HVAC OPERATION UNCERTAINTY IN

ENERGY PERFORMANCE GAP

A Thesis
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Master of Science in the
School of Architecture

Georgia Institute of Technology
May 2015

HVAC OPERATION UNCERTAINTY IN

ENERGY PERFORMANCE GAP

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ACKNOWLEDGEMENTS

I would like to express my immense gratitude to Prof. Godfried Augenbroe, for his wisdom and kindness that guided me all the way in the past 2 years, whether in accepting me in HPB program, or supporting me on co-op training, or providing generous help in my academic work. His philosophical way of thinking had great impact on my attitude whenever I made choices both in research and in life.

I would also like to show my greatest gratitude to Qinpeng Wang, Roya Rezaee, Dr. Sun for their generous help in my thesis work, and excellent guidance from the very beginning to the end.

Special thanks to Prof. Jason Brown, Sandeep Ahuja, Patrick Chopson, Yuna Zhang, Tina Zhang, Qi Li, Ji-hyun Kim, Tyrone, Victor Renteria, Di Sui, Gustavo, Guangyao Shao and all the rest of the BT group, who offered me a place called home in Hinman and helped me grow up. I am heartily thankful to my supervisors Dr. Pang, and Dr. Granderson in LBNL, who has impacted my career planning ever since.

Finally, I owe my all to my parents, boyfriend, and distant friends all around the world, who back me up, like always.

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LIST OF SYMBOLS AND ABBREVIATIONS

EUI	Energy Use Intensity
GURA-W	Georgia Tech Uncertainty and Risk Analysis Workbench
HVAC	Heating, Ventilation and Air-Conditioning
kWh	Kilo-Watt-Hour
PIT	Probability Integral Transform
UA	Uncertainty Analysis
UQ	Uncertainty Quantification
CDF	Cumulative Distribution Function
APE	Absolute Percent Errors
LHS	Latin Hypercube Sampling

SUMMARY

This study aims at a preliminary characterization of system operation uncertainty. It bases this on an analysis of the energy consumption of 6 existing buildings on the Georgia Tech campus. The analysis is speculative in nature. By studying the performance gap between predictions and actual consumption for the 6 buildings, we hope to be able to identify the role of HVAC (Heating Ventilation and Air-conditioning) operation uncertainty after we have either ruled out or quantified other sources of uncertainty. We first build EnergyPlus V7.0 models for the 6 selected campus buildings and use them to run in the GURA-W (Georgia Tech Uncertainty and Risk Analysis Workbench) and its Uncertainty Quantification (UQ) repository to quantify the model input parameter uncertainty. GURA-W executes an uncertainty analysis based on the Mote Carlo simulations with 300 samples. This leads to a probabilistic prediction of energy consumption for the 6 buildings for 12 months for which we derive mean and standard deviation. We compare this "Measurement consumption" from the utility bills provided by building managers from 2010 to 2013. We compare the annual/monthly EUI result for one "clean" year. In order to explain the gap between prediction and measured, we use a technique called PIT (Probability Integral Transform), a method for probabilistic prediction verification. In our specific use of PIT, we try to verify whether the gap between prediction and measured could be explained by the inclusion of HVAC uncertainty. To do so, we postulate the simplest characterization of HVAC uncertainty, i.e. through a macro loss factor or "HVAC efficiency factor" (as a stochastic factor, or uncertainty factor) that can be superimposed on the predicted energy consumption. In this

vital step, we will try out different distributions for the efficiency (uncertainty) factor. We use different distributions for summer and winter because of the different HVAC system and operation in heating and cooling season. By using a heuristic approach, we intend to reach important conclusions about the distribution of an efficiency factor (uncertainty factor) that best "closes" the performance gap. The optimistic expectation is that by going through this procedure, we hope to successfully identify the HVAC operation uncertainties in energy simulation.

CHAPTER 1

INTRODUCTION

Heating Ventilation and Air-conditioning (HVAC) system, according to U.S. Department of Energy, is responsible for 40% to 60% of the energy use in industrial and commercial buildings. (Ron, 2014) In U.S, buildings consumption takes up to 38.9% of the whole energy usage, and 72% of the whole country's electricity usage, and this number will potentially rise to 75% by 2025. (A'Hearn, 2012)

For both newly-built and existing buildings, improving the HVAC performance capability is an important issue both during early design stage and on retrofitting stage. The bias between the actual measured data by metering, and the predicted data by energy simulation or management software is called "*Energy Performance Gap*". Usually people treat it as a part of the modeling, but it differs for different systems in different buildings, and if the smaller the gap becomes, the more reliable our predictions will be. The widely used energy simulation software EnergyPlus is not sufficient enough to accurately model a building's HVAC consumption, leading to a significant uncertainty in a simulation result, together with other factors like modeler's bias and unknown occupancy deviation. We base our whole study on creating EnergyPlus models for selected example buildings as a baseline and later improve simulation result by using an uncertainty analysis (UA), and testing UA result against actual measurement for statistical verification.

Based on "Closing the building energy performance gap by improving our prediction" (Sun, 2014), the energy performance uncertainties are the main causes that predicted and actual energy use do not match. For his study, Sun finds that parameter and model form uncertainty and occupancy uncertainty mostly explain the performance gap. However, the modeled buildings in this prediction, are all connected to district heating and cooling systems, and therefore have no on-board HVAC systems. This is the reason that HVAC uncertainty is not considered as part of the gap in Sun’s study, thus leaving a remaining gap when we make predictions for buildings with local HVAC systems. Hence, to capture uncertainty on HVAC operation, this thesis discusses the modeling of 6 GT campus building with complete HVAC system. We assume that in this case operation uncertainty is a significant part of the gap, and would like to magnitude it. Note that we do not introduce actual model parameters (bottom-up) to quantify how big the HVAC operation uncertainty is. Instead, we can quantify it by introducing a macro loss parameter (or “phantom” effect) that captures the role of HVAC uncertainty.

We use a classical statistical method “Probability Integral Transform” to estimating the magnitude of the loss factor based on the 6 selected buildings.

CHAPTER 2

PREDICTION ANALYSIS

The 6 existing GT buildings are Alumni House, Georgia Centers for Telecommunications Technology, Institute of Paper Science and Technology, Ivan Allan College, Office of Human Resource and O'Keefe buildings located in Georgia Tech campus, and all of them have complete HVAC systems with boiler and chiller.

Table 2.1 Building modeling information

Category	Model parameters/ modeling strategy
Weather	20010,2011,2012,2013 AMY
Building Geometry	Design specification
Thermal zoning	Detailed zoning based on HVAC mechanical design specification
Construction and material properties	Design specifications
HVAC systems	HVAC mechanical design specifications
Internal loads	Building average peak use; Office building average weekday, weekend, holiday schedule;
Lighting & plug load peak use (W/m^2)	ASHARE Standards;
Building Operation	Standard hourly occupant density and schedules

The basic workflow of prediction procedure shows below.

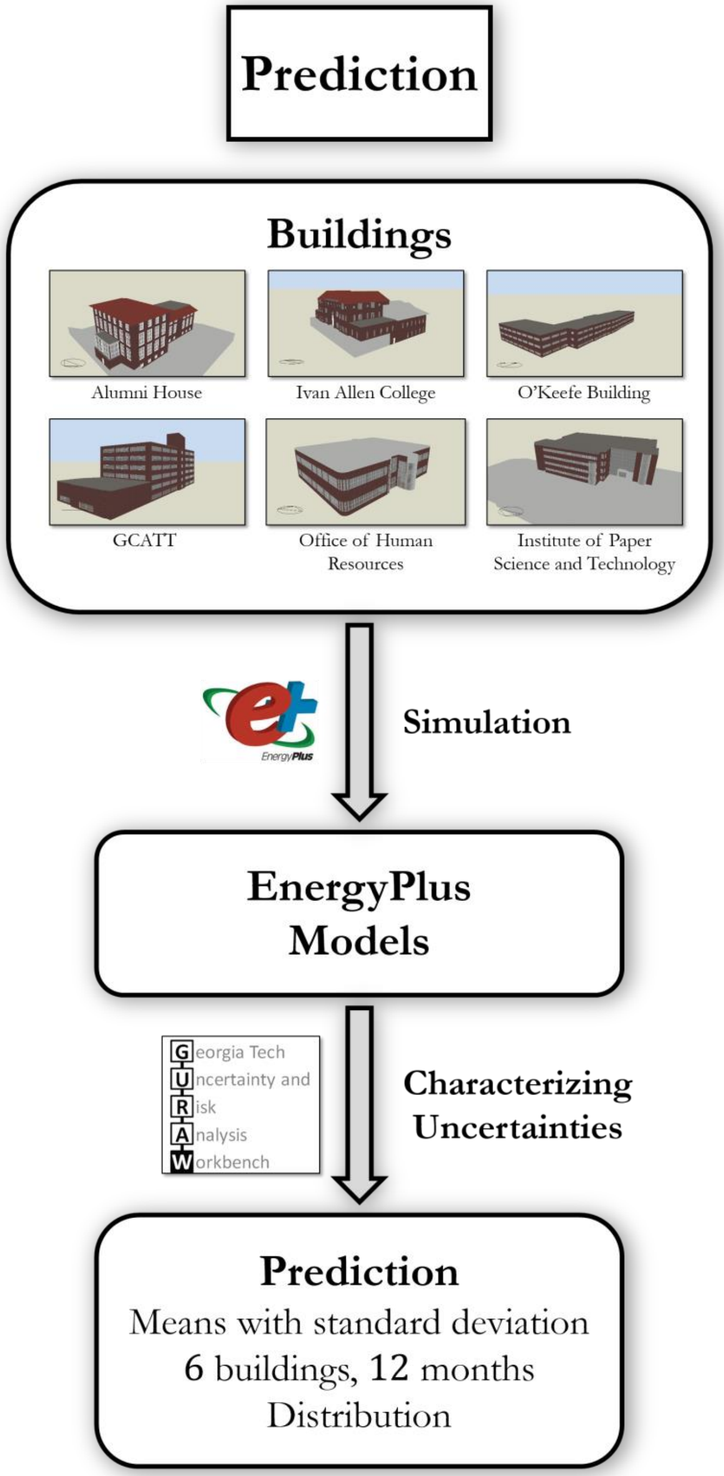

Figure 2.1 Prediction workflow

In the modeling stage, by following standard guideline ASHRAE 2007, we build our building models in EnergyPlus V7.0 covering individual construction documents ranging from lighting schedule, construction type, glazing type to HVAC systems. Contrary to Sun's study, we do not use standardized lighting and plug load according to ASHRAE standard, and which are considered as DOE reference medium size office building. Instead, we want to rule out occupancy uncertainty by creating schedules for occupancy, lighting and plug loads that are as close as possible to observed reality.

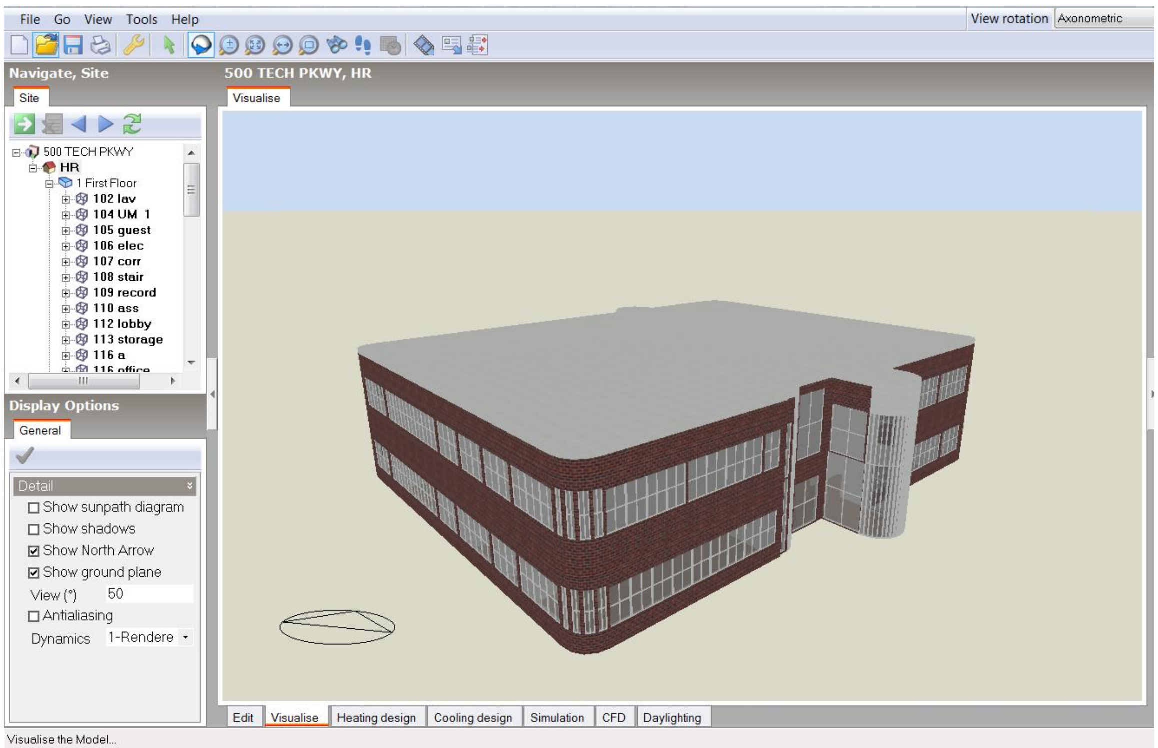

Figure 2.2 Office of Human Resources

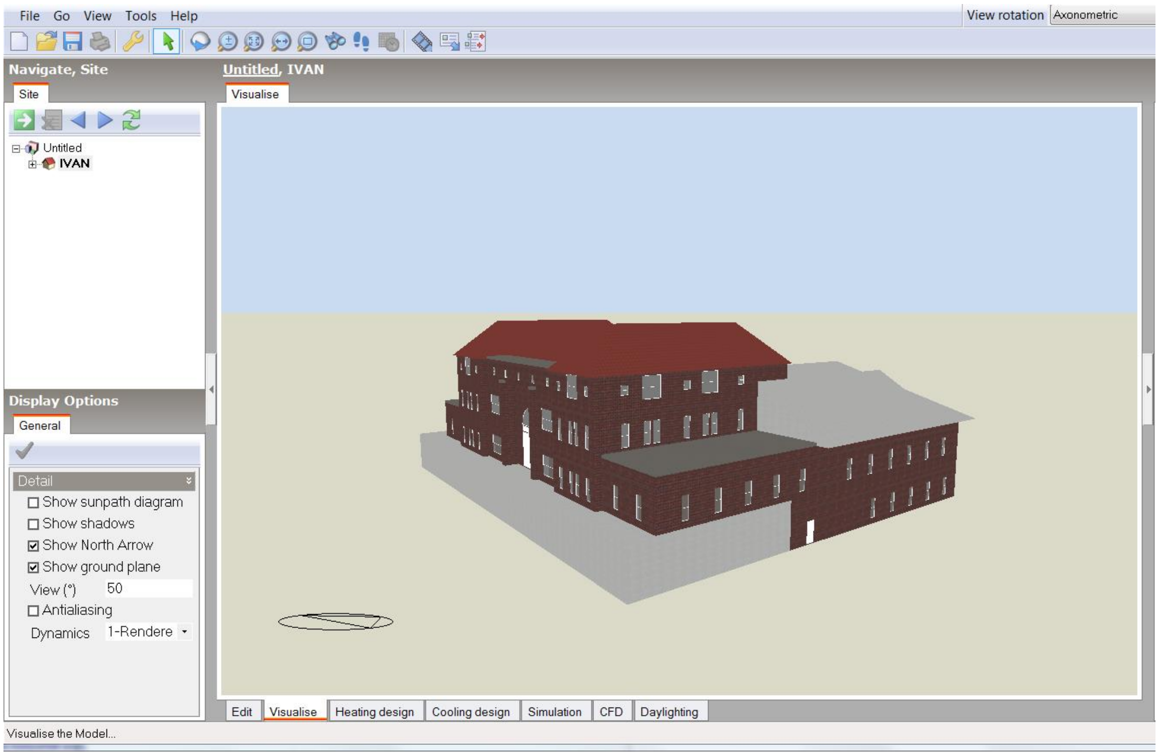

Figure 2.3 Ivan Allen College of Liberal Arts

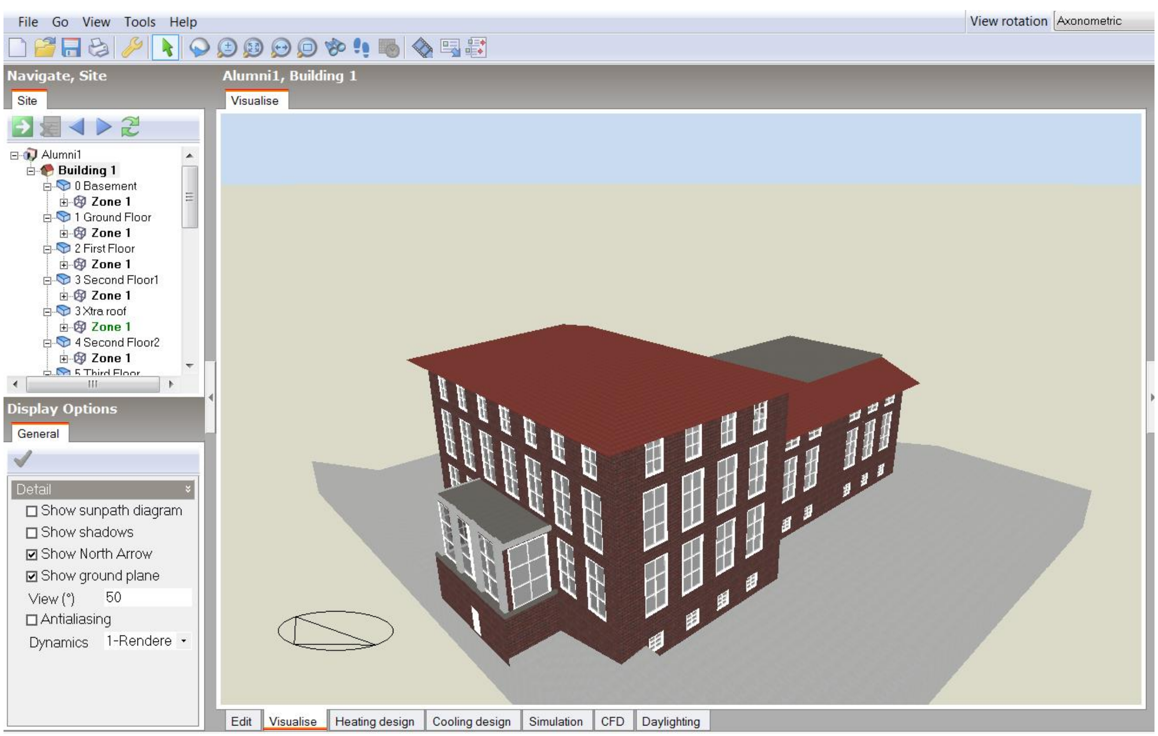

Figure 2.4 Alumni House

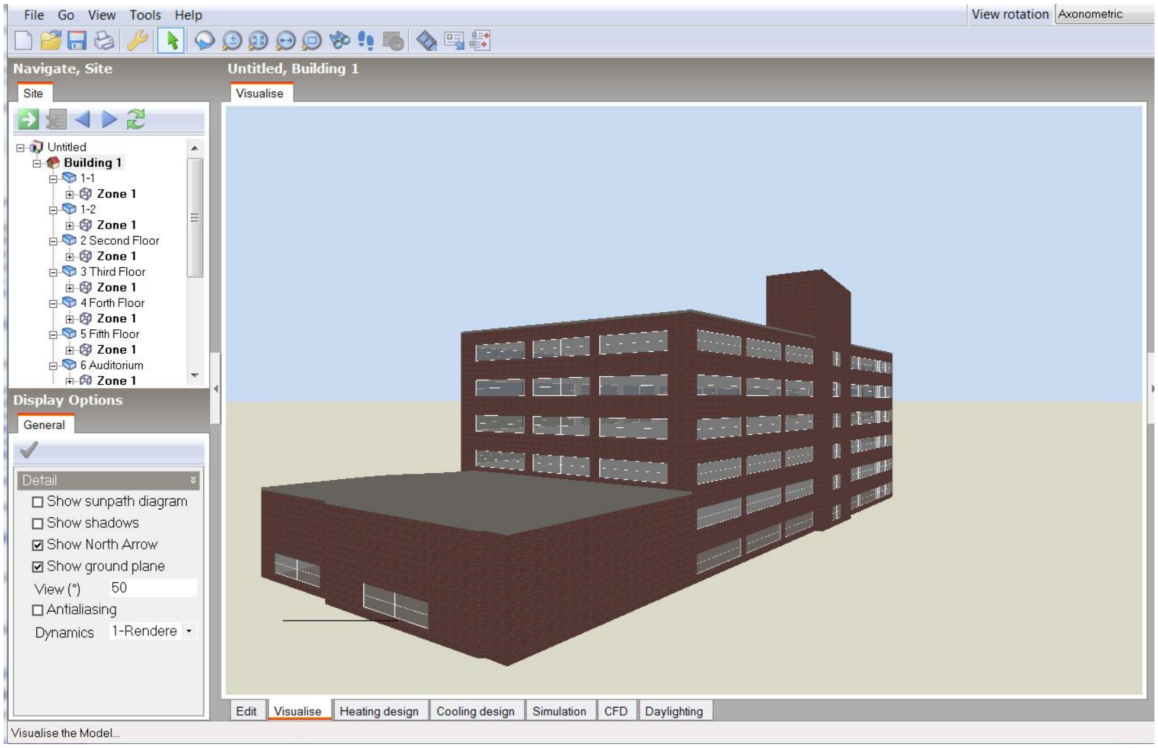

Figure 2.5 Georgia Centers for Telecommunications Technology

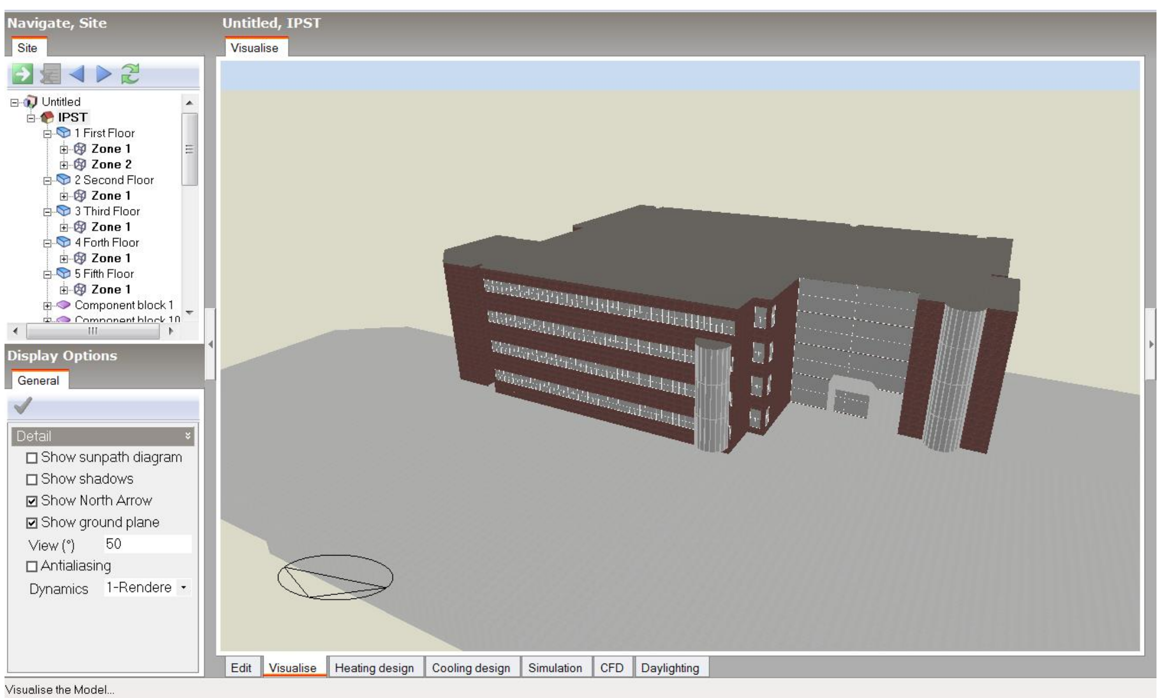

Figure 2.6 Institute of Paper Science and Technology

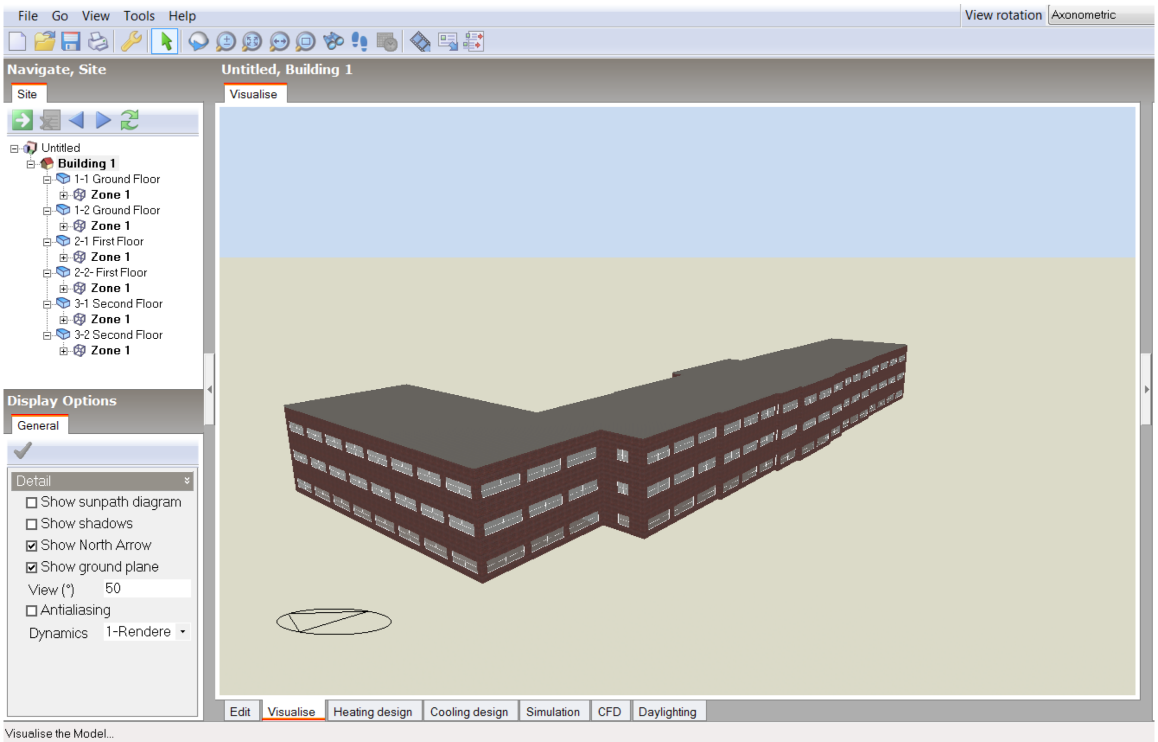

Figure 2.7 O'Keefe Building

After the EnergyPlus modeling is done, all models are run through GURA-W for the uncertainty analysis. By making full use of full capability of the GURA-W and the UQ (Uncertainty Quantification) repository, we consider all the parameters and models form uncertainty. The resulting probabilistic predictions will be the baseline for the PIT based assessment as described in Chapter 4.

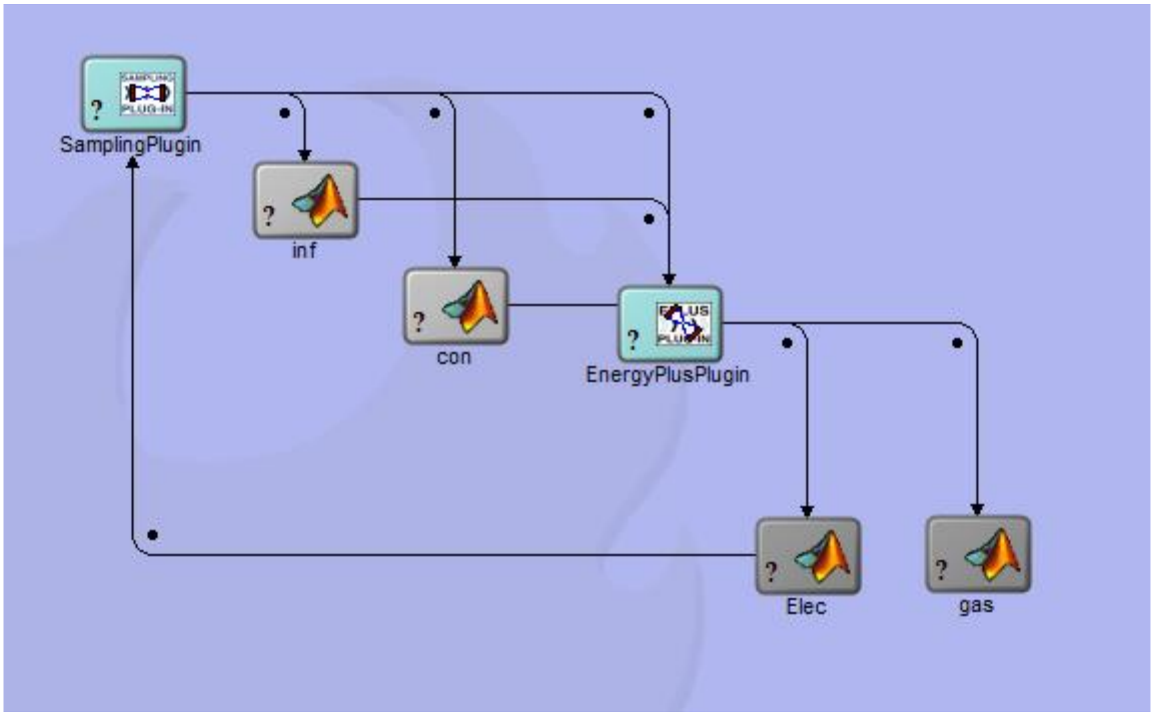

Figure 2.8 GURA-W running workbench

After running 300 samples, we derive the mean value for each month of the year, and compare for all 12 months in a year. By using MATLAB, we plot distribution of 6 building's total energy consumption with boxplot, We neglect any extreme outliers.

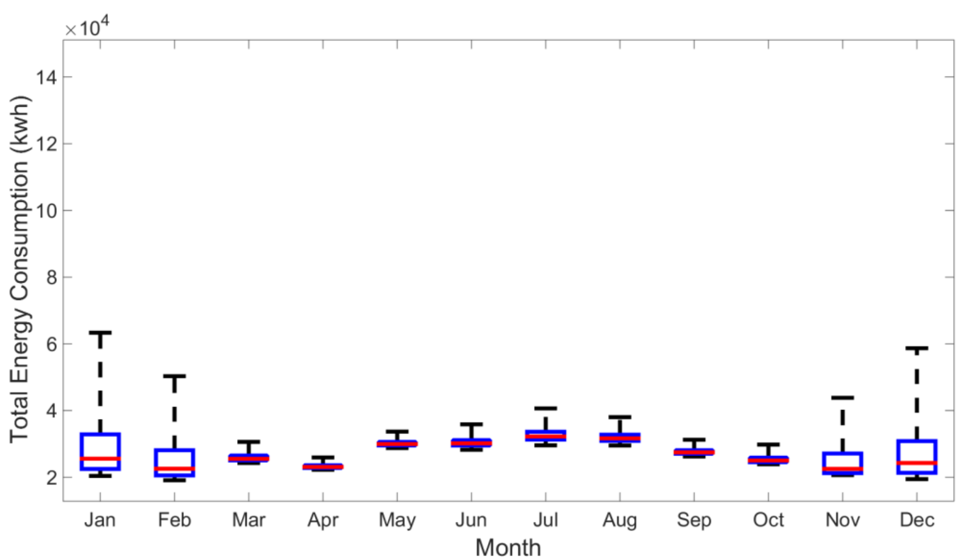

Figure 2.9 Ivan Allen College of Liberal Arts boxplot

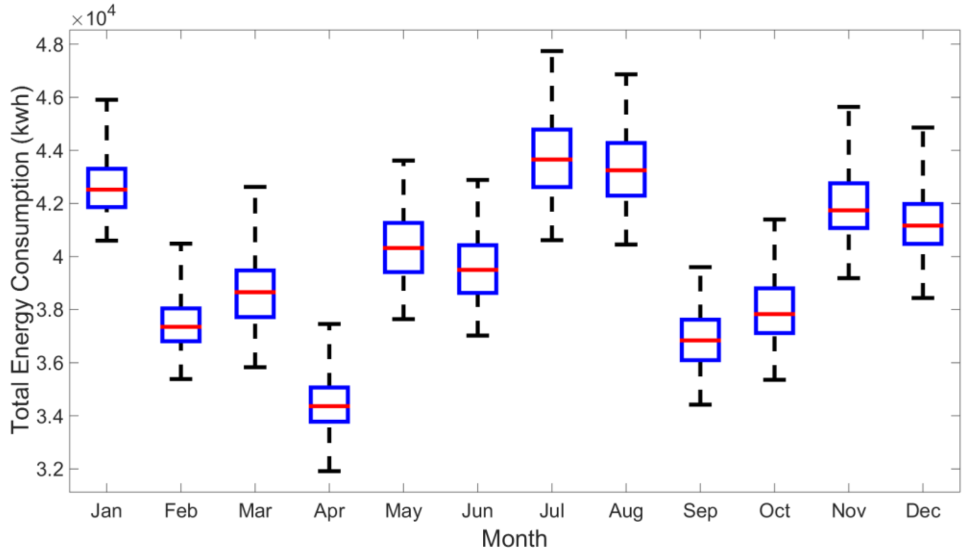

Figure 2.10 Alumni House boxplot

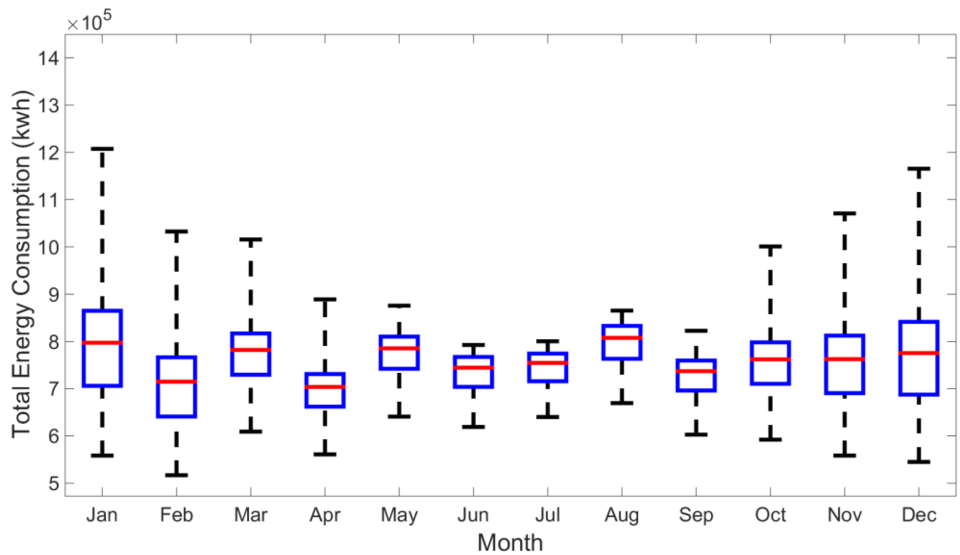

Figure 2.11 Georgia Centers for Telecommunications Technology boxplot

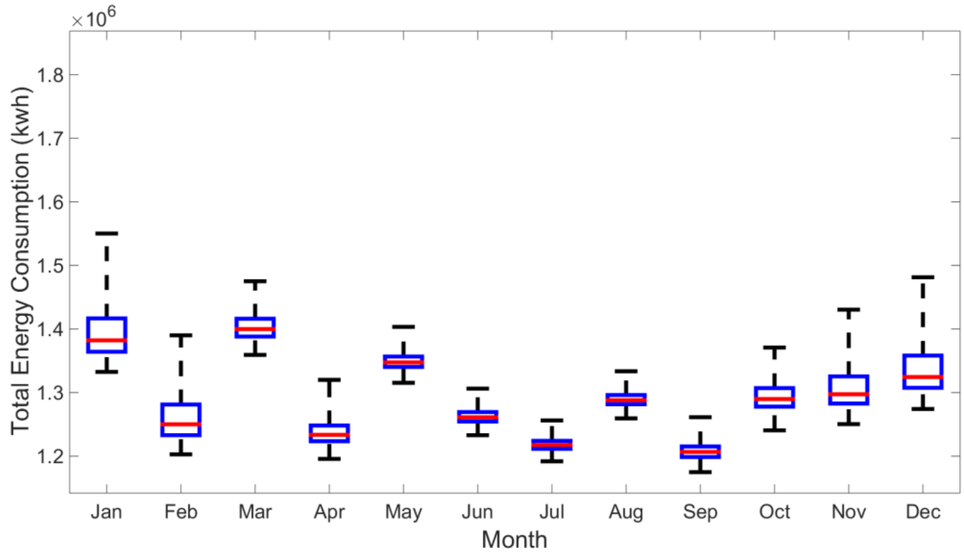

Figure 2.12 Institute of Paper Science and Technology boxplot

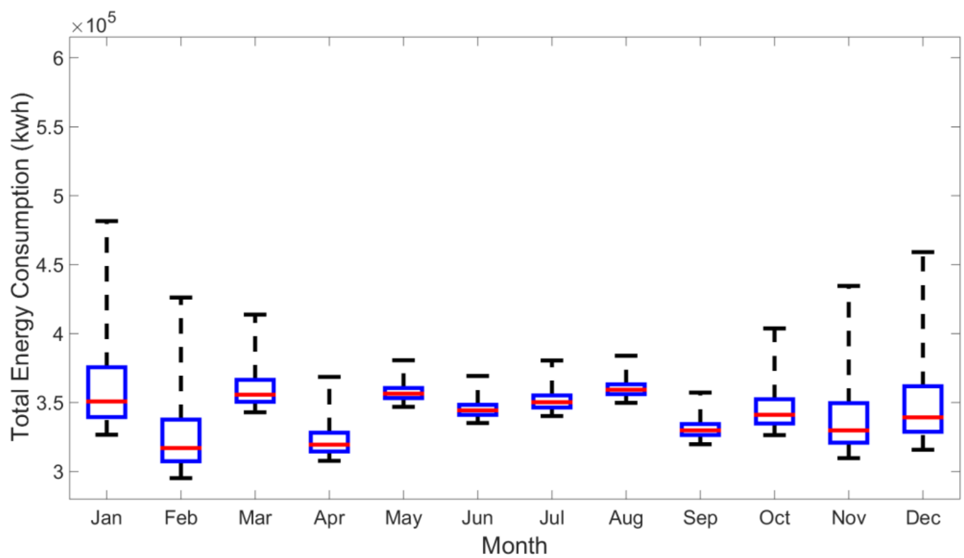

Figure 2.13 O'Keefe Building boxplot

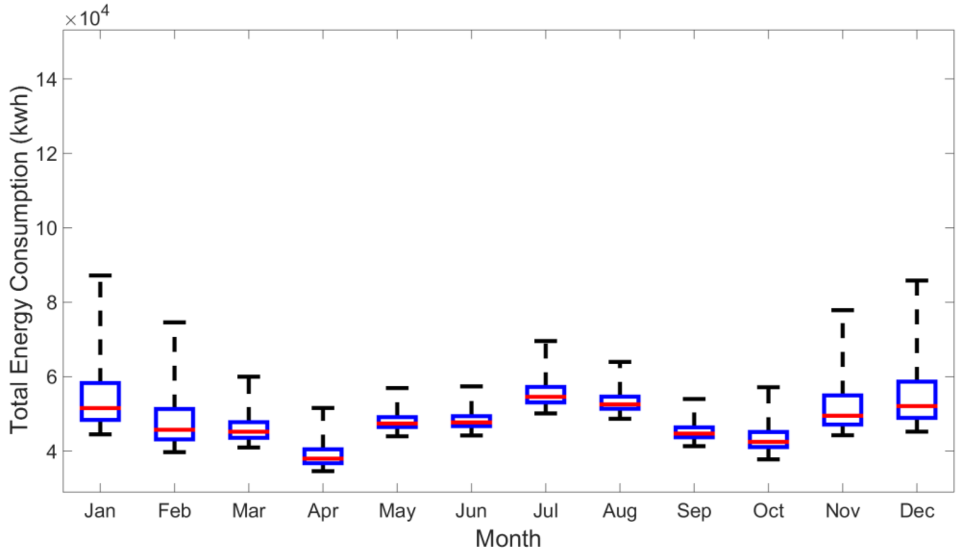

Figure 2.14 Office of Human Resource boxplot

CHAPTER 3

MEASUREMENT ANALYSIS

With full access to Georgia Tech Facilities management, the “Location energy profile” from Aug 2010 to Aug 2013 will be used as the actual data to compare with the probabilistic prediction of energy consumption. The actual utility data contains the use in MMBTU in 12 months, with the specific detail to the percentage, common use, energy use, energy use per area and total cost of each energy commodity type, electricity, natural gas and steam.

The results are illustrated as follows. For the predicted consumption only the mean monthly value is shown.

Figure 3.1 Office of Human Resources predicted and actual data comparison

Figure 3.2 Ivan Allen College of Liberal Arts predicted and actual data comparison

Figure 3.1 Alumni House predicted and actual data comparison

Figure 3.3 Alumni House predicted and actual data comparison

Figure 3.4 Georgia Centers for Telecommunications Technology predicted and actual data comparison

Figure 3.5 Institute of Paper Science and Technology predicted and actual data comparison

Figure 3.6 O’Keefe Building predicted and actual data comparison

After organizing the utility monthly consumption for each year, there creates the "location energy profile" distribution of 6 buildings in 3 or 4 years. In these monthly measurement distribution, there are some anomalous data, indicating that the building was not well monitored or abnormally used i.e close-down or open-up of certain area causing the sudden decrease and increase of the measurement. These months are left out in later work. The result is shown below.

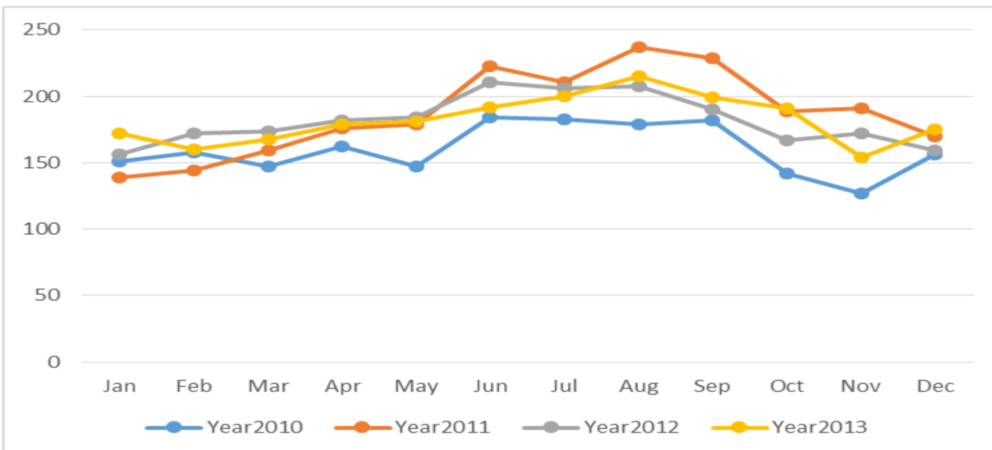

Figure 3.7 Office of Human Resources monthly measurement distribution

Table 3.1 Office of Human Resources monthly measurement

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
2010	151	158	147	162	147	184	183	179	182	142	127	156	1919
2011	139	144	159	176	179	223	211	237	229	189	191	170	2247
2012	156	172	174	182	184	211	206	208	190	167	172	159	2184
2013	172	160	168	179	181	192	200	215	199	191	154	175	2186

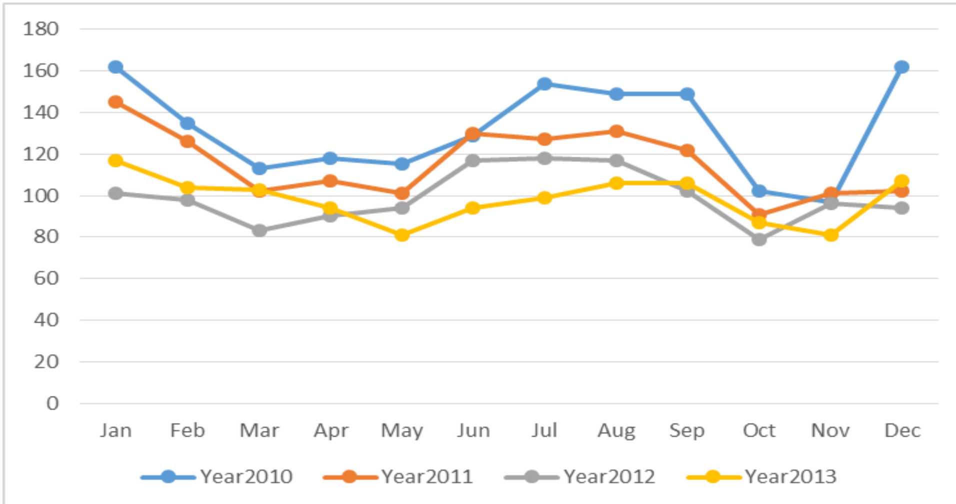

Figure 3.8 Ivan Allen College of Liberal Arts monthly measurement distribution

Table 3.2 Ivan Allen College of Liberal Arts monthly measurement

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
2010	162	135	113	118	115	129	154	149	149	102	97	162	1585
2011	145	126	102	107	101	130	127	131	122	91	101	102	1387
2012	101	98	83	90	94	117	118	117	102	79	96	94	1189
2013	117	104	103	94	81	94	99	106	106	87	81	107	1181

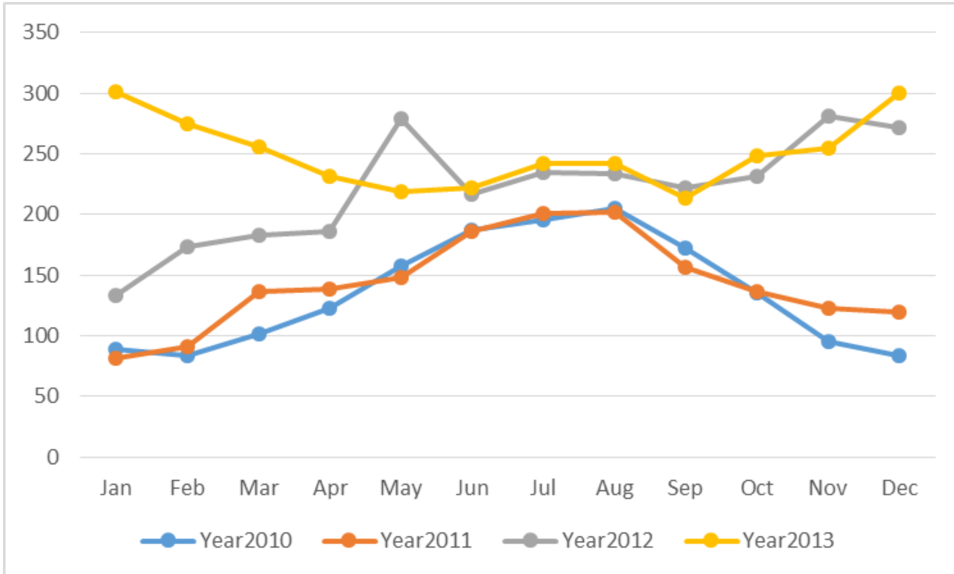

Figure 3.9 Alumni House monthly measurement distribution

Table 3.3 Alumni House monthly measurement

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
2010	89	84	101	123	157	187	196	205	172	135	95	83	1627
2011	81	91	136	138	148	186	201	202	156	136	123	119	1717
2012	133	173	183	186	279	217	235	234	222	231	281	272	2648
2013	301	275	256	231	219	222	242	242	214	248	255	300	1847

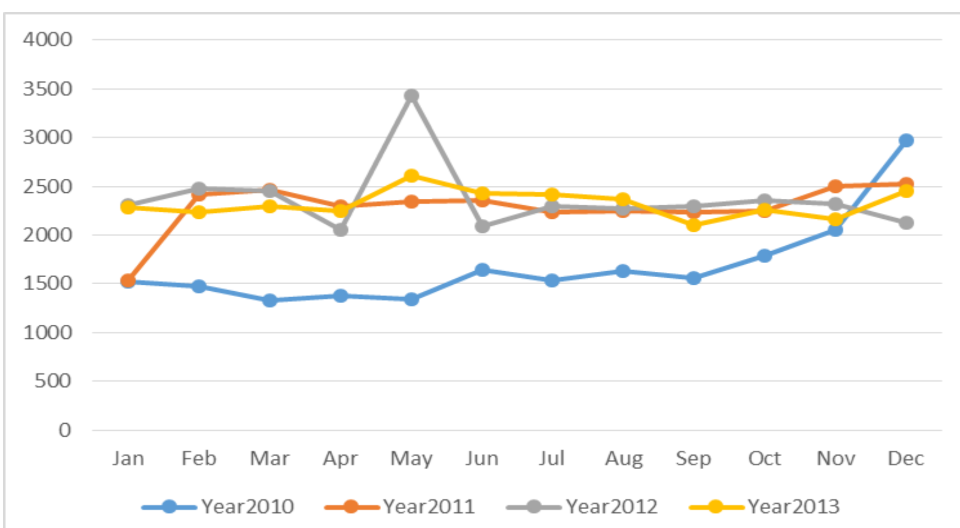

Figure 3.10 Georgia Centers for Telecommunications monthly measurement distribution

Table 3.4 Georgia Centers for Telecommunications monthly measurement

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
2010	863	942	1059	1075	808	763	890	991	962	802	883	917	10955
2011	990	1095	1063	957	927	1067	867	867	926	763	1079	1184	11986
2012	1177	1321	1519	987	1863	1156	1425	1448	1288	1334	1341	1303	16162
2013	1360	1476	1417	1239	1257	1287	1395	1417	1307	1324	1078	752	15308

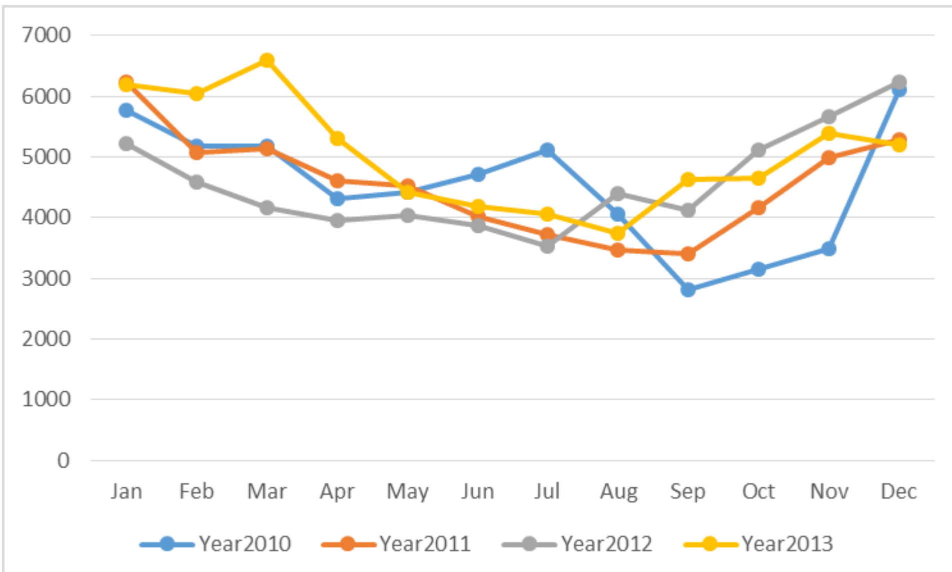

Figure 3.11 Institute of Paper Science and Technology measurement distribution

Table 3.5 Institute of Paper Science and Technology monthly measurement

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
2010	5778	5174	5172	4306	4422	4719	5107	4054	2816	3142	3497	6102	54290
2011	6230	5066	5145	4604	4535	4018	3719	3478	3395	4157	4981	5293	54712
2012	5229	4586	4172	3960	4031	3872	3529	4390	4121	5123	5669	6246	54927
2013	6186	6040	6595	5314	4413	4195	4068	3737	4637	4658	5385	5211	60440

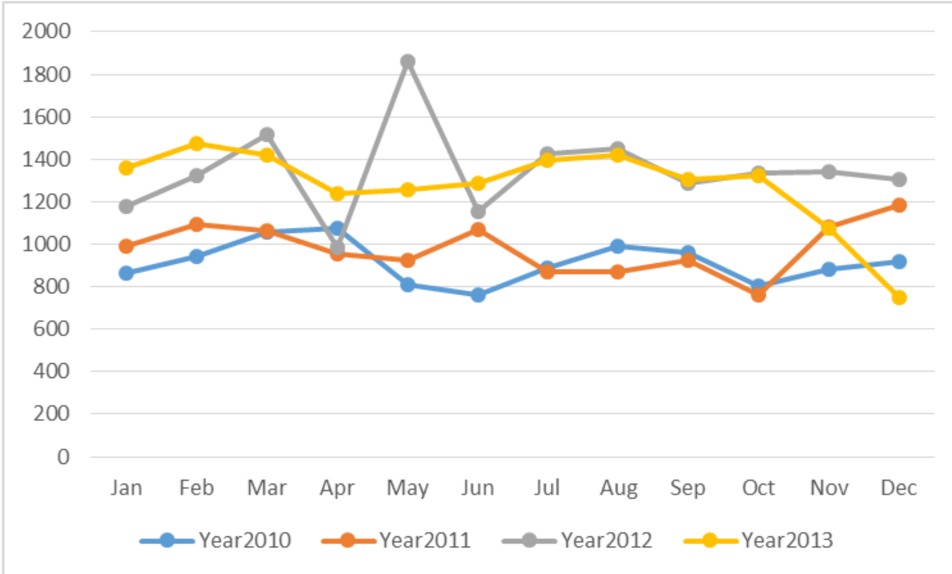

Figure 3.12 O’Keefe Building monthly measurement distribution

Table 3.6 O’Keefe Building monthly measurement

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
010	1520	1469	1329	1374	1345	1638	1540	1628	1558	1792	2059	2971	7693
2011	1534	2415	2468	2294	2345	2355	2231	2251	2231	2251	2503	2530	20222
2012	2304	2475	2458	2055	3427	2087	2290	2269	2296	2358	2318	2131	28467
2013	2280	2232	2293	2253	2612	2431	2415	2363	2108	2262	2161	2450	27859

Due to the fact that measurement data’s starting time and year varies, and the comparison with GURA-W prediction shows abnormal results in certain years, the most ideal measurement data is from year 2012. In the next chapter, we choose this year for further analysis by conducting PIT analysis as described.

CHAPTER 4

PROBABILITY INTEGRAL TRANSFORM ANALYSIS

After finishing the Monte Carlo simulation with GURA-W, the result are used to compare with the year 2012's measurements. This is the starting point for experimenting whether HVAC operation performance is a major part of the energy performance gap, and if so, quantify its magnitude. PIT, which is known as Probability Integral Transform, is used for this purpose. It allows the verification that data values are modeled as a random variable from a distribution. This method has already been widely used in weather forecasting (Jolliffe and Stephenson, 2003) where the PIT pools information from different model prediction. For a continuous variable, the probability integral transform, Z_F, is simply the predicted CDF (cumulative distribution function), F, evaluated at an observation point at Y, i.e. $ZF = F(Y)$. (Sun, 2014)

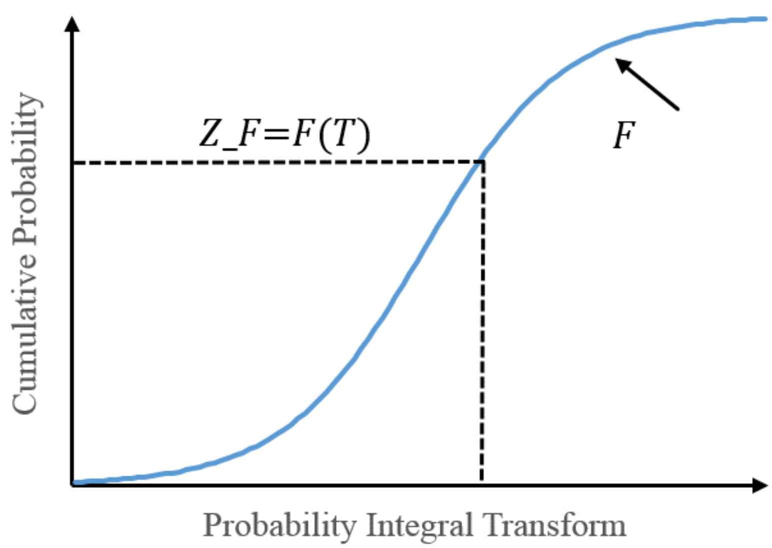

Figure 4.1 Probability integral transform

As there is no HVAC uncertainty contained in our UQ (Uncertainty Quantification) repository, it is impossible to conduct an UA (Uncertainty Analysis) on HVAC uncertainty with GURA-W. So PIT is used post rationalize the existence of HVAC uncertainty of all other sources of uncertainty are accounted for. In this study, PIT is functioning to enable us to see how the prediction and measurement can match by introducing HVAC uncertainty. As a first step, we can test the performance gap without additional HVAC operation uncertainty. If no gap exists, then the study implies that HVAC operation uncertainty have nearly zero impact on energy performance gap. The results in boxplot show however that there is a significant gap in both electricity and gas consumption.

By assuming HVAC efficiency factors, which range between 0.1 to 1.0, separately for summer and winter, we characterize the effect of HVAC uncertainty for the heating and cooling system. This is a “macro characterization” which by necessity, includes everything from model simplification/discrepancy, parameter impreciseness, tolerances, faults and malfunctions. We test different distributions for the efficiency factors until PIT results implies a satisfactory match. The procedure is explained in Figure 4.2.

It should be noted that the two HVAC efficiency factors are multipliers for HVAC electricity and HVAC gas consumption respectively, which creates a separate complexity that HVAC electricity consumption must be separated from all other electricity consumption. The same applies for gas, in case there are the consumers rather than the HVAC system for heating.

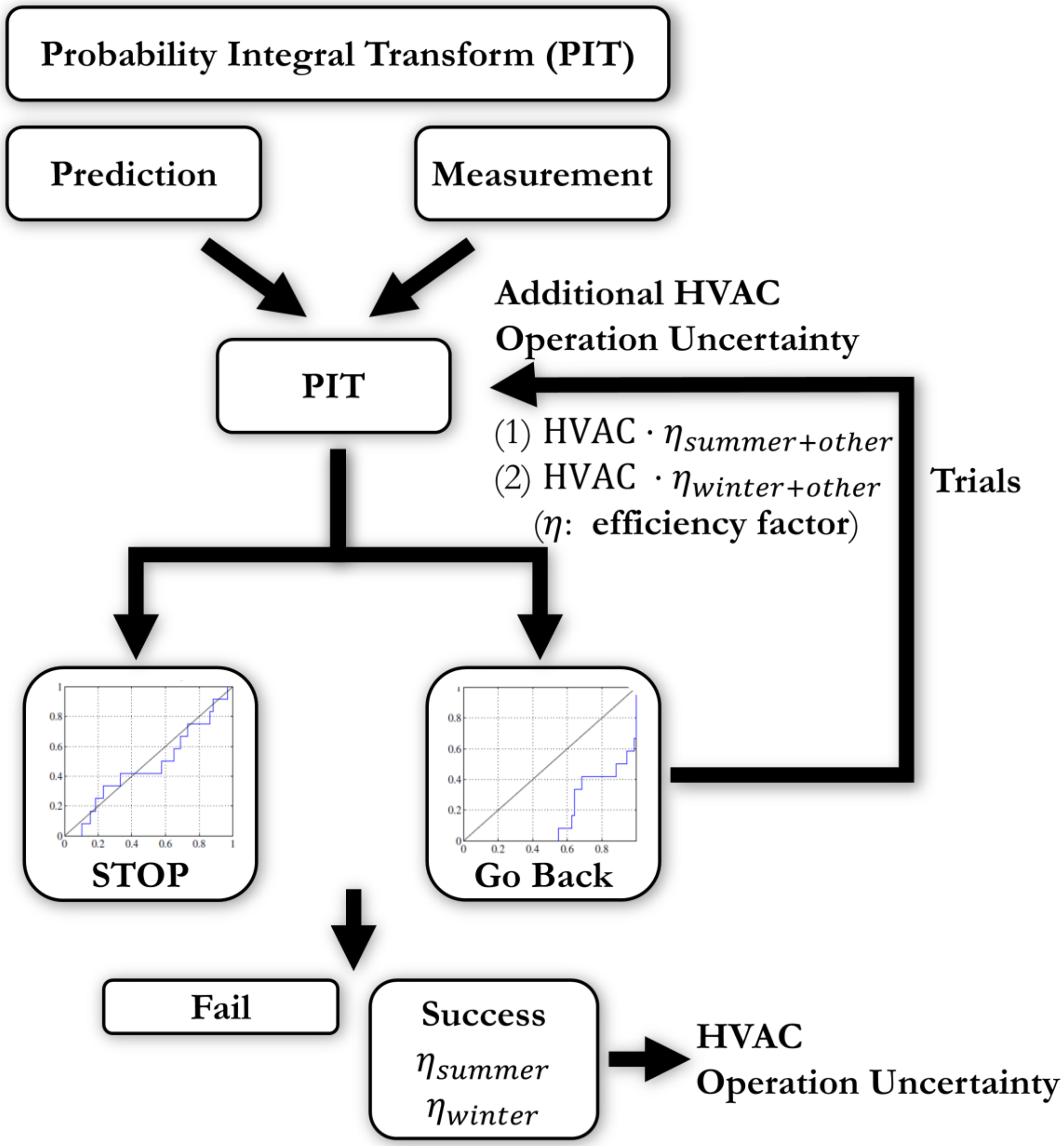

Figure 5.1 PIT workflow

CHAPTER 5

RESULT

After conducting PIT without HVAC uncertainty factor (efficiency factor), we can see from the figure below, the PIT does not pass. Here, we introduce cumulative distribution function (CDF), which characterizes the cumulative probability associated with a distribution. Specifically, it calculates the area under the probability density function, up to the value that we specify. We can use the CDF to determine the probability of a response being lower than a certain value, higher than a certain value, or between two values. (MINITAB)

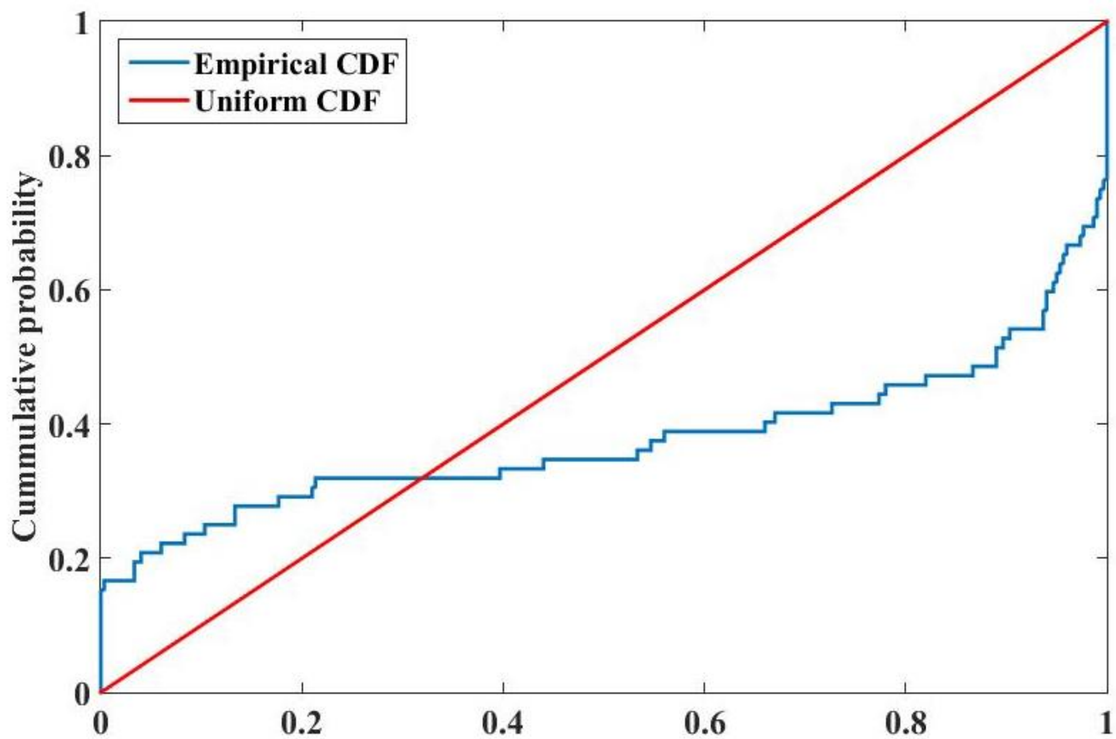

Figure 5.1 PIT result without HVAC uncertainty factor

By examining the shape of the CDF to see how close the empirical CDF is to the uniform CDF, and referring to Sun's study on Absolute Percent Errors (APE), we can tell that the mean is comparatively low and the prediction is under dispersed, which suggests us include the additional HVAC operation uncertainty to run the test.

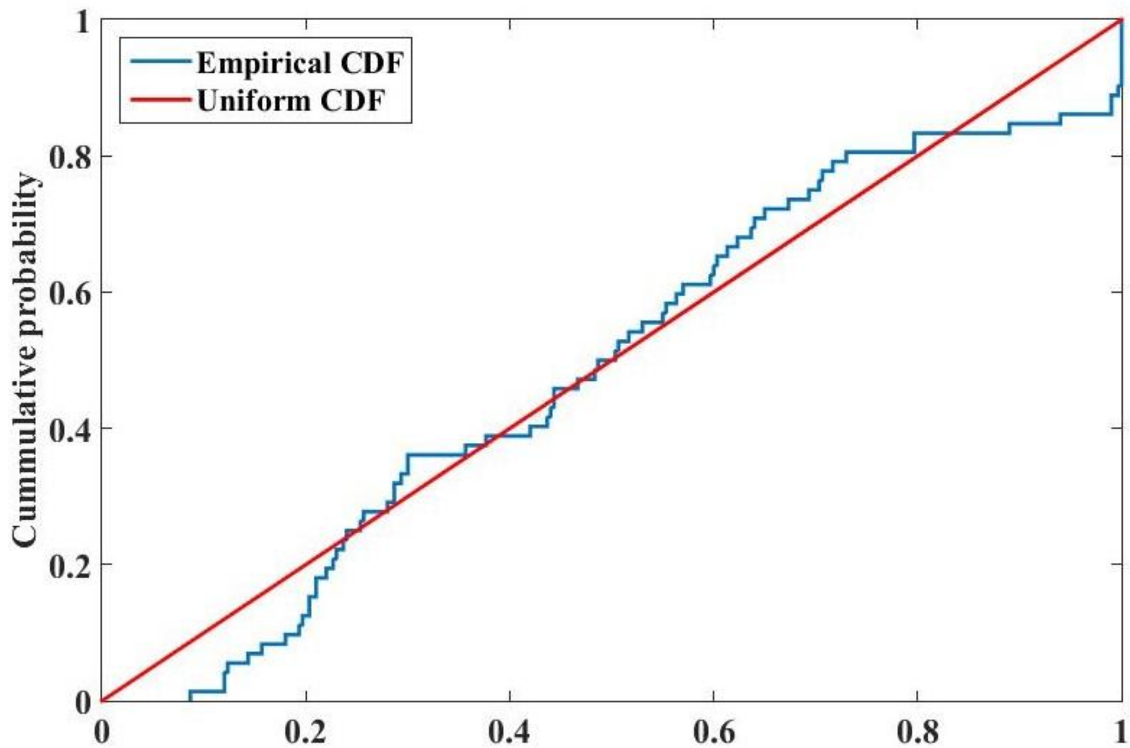

Figure 5.2 PIT result with HVAC uncertainty factor

After trial with HVAC uncertainty factor, Ƞsummer and Ƞwinter, we can get the results showed above, the empirical CDF and uniform CDF is getting closer than the one without HVAC uncertainty factor, which indicates the success of PIT.

The result is obtained after we multiply the consumption for summer and winter with the respective HVAC operation uncertainty factor and add other (non HVAC related) consumption, to compare them with the measurement. The result is to test whether the tested HVAC uncertainty factor Ƞsummer and Ƞwinter are giving better results to pass the PIT. We explore the factors distributions. Firstly, we use Latin Hypercube Sample (LHS) method, to generate a sample of plausible HVAC uncertainty factors with means between 0 and 0.2 and standard deviation between 0 and 0.4. Then we evaluate the PIT plots by conducting the K-S test of the value. The Kolmogorov-Smirnov test, is a nonparametric test for the quality of the probability distribution. For the K-S test result, the higher the value is, the closer the HVAC uncertainty factor is. Through this test, we find the optimal result shown below.

Table 5.1 HVAC operation uncertainty factor result

	Mean Value	Standard Deviation
Summer	0.1844	0.3035
Winter	0.1633	0.3784

CHAPTER 6

CONCLUSION

This study has helped us identify the role of HVAC operation uncertainty in buildings with local HVAC systems. We find the optimal Ƞsummer and Ƞwinter distribution. This complements Sun’s study on “Closing the building energy performance gap by improving our predictions which was conducted for buildings connected to district heating and cooling systems.

However, there are still some problem existing in this work, which we can improve in the future. As we noticed in the boxplots graph, there are significant outliers which cannot be fully explained except by assuming that our EnergyPlus model for the building has some deficiencies especially in the representation of the schedule of operation and occupancy. Other deficiencies result from modeler’s bias. For the 6 GT buildings, there will be an unusually high energy consumption during May and December, the final week, and a big decrease during summer and winter break. While the measure data change accordingly, the simulation result won’t be comparatively accurate. How occupants set the comfort criteria (including thermal, visual, and acoustic), interact with building energy and services systems, and response to environmental discomfort directly affect the operation of buildings and thus their energy use.(Hong, 2013). Another issue is the limited number of samples (300) in this study.

Future work should be Select a good set of buildings, with accurate occupancy and operation monitoring. This should lead to higher quality energy models for which the study should be repeated.

The current study indicated that there is a good reason to assume that HVAC operation uncertainty has a role that could lead to approx. 15% of additional energy consumption for heating and cooling. But the standard deviation that we found is large which calls for repeating our procedure for other sets of buildings.

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