in the subway station, which can be calculated by the geometrical information of the station, such as the length, width, height of the station and the tunnels. $\Delta(t) = (T(t+1) - T(t))$ is the temperature difference between time t and time $t+1$.

By substituting (5) and (2) into (6), we can set up linear equations to identify the unknown parameters in the load and supply functions. Without losing of generality, we assume the HVAC is working in the refrigerator mode, by substituting (2) and (5) into (6), we have:

$$\begin{bmatrix} n(t)(T_p - T(t)) \\ T_o(t) - T(t) \\ V^w_{cool}(T^w_{in}(t) - T^w_{out}(t)) \end{bmatrix}^T \begin{bmatrix} c_p \\ \alpha \\ -\beta_{ac} \end{bmatrix} = cM_z\Delta(t) \tag{7}$$

where $\alpha = cM_{air} + \frac{1}{R_{eq}}$ is the coefficients of $T_o(t) - T(t)$ in the load model, which is modeled as one unknown coefficient. We can rewrite (7) as $\mathbf{A}(t)\theta = \mathbf{B}(t)$. Then by sensor measurements and HVAC states from 1 to t, we can set up an overdetermined observation matrix $\mathbf{A}_{1:t} = [\mathbf{A}(1), \mathbf{A}(2), \cdots, \mathbf{A}(t)]^T$, and an observation vector $\mathbf{B}_{1:t} = [\mathbf{B}(1), \mathbf{B}(2), \cdots, \mathbf{B}(t)]^T$. Then the problem of identifying the load signature is to identify the vector θ by solving $\mathbf{A}_{1:t}\theta = \mathbf{B}_{1:t}$, with the constraints that c_p, α, β_{ac} are nonnegative.

V. Techniques to Solve the Regression Model by Real Data

We used real data collected from HaiDianHuangZhuang Station to calculate the model parameters in (7) and to investigate the signatures of the loads.

A. Calculate Coefficients by Real Data

Data collected from HaiDianHuangZhuang station from a timespan of Aug 21th, 2013 to Aug 23th, 2013 was selected to solve the linear regression model. The dataset provides real-time $T(t)$, $T_{ac}(t)$, $T^w_{in}(t)$, $T^w_{out}(t)$, V^w_{cool}, and E_v, which are in one-minute resolution. In addition, passenger flows are acquired by the ticket checking system in per-hour resolution. We estimated the per-minute resolution passenger amount by linear interpolations. Based on these data, the observation matrix $\mathbf{A}_{1:t}$ is constructed and the vector $\mathbf{B}_{1:t}$ are constructed. Note that the volume of air M_z in the subway station is inferred by the geometrical data of the station.

Since the coefficients are required to be nonnegative, directly applying the least square estimation is inefficient. We propose a search algorithm to solve this constrained optimization problem:

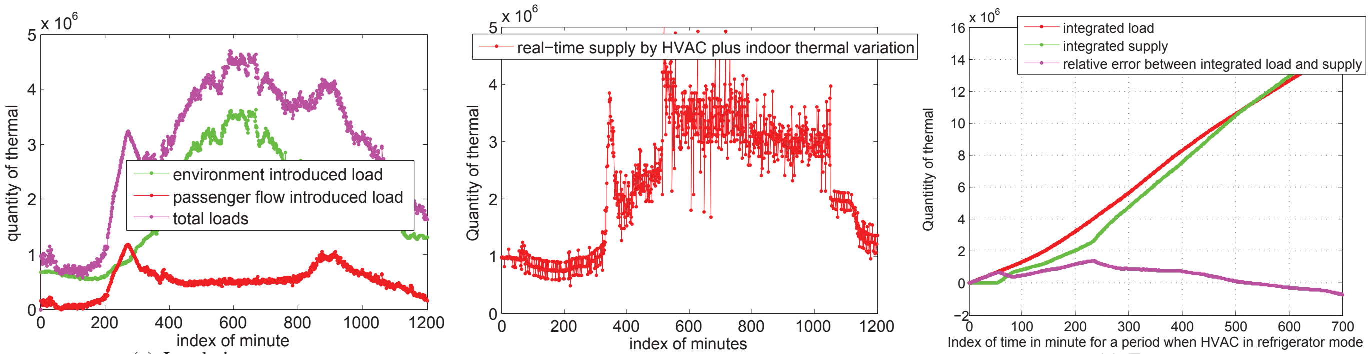
$$\theta = \arg\min_{[c_p, \alpha, \beta_{ac}]} \frac{\sum_{i=1}^{t} |\mathbf{A}_{i,1}c_p + \mathbf{A}_{i,2}\alpha - \mathbf{A}_{i,3}\beta_{ac} - \mathbf{B}_i|}{\sum_{i=1}^{t} (\mathbf{A}_{i,1}c_p + \mathbf{A}_{i,2}\alpha)} \tag{8}$$

$$\text{subject to: } c_p > 0, \alpha > 0, \beta_{ac} \geq 0$$

$\mathbf{A}_{i,j}$ is the item in ith column and jth row in the matrix $\mathbf{A}_{1:t}$. Note that we divide the accumulated absolute difference of the loads and the supplies by the accumulated loads, which is to find the coefficient vector that can provide the minimum relative difference between the load vector and the supply vector. Otherwise, smaller parameters providing smaller absolute error tend to be voted for the lacking of normalization. The search algorithm searches all combinations of $[c_p, \alpha]$ for $c_p < 1000$ and $\alpha < 10000$. For each combination of c_p and α, β_{ac} that provides the minimum relative error is calculated. The parameter set $[c_p^*, \alpha^*, -\beta_{ac}^*]$ which provides the overall minimum relative error is chosen as the optimal solution of problem (8). For the number of coefficients is limited, the computing complexity of the algorithm is tolerable.

B. The Load Signatures

Another difficulty to solve (8) is that we found the vector $B_{1:t}$ is highly zigzagging over time, which is due to the noises of the measurements of the temperature sensors, i.e., the difference of indoor temperature of successive time cannot be accurately measured because of the accuracy limitation of sensors. To overcome this noise issue, we further proposed to calculate the coefficients by minimizing the differences



(a) Load signatures

(b) Supply signature

(c) Error

Fig. 3. Derived load signatures Vs. Variation Signatures of Supply Vs. the relative error between integrated load and integrated supply

of the *integrated loads* and the *integrated supply*. We define the difference between the integrated load and the integrated supply by $\mathbf{C}(T) = \sum_{t=1}^{T} \mathbf{A}(t)$; the integrated indoor thermal variation is defined by $\mathbf{D}(T) = \sum_{t=1}^{T} \mathbf{B}(t)$. Then we solve (8) by replacing $\mathbf{A}_{i,j}, \mathbf{B}_i$ by $\mathbf{C}_{i,j}, \mathbf{D}_i$. This method gives robust estimation of the coefficients which can tolerates the sensor noises. For the particular dataset of August 23, 2013 of HaidianHuangZhuang station, we calculated the optimal parameter set θ as $[83, 53703, -1290071]^T$. When varying the scope of the data, we found the solution vary within tolerable range of errors.

After substituting the calculated coefficients into the load model, we plot the derived load signature in Fig.3a). It shows that *the loads from the outdoor temperature take the major portion, while the thermal loads introduced by the passengers take a small portion*. The real-time supply calculated by the supply model is plotted in Fig.3b). We can see the variation of supply has a similar pattern as the load. The integrated load and supply overtime are shown in Fig.3c). The relative error, i.e., the difference between the integrated load and integrated supply overtime is also plotted in Fig.3c) in the purple dashed line. We can see that by using the derived load signature, the relative error between the integrated load and the integrated supply is small, which indicates the effectiveness of the proposed linear regression model and the proposed searching algorithm.

VI. Conclusion and Discussion

This paper investigated the load signatures of HVAC system in subway station based on real data collected from subway station. By extensive sensor data collected from environment and the HVAC system, we proposed a linear regression model to describe the impacts of loads and the cooling supply on the indoor temperature. We then present a search algorithm to identify the model coefficients by minimizing the integrated differences between load and supply, which can tolerate the noisy measurements of temperature sensors. Experiment results on real dataset show the proposed method can provide rather confident load signature, which highly coincides with the real-time supply measurements. In the future work, we will further utilize the derived load signature to design simulation model and to design predictive control strategies, which can on one hand further validate the load signature, and on the other hand can design energy efficient control strategies. We will also study the optimal control systems in our future work.

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