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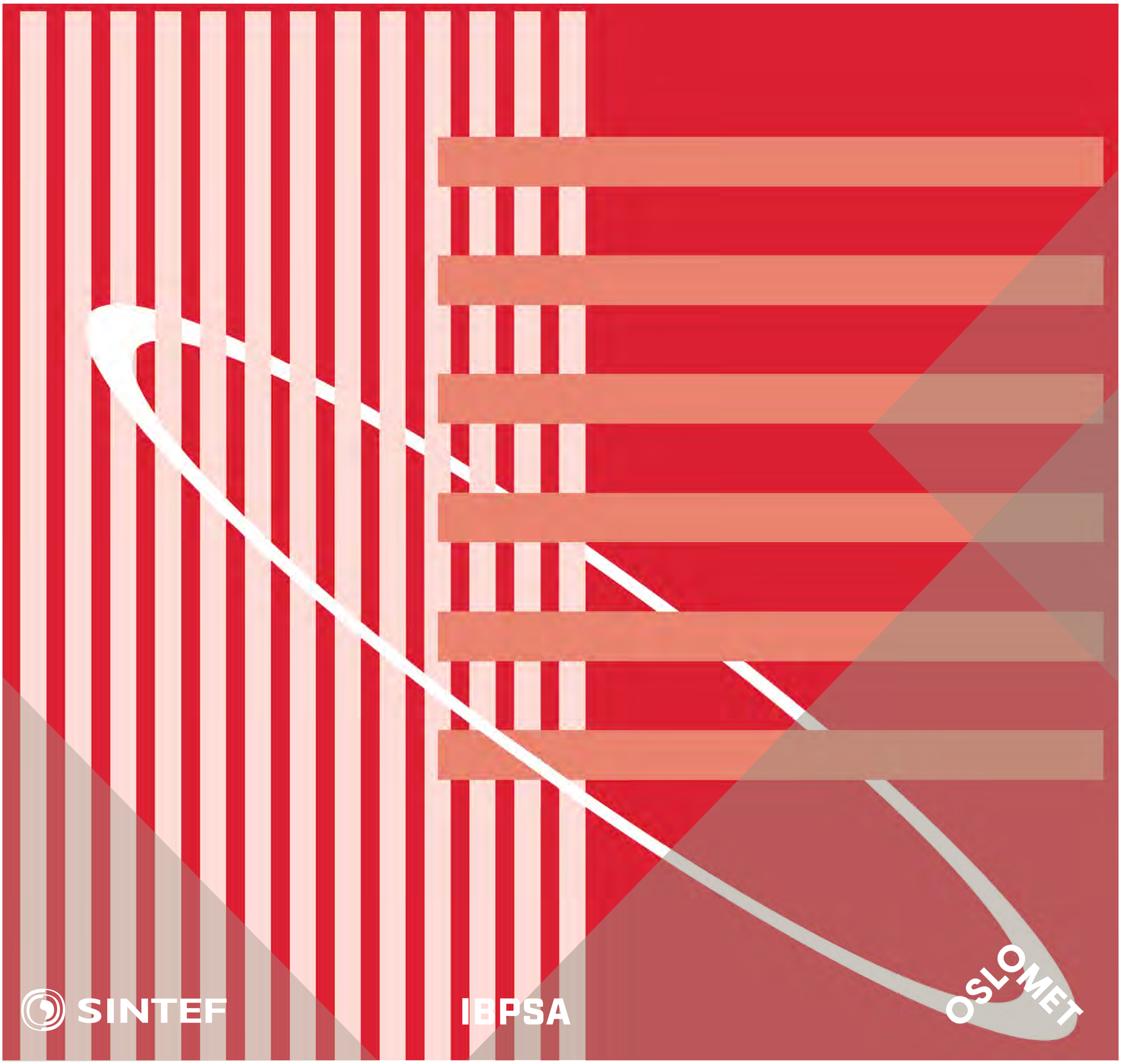
# BuildSIM-Nordic 2020

Selected papers



SINTEF Proceedings

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# Working With a Small and Predictable Performance Gap

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## Abstract

Much is written about the performance gap. Multiple studies show alarming discrepancies between design and actual building energy performance. Should this prove to be a *universal truth*, the need of more detailed dynamic modeling methods can certainly be put into question. The prevalence, of somewhat antiquated, monthly methods in many current building codes seem to support this view.

In this paper we demonstrate a case supporting the opposite viewpoint. When the motivation and tools are right, sufficient accuracy between prediction and actual energy performance can be achieved. We present a building modelling case, where appropriate data was collected over a period of a full year for an office building with gross floor area of 31,809 meter squared in Stockholm, Sweden. We showcase how by abiding by a Keep it Simple and Straightforward approach in modeling one is able to achieve accurate energy performance predictions without sacrificing on capturing building's dynamics and internal states. However the selected project is not a singularity, but represent the mainstream in state of the art Swedish design practice. We end by highlighting some pitfalls with current guidelines regarding calculating goodness of fit measures between empirical data and a dynamic simulation model, and providing some recommendations for more appropriate metrics.

## Introduction

Building commissioning is becoming a vital part of the building construction industry in Sweden, where legislation requires a two year commissioning phase for new constructions. The construction industry has since had to bridge the energy performance gap between initial design models and the physical building in a way that is practical and robust enough for industrial use. Moreover, utilizing a consistent, unbiased, and transparent methodology for building modeling is deemed an important factor for reliable and trustworthy results.

In this paper we describe our methodology behind modeling and simulating a physical building for achieving a small prediction gap. We consider the complex and fast acting dynamics behind the heating and cooling demands of the building, as well as it's underlying custom control structures over a period of a full year. We demonstrate this using the building performance simulation tool IDA ICE,EQUA (EQUA), a commercial tool for whole year building energy and indoor climate simulations, which allows the creation of custom controls and HVAC systems.

The structure of this paper is as follows. In Section II we describe the physical building envelope and zoning, as well as the nature of the collected input data; we also discuss our modeling approach. Section III details the building's HVAC systems and control sequences. along with their implementation within "IDA ICE". In Section IV we present our findings and results, highlighting the attained small prediction gap. We also reflect on the adequacy of the ASHRAE guideline 14-2014,ASHRAE (2014), on describing goodness of fit measures for dynamic simulation models. Conclusions are drawn in Section V.

## A Case Study - Gångaren 11

Gångaren 11, the current headquarters of Skandia AB, a Swedish independent banking and insurance group, is located in the central Stockholm district. The office building was built by Skanska AB, a Swedish project development and construction group, throughout 2010-2011, and is certified as a "Green Building". The building houses around 1200 employees, and spans a gross floor area of 31,809 meter squared over a total of eight floors, seven of which are offices. The building also has access to an underground garage, and has a double skin façade with internal blind control, as well as a glazed atrium running through the center of the building. Figure 1 depicts the building envelope. The zoning of each of the office floors consists of dense private offices along the outer and inner perimeters of the envelope. The first floor also includes a kitchen and food court area, along with a small refrigerated room, and three small data center rooms. A sample office floor layout is shown in Figure 2.

### Zoning and modeling data

Thermal zones were constructed with accordance to ASHRAE 90.1-2007 appendix G3.1.7-9,ASHRAE (2013). For the office floors, two geometric zone configurations were constructed.

The *perimeter* zones extending 5 meters from the outer building envelope, and the *inner* zones covering the remaining inner space. The atrium was modeled as a separate zone. The office floors were sectioned with respect to orientation, classification,

*Figure 1: Gångaren 11, double skin façade building envelope*

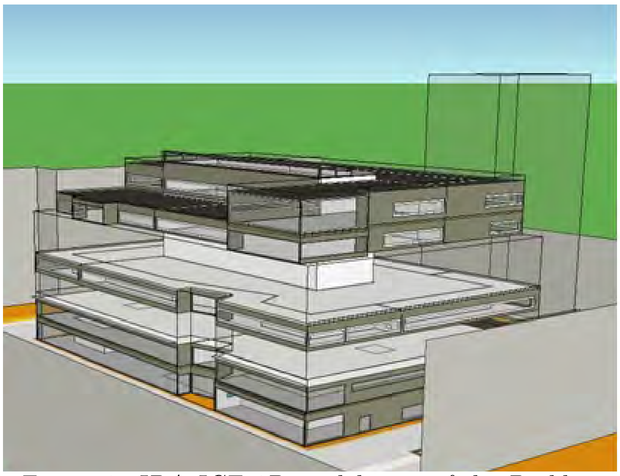

*Figure 2: IDA ICE 3D model view of the Building*

and common HVAC systems. Zone multipliers were used for similar zones, while the building body was divided across the top, bottom, and middle floors. A simplification was made for the double skin façade with the total U-value and SHGC abbreviated into a single glazing. the glazing U-values were supplemented by a 10% increase on the rated value to accommodate Swedish climate conditions. Internal and in between blinds, as well as a 100 mm recession in the window frames were accounted for in the model. The average glazing U-value was around 1.4 W/m$^2$ K with a SHGC ranging between 0.2 and 0.6. The blinds had a multiplication factor for the SHGC of 0.4 when drawn, and a control schedule set to an upper limit of 150 W/m$^2$ of irradiance inside the zone. The ground layer is modeled according to ISO 13370 with 1 meter of soil, while the exterior walls have an average U-value of 0.20 W/m$^2$ K, and a roof U-value of 0.13 W/m$^2$ K. Thermal bridges were defined per joint type, and infiltration was modeled by an air flow network, with an average leakage over the envelope of 0.6 L/s m$^2$ external surface at 50 Pa. Figure 3 shows the building envelope and zoning in IDA ICE.

The weather file, which includes dry-bulb temperature, relative humidity, Direct normal irradiance, Diffuse irradiance, and wind speed & direction, was obtained from the Swedish Meteorological and Hydrological Institute, SMHI, weather service. The service implements a mesoscale analyses system called MESAN for wind, temperature, and humidity measurements, and a modeling system called STRÅNG for global horizontal irradiance, and direct normal irradiance. The measurements have a spatial resolution grid of 11x11 km,MESAN (MESAN); STRANG (STRANG).

**HVAC systems and Controls**

The building is serviced by district cooling and heating, and has four Air Handling Units with liquid-coupled heat recovery and a free cooling circuit, as well as two air recirculation units dedicated for the atrium. The garage is heated via the return air of one of the AHUs, while the toiletries, recycling room, utilities room, and staircases are serviced by forced exhaust fans. A small ground heating unit, for melting snow, is located in front of the garage entrance.

The rooms are cooled through active chilled beam units, and heating is delivered by water radiators with thermostatic actuators regulating room temperature. Most rooms are supplied with Constant Air Volume flow, except meeting areas and the food court which have a Variable Air Volume flow controlled by dry-bulb temperature. The room set-points are 22$^o$C, and 23 $^o$C for heating and cooling respectively. Winter/Summer mode activates according to outside air temperature.

$$\text{Summer:} \quad \begin{cases} T_{out} & > 17^oC \\ \frac{1}{3} \times \sum_{i=1}^{3} T_{out,i} & > 12^oC \end{cases}$$

$$\text{Winter:} \quad T_{out} < 5^oC$$

The building has night set back ranging between 5 and 10$^o$C, depending on outside temperature, from 18:00 till 05:00, except for the month of January. Night ventilation control scheme is as follows:

$$\text{Activate:} \quad \begin{cases} T_{in} & > 23^oC \\ T_{in} - Tout & > 4^oC \end{cases}$$

$$\text{Deactivate:} \quad \begin{cases} T_{in} & < 21^oC \\ T_{out} & < 10^oC \\ T_{in} - Tout & < 2^oC \end{cases}$$

Free cooling is made available whenever $T_{out} < 15^oC$. The free cooling network, recirculates the cold water circuit of the active chilled beam units into a heat exchanger on the supply air side of the Air Handling Units. The control schemes were implemented as is, while the 4 AHUs were lumped into one single AHU. Similarly a single recirculation unit was modeled as a sum of the existing two units supplying the atrium. The kitchen was modeled with a separate AHU, one which contains no heat exchanger. Figures 4 & 5 show the plant and main Air Handling Unit modeled in IDA ICE.

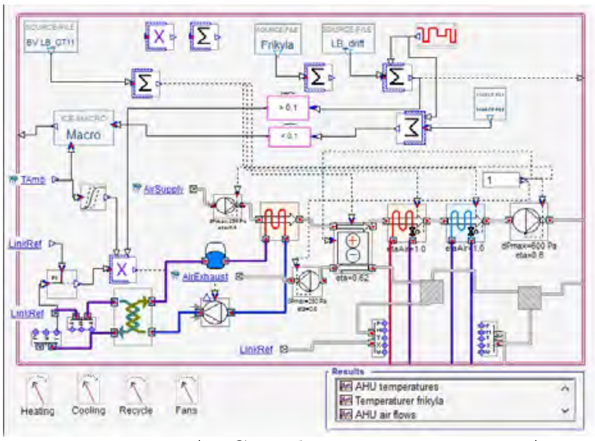


*Figure 3: IDA ICE schematic view main AHU*

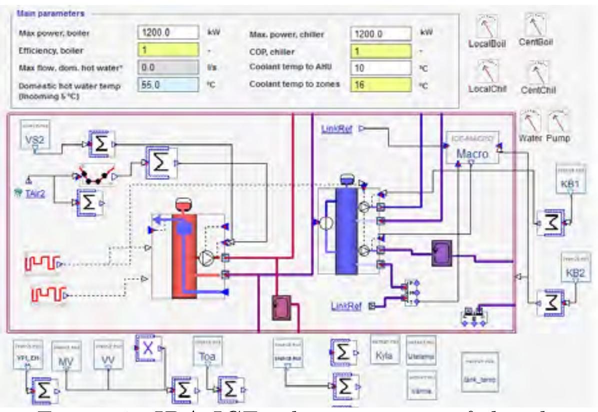


*Figure 4: IDA ICE schematic view of the plant*

The main AHU features a cooling coil, heating coil, heat exchanger with 62% efficiency (see subsection C), and the free cooling circuit. The free cooling circuit has an additional control condition in the form of a delay function. The building has a delay control function of one hour, delaying district cooling for a period of 60 min from 07:00 till 08:00, in order to avoid peak surcharges on cooling. The recirculation unit, is equipped with a heating and cooling coil only, at a set-point of 22$^o$C. While the kitchen is modeled with an AHU, also equipped with only a heating and cooling coil, supplying air at a set-point of 19.5$^o$C.

District cooling and heating are modeled with COP of 1 and capped at 1200 kW. The hot water system provides hot water at a proportional set point between 60 and 20 $^oC$ for outside temperature range of -20 and 20 $^oC$ for the AHU network, and a set-point between 55 and 15$^o$C for the same range, for the room unit network. To account for pipe and network losses, a tank is modeled at the supply side of the room unit hot water network with a capacity of 10 m$^3$, and heat loss of around 10% of total hot water consumption. Cold water is provided at a set-point of 10$^oC$ for the AHU unit cold water network, and at 15$^oC$ for the room unit cold water network. Two tanks were modeled on the supply side of the cold water network of the AHU and room units, each with a capacity of 7 m$^3$.

The office building also contains three small server rooms which contribute to processes cooling consumption, and are serviced by the main cold water network in the model. To simulate this, a separate small room was added, where process heat was injected into the zone and removed by a fan coil unit connected to the main AHU network. To quantify the amount of process cooling needed, we analyzed the collected sensor data from the building. Cooling demand at off schedule hours on a cold winter day, i.e when cooling is not required, gives us an estimate of the base process cooling load, as well as cold water network losses in the building. Those were estimated at around 30 kW. Similarly to get an estimate of heating losses in the domestic hot water network, we examine the heating demand of a building at a hot summer day at peak hour, i.e when heating is not required.

The set-points and control schedule are fed into the modeled plant and AHU from the sensor data of the building. While internal gains were estimated from the electricity consumption of the office building. The electricity consumption can also provide us with a control signal for occupancy presence, due to it's high correlation with occupancy presence profile in an office building setup. A high pass filter was applied on the occupancy presence profile in order to remove the baseline value of occupancy presence during nighttime and off working hours. Moreover in an office type building 100% of the electricity consumption can be considered as added heat in the form of radiation and convection, with the exception of the kitchen area where almost all the heat demand is discarded as losses. The distribution of occupancy was uniform with an occupancy density of 1 person per 30 m$^2$, the figure can be considered sparse but it includes unoccupied spaces.

Domestic hot water was not considered in the model, but was directly fed from measured sensor data from the building. It is often difficult and stochastic to guess and estimate dynamic hot water consumption in a building. The small ground heater was also not included in the simulation model, and was instead fed to the model from measured sensor data.

### Preprocessing of Sensor Data

The building has a total of 460 sensor signals, at a frequency of 0.0016 Hz (1 reading every 10 min). A full year worth of measurement data was collected for 2011. The building has an outdoor temperature sensor, however the building's outdoor temperature sensor was peppered with spikes, due to the sensor being unshaded from direct solar radiation. The temperature signal was therefore filtered with a sliding median filter, and compared with the temperature measurements from the weather file. The two measurements matched well, with an hourly Residual Mean Square Error, $RMSE_h = 0.0029$. The filtered outside temperature sensor was therefore qualified to replace the temperature from the weather file. It is standard practice to use the direct outside temperature sensor from the building's location instead of the weather station temperature readings, due to the prior being a better indication of ground truth.

Accumulated electric power consumption was metered for four different sections in the building; the kitchen area, offices, facilities, and an annex area. The accumulated graphs were differenced to yield instantaneous electric power consumption. Process electricity was subtracted from the total figure, as it was added separately into the model. While only 10% of the kitchen's electricity consumption was considered as heat gains for the kitchen area. All remaining electricity was considered as heat gains, and was uniformly distributed according to floor area across the model, excluding garage, atrium, and storage floor areas.

The electricity consumption of the office areas was converted to a control signal by data normalization:

$$X_{norm} = \frac{X - min(X)}{max(X) - min(X)} \quad (1)$$

the control signal was multiplied by the occupancy density, and uniformly distributed according to floor area across the model.

The temperature transfer efficiency for the heat exchangers were computed, and estimated at around 62% under normal working conditions.

$$\eta_{supply} = \frac{T_{supply} - T_{inlet}}{T_{return} - T_{inlet}} \quad (2)$$

By comparing the supply and return temperature transfer efficiencies, we analyzed the flow balance in the building.

$$\eta_{return} = \frac{T_{return} - T_{outlet}}{T_{return} - T_{inlet}} \quad (3)$$

Since we were lumping the AHU in the model into a single unit, the control signal had to be calculated as the normalization of the total sum of all existing supply fans flow meters. We calculated the measured power of the free cooling circuit from the volumetric flow of the supply fans, and the temperature difference across the cooling coil $T_{in,c}$ and $T_{out,c}$.

$$\dot{Q}_{free,cooling} = \rho * cp_{air} * \Delta T * \dot{V}_{supply} \quad (4)$$

The outlet temperature of the cooling coil in the free cooling circuit was not measured directly, instead the temperature sensor was located at the inlet of the heat exchanger after the supply fans. Thus a correction value of $0.3^oC$ was added to the $\Delta T$ term. The Specific Fan Power was then calculated from measured data by dividing the measured power consumption of the fans with their respective volumetric flow rates.

The supply and return rates of the room ventilation inlets and diffusers, were calculated based on the total sum of the volumetric flow rates of the existing AHUs. The sum was then divided uniformly according to gross floor area across all rooms. Fan and pump electricity was summed up for comparison with simulated output data.

The ground heating system's power consumption was calculated knowing the temperature difference across the supply and return pipes, and knowing the working fluid medium to be Propylene glycol. While Domestic Hot water consumption was calculated, with the assumption of incoming cold tap water temperature to be at $10^oC$, by differencing the metered volumetric flow to obtain volumetric flow rate measurements.

$$\dot{Q}_{DHW} = cp_{water} * (T_{hot} - 10) * \frac{\delta V_{supply}}{\delta t} \quad (5)$$

Both the domestic hot water consumption, and the power consumption of the ground heating unit were added to the heating demand output of the simulation model. Finally, by inspecting periods when the DHW supply valve was off in the building, we were also able to estimate the Domestic Hot water loses which were about 9.5 kW, and consequently the losses were added to the model.

Note that all incoming signals from the building's SCADA, Supervisory Control and Data Acquisition, system were transferred by FTP, File Transfer Protocol, in the form of text files, and were pre-processed to remove NaNs by a moving average interpolation.

## Post-processing and Results

The model was constructed using IDA ICE. The floor layout, building geometry, along with nearby shading objects were all considered, and modeled as described in the section *Zoning and modeling data*. An additional zone with a small floor surface area was added to simulate the process cooling consumption of the building.

Three AHUs were constructed, one for the kitchen without any heat exchange, one for the atrium representing the two recirculation units, and one main unit servicing the remaining areas. The main AHU has the free cooling circuit, and a heat exchanger. The delay function was also included in the main AHU, which controlled the district cooling distribution to the zones. A separate AHU, acting as a fan coil, was servicing the special process cooling zone.

The modeled plant included the district heating and cooling, along with tanks on the supply side of each.

The cold water tanks were modeled with no losses, since the distribution losses were already accounted for in the process cooling zone.

IDA ICE simulates the plant, AHUs, and all zones as one single entity. By compiling all elements into a state matrix, it avoids any error propagation and discontinuities due to mismatches in time steps. Moreover it solves the state matrix with a variable time-stepping mechanism. This means the user does not have to input an appropriate guess for the simulation time step. In this manner, IDA ICE can accurately capture the dynamics of the building, and its custom control structure.

**Results**

The simulation was performed for the year 2011, and the results were reported every 10 min; matching that of the observation data frequency. Since IDA ICE is transparent, and allows access to any variable in the simulation model, we were able to log in detail the cooling, and heating demand profile of the building. The results represent a full year of collected data at a 10 min interval resolution. Figures 6 & 7 show the full distribution of the error profile over the duration of the collected data for heating and cooling respectively.

It is clear from those profiles that the initial building performance model designed by the KISS principles discussed above describe the actual building performance to a high degree. The maximum error in the heating profile peaks at around 200 kW, while for cooling it peaks at around 1000 kW over the full year profile. For a building this size and data resolution this intricate, it is evident that the initial model without any calibration can indeed predict actual building performance. Figures 8 & 9 show the overlap in dynamics captured by the simulated model.

Refer to Appendix A for comparative three-dimensional carpet plots for the total heating, and cooling profile of the building, over a full year, on a daily basis

## Discussion

ASHREA guideline 14-2014 provides us with quantifiable measures to evaluate the building performance gap between the simulated model and the actual building. These measures are the Coefficient of Variation of the Residual Mean Square Error, CV(RMSE), along with the Normalized Mean Bias Error, and are required to be less than 30% and 10% respectively for simulated hourly data, and less than 10% and 5% for monthly data. The CV(RMSE) and NMBE are defined as:

$$\begin{aligned} CV(RMSE) &= 100 * \frac{\sqrt{\frac{\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2}{n-p}}}{\bar{Y}} \\ NMBE &= 100 * \frac{\sum_{i=1}^{n}(Y_i-\hat{Y}_i)}{(n-p)*\bar{Y}} \end{aligned} \tag{6}$$

$n$,is the number data measurements, 8760 for a full simulation year.

$p$,is the degree of freedom in a model, p = 1. (7)

For the simulation results obtained we accumulated the 10 min data to hourly data as requested by the guideline, and calculated the goodness of fit metrics on the total delivered energy, as well as on each of the heating and cooling profiles.

| Metric/Type | Total | Heating | Cooling |
|---|---|---|---|
| CV(RMSE)hourly | 25.5% | 23.9% | 56.8% |
| NMBE hourly | -0.2% | -1.3% | 1.6% |

| Metric/Type | Total | Heating | Cooling |
|---|---|---|---|
| CV(RMSE)monthly | 6.0% | 9.1% | 5.5% |
| NMBE monthly | 0.2% | -0.2% | 1.0% |

Cooling has proved to be particularly difficult to get within the 30% limit of the guideline for the CV(RMSE). This is due to the high dynamic nature of the cooling profile, and having a low mean value in cold climates. Furthermore, it is very difficulty to obtain accurate hourly solar measurements, which have a direct influence on the cooling load. Finally, there was no direct logging for the free-cooling circuit, and thus the free-cooling circuit estimation was done based on air-flow measurements, which can entail high uncertainties. To aggravate things, the indirect measurement of the free cooling system, meant that the pipe losses in that network were hard to estimate and account for in the simulation model.

The issue with the CV(RMSE) metric is twofolds, the first being the normalization with respect to the mean, while the second is the RMSE bias towards outliers. The first point is highlighted when one tries to utilize the CV(RMSE) metric to compare signals with different observed means. For instance large buildings will have a higher mean value, for say heating demand, than a smaller sized office building, and consequently will have a smaller CV(RMSE) measure overshadowing the quality of the fit. This is also evident when we calculate the CV(RMSE) for heating demand profile vs cooling demand profile. That also explains how the total delivered energy CV(RMSE) is usually lower than the individual CV(RMSE) of

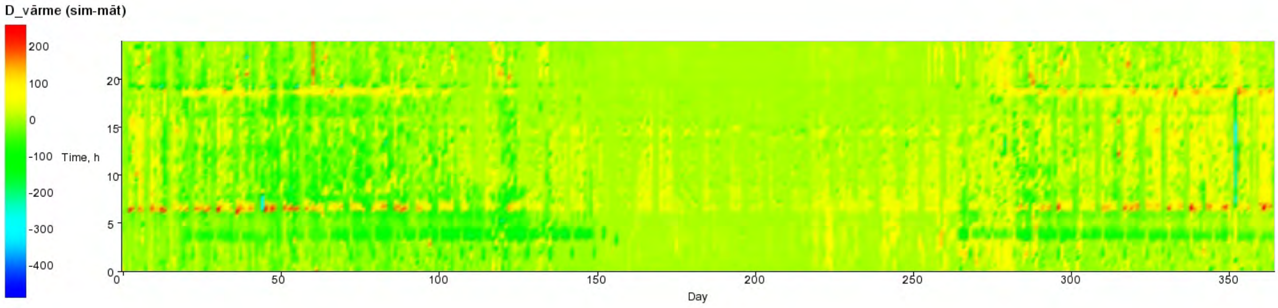


*Figure 5: Error in delivered district heating over full year kW, (Simulated-Measured)*

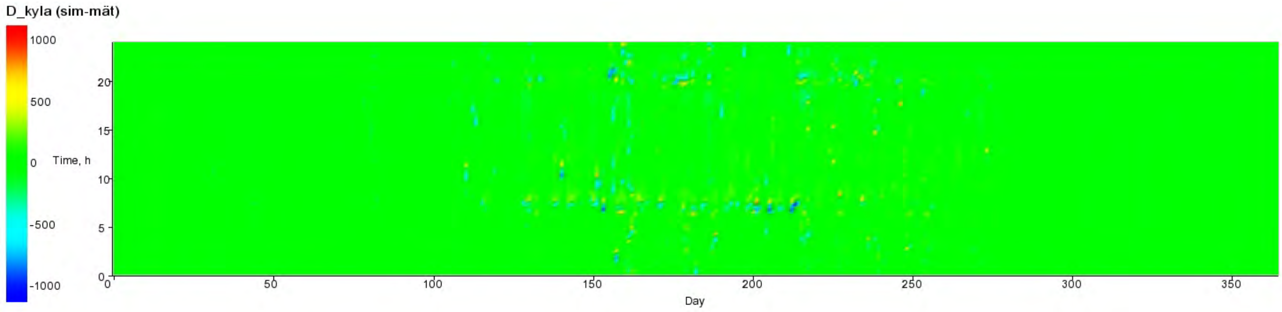


*Figure 6: Error in delivered district cooling over full year kW, (Simulated-Measured)*

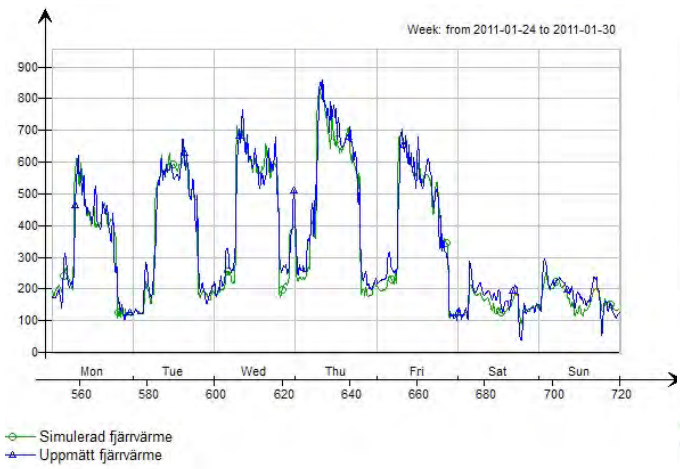


*Figure 7: Delivered district heating profile kW, Measured (Blue) vs Simulated (Red), a week in February*

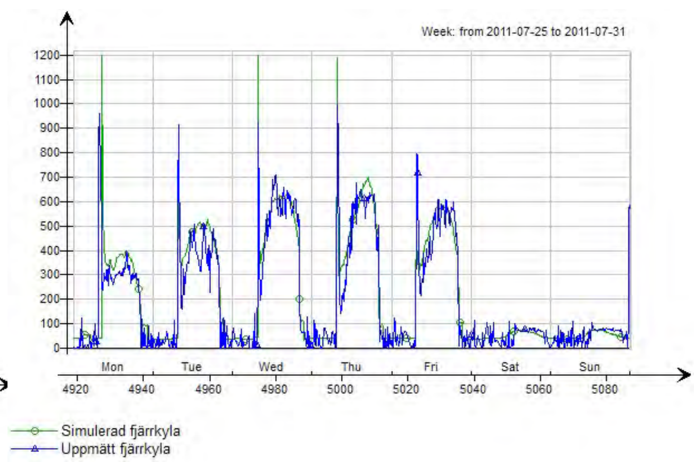


*Figure 8: Delivered district cooling profile kW, Measured (Blue) vs Simulated (Red), a week in July*

either heating or cooling. An alternative would be to normalize the RMSE with respect to the standard deviation, as in a standard score normalization.

$$Z(RMSE) = 100 * \frac{\sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n-p}}}{\sigma_Y} \quad (8)$$

However the metric is still based on the RMSE, which for dynamic simulations is too conservative a measure. Since the RMSE squares the residual error of every data point, which in a full year dynamic simulation translates to 8760 points, this implies that a peak mismatch on any of the measured points will create a large offset in the CV(RMSE) metric. ASHRAE guideline also comments that a well trained artificial neural network is able to achieve a 20% CV(RMSE) error for hourly data. However, this issue becomes less severe when calculating monthly fits, or when reporting over a short exercise period. An alternative would be to rely on a Mean Absolute Error metric, which less sensitive to outliers and peaks.

$$Z(MAE) = 100 * \frac{\sum_{i=1}^{n} |Y_i - \hat{Y}_i|}{(n-p) * \sigma_Y} \quad (9)$$

For the same simulation results, applying the new metrics for hourly, and monthly data we have:

| Metric/Type | Total | Heating | Cooling |
|---|---|---|---|
| Z(MAE) hourly | 22.5% | 13.9% | 20.9% |
| Z(MAE) monthly | 10.0% | 8.1% | 5.9% |

The new metric reflects more accurately on the quality of the simulation model. It is close to the CV(RMSE) results for Total delivered energy figures for both monthly and hourly data, but is less sensitive to outliers. Hence for heating only or cooling only figures, it gives more realistic and practical results reflecting on the true quality of the simulation model. This evidence is further supported by calculating the Coefficient of Determination, which for hourly cooling calculation is at $r_h^2 = 95.4\%$, for hourly heating $r_h^2 = 97.4\%$, and total hourly cooling and heating at $r_h^2 = 94.7\%$.

**On occupancy and the prediction gap**

The results show clearly that occupancy, while modeled by direct correlation with the building's electricity consumption profile, was accurately captured. The small prediction gap, shows that using a simple approach with a guesstimate of occupancy density can yield satisfactory end results. That has been the case, at least, for many non-residential buildings and projects, Song et al. (2010).

## Conclusion

With proper care, one is able to achieve and work with a small prediction gap. Today's tools allow us to model and predict a building's energy performance accurately, and in an efficient manner. We showed how, abiding by a Keep it Simple and Straightforward approach in modeling, one is able to achieve accurate energy performance predictions, without sacrificing on capturing building's dynamics and internal states. We also argued that current guidelines regarding calculating goodness of fit measures for a dynamic simulation model are too conservative for industrial practice, and we provided some recommendations for more appropriate fitness measures.

## Acknowledgment

The authors would like to thank Skanska CDN for accommodating this study, and allowing us access to the building's information and data.

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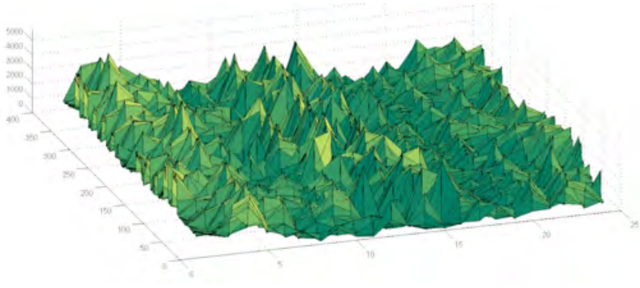
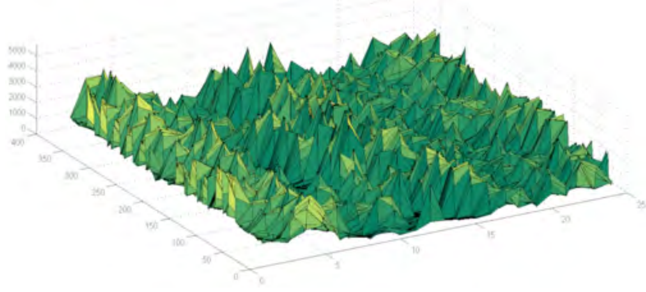
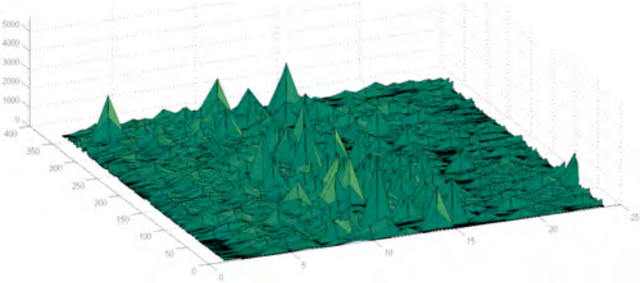


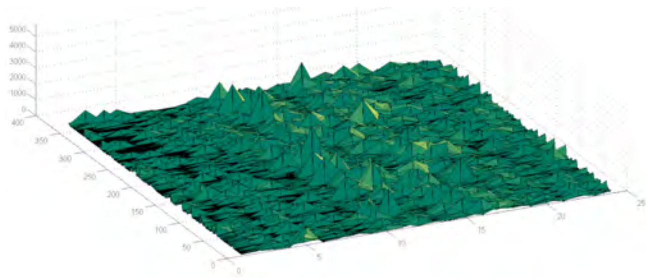
*(a) Measured total delivered energy kW*



*(b) Simulated total delivered energy kW*



*(c) (Measured - Simulated) total delivered energy kW*



*(d) (Simulated - Measured) total delivered energy kW*

*Figure 9: x-axis: Hours, y-axis: Days, z-axis: kW*

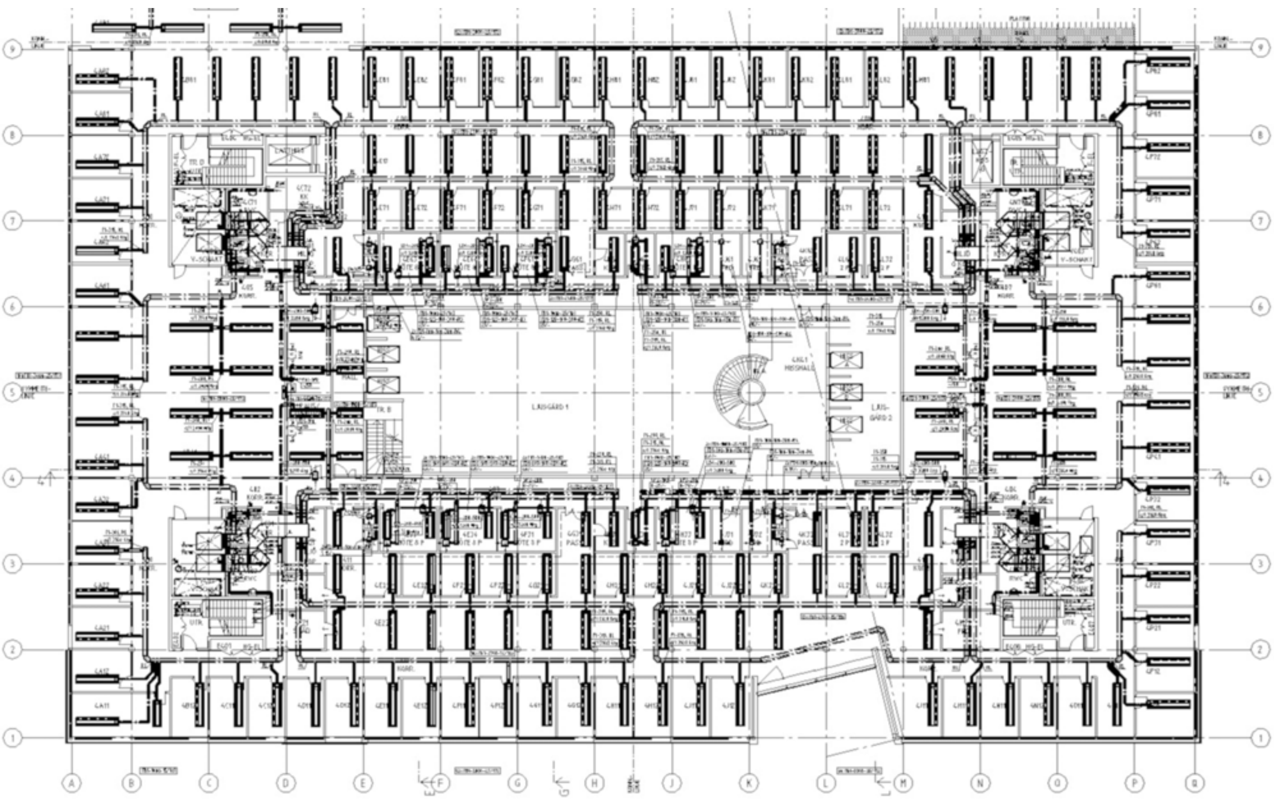


*Figure 10: Office floor layout showing active chilled beams network*