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Estimating uncertainty when using transient data in steady-state calculations

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ABSTRACT

When using measurement data for monitoring there is often a desire for steady-state analysis. On-line condition monitoring and fault detection systems are typical applications where the traditional way of treating transient data is to remove it using methods that require tuning using thresholds. This paper suggests an alternative approach where the uncertainty estimate in a particular variable is increased in response to the presence of transients and through propagation, varies the uncertainty in the result accordingly. The formulation of the approach is described and applied to two examples from building HVAC systems. The approach is demonstrated to be a pragmatic tool that can be used to increase the robustness of calculations from time series data.

1. Introduction

The work described in this paper developed out of the application of condition monitoring and fault detection to heating ventilation and air conditioning (HVAC) systems in buildings. This has been the focus of research over the last 15–20 years, the aim of which is to help to manage complex systems in some automated sense using data [4,7,16,9,15,11].

The decreasing cost of measurement is increasing the use of smart metering and home energy monitoring systems, where information can be feedback to home owners and also to third party service providers [2]. Additionally, the complexity of building systems needed to cope with on-site generation and energy distribution is all buildings will increase the management of systems [13,14]. The developments in the built environment are further complicated because it is interconnected through the energy generation and supply systems and so building performance will become increasingly interdependent. Management of these systems will require greater levels of robust automated supervision and since much of the time series analysis in the built environment is based on steady-state calculation methods, having robust means to handle the transient components are important.

Monitoring applications in buildings have fundamental issues of robustness due to unmeasured and typically unidentifiable disturbances, often by the interaction of people. These disturbances combined with the response of the control systems to diurnal variations in ambient conditions result in measurements that will always be transient to some extent and hence 'steady-state detection' methods have been developed to filter out transient data [3,6]. The algorithms often require threshold selection and can prone to mis-classifying steady-state. This results in a loss of 'good' information and the inclusion of unwanted transient data in the calculation, which tends to generate spurious results and in the case of fault detection, lead to false alarms, which is undesirable.

Fig. 1 depicts the problem (taken from [1]). A cooling coil is opened in increments of 10% of the control signal and left to attain steady-state for about 15 min, the goal of which is to characterise it over it's operational range (bottom plot). An algorithm is used to tune the parameters of a steady-state coil model to the data by comparing the predictions of temperature off-the coil (PTSUP) with the measurements (TSUP). The centre plot gives the resultant fit, but attention is drawn to the upper plot. The dots represent the data that are deemed to be in steady-state, using a low-pass filter and gradient threshold method given taken from [10]. The problem is that many steady-state samples are rejected, so much so that the model parameter estimates could be biased. Further 'tuning' only leads to either fewer good points, or the introduction of data from transient region of operation, rather than classifying the data correctly.

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0263-2241/

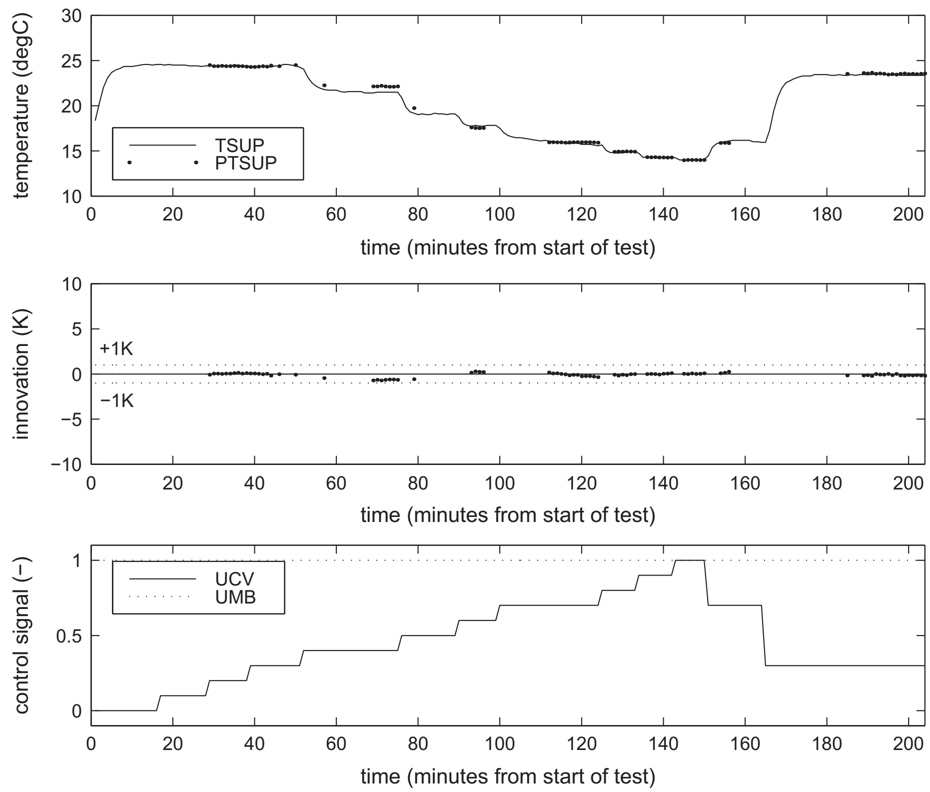

Fig. 1. Issues with threshold selection and the reliability of detection of steady-state.

Rather than determining rejection criteria, this approach retains all data but scales the uncertainty in the observations according to the detection of transients, thus alleviating the tricky threshold selection and retaining all available information in the data. This uncertainty can then be combined with the other uncertainties and propagated to the result [8]. The technique would typically be applied to each variable under observation and it can be applied in batch format, or recursively for on-line applications. This paper presents the formulation of the method and gives examples of its use in practice.

2. Method

The uncertainty in measurements are due to bias in calibration, indeterminable noise, interference from other effects that cannot be eliminated or in the approximation to bulk average properties or quantities. These individual sources are termed elemental uncertainties and are usually quoted at a 95% confidence interval and combined in quadrature to yield a 95% confidence level for the measurement,

$$U_i^2 = U_a^2 + U_b^2 + \ldots + U_n^2, \tag{1}$$

where U_i is the uncertainty in the variable and $U_a \rightarrow U_n$ are the elemental uncertainties quoted at the 95% level. Once the variable uncertainties are established, they can be propagated through a particular calculation or analysis using the approach described by Kline and McClintock [8],

$$U_y = \left[\sum_{j=1}^{n}\left(\frac{\partial y}{\partial x_j}U_j\right)^2\right]^{\frac{1}{2}}. \tag{2}$$

Many calculations yield the best results when the system being monitored is stable and close to steady-state, i.e. does not vary with time [7]. Hence, if the data is at or very close to steady-state, then there is negligible uncertainty due to transients in any subsequent calculation. If the system has had an input that drives it towards a new operating condition, then the data will become transient for a period of time, during which any calculation will yield poorer results, because the system is not in steady-state but is 'looking forward' to the new state. In this case, the additional uncertainty in the result of the analysis will be due to the transient nature of the data and hence if accounted for, will yield robust results. Eq. (1) can therefore be expanded to become,

$$U_i^2 = U_\tau^2 + (U_a^2 + U_b^2 + \ldots + U_n^2), \tag{3}$$

where U_τ is the uncertainty due to the transients in the data. The left hand plot in Fig. 2 depicts a system that begins in steady-state then at some time $t1$ there is a step input to the system, such that is drives the variable to a new steady-state, some time later, $t2$. The variable might respond as shown by the dashed line. If the aim is to calculate a steady-state value from the variable at either the old or new state, then $U_\tau = 0$ before $t1$, $U_\tau = maximum$ just after the step input and then $U_\tau \rightarrow 0$ as time progresses.

In order to detect the change in state, measure it and evaluate it with respect to the implications on the uncertainty for a calculation, the variable needs to be sampled. The dot-dashed line in the right hand plot of Fig. 2 depicts the effects of applying mean and variance calculations to a moving window filter applied to the variable.

Two common methods used to recursively generate the mean and variance in time series data are: a fixed time window approach which averages consecutive data samples over the length of the window and hence applies an equal weighting to each sample,

$$\bar{x}_n = \frac{1}{w}\sum_{k=0}^{w} x_{(n-k)}, \tag{4}$$

$$\sigma_n = \frac{1}{w-1}\sum_{k=0}^{w}(\bar{x}_n - x_{(n-k)})^2, \tag{5}$$