Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 50-1 (2017) 4184–4190

A Message Passing Algorithm for Automatic Synthesis of Probabilistic Fault Detectors from Building Automation Ontologies

R. Ferrari * **H. Dibowski** ** **S. Baldi** *

* *Delft University of Technology, Delft, The Netherlands (e-mails: r.ferrari@tudelft.nl, s.baldi@tudelft.nl).*
** *Honeywell, Home and Building Technologies Laboratories, Prague, Czech Republic (e-mail: henrik.dibowski@honeywell.com)*

Abstract:
Model-based fault diagnosis has been indicated as a fundamental method in enabling optimal maintenance of buildings, thus leading to important energy savings. However, accurate models of buildings and their technical equipment are seldom available, and this lack of knowledge applies even more to descriptions of modeling and measurement uncertainties, which are needed for developing robust fault detection thresholds with given performances in terms of False Alarm Rates. In the present paper we propose to overcome both limitations, by introducing: 1) a methodology for the automatic synthesis of a global model of a building and its equipment, leveraging a purposely built ontology-based Building Information Model; and 2) a novel message passing algorithm called MP-BUP for automatically propagating the effects of uncertainties in interconnected bilinear systems and derive robust probabilistic thresholds.

Keywords: Building automation, Fault detection and diagnosis, Lumped-parameter modeling, Building information model

NOMENCLATURE

Decorations and general notation

x, X	A scalar or array, a matrix
$\mathscr{X}$, $\mathcal{X}$	A set, another mathematical object
$\bar{x}$	Mean value
Var	Variance
Cov	Covariance
x, $\hat{x}$	Actual value, estimated value
$\tilde{x}$	Difference between nominal and actual value
$m[x]$	Measurement of x

Parameters

ρ	Density of the transfer medium
A	Contact area for convection/conduction
c	Specific heat capacity of the transfer medium
h	Convective/conductive heat transfer coefficient
p	Fraction of solar radiation directly impinging on the thermal zone
V	Volume of the transfer medium

Variables

P	Power provided from outside
R_{sol}	Solar radiation
T	Temperature of the transfer medium
u	Control input
w	Mass flow rate of the transfer medium

Indexes

$1, 2, \ldots$	In/outlet of multiway mixer/splitter
a_D	Air supplied by the fan to AHU ductworks
B	Boiler
br	Boiler room
e	Building envelope
ma_D	Air mixing inside the AHU ductworks
p	Piping transferring water to the AHU coil
R	Radiator
rw	Boiler return water
sa_D	Supply air to the AHU
sw	Boiler supply water
v	Splitter valve
z	Thermal zone

1. INTRODUCTION

Commercial and residential buildings are estimated to account for as much as 40% of global CO_2 emissions (Eurostat, 2012), and as such any improvement to their energy efficiency will lead to important environmental benefits. In particular, advanced fault diagnosis (FD) methods have been indicated as a key technology for maintaining optimal operation of energy intensive technical equipment in buildings (Hensen and Lamberts, 2012), such as Heating, Ventilation and Air Conditioning (HVAC) components and the related Building Automation System (BAS). Model-based FD techniques are a powerful and effective solution (Blanke et al., 2006), but their applicability is hindered by the lack of accurate dynamical models, especially in the building sector. Furthermore, robust FD approaches do also require some deterministic or probabilistic knowledge of all the sources of uncertainties affecting the system being modeled (Ding, 2008).

While basic FD methods may be embedded inside BAS equipment itself, more advanced FD require a precise and detailed building model. Developing such models, however, can be done manually only and is thus a rarely justified activity (Bonvini et al., 2014; Bruton et al., 2014). Hence, there is a need for automatic methods for synthesizing models of complex systems, such as an entire building, starting from a description of its components and their interconnections. Works in this direction, in different domains, are documented in (Cellier and Elmqvist, 1993; Blanke et al., 2006; Carpanzano and Maffezzoni, 1998). In the building case, it would be natural to exploit the decades long efforts which lead to the modeling approach called *Building Information Model* (BIM) (Conover et al.,

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2017.08.809

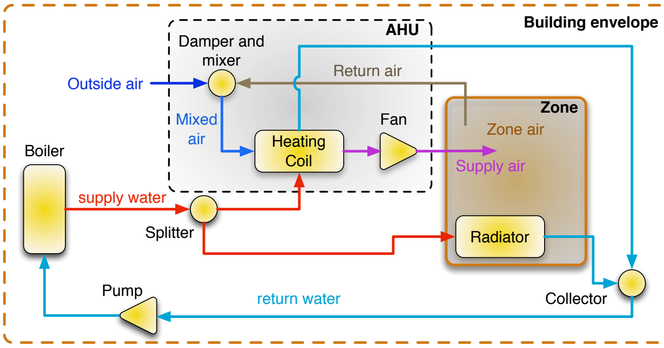

Fig. 1. Building automation system example used as test case (details such as bypass piping are not shown).

2009). The opportunity to leverage BIMs has been recognized for instance by Hensen and Lamberts (2012), and inspired the Annex 60 project [1] and the recent works of Wetter et al. (2016) and Jeong et al. (2016). Although such works solved the problem of automatic translation of BIM data using an *Object-Oriented Physical Modeling* (OOPM) paradigm, still they did require human intervention for defining its *semantics*, and correctly map it to relevant physical parameters and models. Furthermore, the problem of automatically assessing and propagating modeling and measurement uncertainties is yet to be addressed in the literature, to the best of the authors' knowledge.

To overcome both limitations, we propose to introduce: a semantic rich *ontology* for coupling existing BIM data to a library of physical components models which can then be automatically instantiated and connected; and a novel algorithm, called *Message Passing Bilinear Uncertainty Propagation* for the automatic propagation of uncertainties, thus allowing to compute probabilistically robust fault detection thresholds. The rest of the paper is organized as in the following: first principles models covering the thermal dynamics of common HVAC components are introduced in Sect. 2, while Sect. 3 deals with how to instantiate and parameterize them automatically using an ontology-based BIM; their integration in an overall model-based building FD architecture is covered in Sect. 4, and the novel automatic uncertainty propagation algorithm in Sect. 5, while concluding remarks are given in Sect. 6.

2. HEAT AND MASS TRANSFER MODELS OF AN HVAC SYSTEM

Throughout the paper a HVAC test case is used to guide the reader in the development of the ideas and methods (Figure 1). Hot water from a boiler is pumped and then split into two flows, feeding a radiator and an *Air Handling Unit* (AHU) in order to heat a single thermal zone. The AHU is supplied with a mixture of fresh outside air and return air from the zone. A coil fed by hot water is used to heat the mixed air flow, which finally is blown by a fan through ducts and delivered to the zone. The splitter valve controls the ratio between the AHU and radiator heating.

Nominal dynamical equations, that is ignoring uncertainties, are obtained using the approach in (Satyavada and Baldi, 2016) and are reported in (1) for all components.

[1] "New generation computational tools for building and community energy systems based on the Modelica and Functional Mockup Interface standards", http://www.iea-annex60.org .

3. ONTOLOGY-DRIVEN AUTOMATIC GENERATION OF HVAC SYSTEM MODELS

The following steps should be implemented for building an overall model of a given BAS for the purpose of FD: first individual models should be *instantiated* according to the actual specific components present in the BAS; then they should be connected. An ontology-based BIM is in our opinion the cornerstone for solving such a task (semi) automatically. Ontologies have been used in (Pauwels and Deursen, 2012; Zhang and Issa, 2013) for automatically formalizing and semantically enriching BIM data. *BASont*, an ontologythat formalizes a BAS-specific vocabulary with the *Web Ontology Language* (OWL), was proposed in Ploennigs et al. (2012). OWL is an expressive ontology language with formal syntax and semantics based on description logics (DL) theory (World Wide Web Consortium, 2012). Instead of just being an information model, i.e. data container, OWL technically turns a BIM into a knowledge base thus enabling advanced features such as semantic retrieval and DL logical reasoning.

3.1 Instantiation of Components Models

A domain specific ontology such as BASont represents a given physical component, i.e. a boiler, through a class called *Boiler* and some subclasses *CondensingBoiler*, *NonCondensingBoiler*, etc., for example. We propose to extend the existing class attributes by encoding its first principles equations, through an annotation property of type *string*. For the boiler, assuming the usual case in which the BAS includes a sensor for measuring the supply water temperature, we would thus encode both the following equations

$$\begin{cases} \dot{T}_{sw} & = (c_w \rho_w V_B)^{-1} (P_B + c_w w_B (T_{rw} - T_{sw}) \\ & \quad + h_B A_B (T_B - T_{sw})) + \chi_B \\ m[T_{sw}] & = T_{sw} + \xi_B \end{cases}, \quad (2)$$

where, in addition to (1), we introduced the process and measurement uncertainties χ_B and ξ_B, respectively.

Following Blanke et al. (2006), we will further describe each component through a structural bipartite directed graph. For instance, the boiler structural graph $\mathcal{G}_B = (\mathcal{N}_B, \mathcal{E}_B)$ is represented in Fig. 2, where $\mathcal{E}_B$ is the edge set and $\mathcal{N}_B \triangleq \mathcal{X}_B \cup \mathcal{C}_B$ is the node set, partitioned in a variables set $\mathcal{X}_B \triangleq \{P_B, T_{rw}, T_B, w_B, \dot{T}_{sw}, T_{sw}, m[T_{sw}], \chi_B, T^0_{sw}, \xi_{T_{sw}}\}$ and a constraints set $\mathcal{C}_B \triangleq \{\mathcal{C}_B, \int, \mathcal{M}_B\}$. $\mathcal{C}_B$ is the differential equation in (2), $\int$ denotes the integration of $\dot{T}_{sw}$ which leads to T_{sw}, and $\mathcal{M}_B$ the measurement equation of T_{sw} in (2), which leads to $m[T_{sw}]$. The additional variable T^0_{sw} represents the uncertain initial conditions of the integrator. We notice now that (2) is still a general equation for all boilers, whose symbols act as placeholders for actual quantities related to the boilers present in the BAS. We thus need a mechanism that can determine 1) the actual physical variables corresponding to such placeholders in (2), and 2) a probabilistic description of the physical parameters and the uncertainties χ_B and ξ_B in terms of their mean and variance. The rationale for this last requirement is that while the mean value of a parameter will represent its nominal known value, the variance will be used to account for the parametric uncertainty of the model. The mean of the non-parametric uncertainties χ_B and ξ_B will be assumed to be null, for well-posedness. In order to build such mechanism, we will assume that each variable and parameter of interest for