Investigation and prediction of Energy consumption at St. Olavs Hospital

by Hans Smedsrud Kristofersen¹, Kai Xue², Zhirong Yang¹, Liv-Inger Stenstad³, Tor Emil Giske³ and Guangyu Cao¹

¹Norwegian University of Science and Technology (NTNU), NO-7041, Trondheim Norway

²School of Civil Engineering Chongqing University, Chongqing, 400045, China

³ St. Olavs Hospital, NO-7041, Trondheim, Norway

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Abstract

The objective of this study is to evaluate and predict the energy use in different buildings during COVID-19 pandemic period at St. Olavs Hospital in Trondheim. Based on machine learning, operational data from St. Olavs hospital combined with weather data will be used to predict energy use for the hospital.

Analysis of the energy data showed that the case buildings at the hospital did not have any different energy use during the pandemic this year compared to the same period last year, except for the lab center. The energy consumption of electricity, heating and cooling is very similar both in 2019 and 2020 for all buildings, but in 2020 during the pandemic, the lab center had a reduction of 35% in electricity, compared to last year. An analysis of the energy needed for heating and cooling in the end of June to the end of November was also calculated for operating room 1 and was estimated to 256 kWh/m² for operation room 1.

The machine learning algorithms perform very well to predict the energy consumption of case buildings, Random Forest and AdaBoost proves as the best models, with less than 10% margin of error, some of the models have only 4% error.

An analysis of the effect of humidification of ventilation air on energy consumption in operating room 1 was also carried out. The impact on energy consumption were high in winter and will at the coldest periods be able to double the energy consumption needed in the ventilation.

1. Introduction

Hospitals are complex buildings with relatively constant needs, regardless climate. Medical equipment, hygiene and ventilation are some of the things that separate hospitals from other buildings. Hospitals are buildings with sick people, bacteria and viruses could be critical. A survey from 2018 showed that 3.1 % of annual patients in Norway in hospitals got infections [2]. This corresponds to 61,600 people in 2019 [3]. A sedentary person emits around 10,000 bacteria-bearing particles per minute [1]. For this reason, there are high demands on air replacements.

Heat exchangers that exchange indoor air with outdoor air (rotary heat exchanger) are not desirable for rooms with strict requirements. Examples of these are isolation rooms, operating rooms and laboratories. Plate heat exchangers are often used for ventilation in large parts of the building, in some cases there is no use of heat

exchange. This causes a bigger energy consumption than other buildings. HVAC systems alone often contribute almost 40-50% of the total energy use [7]. In some rooms there is a need for large air changes per hour, which is also a reason for this high number. A survey from Statistic Norway (SSB) shows that hospital buildings use around 375 kWh / m², which is almost 80 % higher than commercial buildings [4]. In the United States, the average hospital energy intensity is as high as 738 kWh / m² [5]. The thesis deals with several buildings at St. Olavs Hospital in Trondheim.

2020 has been marked by Covid 19 pandemic. For this reason, it will also be investigated how a pandemic like this affects energy use for hospitals. Based on machine learning, operational data from St. Olavs combined with weather data will be used to predict energy use for the hospital. The machine learning scripts will be based on previous work by Kai Xue and Zhirong Yang.

Corresponding author: hansskr@stud.ntnu.no

The energy analysis is based on final energy consumption, and do not consider losses in power production. A distinction is made between energy need for heating, cooling and electricity. Heating is needed most of the year in Norway and involves space heating, heating for ventilation and hot water. Cooling is needed on the hottest summer days but has a short duration in Trondheim. Cooling only involves the cooling coil in the ventilation unit. The electricity goes to all the equipment in the hospital and is relatively constant.

In Norway, development and renovation projects must follow the Plan and the Building Act, which also have technical descriptions in the Building Regulations called TEK 17. The current building regulations (TEK17) set requirements for net energy needs for hospitals in § 14-2. This is generally 225 kWh / m², but if normal heat recovery is not desirable under the circumstances, the requirement is 265 kWh / m² [10]. The last of these two numbers are affecting especially the operating rooms, isolation rooms and laboratories.

Operating rooms are special in the form that they require a high degree of hygiene. To ensure this there are large amounts of air that are replaced every hour and very strict air filters (HEPA). This gives rise to large fan effects and supplied heat /cooling in the coils. To maintain hygiene, the systems need to always be in operation, which ensures a large energy consumption. A study from 2016 in Germany showed that the power consumption in form of electricity in an operating room may vary a lot, from 364 kWh/m² to some extreme cases with 1275 kWh/m² [15]

2. Methods

2.1 Case Buildings

There are 6 buildings that are used to collect energy consumption data at St. Olavs Hospital. Data collection has been done by the data collection system at St. Olavs Hospital, energy collection includes electricity, heating and cooling data. Below is a summary of each building and the type of use.

2.1.1 Gastro center

The Gastro center was opened in 2009 and the total usable area is around 30,700 m². Here, patients with cancer, digestive problems and liver problems are treated. In total, there are around 282 patient places and 7 operating rooms here [8].

2.1.2 Laboratory center

The Laboratory center is 25,500 m² in gross area. It was built in 2005 and is used for medical research and teaching, furthermore there is a blood bank and chapel here [8].

2.1.3 Acute heart and lung center

The Acute center was opened in 2010 and provides emergency care. It has a gross area of 40,100 m². In addition to heart and lung treatment, it is also used for research and teaching. The building also contains a casualty department and an orthopedic injury clinic [8].

2.1.4 Woman-child center

The Woman-child center is 31,200 m² in gross area and was opened in 2006. It is used for births, gynecology and pediatrics. The building is further used for research and teaching. In addition, there is a hospital school here. There are 187 patient places here, 9 operating rooms and 14 birthing centers [8].

2.1.5 Knowledge center

The Knowledge center is around 17,000 m² in gross area and was completed in 2013. The building is divided between the university and the hospital. The building is used for research and teaching, in addition to clinical treatment of skin diseases. No operations are performed here. The building is one of the first in its kind with passive house standard.

In total, there are 44 patient places [9].

2.1.6 Movement center

The Movement center was completed in 2009 and has a total gross area of 19,300 m². The building is used to treat patients with diseases that reduce mobility. A heated pool is available in the building for treatment. The building is also used for research and teaching. There are 118 patient places here and 8 operating rooms [8].

2.2 Machine learning- Decision Tree and optimization algorithms

2.2.1 Decision Tree

Decision tree is based on many so-called nodes that branch out like a flowchart tree. Each node consists of one criterion. The way forward from each node will be based on whether the criterion is met or not met. The end of each node path that does not split anymore is called a

decision leaf; this leaf predicts a value in regression modelling. When you merge all these nodes, you get a very strong algorithm [11].

2.2.2 Bagging Decision Tree

Based on the same principle as Decision Trees. The difference is in the samples. A bagging decision tree makes random sub-samples of our data samples. For example, if we have 1000 measurement points, the bagging can create 100 new datasets of this data, by random picking up data from the given dataset. This is used to create 100 new decision trees. By merging several such models, we can get a strong model of the data [12].

2.2.3 Random Forest

Random Forest is based on decision trees, but instead of using all the features, it takes out only a few and randomize it. This causes a lower error than using all the

features in one training set. By using fewer features, it also runs faster. The advantage of random forest is that all sub-models have lower correlation than with bagging and decision tree [12]

2.2.4 AdaBoost

A very powerful optimizing algorithm, it makes a series of learning models where the weak models are combined to a stronger one. It selects random data to train models, each model is weak, but by emphasizing poorly modelled data, new models will be trained to hit better [13].

2.2.5 Support vector regression

Support vector regression uses a hyperplane when working with more than 3 variables, which is difficult to visualize. Based on a given tolerance limit (epsilon), the hyperplane will adjust to get as much data as possible within the given tolerance limit. The big difference between regular linear regression and support vector regression is that SVR only aims to get within the threshold value for error. Linear regression calculates the smallest possible deviation between the function and the

threshold [14].

2.2 Machine learning for energy prediction and collection of weather data

The machine learning is based on previous research by Kai Xue. The program requires input of weather data and energy use in form of electricity, heating and cooling. For this reason, an excel sheet has been set up with data from 2020. Weather data involves the collection of air temperature, relative humidity, wind, global radiation and reflected long-wave radiation. This data has a resolution of one hour and is taken from Norwegian climate service center. None of the weather stations in Trondheim could retrieve all the data in one place. Voll is used to extract average wind, air temperature and relative humidity. Gløshaugen's climate station provided data for Global radiation and reflected long-wave radiation. Voll is about 100 meters higher than Øya, which can give rise to more wind than it is at St. Olavs. In any case, this was the only station with wind data.

To investigate how a pandemic in the form of Covid 19 affects energy consumption in hospitals, it has been chosen to look at the period from February to the end of September. The data has a resolution of one hour and are used to calculate daily averages and variations. Energy data from the examined buildings are uploaded as excel documents through their energy monitors, at St. Olavs Hospital's database. All this data is further uploaded to a main document and processed.

The machine learning script is based on numerical data for the examined building and a description of the input/output data is given in table 1 below.

Month, day and time have been converted from string to numeric value in the form of sin / cos functions to get a period between 2π and -2π . This data was obtained from Kai Xue's previous research [5].

Variable	No.	Name	Unit	Res.	Range	Type
Input	1	Date and time	/	1h	2020.02-2020.10	String
	2	Outdoor temperature	°C	1h	-15 - 25	Numerical
	3	Relative humidity	%	1h	0-100	Numerical
	4	Wind speed	m/s	1h	0-15	Numerical
	5	Global radiation	W/m2	1h	0-800	Numerical
	6	Longwave radiation	W/m2	1h	0-500	Numerical
Output	1	Electricity	kWh	1h	0-1200	Numerical
	2	Heating	kWh	1h	0-1300	Numerical
	3	Cooling	kWh	1h	0-600	Numerical

Table 1 Data description for the machine learning script

The data in table 1 is further uploaded as an CSV-file that could be read by the machine learning script. The script is based on 6 phases, and below in figure 1 is a flow chart for the whole process.

Figure 1 Flow chart for the machine learning

2.3 Impact of lower limits for indoor humidity on energy consumption

This analysis is only done for operating room 1 at St. Olavs and is based on Equation (1). The formula calculates the energy that needs to be supplied to the desired amount of steam, to humidify the air. The calculation is based on pure energy that is needed to humidify the air without any losses. The operation room does not use humidification, but the equation is used to investigate how much energy will be consumed to fulfil lower humidification limits of 30% and 50%. When the humidity in the outside air is below the demand to reach these values, a steamer will humidify the air.

The logging data from the operating room is based on a study from 2019, with a logger set out in the microenvironmental zone. The resolution in this data is set to 5 minutes.

$$Q_{steam} = 2502 \frac{kJ}{kg_{water}} * x_{humidification} * \dot{m}_{air} * h \quad (1)$$

Q_{steam} = Energy added to the steam [kWh]

$x_{humidification}$ = amount of humidity added to the air [kg_{water}/kg_{air}]

$\dot{m}_{air}$ = massflow of air [kg/s]

h = time resolution 0.0833h (5 minutes) [hour]

3. Result

3.1 Climate

The climate in Trondheim is very periodic. As the figure 2 below show, there is not much change from year to year. The temperatures are mostly similar from month to month, with some variation in the length of the coldest and warmest periods. The wind and relative humidity can be seen to vary to a greater extent. On average, it looks like there is good agreement in wind speed, but it seems to be slightly larger in the beginning of 2020 than 2019. The radiation has good agreement in the form of global radiation. Longwave radiation varies a little more in the form of radiation peaks. All in all, there is very good agreement from year to year in the weather data, the climate is stable in Trondheim.

Figure 2 Weather data in Trondheim 2016-2020

3.2 Energy consumption for the case buildings in the pandemic period 2020 and the same period in 2019

As Figure 2 shows, there is relatively similar use of energy for the various departments at St. Olavs, except for electricity for the Lab center. The Lab center had a reduction of about 35% in electricity consumption, for 2020. The shares for energy use are relatively equal for all the buildings,

Operations at St. Olav's Hospital were reduced from March, with regard to covid 19. All planned operations that were not urgent were postponed. This was to

ensure having enough beds to be equipped for the pandemic. Visits to the hospital were also strictly forbidden and guards were placed outside to keep people out. Eventually it was seen in Trondheim that there were not as many covid patients as feared, so that the activity could be increased again. Many employees have had home offices during this period. It was eventually opened for a 1-hour visit for newly operated and sick patients.

Figure 3 Energy consumption from February-September, 2020 and 2019, for the case buildings

3.3 Energy Predictions using machine learning, Gastro Center

Figure 4 Energy prediction for heating at the Gastro Center, February-September 2020. The x-axis shows hours

Figure 5 Energy prediction for cooling at the Gastro Center, February-September 2020. The x-axis shows hours

Figure 6 Energy prediction for electricity at the Gastro Center, February-September 2020. The x-axis shows hours

All models hit well except for the Bagging Decision Tree and Support Vector Regression, the SVR was only tested in the heating model. In summary, Ada Boost and Random Forest are the best algorithms and have a coefficient of determination well above 0.9 on all

models. As figure 6 shows, the predictions miss a lot at the cooling peak at 500kWh around time 3400 h. This is due to low distribution of such high cooling, which means that this area is less well described by machine learning.

Figure 7 The coefficient of determination for the Gastro Center, first (heating), second (cooling), third (electricity). For training (blue) and test data (orange)

3.4 Impact of indoor relative humidity lower limits on energy consumption

In Norway, as mentioned earlier, there are no requirements regarding humidity, but recommendations. Figure 8 shows what effects in form of steam that must be added to the air, in the form of humidification to keep 30% and 50% as lower values, respectively. As the figure shows, there are large effects needed to heat up

the steam. To keep 50%, it must be moistened almost the entire period. At 30% as a minimum value, the humidifier must work evenly from October. The humidifier with 50% limit will from this period be about twice as high in effect as the 30% humidifier, which will also give twice as much energy consumption.

Figure 8 Operation room 1, effect that need to be supplied in form of steam, for humidification, to keep 30% or 50% relative humidity

Figure 9 shows energy consumption every 5 minutes for operating room 1. When summing all the points, 6944 kWh is obtained for 30% humidity and 22 535 kWh for 50%. Operating room 1 has a total of 60 m² which gives 116 kWh / m² and 375kWh / m².

This is only based on half a year; it will therefore require large amounts of energy to maintain these values for humidity. The energy framework in the building technical regulation (TEK 17) will be difficult to maintain with such a solution for modern hospitals.

Figure 9 Energy consumption for humidifying of air in operation room 1

4 Conclusion and discussion

The energy consumption of the five investigated hospital buildings in the Covid-19 period turned out to be very similar as in the same period last year. The lab however had a reduction of 35% in electricity. Energy consumption is above current requirements in building technical regulations (TEK17), but the hospital is designed against an earlier version than today, which explains this finding.

Machine learning was performed at the lab center and gastro center, and a total of 5 machine learning algorithms were tested. Random Forest and AdaBoost were the algorithms that hits best on all 6 tested models and had a coefficient of determination well over 90% for all types of models that was predicted. Cooling prediction for the Gastro Center was almost perfect, the heating models were also very good. Electricity was a bit more complex to predict, but with AdaBoost and Random Forest, the electricity model also came out well

with a coefficient of determination around 90% on the test data. All in all, Random Forest and AdaBoost are models that predict energy consumption very well.

It was also investigated how humidification will affect energy consumption, in the form of a lower limit of 30 and 50% Relative humidity. There was large need for supplied effect to the steam, in the form of humidification. In the coldest months, there is a need of 10kW for humidifying, to keep 30% RH. 50% will require 20kW. This also means that that the energy consumption in operating room 1 almost will be doubled in the coldest months with humidifying, compared to no humidification, 30% as lower limit will increase the consumption with over 116 kWh/m², while 50% will increase the consumption with more than 375 kWh/m² in the surveyed period. This corresponds to 45% and 146% of the energy amount needed for heating and cooling in operation room 1.

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