Comparing methods aimed at model based sensor fault detection analysis of smart building systems.

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Abstract

The Hague University in Delft uses an advanced climate control system. However the system is not always working as intended. The building manager has to make an educated guess by combining sensor data in order to determine which sensor is defective, or not. In this paper, four methods to analyse and represent real-time sensor data are described. The four methods are: 'Rule Based System', 'Bayesian Belief Network', 'Long Short Term Memory', and 'Clustering method'. First there is a necessity to know which anomalies are currently taking place at The Hague University in Delft. After that, a method to find these, and other anomalies is needed. Finally, the found anomalies have to be reported. The results show that the methods Deep Learning and Clustering seem preferable. However there is a need for a universal validation to make this statement definitive.

Keywords: Bayesian Belief Networks, Expert System, Deep learning, HVAC-systems, sensor fault detection

1. Introduction

Heating Ventilation and air conditioning systems ('HVAC-systems') are data driven ventilation systems. Through the years, new techniques have been developed to utilize this data in order to improve comfort and energy-efficiency within indoor climates. An example of these techniques is anomaly detection in indoor climate systems. To make anomaly detection more adoptable, this paper will make a comparison of Rule Based Systems ('RBS'), Bayesian Belief Networks ('BBN'), Clustering method and 'Long Short Memory' (LSTM) networks. They will be compared on how well they detect anomalies within a given dataset. The dataset that is analyzed, originates from a range of sensors e.g.: CO2, temperature, occupancy ('PIR'), light, ventilation rate and ventilation valve position. The dataset has been gathered from The Hague University of Applied Sciences in Delft. Using data from the past seven years we can analyze how these different methods operate. Comparing these results will generate a preferred method for 'HVAC-systems'.

2. Expert System

In previous researches[1] a 'RBS' has been build to analyze the available data from the climate system of The Hague University of Applied Sciences in Delft (Kortekaas & Vuuren; 2016). The application, build for this 'RBS', is 'SAW' (Sensor Application Wrapper)[2]. By composing rules for a situation in a room, the data can be analyzed in order to find whether the system is performing within its boundaries. One of those 'rules' is shown in the table below (the situation shown is 'normal'):

	Is functioning	MaxDeviation	MaxDeviation Violated	hasConstant Value	maxAccepta ble	maxAcceptabl eViolated
co2 sensor	True	400	false	false	1400	false
Temperature	True				22	False
Airflow	True	50	false			
Lightstate	True					
PIRsensor	True					

This could be a defect, for instance a malfunction of a sensor, or there could be a different cause, for example an over-occupied room.

For this research on 'RBS' the following tasks were performed:

- Analyse and visualize the previously obtained results
- Creating a new web-application to improve accessibility.

[1] Foutdetectie van sensoren in het klimaatregelsysteem; Vuuren B. van, Kortekaas C. (HHS, faculty ITD, research minor)

[2] Eindverslag: Sensor Application Wrapper; Ast T. van, Scholte J., Wazir F. (HHS, faculty ITD, research minor)

2.1 Process

Earlier research[3] delivered results of the analysis belonging to data from January 2012 until the end of June 2016. These results have been used to get a better view of the current anomalies in the climate system.

Because the SAW application can only be used locally with access to the production database, the accessibility of the application is low. To improve the current workflow, the SAW application has been translated to a new web-application. This environment contains two separate applications. The user-side consists of a web-interface written in Angular, Typescript, HTML, and SASS, while data processing and analyzing is being done at the backend-application, this is written in C#. The backend application is an improved copy of the SAW application.

3. Bayesian Belief Networks

'BBN' is foremost used in the medical world (Deborah, A; 2006). That is why the building is often compared with a person by the lectorate 'Lectoraat Energie en de Gebouwde Omgeving' ('LEGO'); when he/she is sick, he/she has a number of symptoms and by combining them together there is a chance of a disease. This is also applicable on a building; examples of symptoms are: a high CO2, high temperature or low airflow value. A defective airflow -, CO2 sensor or over-occupancy are examples of results/diseases. By combining the active symptoms and using the theorem of Bayes, the conditional chance of an occurring result can be calculated. By using a chance instead of using a definitive result, multiple possible results can be taken into account.

In this research 'BBN' is used performing the following tasks:

- Adjusting an C++ application (Wazir, F.; 2017), named 'smileApp', so it can use the given 'BBN' model from the lectorate.
- Making a predicting model, which uses a form of supervised learning, in Python.

3.1. Analyzing with an application

Before the 'SmileApp' can be used to evaluate the given 'BBN' model, the features of the application must be altered. The implemented changes are: accept multiple delimiters, include last data line in analysis, and incorporate the use of the older database (data until April 2016).

To assess the given 'BBN' model, data from room 2.008 was used where it is known that the 'PIR' sensor was defect (Schagen, Taal, Itard; 2016). The figure below visualises this, the airflow is plotted together with the CO2 value against time (12 April 2015 until 7 June 2015).

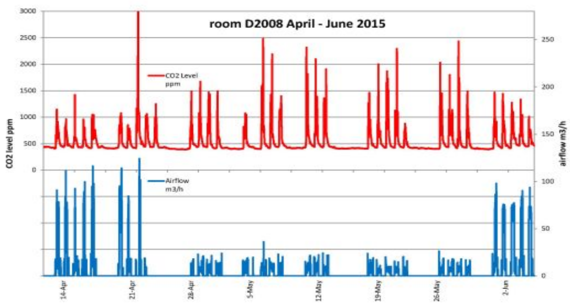

Figure 1, Graph of data from broken 'PIR' sensor

Until 20 April the ventilation was on average 80 m3/h and CO2 levels are around 800 – 1000 ppm. In the next period the ventilation is low (15 m3/h) and the CO2 levels are high (above 1500 ppm). The lights were off in that period, but that is not unusual for a room with a window to the South side of the building (Schagen, Taal, Itard; 2016).

Data from 28 April 2015 6:00 up to and including 1 June 2015 23:00 was analyzed via the 'smileApp'. The airflow -, CO2 -, and 'PIR' sensor data were retrieved from the old database. If the 'BBN' model is correctly configured it should predict a low probability of "PIR", meaning that the sensor is probably defect.

3.2. 'BBN' in Python

The principles of Bayes theorem were used in another approach to build a 'BBN' model in Python. As mentioned before, the purpose of the model is predicting the onset of sensor faults. The model algorithm is a method that uses the probabilities of each attribute belonging to each sensor to make a diagnosis and prediction. To make a prediction, the conditional probability of each sensor needs to be multiplied at a certain time and return the state with the highest probability. In other words, is the model predicting a working sensor or has it a higher chance of a broken sensor?

First the data of each sensor was summarized. This is done by calculating the mean and standard

[3] Eindverslag: Sensor Application Wrapper; Ast T. van, Scholte J., Wazir F. (HHS, faculty ITD, research minor)

deviation of each sensor. The mean is the tendency of the data and will be used to calculate probabilities. The standard deviation is used when calculating probabilities of future values. In this experiment data of nine sensors is used over a period of one year.

The model uses a function to estimate the probability of a given value, given the known mean and standard deviation. Given the summary per sensor, the conditional probability of a value can be calculated. For example CO_2 usually varies between 400 and 1000 ppm, a value of 0 or 1500 ppm would result in a higher chance of a defective sensor. High probabilities of broken sensors should have a high accuracy.
Unfortunately the model has yet to be validated on predictions and their accuracy.

4. **Deep Learning**

Out of the four chosen methods, ‘Deep Learning’ was chosen to further answer the research question of Laure Itard, the lector of LEGO. The research question is stated thus: ‘Is it possible to develop a fool-proof system that is comprehensible for non-experts and able to detect anomalies?’(Itard L., 2018) The definition of ‘non-expert’ within this question is as follows: ‘An individual that does not have the same knowledge as someone with professional experience in the field of indoor climate maintenance’ (Aelen, 2016).
Deep Learning is a type of Machine Learning which is inspired by the human brain (Goodfellow, Bengio, & Courville; 2016, p. 1). The network can determine what the default sensor values would be in normal conditions. When enough knowledge is gathered to define normal behavior and sensor values, this model can be used as a baseline. Every value that has a large differentiation from this baseline can be classified as an anomaly.
Certain tasks have been executed in order to further this stated research; these are:

- Research to find out which neural network is suitable for solving the research goal.
- The development of a neural network that is able to detect anomalies within a time-series dataset.

The goal of the research is to find a neural network that supports unsupervised data, this made the scope of neural networks smaller. The neural networks that were researched were; Autoencoder (AE), Recurrent Neural Network (RNN), and Long Short Term Memory (LSTM). The problem with Autoencoder was that it wasn’t suited for time-series. Then the RNN was researched, however the RNN has a so-called ‘Vanishing Gradient Problem’ (Hochreiter, 1997). This means that past data have less influences on the neural network, which makes the past data eventually insignificant, also every iteration will increase the time to train the neural network. The LSTM doesn't have the Vanishing Gradient Problem because it uses a Memory Cell, which stores data from previous timestamps.

5. **Clustering method**

Clustering is a method which is generally used to group research objects together based on recorded characteristics. These characteristics are dependant on the variable being observed. This technique can be used to gain insights as to how well the system functions regarding comfort, based on characteristics from the data. Within the stated research a massive amount of data has been made available. However, not much is known about the semantics of the stated data. In order to solve this, literary research has been conducted.
This research showed that the usage of factor analysis can be a very useful technique in order to reduce the amount of variables. This makes it possible to analyse multiple, even all available, variables at the same time (Ramawadh S., 2017).
In order to achieve this, the given data firstly needs to be transformed by the means of a Min-Max normalisation, thus eliminating scalar differences. Secondly the n amount of components needs to be determined. There are a number of different ways to determine this amount (Ramawadh S., 2017), whereof the ‘scree plot’ was used during this research. The n amount of components is the argument for the factor analysis function, belonging to Python’s ‘sklearn’ package, which delivers an (a x n) sized matrix. The used data, sized (m x a), is then multiplied with the given matrix in order to get the respective factor values of every data entry. This results in an (m x n) sized dataframe with m amount of data entries, each transformed into n amount of components.

6. **Results**

6.1. RBS

RBS was researched with the purpose to validate our results. However, due to difficulties in the SAW application there was decided to check the results by hand (figure 2) and visualize some of the found anomalies(figure 3 and 4).

Normal situation	Empty classroom	Lots of people present	TEMP sensor probably broken	PIR sensor probably broken	AIR sensor probably broken	C02 sensor probably broken		Normal situation	Empty classroom	Lots of people present	TEMP sensor probably broken	PIR sensor probably broken	AIR sensor probably broken	C02 sensor probably broken		Normal situation	Empty classroom	Lots of people present	TEMP sensor probably broken	PIR sensor probably broken
82	492	172		2	12			55	431	184			67			20	223	499		6
145	537	13		7	29	29		131	517	6		1	82			402	278	67		
99	500	125		42	6			96	439	108		35	60			59	167	481		49
129	527	68		5	3	28		153	501	50		2	31			167	393	28		171
						760								737						
						760								737						
						760								737						
119	543	66			32			139	486	68			44			255	226	226		
						760								737						
						760								737						
2	457	207		17	77				412	207			118			2	190	514		3
						760								737						
196	553	10			1			215	476	38		2	6			251	251	240		1
150	537	69			4			108	482	85			62			75	242	431		1
45	584	88			14	29		28	523	87			99			1	278	50		4
164	596							232	501	3			1			481	181	13		
110	591	27		21	11			115	565	10		11	36			171	550	23		8
138	491	72		31	8	28		162	469	37		21	54			183	240	317		6
171	573	8			8			239	494	2			2			371	218	27		
101	592	22		30	15			60	579	17		24	59			22	637	28		56
85	528	110		2	35			61	446	122		10	98			87	203	421		30
113	550	86			11			117	493	94			33			32	237	476		3
138	516	47			50			156	478	52			49			219	239	251		
						760								737						
						760								736						
231	501					28		263	474							192	229	339		
215	244	126		1	174			63	442	54		149	29			30	211	509		
						760								737						
169	533	17		11	2	28		228	491	9		9				128	241	367		12
						760								737						

Figure 2, some of the results checked by hand

Lokaal	Vanaf wanneer	Tot wanneer	Situatie	Verandering	Opmerkingen
0.005 (B4.01) Studielandschap	1-01-12	-	C02 sensor probably broken	T/m de periode 01-07-2013 - 01-08-2013 wordt er alleen de genoteerde situatie berekend. Hierna komen er "AIR sensor.." situaties bij.	Hier lijkt het goed mogelijk dat de sensor vanaf begin af aan al kapot is. De vraag is tevens waar dit lokaal gesitueerd is, heeft het te maken met de deuren naar buiten e.d.?
0.014 (B3.03a) Praktijkruimte	1-01-12	1-08-2013	C02 sensor probably broken	Vanaf de omschakeling komen er meerdere andere situaties bij, waaronder normale situaties e.d.	
0.014 (B3.03b B3.04) Praktijkruimte	1-01-12	1-08-2013	C02 sensor probably broken	""	
0.031 (E07) Facilitair Kantoor	1-01-12	1-08-2013	C02 sensor probably broken	""	
0.033 (E05) Schoonmaak Kantoor	1-01-12	1-08-2013	C02 sensor probably broken	""	

Figure 3, some of the found anomalies

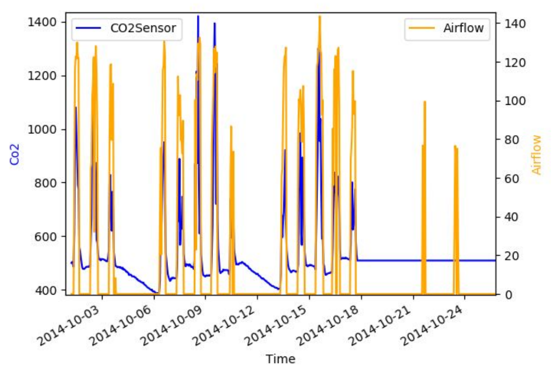

Figure 4, graph showing CO2 vs Airflow

During the period between January 1st 2012 till June the 23rd 2016, anomalies where detected in 66 of the 119 rooms. In 64 of these cases the CO2 sensor was probably broken. Because of the trouble with the SAW application it was decided to write a new application to analyse the available data (figure 5).

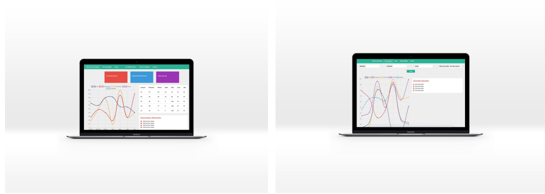

Figure 5, mockups for web-application

The application was written in Angular and a Backend application for the analysis in C#. Unfortunately, due to a lack of time, the back-end of the application is still under development.

6.2. BBN

The outcome for 'BBN' in combination with the ‘smileApp’ is disappointing. The analyzed room is 2.008 and the time frame is from April 4th 2015 up to and including June the 6th 2015.

The application predicted a broken damper with a mean probability of 66% over thirteen measurements. The prognosis of a defective 'PIR' sensor, however, has a mean probability of 0% over the thirteen measurements. The result does not match the expectation, thus the ‘BBN’ model has to be revised before it can be used to analyze data.

For ‘BBN’ in Python, the lack of validated training and test data sets causes the model cannot be validated. Furthermore, the accuracy of the predictions, train and test, needs to be calculated. The current set is trained on one room, so the model has to be trained and tested on a different set of rooms. Besides, the model has to be trained and validated on a multiclass prediction.

6.3. Deep Learning

In figure 6, a LSTM was used to predict a time series of three weeks; a normal school week, followed by a week of holiday and another school week. As shown, the LSTM makes a fairly good prediction. However, there are still some particularities in this graph. For example, during the first monday of the holiday the LSTM predicts a new school day because of a limited window-size. To solve that problem, the window-size is increased to a week instead of 24 hours. Further optimization can be done by tuning the hyperparameters of the LSTM network. The LSTM-model can be used as a baseline. Whenever the real value deviates to much from this baseline, an anomaly is detected.

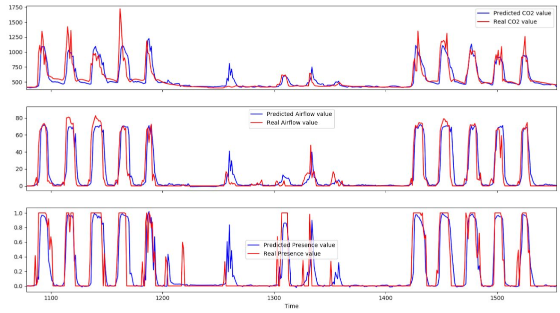

Figure 6, Prediction of LSTM model

6.4 Clustering method

In order to validate the applicability of transforming data by means of Factor analysis to find clusters, a dataset in which a known defective presence sensor has been analysed. The sensor was defect during the time between April 20th and the 1st of June. This period was found by transforming a year of data, including the searched period, into five distinctive “factors”. The found factors were then analysed and grouped into clusters by means of the cluster recognition method known as “HDBscan”. Multiple cluster recognition methods were reviewed whereof the “HDBscan” was the best method to apply. This is concluded because it does not include every analysed data-point it receives, so it does not add random data-points to existing clusters. In figure 7, a ‘scatterplot’ is displayed between two of the five factors which resulted in four found clusters, which have been given distinctive colored, and a bunch of points that do not belong to any cluster, given a black color. The blue cluster in this figure is the period in which the presence sensor was defect. This gives proof that transforming and clustering a reasonably sized dataset can be used to detect defective sensors.

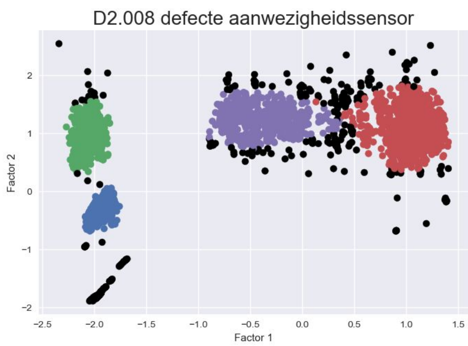

Figure 7, Scatterplot of two factors

7. Discussion

The results of the research into the expansion and improvement of the ‘RBS’ quickly showed that the user-system ‘SAW’ (Sensor Application Wrapper) does not meet the requirements. The reason is existing ‘bugs’ within the system. The biggest disadvantage of this is that the ‘RBS’ can not be validated. Although it is currently the best method to benchmark other methods with, that does not mean a better method does not exist. Because of this, an attempt has been made to detect the anomalies manually. The attempt was unsuccessful. Therefore, validity has not been achieved.

For future follow-up research, it is highly advised, to have sufficient knowledge of ‘BBN’ as well as ‘Deep Learning’ to be able to fine-tune used methods. It is also advised to develop a web-application, together with the ‘RBS’ and in combination with an ‘Backend’ application for LSTM-models and ‘BBN’. Furthermore, it is of utmost importance that a validation method, that is applicable for all detection methods, is found or developed. With such a validation method, detection methods can be validated and benchmarked.

8. Conclusion

This research explored different ways The Hague University of applied sciences in Delft could use sensordata to automatically analyse and visualize the data, in order to find real time anomalies and report them.

The results conclude that the ‘Clustering method’ and ‘Deep Learning’ both displayed useful results, whereas the given ‘BBN’ model needed to be revised to produce similar results. Finally was shown that transforming and clustering the data may also be a good way to detect anomalies.

The first subquestion was what specific anomalies were happening. Out of the data and models that were used, the only outcome we found was ‘CO2 sensor is probably broken’. Through training and expanding the models more anomalies would have been known.

By operating the cluster analyses, two known anomalies have been detected, this showcases the validation and usability of the clustering method. The second subquestion; ‘In which way can sensordata be used to find anomalies’. To answer this question four methods have been researched, these are: ‘RBS’, 'BBN', Deep Learning and cluster analyses. Whereby every method can be used to find anomalies.

For the third and last subquestion which states: ‘In what way can the found anomalies be reported’. In the research it is shown that a web-application has all the functionality to answer this question.

The main question of the research is: How can The Hague University in Delft use it’s sensordata to automatically analyse and visualize the data, to find real time anomalies and report them.This question can be solved by using a web-application to show the data, which uses a LSTM method with a clustering function to find the anomalies. This is because the LSTM and clustering method are the only two methods that can automatically analyse the data without a expert.

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