Diagnosis of Heating, Ventilation and Air Conditioning Systems

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Abstract

Faults in heating, ventilation and air conditioning (HVAC) systems often go undetected because they are corrected by control loops at the expense of decreased efficiency. We present an experimental system which diagnoses faults based on measurements of system behavior and a model of its structure. It is based on model-based diagnosis techniques and could be used on-line to alert building managers so that costly faults can immediately be corrected.

1 Introduction

Heating, Ventilation and Air Conditioning (HVAC) systems are provided with set-point controllers which automatically maintain the desired room temperatures. Faults in the system are often *masked* by this control and manifest themselves only in increased energy consumption which goes unnoticed by the users. It is thus important to provide assistance for automatic *diagnosis* of such faults based on more detailed measurements taken within the system.

Faults in HVAC systems can occur at several levels:

- installation faults, for example a controller which is incorrectly connected.
- hardware faults, for example sensors or valves which fail to operate correctly.
- intermittent faults, for example sensors covered by other objects placed against them or blocked air outlets.

Automatic diagnosis systems can be targeted to cover different types of faults. For detecting installation and hardware faults, it is sufficient to use an off-line system operating on a large quantity of recorded data. For detecting intermittent faults, the diagnosis system has to operate on-line, for example by being integrated with the control room software. Implementing such on-line diagnosis poses the following problems

- very little measurement data is available. However, often the fault can be detected through inconsistencies between different elements of the system.
- the diagnostic process itself must be efficient. This rules out the use of elaborate numerical analyses and favors the use of a more *qualitative* model.

In this paper, we report on an experimental system that addresses these problems using techniques of *model-based diagnosis*, following the paradigm established by work on the general diagnostic engine (GDE, J. de Kleer [3]). We have examined the performance of GDE on a HVAC reference example with both purely qualitative and interval arithmetic models, with encouraging results. The system can diagnose all three kinds of faults, and makes use of consistency criteria in the network as well as the cumulative information in measurements taken over time to obtain optimally precise diagnoses.

2 Methodologies for Diagnosis

The simplest form of diagnosis detects faulty components by individually measuring their inputs and outputs and comparing these to the correct behavior. This method is not generally applicable to HVAC systems, since sensors are expensive and may themselves be unreliable.

More powerful methods are possible when the interconnection topology of components is taken into account. In this case, each unexpected measurement may point to faults in various components, and it is the *consistency* of all measurements which determines the diagnosis. Such a method can be implemented in a rule-based expert system constructed explicitly for one particular interconnection topology.

In HVAC systems, each installation has a different topology and it is thus much more cost-effective to base the diagnostic system on a general methodology which can be applied to any device topology. This is the idea underlying model-based diagnosis, as implemented for example in the general diagnostic engine (GDE). GDE takes as input any number of *conflict sets*, which are sets of components that might be responsible for an unexpected measurement. It produces from this the set *diagnostic candidates*, which are possible combinations of faulty components that would account for the discrepancies. GDE always produces the optimal candidates given the input information. Using *fault models* [6, 2], it is possible to make the process converge faster and use less measurements.

The conflict sets required by GDE could be produced by a numerical simulation, but this would normally be too slow for an HVAC system of realistic size. Alternatively, the system can be modelled *qualitatively* using only certain key parameters. This may result in a loss of accuracy in the diagnosis, but this is more than compensated by increased computational efficiency. Burkhard[1] and Fornera, Glass, Gruber and Toedtli[4] have shown how qualitative models can be used to detect certain faults in a particular reference system, showing the feasibility of the approach. In this paper, we go further and show methods based on constraint propagation which can be applied to networks of any topology.

The rest of this paper is sectioned as follows. Section 3 gives a description of the HVAC system and specifies our working hypotheses. In section 4, diagnostic techniques based on a qualitative model are discussed. Section 5 compares two models used to diagnose the HVAC reference system and shows difficulties encountered.

3 Description of the Air-Handling Unit

Our model is a simplified version of the reference air handling unit described by Kelly[5].

3.1 Topological structure

The HVAC system is divided into two parts, a *preheating* section and a *zone* section as shown in Fig. 1.

The preheating section consists of a central heater, a cooler and three dampers: the input air damper *Dinput*, the return air damper Dreturn and the relief air damper *Doutput*. Dinput and Doutput are controlled in unison whereas Dreturn is controlled in reverse to Dinput. Part of the return air flowing through Dreturn is used to modulate the incoming outside air in order to attain the set point of the supply air temperature T_S (between 13° and 18° C). If the incoming air cannot be sufficiently conditioned, either the heater or the cooler is switched on. The main controller, also called economy controller E, operates the heating coil, dampers and cooling coil in sequence. Each room in the zone section has a Variable-Air-Volume (VAV-) box with

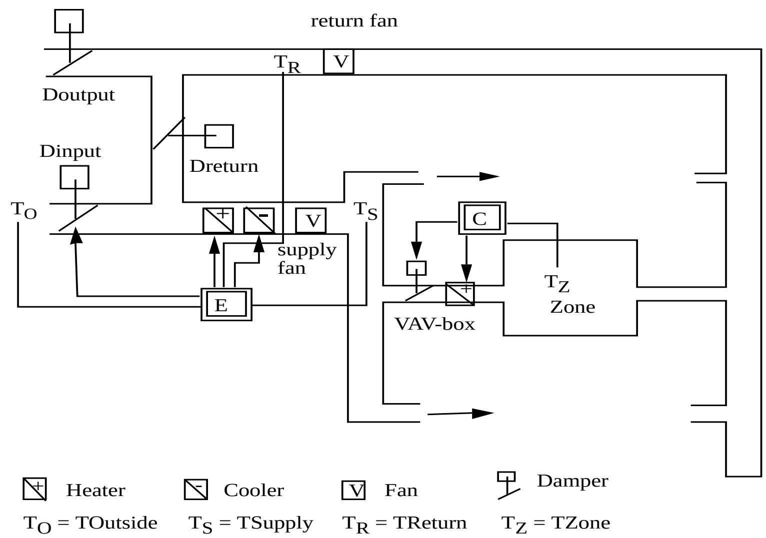

Figure 1: *Example of a HVAC system.*

a damper and a heating coil. Zone controllers of type C attempt to maintain the zone air temperatures at their respective set point by operating in sequence on the damper and the zone heater.

3.2 Functional Model

The HVAC model is defined by the generic components heater, cooler, damper, zone, controller, distribution pipe and mixer pipe. Each of them is described in terms of its variables (power rates P, openings ϕ_i, temperatures T_i, air flow M_i), constants and steady state equations. Interactions between components are simple connection constraints, i.e. the heater's output temperature equals the cooler's input temperature. The underlying assumption in this model is correct behavior of each component.

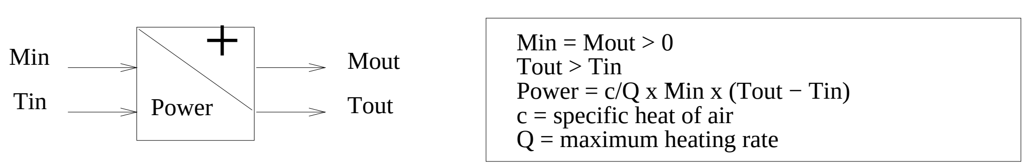

Figure 2: *Simple model of a heater with air temperature T_i, air mass flow M_i in $\frac{kg}{s}$ and relative power rate in % of the maximal power.*

3.3 Steady States in the System

According to the main controller E, several system states can be identified during daytime. If it is cool outside (usually below 0° C), the central heater is on and the input air damper in its minimal position (*heating* in Fig. 3). Between 0° and 16° C the supply air temperature is attained by gradually opening the input damper (*free*

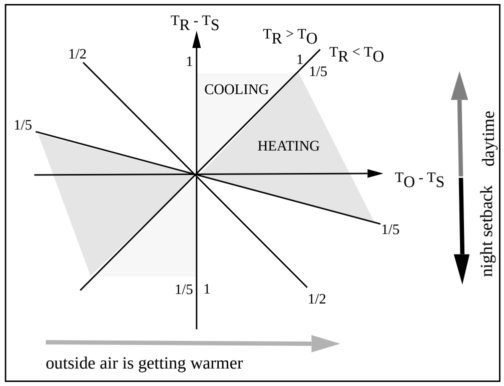

Figure 3: *Different system states - heating, free cooling, cooling - relying on the basic temperatures T_O, T_S, T_R, Landis & Gyr.*

cooling in Fig. 3). As soon as the input air becomes too hot, the damper is in its minimal position and the cooler is switched on (*cooling* in Fig. 3).

3.4 Working Hypotheses

To simplify diagnosis several working hypotheses have been adopted:

- Pressure in the system is supposed to be constant. Ventilators are therefore not modeled.
- Air losses are neglected. This means that the total airflow equals the sum of the airflows through the various rooms.
- Diagnosis is performed only in steady state. We assume the existence of a steady state detector filtering relevant data.
- Controllers are modeled by simplified functional relations between input temperatures and control variables. Their set point is fixed in advance.

4 Qualitative vs. Quantitative Modeling

The general diagnostic engine takes as input conflict sets from which minimal candidates are calculated. To find these conflict sets, known values - measurements or initial conditions - are propagated through the system. This value propagation is defined by constraints specified in the device's model. Consider the example of a heater element H in Fig. 4, and assume that $T_{in} = 13°C$, $Power = 0.5$ and $M_{in} = 2\frac{kg}{s}$ are asserted by measurement. The constraint $Power = \frac{c}{Q} \times M_{in} \times (T_{out} - T_{in})$ can then be used to derive the prediction $T_{out} = 17.9°C$. Each prediction can be *labelled* by the set of constraints which have been used in its derivation. This set indicates the set of components which must all function correctly in order to obtain this value. If a value can be derived in different ways its label consists of several component sets. The air temperature in the dampers of the HVAC system for example are derived from the

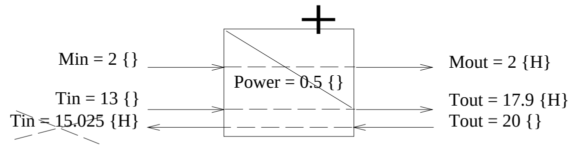

Figure 4: *Derivation of values in a numeric model.*

supply air temperature and from the return air temperature. In the heater example we would label the measurements T_{in}, M_{in} and $Power$ by $\{\}$ (the empty set) and T_{out} by {H}. A *conflict* occurs when an inferred value is different from a measured one. In this case at least *one* of the components in the justification of the derived value must be faulty. The measurement $T_{out} = 20°C$, for example, generates a conflict with the conflict set {H}. Notice that propagation stops as soon as a *minimal* conflict is detected. A minimal conflict is a conflict which has no proper subset being a conflict. Application of the constraint in the inverse direction may result in $T_{in} = 15.025$ with label {H} and produces no additional information. Any of the resulting justifications will always contain the assumption H and no conflict can be generated being a proper subset of {H}. To cut infinite propagation loops, we introduce a principle of back-propagation control. We say that a label L_1 is subsumed by a second label L_2 if there exists a component set $S_1 \in L_1$ which is a subset of component set $S_2 \in L_2$, and define:

Principle 1 *Control of backpropagation: A new value is only derived if there is no value for the same variable whose label is subsumed by the new label, i.e. no other value's label contains the assumptions from which the value is derived.*

This first principle prevents the derivation of already calculated values by back-propagation. It is particularly interesting for devices containing loops in their topology. In this case value propagation must stop after one cycle because minimal conflicts are detected by then. In the HVAC system such a loop exists due to the heated zone air reinjected into the system through a return damper.

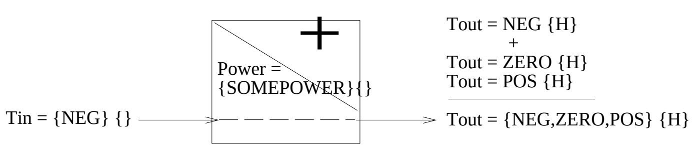

Figure 5: *Derivation of qualitative values.*

Since not all systems provide sufficient inital data, simulation must often be performed qualitatively. This has the advantage of a more intuitive understanding of the system's behavior. However, ambiguity in value interpretation is introduced since a qualitative approach can generate several possible discrete predictions in some places wich aren't contradictory. It follows that several individual values (symbols) are simultaneously acceptable for one variable as long as they share underlying assumptions, e.g. they are derived from the same subset of constraints. A qualitative value

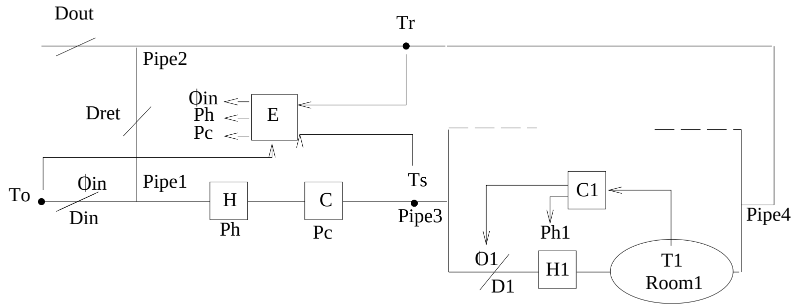

Figure 6: *Schematic HVAC reference model.*

is therefore defined as a set of symbols, for example $T_1 = (ZERO, POS)$. A *conflict* between two qualitative values occurs if their intersection is empty. A qualitative value cannot be propagated as a whole consistent set since not all of its symbols will have the same justifications, some can even be contradictary. It follows that each symbol in a qualitative model has to be propagated individually. In the heater example in Fig. 5, possible temperature values could be POS, $ZERO$, NEG; power rates $NOPOWER$, $SOMEPOWER$ and the qualitative constraint based on the steady state equation is simplified to $T_1 \leq T_2$. Suppose that initially the heater is on and $T_1 = (NEG)$. When propating individual symbols only $T_2 = (NEG)\{H\}$ is derived. The first principle of backpropagation control is too restrictive; other symbols derived from the same constraint have to be considered but not those which are inferred by backpropagation. For qualitative value propagation the first principle has to be replaced by principle 2:

Principle 2 *A new symbol is only derived if there is no other variable symbol with a label L_1 so that there exists a component set $S_1 \in L_1$ which is a proper subset of a second component set $S_2 \in L_2$ the new symbol's label.*

The expected result $T_2 = (NEG, ZERO, POS)\{H\}$ can then be inferred correctly.

5 Diagnosing HVAC Systems

We will investigate the use of two qualitative models for diagnostic purpose, a purely qualitative model based on landmarks and an interval model. The subsequent discussion is based on a diagram of a HVAC system in Fig. 6. We used the following settings in our test case:

- outside air T_O measures 10° C,
- air coming from the rooms T_R is heated to 21° C,
- supply air temperature T_S has reached its set point at 16° C,
- room temperatures are respectively 20° C and 22° C

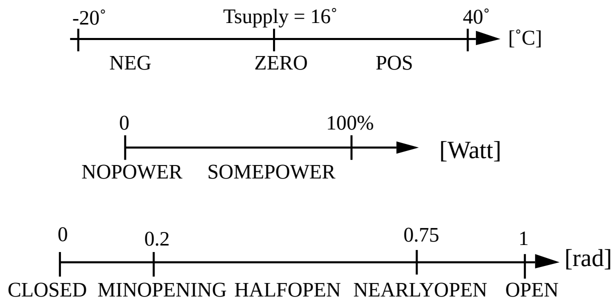

Figure 7: *Qualitative values (temperature, power rate, damper opening) generated from landmarks.*

From the first three statements the current system state can be deduced: the system is in the free-cooling state where damper openings are regulated to heat the incoming air up to the set point of 16° C.

5.1 Model Based on Landmarks

In the HVAC system the main controller labelled E defines several system states (Fig. 3) based on its input T_S, T_O and T_R. The control cycle basically consists of generating control outputs for the heater, cooler and damper elements by comparing T_O and T_R to T_S. The supply air temperature is a landmark; a value on the boundary of two system states. All other temperature values are defined relatively to it by $T_i\prime = T_i - T_S$. Landmarks for power rate and damper opening are derived from the system states (Fig. 7).

In this model the behavior of a component is characterized by acceptable value combinations for the simplified steady state equations. One of the qualitative constraints for a heater element is $T_{in} \leq T_{out}$ which can be compiled into a table containing all consistent value combinations.

We tested our qualitative model on the preheating section of the HVAC system. The initial settings - described in the introduction of this section - outside air temperature $T_O = (NEG)$, return air temperature $T_R = (\mathrm{POS})$ and supply air temperature $T_S = (ZERO)$ allow prediction of qualitative values within the system (Fig. 8). The measured value of the air temperature between heater and cooler (NEG) is propagated in all directions to produce three conflict sets: {E,C}, {E,H} and {H,E,Dret,Din,Pipe1,Pipe2}. These can be reduced to the minimal conflict sets {E,C} and {H,E}. Following the principle of GDE, diagnostic candidates are those combinations of components which cover *all* conflict sets, i.e. contain at least one member of every conflict set. Minimal candidates are those for which no subset is also a candidate. The minimal candidates derived from these minimal conflicts are {E} and {C,H}. The candidate set {C,H} shows that errors can occur as a result of malfunctioning of several components. No hypothesis is made in GDE for errors to be locally bound to a certain element; even unknown errors produced by several simultaneously defective components can be detected. A temperature value of $13°C$ could be a result of incorrect control parameters as indicated by the candidate set

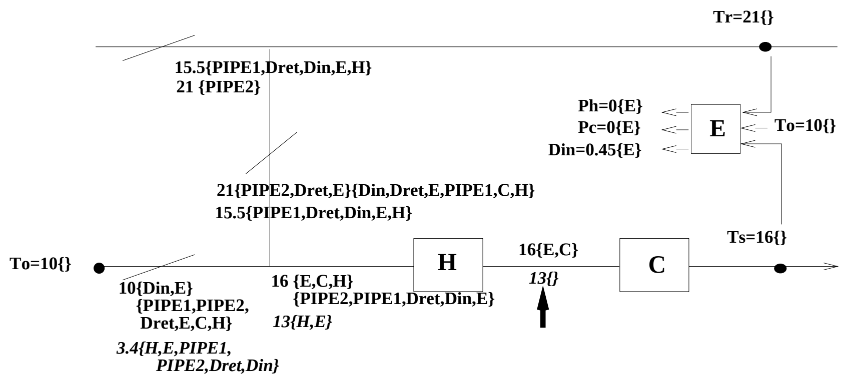

Figure 8: *Conflict detection in a qualitative HVAC model. Predicted and observed (in italic) values are compared.*

{E}. The set {C,H} explains the temperature difference between heater and cooler as the heater's not heating enough and the cooler's cooling its input air. Since a cooler cannot cool its input instead of its output this result is to be rejected. A similar analysis is proposed by Struss [6]. His augmented framework GDE+ takes into account different fault models of the components in order to filter out plausible candidates. The final candidates in our example would be the economy controller E. Note, that none of the dampers are candidates as inaccuracy of qualitative values inhibits conflict detection in the input air or the return air pipe.

5.2 Interval Model

Since propagation control based on the purely qualitative model turns out to be too imprecise in value generation and propagation, a numeric approach seems to be more appropriate. In the second model a value for a variable x is an interval [a,b] where $a \leq x \leq b$. Here, interval calculus is used to infer new values from the given steady state equations. A conflict is detected for a variable x if x = v1 and x = v2 and v1 $\cap$ v2 = $\emptyset$. Using the interval approach we were able to diagnose the whole system including the feedback loop. Numeric calculation initially caused too many conflicts. First, all the constraints used in the numeric model are equalities, and second, for a few variables in the system very precise punctual information - in form of a measurement - exists. Whenever such a value can be inferred by several constraints roundoff errors in floating point calculations on interval boundaries can result in an empty intersection. This problem can be avoided, using, for example, rational arithmetic, or allowing a cerain error tolerance when detecting conflicts. We use the example mentioned in the introductory part with qualitative values represented as intervals. Introducing a measurement of 13° C between the heater and cooler results in the conflicts {Pipe3,E,C}, {E,Pipe1,C,H} and {Pipe2,E,Pipe1,Dret,Din,H}. The candidates derived are {Pipe3,Pipe1}, {H,Pipe3}, {E}, {Pipe2,C}, {Dret,C} and {Din,C}. In this example the diagnostic result is much more accurate for two reasons. First more conflicts in the system are localized (the input air damper could also be defective) and second the entire model was used for diagnosis. Likely explanations for misfunctioning are the heater's being defective and the pipe leading to the zone section not conducting enough heated air ({H,Pipe3}), or one of the dampers being blocked in conjunction with the cooler's cooling so that over the loop in the system the air reinjected is too cold. Further restrictions could be obtained when continuing to measure temperature values. If, in this example, the air flowing through the return damper is measured to be $2°C$ the diagnostic output is {Pipe1,Pipe3}, {E}, {Pipe3,H}, and {Din,C}. All the candidates in the return air pipe are eliminated because its air temperature really is $2°C$. In a cycle of measurement - candidate generation - next measurement proposition - the diagnosis process converges to the most likely candidate sets.

6 Conclusion

Qualitative simulation helps to understand system behavior in a simpler, more intuitive way. Pure qualitative modeling, however, is not precise enough for diagnosis tasks. Theoretically, information loss due to qualitative modeling does not falsify the diagnostic result. In fact, missing conflicts only result in less precise candidate generation. Ambiguity of qualitative reasoning, however, produces too many value combinations and this has to be prevented by propagation control. Still another problem is the determination of landmarks. Such values depend on the dimensioning of heating coils and set points for temperature. Whenever the type of HVAC system to diagnose changes, these symbolic values have to be redefined in a way determined by the new system's parameters.

Interval propagation seems to be a more interesting approach. Obtained results are promising. Contrary to a purely qualitative approach, numeric constraints can be used directly for propagation of new values. Faults inherent to the model are more easily detected. Execution is fast and such a method could be used for monitoring an on-line system.

The present experimental system could be enhanced by:

- comparison of several steady states over a given time period
- analysis of dynamic behavior
- use of physical negation to focus candidate search [6]

7 Acknowldegments

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