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A data-processing approach for exploring water-use maneuver of high-rise building

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Abstract

Recognizing high-rise building water-use maneuver should be helpful for developing some practical strategies when indoor room space safety becomes a crucial feature in the building operation. This paper presents a data-processing approach for exploring the water-use maneuver of high-rise building. This approach combines the empirical mode decomposition and statistical analysis to process the mezzanine-floor air-pressure data measured in the drainage stack system of Li Ka-Shing building at PolyU of Hong Kong on 28th of April of 2008. Because the mezzanine-floor air-pressure signals in the building drainage system are recorded within about 10 hours with a recording rate of one signal per second, data re-sampling is obviously needed. Otherwise, the direct application of empirical mode decomposition should be unavailable because the mezzanine-floor air-pressure data are too massive. Statistical analysis is further encompassed after the empirical mode decomposition to seek the influences of re-sampling time interval and the empirical mode decomposition index so that the building water-use maneuver can be understood in detail.

Practical application: From the viewpoint of Building Services Engineering, any occupied space should be safeguarded, because the depletions of the trap seals[1] and the bathroom floor drain traps[2] can result in cross-contamination via the drainage system. This suggests that it is crucial to investigate building water-use maneuver when indoor room space safety becomes urgent. To explore the water-use maneuver, an indirect way is by analyzing the mezzanine-floor air-pressure in the drainage stack system in terms of an appropriate approach. Since the mezzanine-floor air-pressure in the drainage stack system of an 18-floor building, i.e. Li Ka-Shing building at PolyU of Hong Kong has been recorded,[3] it can be used to propose the water-use maneuver approach which is helpful for developing some practical strategies for indoor room space safety when the safety should be carefully and urgently faced.

Keywords

Building water-use maneuver, re-sampling, empirical mode decomposition, statistical analysis

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Introduction

As the tallest at PolyU, the LKS building is located in the campus center. The sanitary appliances, a floor trap inlet, and branch and vertical stack pipes constitute the drainage system of the LKS building. The stack and branch pipes are made of hubless cast iron. The stack pipe with 4-mm thickness has an internal diameter of 150 mm. The test of the drainage system of LKS building was started in April 2008. The air pressure in the primary drainage stack was measured at the survey station arranged on the mezzanine (M), the height of survey station is 7.95 m. In the measurement, a pressure sensor named IP67 of the WIKA type was used. This type sensor has a measuring range of about $\pm$200 mbar, with an accuracy of about 0.25%. Calibration was done using a 150-mm-high U-tube manometer, which was connected to the pressure sensor and an air pump. The pressure sensor can detect the air pressure in the stack of the test building by sending electric current signals in mA units, which are linked to a data logger.

The data logger had two parts: an analog input module used to convert mA signals to digital signals and a programmable logic controller (PLC) used for signal control. The PLC was a Micrologix-1500. The software RSLogix-500 was used for data logging in the PLC. Digital signals were sent to the personal computer using the DH485 communication port and cable. The mezzanine-floor air-pressure (MP) data for the present processing were recorded at a rate of one signal per second.

After measuring the MP data in the Li Ka-Shing (LKS) building at PolyU of Hong Kong on 28th of April of 2008, to seek the water-use maneuver of the LKS building, the problem of developing appropriate MP data processing approach occurs. The MP recording rate is as high as one signal per second with the recording time ranging from 8:00 a.m. to 6:32 p.m., which is about 10 hours. The MP data recorded in the initial 2 hours has been reported elsewhere.[3] Even though merely the MP data recorded on 28th of April of 2008 is treated, it is just because we have an interest of analyzing the MP data, and see that its relevant approach of processing should be significant in academics and practice.

It is well-known that the empirical mode decomposition (EMD)[4] is an approach in data processing. Notably, it is merely a method for dealing with the input data to seek the intrinsic properties on the basis of regulating interpolation.[4,5] These intrinsic properties are described in terms of mode functions, which should have zero means, and generally oscillate in the mode number-dependent frequencies. The larger the mode-number, the lower the frequency is for mode function. The EMD has been applied successfully to analyze non-linear water waves, and to develop a concept called Hilbert power spectrum[4] related to the Discrete Hilbert Transform,[6,7] which is just a convolution with time reciprocal for a data train.

However, as reported previously,[6,7] the convolution with time reciprocal should output a data train having the same power spectrum as that of the input train, unless some input data information such as the residual part has been removed artificially.[4]

The EMD method has a potential in seeking the intrinsic modes of an input data train, in particular when the train has apparent non-linear characteristics, such as irregular temporal fluctuation which looks like a combined variable evolution of a low-frequency base wave (BW) accompanied with high frequency (HF) waves similar to white noise.

Recently, the application of EMD has been extended to information science society.[8,9] For instance, considering a given instant multiple oscillation should appear in the intrinsic mode function when hidden scales are involved, an oblique-extrema empirical mode decomposition has been developed.[8] To achieve high detection performances, which can be mathematically described by means of both the sensitivity and the specificity parameter, an improved EMD-based algorithm for the purpose of QRS (i.e. a major wave in electrocardiogram) complex detection has been proposed.[9]

In this paper, a data-processing approach for exploring high-rise building water-use maneuver is reported, which combines the EMD[4] and statistical analysis. It was used to process the MP data in the drainage stack system of LKS building at PolyU of Hong Kong on 28th of April of 2008. Since the original MP data are too massive, re-sampling has to be utilized as an intermediate means. To some extent, the re-sampled MP data train depends on the pre-assigned time interval (TI), implying that correctly understanding the high-rise building water-use maneuver is not an easy problem as could be expected superficially.

For the convenience of description, we still call the re-sampled MP as MP. For the re-sampled MP data train, the EMD is applicable with a smaller EMD index (generally, ≤ 8). Statistical analysis is further used after the EMD to seek the impacts of re-sampling TI and the EMD index.

Not similar to the original work,[4] we call the residual part as the BW, with the summation of the mode functions called HF wave. It is the BW that does contain some peculiarities of water-use maneuver of the high-rise LKS building, indicating that the role of BW in this problem cannot be neglected completely.

Data-processing approach

The approach for the MP data-processing has two steps: EMD and statistical analysis. As mentioned in the foregoing section, re-sampling should be used as an intermediate means since the original MP data train is too massive. Based on the EMD, the re-sampled MP data train can be viewed as a superposition of BW and HF wave, hence a statistical analysis can be used to find the variation characteristics of the MP data train. Both waves are significant for the building operation and indoor environment management.

Let the intrinsic mode functions be C_k, for $k = 1, 2, \ldots, m$, with m denoting the EMD index. The mode decomposition is empirical, mainly because the mode functions are yielded by spline-interpolation according to the local minima and maxima distributions in the data train.[4,5] Decomposing the MP data train to the BW and the HF wave, we have

$$MP(t_i) = BW(t_i) + \sum_{k=1}^{m} C_k(t_i), \quad \text{for} \quad i = 1, 2, \ldots, n \tag{1}$$

where the re-sampled MP data train is represented by $MP(t_i)$, the HF wave can be expressed as $HF(t_i) = \sum_{k=1}^{m} C_k(t_i)$. The re-sampling is encompassed with the artificially pre-assigned TI.

This means that the TI is taken as an input parameter in the data-processing software, which is self-coded in Fortran language. In the data-processing approach, the TI values are respectively set as 120, 165 and 210 s. Because a smaller TI (<120 s) needs relatively large EMD index m (>8), a larger TI (>210 s) may lead to the increase of coincidence loss. The EMD index m is also set as an input parameter, with its impact on the data-processing results being predicted by the relevant software.

It is noted that the present mode decomposition is slightly different from the original work of Huang et al.,[4] where the BW is suggested to be negligible to propose a new viewpoint in seeking the properties of nonlinear water waves. The present empirical mode decomposition splits the sampled MP data train into two parts: $BW(t_i)$, and $HF(t_i)$. The base wave ($BW(t_i)$) is considered as a type of carrying wave, which contains some significant information that is useful for the high-rise building drainage system management and operation. As introduced in the foregoing section, the mode functions have been specially characterized: zero mean value, temporal oscillation with different frequency. The larger the mode number, the lower the frequency is for mode function.

Let the mean value of the MP data train be MP, we have

$$\overline{MP} = \overline{BW} + \overline{HF} \tag{2}$$

where $\overline{BW}$ and $\overline{HF}$ are, respectively, the mean values of the base and HF waves. Assuming the root mean square (rms) value, i.e. the standard deviation, of the MP data train can be represented by σ, we have

$$\sigma = BW_{\text{rms}} + HF_{\text{rms}} \tag{3}$$

where BW_{rms} and HF_{rms} are the corresponding rms values of the base and HF waves. To explore the wave oscillation characteristics, it is necessary to seek the skewness and flatness of both waves. Let the skewness of BW be $C_{s,bw}$, with the relevant flatness being $C_{f,bw}$, as introduced by Wang et al.,[10] we can write down

$$C_{s,bw} = \frac{n}{(n-1)(n-2)} \quad \frac{\sum_{i=1}^{n} (BW(t_i) - \overline{BW})^3}{BW_{\text{rms}}^3} \tag{4}$$

and

$$C_{f,bw} = A \cdot \frac{\frac{1}{n-1}\sum_{i=1}^{n} (BW(t_i) - \overline{BW})^4}{BW_{\text{rms}}^4} - B \tag{5}$$

where A, B are coefficients depending on the re-sampled data's total number n in the form of

$$\begin{cases} A = \left(n^2 - 2n + 3\right)/[(n-2)(n-3)] \\ B = 3(2n-3)(n-1)/[n(n-2)(n-3)] \end{cases} \tag{6}$$

Obviously, for HF wave, the forms of the skewness and flatness denoted by $C_{s,hf}$ and $C_{f,hf}$ can be yielded similarly. It is noted that for any data train having a Gaussian normal distribution, the flatness should be identical to 3.

Results and discussion

To seek the mode functions, each iteration process is encompassed with a criterion of 5×10^{-5}. The empirical mode decomposition is encompassed with various indices, which can be an integer number from 3 to 7. The mode functions certainly have mean values close to zero, partly as given in Table 1, depending on the re-sampling TI value, the HF wave for each EMD index has a mean whose absolute value is also close to zero.

In this section, we discuss the EMD results for the re-sampled MP data train from four aspects: mode functions, re-sampling and EMD index impacts, and characteristics on the basis of further statistical analysis.

Mode functions

The mode functions C_k, for $k = 1, 2, \ldots, 7$ are obtained by the methodology mathematically described by Huang et al.[4] Clearly as seen in Figure 1(a) and (c), each mode function curve certainly occurs temporal oscillation around the horizontal coordinate. The oscillation frequency is mode-number dependent. For instance, the

Table 1. The mean values of the base and high-frequency waves.

	TI = 120(s)		*TI* = 165(s)		*TI* = 210(s)	
m	$\overline{BW}$	$\overline{HF}$	$\overline{BW}$	$\overline{HF}$	$\overline{BW}$	$\overline{HF}$
3	1.19453	−0.01763	1.11627	0.06329	1.21209	−0.02905
4	1.19315	−0.01625	1.11348	0.06609	1.21268	−0.02964
5	1.19403	−0.01713	1.11772	0.06184	1.22816	−0.04511
6	1.19347	−0.01657	1.12473	0.05483	1.22114	−0.03809
7	1.19071	−0.01381	1.13034	0.04922	1.22062	−0.03757

BW: base wave; HF: high frequency.

mode function C_1 does have the highest frequency (Figure 1(a)), while C_7 has the lowest one (Figure 1(c)). The frequency decreases with the increase of the mode number.

The MP and BW versus time are shown in Figure 1(d). We attempt to preserve the residual part in the data treatment process, since the residual part called BW can to some extent reflect

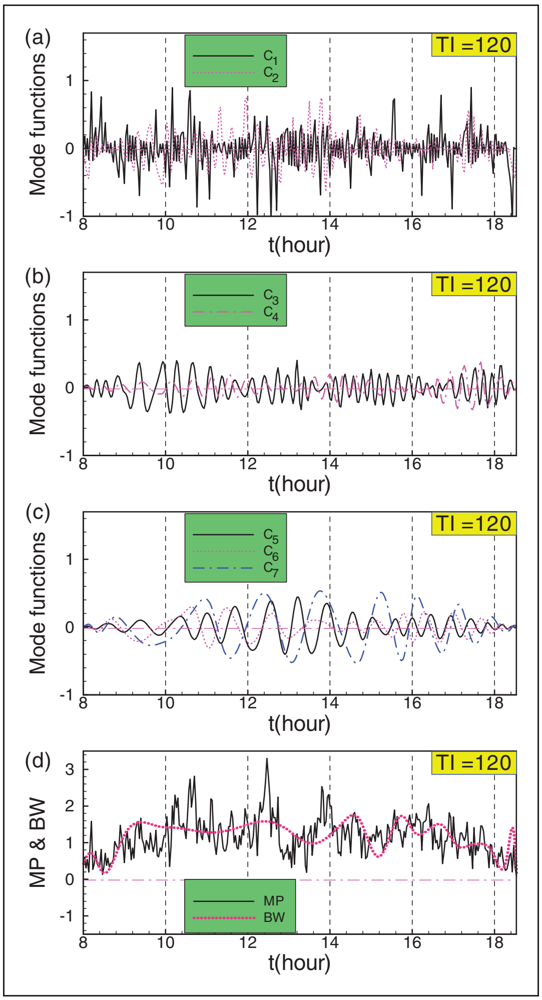

Figure 1. Mode functions, mezzanine-floor air-pressure (MP) and base wave (BW) versus time. (a) C_1 and C_2; (b) C_3 and C_4; (c) C_k, $k = 5, 6, 7$; (d) MP and BW. Note that the MP signal train is re-sampled with a time interval (TI) of 120 s.

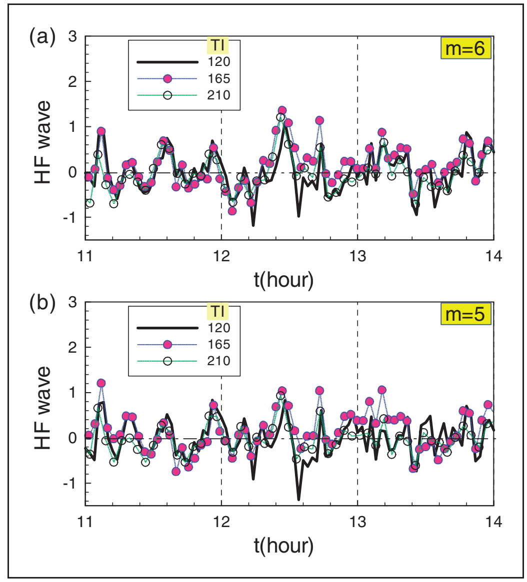

Figure 2. High frequency (HF) wave (i.e. $\sum_{k=1}^{m} C_k$) during the noon period from 11:00 to 14:00, respectively, for the empirical mode decomposition (EMD) index (a) $m = 6$; (b) $m = 5$.

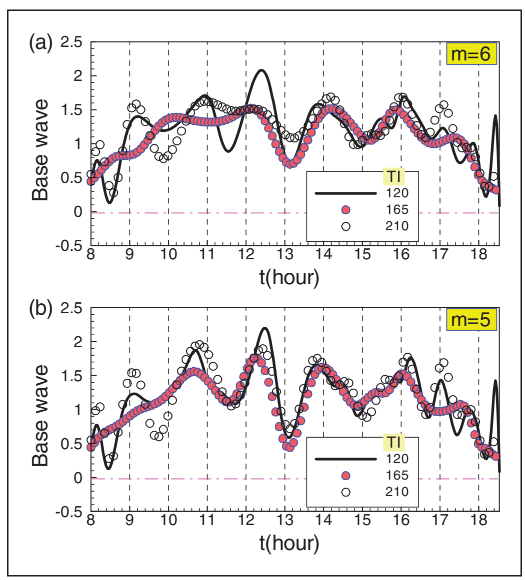

Figure 3. Base wave for different time interval (TI) value and empirical mode decomposition (EMD) index m. (a) $m = 6$; (b) $m = 5$.

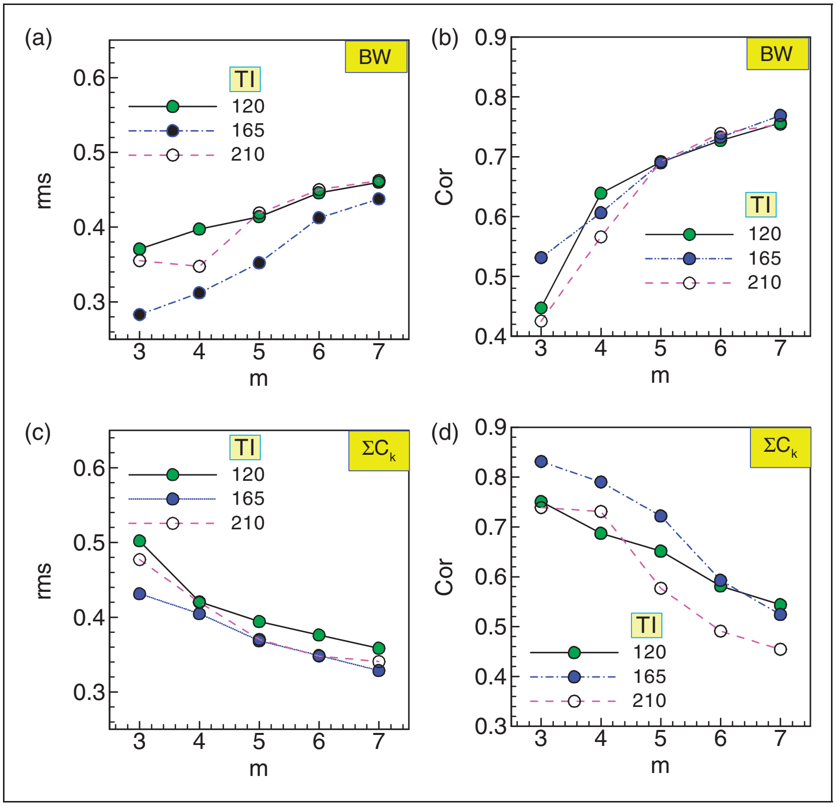

Figure 4. Root mean square (rms) and correlation-coefficient (Cor) with the mezzanine-floor air-pressure (MP) signal train plotted, respectively, as a function of the empirical mode decomposition (EMD) index *m*. (a) rms for base wave; (b) Cor for base wave; (c) rms for high frequency (HF) wave; (d) Cor for HF wave.

the water use maneuver of the high-rise building, i.e. Li Ka-Shing (LKS) building, a grand-sight building located in the campus center of PolyU of Hong Kong. Clearly seen in Table 1, the mean of BW is dependent on the re-sampling TI, while the EMD index impact on $\overline{BW}$ is negligible, suggesting that there is a need of exploring the re-sampling impact, which is discussed in the subsequent subsection.

Re-sampling impact

For HF wave, more clearly to see the time oscillation, merely the HF wave curve during the noon period from 11:00 to 14:00 is illustrated in Figure 2. The re-sampling TI has displayed an observable impact on the HF wave, without regarding the EMD index *m*.

Because the drainage base effect indicates that the larger the water discharged, the larger is the MP value,[3] the BW, to some extent, reveals the building water-use maneuver. As indicated by the solid curve for BW in Figure 3, before the clock 13:00, the local maxima occurs four times, indicating that at the corresponding instants, the amount of discharged water is relatively large. Therefore, when the occupied space safety in the building must be carefully and urgently faced, some compensatory building services strategies should be proposed. The re-sampling impact on the BW is more observable as illustrated in Figure 3(a–b). Comparing parts (a) and (b) in

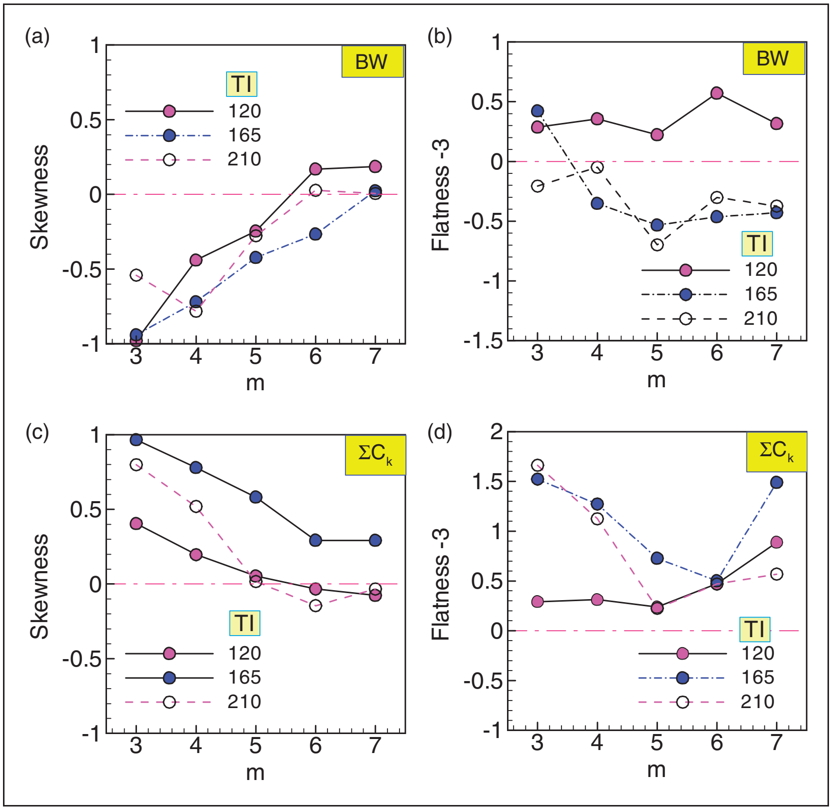

Figure 5. Skewness and 'flatness-3' plotted, respectively, as a function of the empirical mode decomposition (EMD) index *m*. (a) Skewness for base wave; (b) 'Flatness-3' for base wave; (c) Skewness for high frequency (HF) wave; (d) 'Flatness-3' for HF wave.

Figure 3, it is seen that the EMD impact on the BW is significant.

EMD index impact

In addition to the evaluation of the mean values given by Table 1, the EMD index impact can be easily seen in Figure 4(a–d), where the rms and Cor curves are plotted, respectively, as a function of the EMD index m. Here, we use Cor to represent the BW or HF wave's correlation coefficient with the sampled MP data train.

The variation tendency of rms curve can be sought in Figure 4(a) and (c). Slightly depending on the re-sampling TI, the rms curve of BW occurs a growing trend with the EMD index m (Figure 4(a)), while the rms curve of HF wave appears a reverse trend (Figure 4(c)). Similar variation can be found in of Figure 4(b) and (d). The Cor value of BW was plotted as a function of m, as shown in Figure 4(b). It is seen that $m = 5$ is appropriate, at which the Cor of BW can be seen as a critical point, for $m \geq 5$, this Cor of BW occurs an attenuated increasing rate. Also, when TI = 120, as illustrated by the solid line with filled circles, the variation tendencies with m of both the rms and the Cor curves are obviously monotonic.

Skewness and flatness

The skewness and flatness of the input data train are discussed in this subsection. The skewness for BW is given in Figure 5(a), with the skewness of HF wave given in Figure 5(c). Also seen in Figure 4(a), when TI = 210, the rms and skewness vary with m non-monotonically, implying that such a re-sampling TI is to some extent inappropriate. This property of non-monotonic variation can also be seen in part (c) of Figure 5. In fact, any Gaussian normal distribution has a flatness 3. Hence, in Figure 5(b) and (d), we set the variation named 'flatness-3' as the vertical coordinate. The relation of flatness to m is more irregular as compared with that of rms, Cor and skewness. Further evidence can be sought in Figure 5(b) and (d), because when TI = 210, the deviation of 'flatness-3' to zero is larger. On the other hand, when TI = 120, for $m = 5$, the deviation of 'flatness-3' is smaller, suggesting that the BW obtained for TI = 120 contains more crucial information of water-use in the building.

Conclusions

A data-processing approach was developed, which is useful for exploring high-rise building water-use maneuver by analyzing the MP data measured in the building drainage system. It was used to explore the LKS building water-use maneuver on 28th of April of 2008. For the massive data train of MP in the building drainage system, recorded in about 10 hours with a recording rate of one signal per second, re-sampling is needed. The re-sampling TI was set as 120, 165 and 210 s, respectively. Statistical analysis was further encompassed for the re-sampled MP data train after the EMD. For the use of larger re-sampling TI, it was found to be inappropriate due to the increase of coincidence loss. The comparatively appropriate EMD index is 5, for which the BW contains more crucial information of the water-use maneuver in the high-rise building. The data processing approach reported in this paper is simple and significant at least in Building Services Engineering.

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Conflict of interest

None declared.

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