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Automatic Detection and Diagnosis of faults in Sensors used in EMS

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Abstract
A much occurring problem in the Energy Management Systems of existing buildings and HVAC services is that the measurements are unreliable. In this article a methodology is described which can be used to determine the presence of errors in energy monitoring, caused by faulty measurements. These errors can be detected and subsequently diagnosed. Detection of monitoring errors is done based on occurring symptoms. Determination of these symptoms is done using the laws of conservation of energy, mass and pressure. The diagnosis is done by using a statistical method based on Bayesian theory in which the chance of an error occurring is determined based on (combinations of) the symptoms. The method is built in a Bayesian Belief Network (BBN) software tool. The advantage of BBN is that it is consistent with the working methods of experts in installation technology.

Keywords – FDD; Bayesian method; BBN; fault detection; fault diagnosis; systems theory; Building Energy Management System; Energy Monitoring System; sensor faults; model faults, HVAC equipment

1. Introduction

Energy Management Systems (EMS) are becoming increasingly important because of the need for a continuous high level of comfortable and healthy indoor climates. Also governmental regulations on energy are becoming increasingly strict (partly because of the EU-EPBD-regulations) and installations and their control systems more and more complex. Furthermore, in the field of Building Management there is a trend towards continuous commissioning, in which Energy Management is an important element.

Research shows that buildings consume considerably more energy than expected. Measured energy usage can reach up to 2,5 times the calculated values. But it also turns out that energy usage can increase by 25 % within a time span of 4 yours after commissioning. By continuous commissioning energy savings between 10 and 40% are possible [1]. Despite the extensive amount of research on energy management and automatic commissioning, application of energy management systems is still rare because implementation is too complex. It takes a lot of time and expertise, and there is a lack of standardization meaning that the implementation of these systems is always tailor-made, and thus labor-intensive.

In energy analysis, the actual energy consumption is compared to the expected (by experience, calculations or benchmarking) energy consumption. When a negative deviation occurs, a waste of energy is detected. However, the reliability of the energy quantities that are determined using data from the building management system is a cause for concern. In practice, assessing the reliability of these energy quantities proves to be quite complicated. Much effort is needed to get reliable results.

An ideal energy management system must be able to ascertain two different types of error:

- Energy waste by sub-optimally functioning HVAC equipment or improper use of buildings.
- Internal monitoring errors by erroneous measurements because of faults in sensors, or mistakes in model assumptions that the EMS applies for calculating energy quantities.

This article discusses the internal errors of Energy Monitoring Systems, especially sensor faults in existing HVAC equipment for which an EMS is being implemented. First the possible causes for errors in energy monitoring are discussed. Then the use of the Bayesian method in fault detection and diagnosis (FDD) is described. Next a new method is proposed and explained for Fault Detection Diagnosis and Correction (FDDC).The FDDC-method is explained using simple examples. And finally, conclusions and recommendations are presented.

2. Reliability of Energy Quantities

There are various possible causes for unreliable energy quantities. First of all, causes by defective sensors, and by systematic deviations between measured and actual values, the so-called bias-errors. In the latter case, the calculated thermal energy quantities, based on temperature and flow measurements, are unreliable. Second, the lack of reliable results is often caused by a lack of measuring points in installations. And thirdly it can be caused by the influence of the intervals that are used for measurements, storage and analysis. In many cases models are used to calculate energy quantities and to estimate values for missing measurements. Energy quantities can be determined directly by the Building Management System based on the measurement intervals. However, in practice these quantities are often determined based on stored data. This can cause inaccuracy as a result of the data storage intervals, which can exceed appropriate analysis intervals. Furthermore, assumptions in the energy usage models can lead to incorrect determination of energy values. It can also happen that measuring data are missing because of malfunctions.

Of course, the reliability of measurements. can be improved by installing accurate sensors. This is however uncommon in current practice because of the involved costs. Especially in existing HVAC equipment retrofitting sensors is usually not an option. There is therefore a need for a method for automatic detection and correction using the sensors already placed in the HVAC system. This is the focus of the present paper.

3. Methods for Fault Detection and Diagnosis

In literature we find Fault Detection and Diagnosis systems (FDD) for installation components and systems (like heat pumps, chillers, air treatment units and VAV-systems) as well as for sensors. In addition different FDD methods are proposed. See [2] in which an overview of these methods is given. The methods developed are generally component specific and generic methods for detecting and diagnosing monitoring errors are not available, not to mention error correction. The FDD methods can be divided in three main categories: model -based, rule based or based on pattern recognition. [3], [4], [5],[6] and [7] show recent examples of these methods.

All previously mentioned methods have a common disadvantage. The fault diagnosis delivers a Boolean result: a fault is either present or absent. By uncertainties in the measurements, their processing and the applied models, it is impossible to estimate 100 percent correctly whether or not a fault is true or false. In this paper the usage of a Bayesian probability method for fault diagnosis is proposed. A Bayesian based FDD model (see [8], [9] and [10]) delivers a probability of possible errors, in our case monitoring errors. This method fits well with the procedures that experts in the field use doing fault diagnosis. They start by ascertaining symptoms after which they address the errors that, based on their experience and expertise, are most likely related to the observed symptoms.

Another advantage of the Bayesian method is that it can also function when little information is available. The diagnosis becoming more reliable as more information becomes available. The method can even generate good results when conflicting information is provided.

4. Proposal for FDDC Process

Fig. 1 shows the basic scheme for the proposed FDDC process for energy monitoring. The Building Management System (BMS) delivers measurement data to the energy monitoring system. Measurement data are processed into the required data, for example energy quantities, for detecting undesirable situations. Then, using this data and additional process information, the detection process determines what symptoms are present.

The diagnosis process determines the probability of specific errors in the monitoring system (e.g. this could be a bias error, a false assumption, a faulty sensor or leakage). This is done based on the determined symptoms and possibly a combination of symptoms.

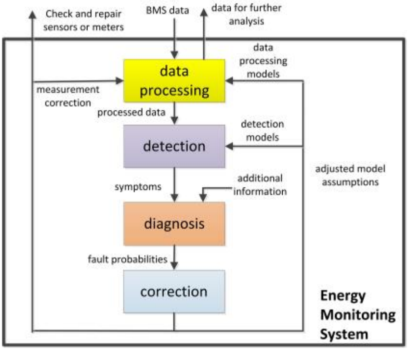

Fig. 1 The basic scheme for the proposed FDDC process for energy monitoring

When no symptoms are present, the possibility of an error in the system is very low. However, when one or more symptoms occur, there will be one or more possible errors with a high level of probability. Subsequently, corrections can be applied in the EMS, addressing firstly the errors with a higher level of probability.

As mentioned, detection of errors is done based on symptoms. For this purpose there are many possibilities. Methods based on pattern recognition are too abstract for daily practice. Therefore we suggest using a method which is based on rules that are understandable for the energy manager and installations expert. The energy monitoring system is part of the Energy Management System that conducts the actual energy analysis. This analysis is done using energy balances as well. It is therefore logical to apply the same method for both the detection of energy-use and monitoring errors. For when a monitoring error is present, it is very likely that an energy balance is incorrect.

Besides an incorrect energy balance there are additional symptoms that can be ascertained, which are based on process information like for instance differences in supply and return water temperatures when the installation is actually not in operation. Also symptoms based on management information like inspections can be added.

The process of correction can result in automatically adjusted assumptions and correction of measurements. For example by changing the systematic deviations of sensors and meters. There are three possible corrections: the model assumptions can be adjusted, the measured values can be adjusted in case there are bias errors or sensors, or meters can be checked or fixed.

5. Detection Process

Energy, mass and pressure balances can be used to determine the reliability of energy values and the kind of measurement errors. To use the energy balances, state values are determined for pressure p, temperature T and volume flow rate q_V and/or the use of thermal and electric energy Q and E, either by measurements or calculations.

In the latter case, assumptions are also done, because the calculations are based on physical models, which are set up using assumptions and simplifications. Using the systems boundaries, the energy input, output and storage are determined. Thermal energy can be measured by a thermal energy meter or calculated using temperatures and volume flow rate.

As previously mentioned, an incorrect energy balance can be used to determine the presence of one or more energy monitoring errors. However, determining which errors are actually present is more complicated. For example: when the energy balance of a system is incorrect, this can be caused by faulty measurements in the input or output of the system, but also in the assumptions for the system itself (i.e. its throughput). For instance, the measured in or outgoing temperatures can be wrong or the flow rates. In case of missing sensors, were a value ahs to be guessed, false assumptions can have been made as well as false assumptions for energy balances, like for instance the assumption of neglecting the heat losses in a component.

In the following we will show that linking the different systems and subsystems of a HVAC system improves the quality of diagnosis drastically. In order to carry out a reliable diagnosis, a sufficient number of systems should be present. It is proposed to select as many subsystems as possible for which it is possible to set up an energy balance (meaning that there should be enough measurement points in these systems). In section 6 this will be shown for a heat pump module. To support diagnosis of measurements on temperatures and flow rates it is also possible to use mass balances. When these appear to be correct, a measurement error caused by a faulty flowrate meter can be ruled out.

It could happen that a mass balance, and therefore the energy balance, is incorrect because of leakage in the flowing medium. In that case a pressure balance can be set up using measured pressures in the system. When this balance turns out to be incorrect, this could be caused by leakage.

6. Diagnosis Process

The diagnosing process analyses the symptoms in an integral manner. In other words, by combining symptoms the probability for the presence of all possible errors is determined. The described process can be compared with the process a medical specialist carries out. Based on multiple symptoms, he or she makes a diagnosis. The more information is available, the better the illness can be identified. The diagnosis described herein uses the probability of a possible monitoring error occurring. For example the chance that a temperature sensor is faulty is set on 5%. For each symptom it is determined by which error it can occur with accompanying probability distribution.

Determining probability distribution takes place at the design stage of the energy monitoring system, based on former experience (e.g. how often a specific sensor breaks). However, it can be adjusted later based on experience with the specific HVAC plant.

When the EMS is operational, appendix I for an explanation on Bayesian Belief Network (BBN).

The (automated) procedure is as follows: When a symptom is identified, the BBN knows which possible errors can cause it. Using the probability that a certain error occurs, it is possible to determine which monitoring element has the highest probability of failure. This is explained in detail in section 7. When multiple symptoms are present that have common underlying causes (possibly faulty elements) in the monitoring system, the reliability of the diagnosis improves. It improves even more by considering different aggregation levels in the system. See also section 7 which demonstrates that analysis of symptoms in the subsystems and of the aggregated system at same time leads to better diagnosis.

Next to detection using balances, it is also possible to analyse additional information. In section 7, an example is shown where this additional information is the COP-value of the heat pump.

7. Diagnosis based on a BBN method

In an example, first the result is shown of a subsystem that is analyzed independently, subsequently, the result when the diagnosis is done in an integral manner by linking both subsystems, and finally when the diagnosis also incorporates the aggregated system. The example also shows the usefulness of incorporating additional information in the analysis. Fig. 2 shows the heat pump and related condensor module in a diagram.

We can see that the total system has 6 sensors for temperature (code TT) and 3 flow rate sensors (code FT). For convenience we assume that all sensors have a failure risk of 5%. Also we assume that the measured work by the compressor (Wcompr) is correct.

In our thought experiment, we assume that in both subsystem a, the heat pump, as well as subsystem b, the condenser module, the heat balance is incorrect because of the faulty sensor TT3. Is our method able to find this faulty sensor?

Now imagine that 2 symptoms are being detected, both incorrect energy balances. The possible underlying errors that can cause these symptoms are diverse; one or more temperature sensors or flow rate sensors can be faulty, there can be a leakage. In the following we show how, based on these 2 symptoms, the error (TT3 is faulty) can be identified. First we consider systems a and b separately and build a BBN-model for both of them. See Fig. 3 for the corresponding BBN-model.

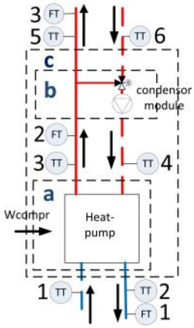

Fig. 2. Heat pump and condensor module

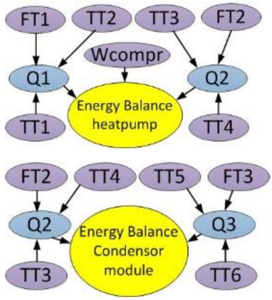

Fig. 3 Separate BBN models

The nodes of the sensors are connected to the energy balance through heat node Q (for which the value is determined by 2 temperatures and a flow rate). For simplicity we assume that the energy balance cannot be correct when one of the sensors is failing. This means that the chance that the energy balance is correct because multiple failing sensors compensate each other is neglected. The diagnose, which is being conducted using the software program GeNie, logically comes up with a 5% chance of failure for all 9 sensors. Meaning that a clear diagnosis is not possible.

Then we built a BBN-model in which both subsystems a and b are connected: TT3, TT4 and FT2 are linked to both the energy balance of subsystem a and b. See Fig. 4 for this BBN-network.

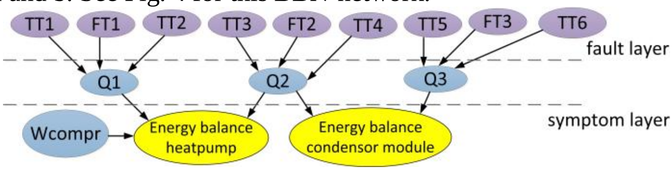

Fig. 4 Integrated BBN network

We can see that in contrast to the BBN-network of Fig. 3 the sensorsTT3, FT2 and TT4 have a relation with both the heat pump and the condenser module. The diagnosis, that now takes into account the integration finds a result for sensors TT3, TT4 and FT2 to have a chance of failure of 31% against 8% of the other sensors. This is a much clearer result than previously. An expert would then look further into TT3, TT4 and FT2.

However it cannot be excluded that one of the other sensors is also defective. Therefore, we also consider system c, an aggregated system, which is composed of both subsystems a and b (see Fig. 2). The systems a, b and c are then built in a BBN-model. See Fig. 5.

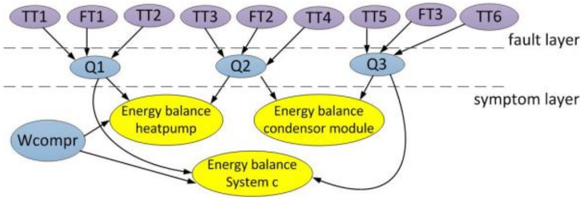

Fig. 5 BBN network extended with aggregated system c

Because in our thought experiment we have assumed that only sensor TT3 is faulty, the energy balance of system c will be correct. After all, TT3 is a sensor within the aggregated system, and the energy balance deals only with flows through the systems boundaries. Because of the extra connection tot system c, the result of the diagnosis changed in such a way that sensors TT3, TT4 and TF2 now have a chance of failure of 35% while the chance of failure for the other sensors dropped to 0%. This excludes the possibility of an error in the other sensors and makes the diagnosis more reliable. It is however still not possible to determine which of the three sensors is faulty.

Therefore, in the last experiment, the COP of the heat pump is determined. We assume that this can be checked using the input temperatures TT1 and TT4 for the heat pump. Because in our thought experiment, those are correct, the calculated COP will also be correct. Adding this information to the BBN leads to a further improved diagnosis, only the sensors FT2 and TT3 can be faulty, both with a chance for failure of 51%. The energy expert now has only these two sensors to inspect.

So far, mass and pressure balances where left out of the analysis. However, when the mass balance is analyzed for the condensor module, it will show that a failure of FT2 can be ruled out, thus isolating the faulty sensor in TT3.

In this case, it turned out to be possible to isolate the error and pinpoint the only faulty sensor. If it would happen that there are multiple faulty sensors present in the installation, extension of the BBN-model could be necessary. So, it could also include energy, mass and pressure balances from complementary subsystems and aggregated systems, as well as additional process information, to pin point these multiple errors.

8. Conclusions and Recommendations

The proposed FDDC system for energy monitoring consists of an expert system which uses a BBN model for fault diagnosis. A big advantage of the presented method is that it uses general laws of conservation for energy (first law of thermodynamics), mass (continuity equation) and pressure (Bernoulli’s principle) and is therefore applicable on a variety of problems regarding technical installations. This article has demonstrated that it is possible to asses accurate diagnosis, by using integral analysis of symptoms in various interconnected subsystems and using different levels of aggregation. The use of additional information further improves the quality of diagnosis. The proposed framework has been validated on a part of the HVAC equipment of the building of The Hague University in Delft, consisting of an ATES (Aquifer Thermal Energy Storage) system with a heat pump showing the applicability of the framework, but is has not be possible to include the results of the validation in this paper. These results will be published later in a journal paper.

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Appendix I Explanation BBN Method

Conditional probabilities can be determined using Bayesian Theory. For example: When the probability that a certain event will occur is greater than zero (P(B)>0), the conditional probability P(A|B) that event A occurs while B is true, can be determined by using a BBN-model. The BBN model can be displayed in a graphical model in which the relation between variables can be shown. This graphical model is made up of nodes representing the variables and lines representing the relations between the variables. In the nodes a table is used to specify the chance that a certain state is present depending on the state of other nodes.

Fig. I shows a diagram of a heat exchanger. The volume flow rate through the heat exchanger is measured by a flow rate meter FT1. The input temperature by TT2 and the output temperature by TT1. The exchanged heat Q can be determined using a heat balance.

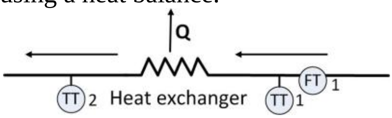

Fig. I Principle diagram for a heat exchanger

The reliability of the calculated heat Q depends on the reliability of the measured values for TT1, TT2 and FT1. For simplicity, we assume that in this example, Q is only correct (true) when TT1, TT2 and FT1 are all correct. So we ignore the small chance that Q is true while TT1, TT2 and/or FT2 are faulty and the errors compensate for each other.

In a thought experiment we assume that the chance for TT1 (P(TT1) to be correct is 95%. This value will also be used for P(TT2). For chance P(FT1) we assume 90 %.

In this case calculating the probability for Q to be true (P(Q)) is simple because TT1, TT2 and FT1 are statically independent from each other: $P(Q)=P(TT1 \wedge TT2 \wedge FT1)$

$=P(TT1).P(TT2).P(FT1)=0.95*0.95*0.9=0,812=81.2$ %.

The graphical representation of the resulting BBN model is displayed in Fig. II.

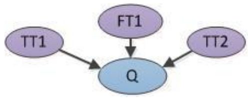

Fig. II BBN model of the heat exchanger of Fig. I

For this research it is important that, conversely, it is also possible to determine P(B|A) when state A is known. When we assume that the value for Q is incorrect, so P(Q)=0 (in reality this would follow from the detection of a symptom, in that case an incorrect energy balance), the BBN model comes up with P(TT1)=P(TT2)=73.4 % and P(FT1)=46.7 %. In other words, the chance that measurement FT1 is incorrect is smaller than the chance for TT1 and TT2 to be incorrect. This is logical, because the reliability for FT1 (90%) is lower than for TT1 and TT2 (95 %). Combining various systems and subsystems makes it possible to make an accurate diagnosis.

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