DISTRICT LEVEL ENERGY MANAGEMENT USING A BOTTOM-UP MODELING APPROACH

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ABSTRACT

An efficient urban energy system could be a highly diverse and well-integrated structure of buildings and systems. Such a structure needs an energy management framework capable of providing information on appropriate energy saving measures at any scale of implementation. This paper proposes a method to design such a framework. For quality assurance, a method to deal with the uncertainty in building properties and in operational conditions of buildings and systems is designed into the framework in order to model the energy use during the operation phase of buildings.

INTRODUCTION

A transition to sustainable urban energy systems will require a well-integrated structure on all levels; from the equipment level, via the whole building and systems level, to the neighborhood and city level. Jaccard et al. (1997) explains the concept of community energy management (CEM) that encompasses land use planning, transportation management, site design, and local energy generation and distribution planning. They showed how large impact a CEM can have on energy consumption and emission of CO_2 and NO_x. Additionally, many researchers have recently turned their attention to local energy generation and distribution planning based on the growing recognition of its benefit. For example, according to simulation results by Burer et al. (2003), a district heating and cooling (DHC) system integrating a solid oxide fuel cell and gas turbine combined cycle could potentially reduce CO_2 emission by 50% compared to a conventional system. Yamaguchi et al. (2004) shows that implementation of the distributed generation technology in a centralized plant that supplies cooling and heating energy and electricity to a small number of neighboring buildings is more energy efficient and cost effective than separate implementations of this technology in individual buildings. From simulations based on practical operational conditions derived from field measurements, Shimoda et al. (2005) concludes that DHC systems are more energy efficient than systems individually embedded in each building.

In the current study, what we mean by district-scale energy management (DEM) is the energy management encompassing the site design and local energy generation and distribution planning at a scale from the building to neighborhood and district.

Implementation of DEM does not necessarily result in installation of a large-scale energy infrastructure. Rolfsman (2004) shows that, depending on the building characteristics, investment in building insulation could be a better solution than investment in district scale energy generation and distributions systems. The essence of DEM is to adopt appropriate measures according to the characteristics of buildings and the district as a whole. The net result will be a highly diverse and well-integrated structure of buildings and systems. Thus, DEM heightens the need for an energy management framework capable of carrying out the following tasks:

- modeling the total energy use in buildings with a sufficient resolution, and
- comprehensively evaluating various kinds of energy saving measures at various scales.

These two tasks are strongly related to each other. Understanding the structure of the energy use contributes to raising the quality of evaluation while the resolution at which the energy use is modeled depends on the evaluation task.

However, traditional approaches to model the energy use on a large-scale fail for the first task. Thus, these approaches are not suitable as basis for the management framework. In one traditional approach, the fixed demand per unit floor area or per household, given by field measurements of representative buildings, are used as the heat and electricity demand of buildings to simulate the total energy use. In another approach (Huang et al. 1991, Jones et al. 2001, Clarke et al. 2003, Shimoda et al. 2004) a number of prototypical building models are used as follows:

1) designing building prototypes each representing a building stock category with particular characteristics in terms of energy use,
2) performing simulations using these prototypical building models as input in order to predict the energy use in each building stock category, and

3) aggregating the total energy use by summing up the predicted energy use of all building stock categories.

Usually, this approach does not consider many building properties as determinants of energy use. This is especially so in case of commercial sector buildings. A very limited number of prototypical building models have been developed in earlier studies (mostly three or four per sector), mainly as it is practically impossible to collect detailed data on buildings (Jones et al. 2001). The framework for DEM, which will be applied to a local problem, requires a more detailed consideration of energy use in buildings, thus results in the need of redesigning it.

On the other hand, for quality assurance (Hensen et al. 2004) of a simulation task, a useful procedure to ensure the quality of simulation results has been established. Djunaedy et al. (2003) proposes a methodology (Coupling Procedure Decision Methodology: CPDM) to select a proper model resolution for a given problem. This CPDM mainly focuses on uncertainty, which arises from simplifications in the models that are used. By following the CPDM, we can reduce the uncertainty to an acceptable level by addressing the problem with a higher resolution model than the original one, in case the uncertainty due to the original model would be significant.

The concept of the CPDM in order to maintain the quality of the results can be used in the development of the DEM framework so that it will provide reliable information. For this purpose, the methodology has to be applied not only to gathering information on building properties by a simple survey, but also to preparing more detailed information by measurements to find out, for example, how the target buildings are operated and whether components of the HVAC system are properly designed and operated as a whole.

The current paper proposes a quality assurance procedure in the context of developing the DEM framework. This procedure employs a parameter screening technique (Wit 1997) to decide the aspects that need particular attention when modeling the energy use in buildings. The final part of this paper shows a demonstration of the framework.

FRAMEWORK FOR DISTRICT SCALE ENERGY MANAMEMENT

The energy management framework has to focus on the energy use during the operation phase of buildings. In order to evaluate various energy saving measures, building and system modeling and simulation is very useful. During the design phase of buildings, simulations are carried out using low-level data, such as coarse building properties for peak cooling and heating load calculations or fixed demand per unit floor area for the selection of energy supply systems. On the contrary, the model for predicting energy use during operation phase needs relatively high-level data, which may be influenced by, for example:

- operational conditions of buildings (such as behavior of occupants, operation hours of HVAC systems, and type and density of office equipment)
- uncontrolled heat losses/gains from heating/cooling distribution systems (duct and pipes)
- energy increase due to inappropriate design and operation of HVAC systems (e.g. if the inlet/outlet temperature difference of chilled/hot water does not reach the design value, the number of heat source machines operated will increase, thus causing the heat supply efficiency to deteriorate due to a lower part load ratio).

Although to correctly incorporate such factors would require certain field surveys and/or measurements, it is important to provisionally take these factors into account in the model of the energy use and the sequent evaluation task. Unfortunately, it is not exactly clear which factors would bridge the gap between simulation and reality and would have to be dealt with in the energy management framework.

Uncertainty has traditionally been established by sensitivity analysis (Macdonald et al. 2001). Wit (1997), however, introduced a screening technique (factorial sampling method: FSM) to specify those model input parameters that have a large influence on the simulation outputs. In order to address the problem described above, we adopted FSM in a simulation model (Yamaguchi et al. 2003) in which we assumed uncertainty in both the input parameters related to construction properties and to the actual operation of the buildings and systems. According to the impact of the uncertainty on the operational energy use we designed the method to deal with uncertainty during the implementation of DEM.

Firstly, some important parameters can be gathered just by a simple survey of the building properties database. Next, additional important parameters can be identified from a relatively difficult field survey and/or measurements. In cases, however, where addressing these uncertainties a priori is infeasible, possibly because of lack of detailed information on building properties or lack of resources (e.g. time and money), the influence of these uncertainties is taken into account at the stage of evaluation of the simulation outputs.

Thus, model input parameters are categorized into the following four groups according to importance and data availability:

1) parameters stored in the building properties database,
2) parameters resulting from a field survey and/or measurements,
3) parameters of which the uncertainty has to be addressed in the stage of evaluation of simulation results, and
4) parameters of which the uncertainty can be ignored.

This approach could be practically feasible, as the DEM is implemented in a relatively small area covering a few neighborhoods where relatively detailed data could be available.

Problem statement

In this paper, we develop the framework to model the energy use for cooling and heating as a case study. To investigate the important uncertain factors, we identified three typical cooling and heating generation, distribution and delivery systems relating to different scales (room, building and (small) district) as shown in Figure 1. Each system requires different consideration of the uncertain factors. For example, a local (distributed) air-conditioning system that supplies cooling and heating to a specific thermal zone, may be strongly influenced by the thermodynamic characteristics of the room. On the contrary, central HVAC systems and DHC systems may be less influenced by the local thermodynamic characteristics since the loads from rooms and buildings are aggregated and thus averaged out. In such systems, the characteristics of the actual heat delivery itself may more significantly influence the system performance.

According to the scheme indicated in Figure 1, we carried out four parameter screenings. The purpose of the first screening is to understand the influence of building properties on the thermodynamic characteristics of rooms. Then, in addition to building properties, parameters relating to system alternatives were examined in order to specify the influence of uncertainty in those parameters on system performance indicators. Based on the results, the parameters were categorized into four groups as explained above by following the procedure shown in Figure 2.

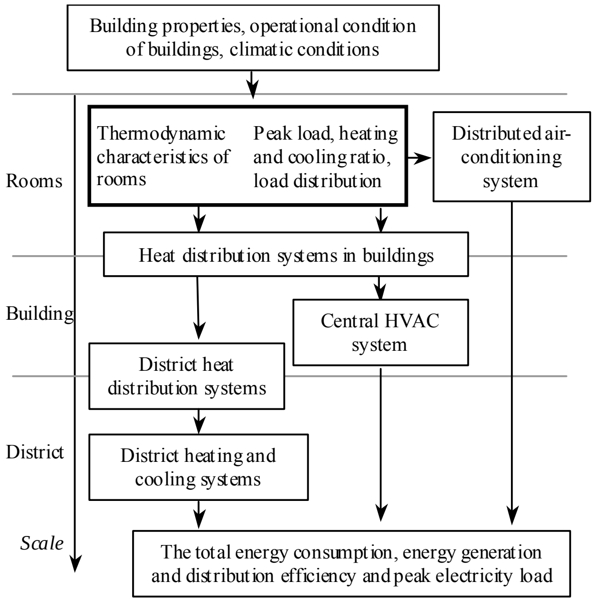

Figure 1 System alternatives and corresponding scale

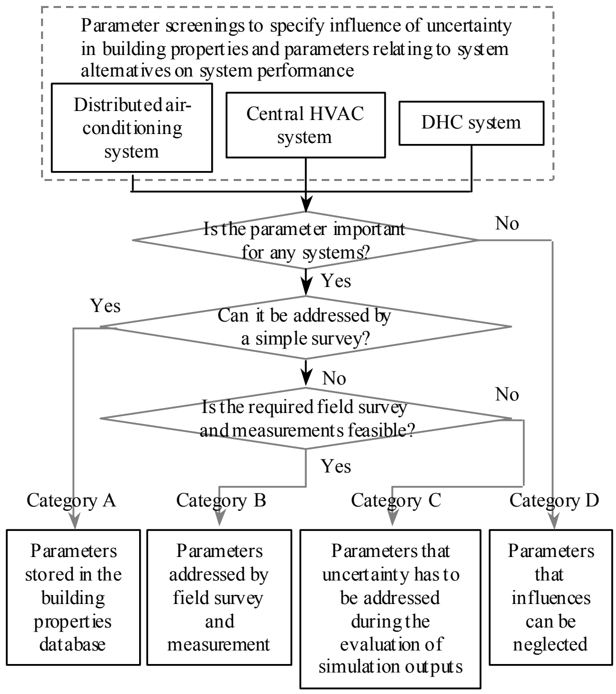

Figure 2 Procedure to determine how to deal with the uncertainty in parameters

Factorial sampling method (FSM)

FSM is a useful technique for finding parameters that have a large influence on the outputs of a simulation model with a large number of input parameters. In this study, we used the FSM procedure as suggested by Wit (1997).

In this procedure, we only used the two extreme values of each parameter range. These values are labeled as 'OFF' and 'ON'. Initially, all parameters are set to 'OFF'. Then one parameter is randomly selected and its value is changed to 'ON'. This parameter's elementary effect (= change in the output solely due to changing the selected parameter) can be observed by comparing the simulation outputs with the two sets of input parameters. Next, another parameter is randomly selected without changing the values of any other parameter to observe the elementary effect of the secondly selected parameter. This process is repeated until the values of all considered parameters have been changed to 'ON'. Repeating this observation of elementary effects m times then results in a set of elementary effects F_i^r (r = 1 to m) for parameter i. The mean value and standard deviation of the elementary effect can be used as an indication for the influence of uncertainty in a particular parameter on the simulation output. A large mean value means that parameter *i* affects the output significantly on its own. A large standard deviation means that the influence of parameter *i* varies according to the value of other parameters. In order to show the influence quantitatively, the following definition was used in this paper:

$$R_{n,i} = \frac{\left|d_{n,i}\right| + 2 \cdot S_{n,i}}{Mean_n} \qquad (1)$$

where $d_{n,i}$ and $S_{n,i}$ are the estimated mean and standard deviation of the elementary effect of parameter i on a performance indicator n, while $Mean_n$ is the mean value of the performance indicator observed in the screening process. As $2{\cdot}S_{n,i}$ would represent half of the 95% confidence interval if the elementary effect would have a normal distribution, the numerator represents the possible change due to parameter i. Thus, $R_{n,i}$ is a non-dimensional value that represents the estimated influence of the uncertainty in the input parameters on the performance indicator.

First screening - influence of building properties on thermodynamic characteristics of rooms

In the first parameter screening in Figure 2, thermal building simulation was performed for a building

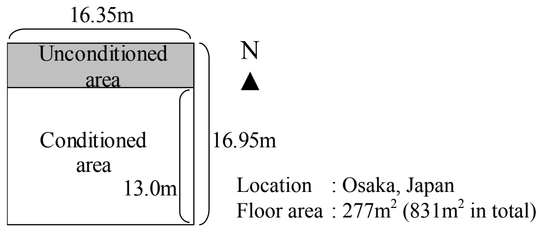

Figure 3 Floor plan of the dedicated building

with a floor plan as illustrated in Figure 3. This is the second floor of a 3-story-building of which all are operated similarly. The building properties and parameter screening results are summarized in Table 1. The elementary effect of these parameters are indicated with '+' and '-' marks. The direction of change (+ or -) follows the sign of $d_{n,i}$, while the number of marks indicates the extent of the influence given by the size of $R_{n,i}$. These results help to understand how building properties affect the performance of HVAC systems.

Parameter screening for 3 kinds of HVAC system

Starting from the above first parameter screening, we carried out three more parameter screenings for the HVAC systems as shown in Figure 2. We selected heat pumps or compression chillers driven by electricity (Table 2) for the parameter screenings, as their coefficient of performance (COP) is more

Table 1 building properties and result of parameter screening†4

Index	Description of parameters	values at 'OFF' and 'ON'		Cooling†1		Heating†2		H/C ratio†3
		OFF	ON	Total	Peak	Total	Peak	
1	thickness of concrete layer in outside wall	150mm	225mm	++	++	----	--	++
2	thickness of insulation in outside wall	0mm	20mm	++++	++	----	----	++++
3	height of floor	3.6m	4.2m	----	++	++++	++++	----
4	thickness of concrete layer in floor slab	150mm	225mm	++	+	++	+	-
5	area of window on façade	20%	40%	----	--	++++	++++	----
6	kind of window	normal glass	pair glass with thermal insulation	++		--	--	++
7	length of overhang	0.05m	1m	-		+		
8	radiation emissivity of outside wall	90%	80%					
9	solar absorptance of outside wall	0.8	0.25		--		++	
10	thermal conductivity of insulation	0.028W/m°C	0.035W/m°C	--		++	++	--
11	air change ratio due to infiltration	0.2ACH	0.5ACH	--	++	++++	++++	--
12	sensible heat capacity of rooms	40kJ/m^2°C	60kJ/m^2°C	++++	++	----	--	++
13	schedule of occupants	with overtime working	without overtime working	----	--	++++	++	--
14	light wattage	20W/m^2	14W/m^2	----	--	++++	++	--
15	number of occupants	0.15 person/m^2	0.1 person/m^2	----	--	++	+	--
16	internal heat gain from office equipment	normal setting	2 times large setting	++++	++++	----	--	++++
17	convection/radiation split ratio of heat gain fr. office equipment	0.8 to 0.2	0.6 to 0.4	-	-	++		
18	set point temperature of conditioned rooms	26°C(cooling), 22°C(heating)	28°C (cooling), 20°C (heating)	++	++	++	++	
19	air supply temperature for cooling	15°C	13°C	----	--	----	--	++
20	efficiency of total heat exchanger	60%	30%	++	++			+
21	quantity of outdoor air intake	5m^3/m^{2}hour	7m^3/m^{2}hour	++	++	++++		-
22	adoption of natural ventilation	No	Yes	--	++	++++	++	--
23	operation hours of HVAC systems	8 a.m. to 18 p.m.	8 a.m. to 22 p.m.	--		----		++++
24	interruption of direct solar radiation by neighboring buildings	No interruption	Interrupted on 2 sides of outside wall	++	----	++++	--	--

†1 and †2 The "total" and "peak" is the annual load and peak load, respectively.

†3 H/C ratio is the ratio of the annual haeting and cooling loads (heating / cooling).

†4 The number of '+' and '-' marks is decided as follows: (1:$R_{n,i}$ > 2.5%; 2:$R_{n,i}$ > 5; 3:$R_{n,i}$ > 10%; and 4:$R_{n,i}$ > 20%)

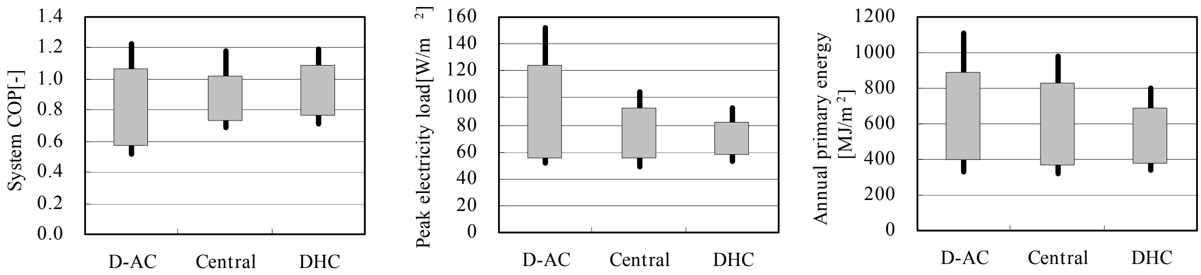

Figure 4 Range of performance indicators observed in the parameter screenings (Min and max, and 95% confidence interval)

sensitive to part-load operation than other systems such as absorption chillers. Thus, the results of these parameter screenings would be applicable to different system alternatives. Table 3 shows the definition of examined parameters relating to system alternatives.

In these screenings, the parameters listed in Table 4 were examined in terms of the following performance indicators:

- COP of the heat generation system (annual cooling and heating demand / annual primary energy consumption of the heat generation system),
- peak electricity load,
- total annual primary energy consumption for heat generation and distribution.

Table 4 shows the influence of each parameter on these performance indicators in the same way as the first parameter screening. For each system, a few building configurations were considered. The influence of the building configuration (size and zoning, index 25 and 26) are shown in Table 4 by using '*' instead of '+' and '-' marks. For the D-AC system, some cells contain both '+' and '-' marks, indicating that the parameter works either positively or negatively on the indicator depending on the building configurations. (Note that we assumed two buildings for the DHC systems.)

Table 4 also contains the following information in three columns from 'Kind' to 'Category':

1) whether uncertainty arises from building properties or from the operation of buildings and systems (P or O),
2) the difficulty of field survey and measurements,
3) category (A to D) of the way of treating uncertainty in parameters decided by following the flowchart in Figure 2 (explained further on in this paper).

Table 2 Description of system alternatives

Term	System	Heat source machines	
		Cooling	Heating
D-AC	Distributed air-conditioning system	Air-source heat pumps driven by electricity	
C or Central	Central HVAC system	Compression chiller	Boiler
DHC	District heating and cooling system	Compression chiller	Boiler

Addressing the source of uncertainty

The variance of the performance indicators obtained in the parameter screenings indicates how strongly the uncertainty in parameters affects the simulation outputs. Figure 4 shows the maximum and minimum values and the 95% confidence interval for the performance indicators. It can be seen that the variance is so large that the uncertainty would conceal the effect of energy saving measures if the model would be used for evaluating these. In order to avoid the situation in which introduced energy saving measures will not function well due to the unexpected characteristics of buildings and systems, the source of uncertainty in the model has to be appropriately addressed during the implementation of DEM.

In order to deal with the uncertainty, we observed the

Table 3 Parameters relating to system alternatives

System alternative	No	Description	Values at 'OFF' and 'ON'	
			OFF	ON
Distributed AC system	30	grade of rated COP	COP = 2.6 for cooling, 3.1 for heating	25% increase
	31	heat loss from refrigerant pipeline	5%	20%
	32	air short circuit arround the outside unit	no consideration	considered
	33	deterioration of rated COP	no deterioration	10%
Central	34	grade of rated COP for cooling	COP = 5	20% increase
	35	deterioration of rated COP for cooling	no deterioration	10%
Both in Central and DHC	36	heat loss from duct	5%	15%
	37	heat loss from pipe in building	2%	10%
	38	temperature fluctuation of returned chilled water	not considered	considered
DHC	39	grade of rated COP for cooling	COP = 5	20% increase
	40	heat loss from district heat delivery pipeline	5%	15%
	41	pressure loss of heat delivery pipeline	30m(length of pipeline)	45m
	42	deterioration of rated COP for cooling	no deterioration	10%

95% confidence interval of the performance indicators as we gradually increased the number of fixed parameters by 5 steps (Case 1 to Case 5). The last 5 columns of Table 4 shows the parameters fixed in each case. Case 1 and Case 2 assume that the energy management framework is based on the traditional approach of using fixed demand per unit floor area. Case 3 assumes the traditional approach of prototypical buildings. Case 4 assumes that certain building properties, which can be gathered by a simple survey, are available. Case 5 assumes that detailed information is available for uncertain factors that require more difficult field survey and measurements.

Figure 5 shows the observed 95% confidence interval of the performance indicators caused by un-fixed parameters. As shown in the relatively large interval of Case 1 to Case 3, it is clear that the energy management framework based on the traditional approaches is not capable of providing reliable information to the evaluation of energy saving measures. As shown in Table 4, some parameters, such as thickness of insulation of outside walls and internal heat gains, work differently on the system COP of distributed air-conditioning systems compared to others. Thus, taking into account the characteristics of buildings in the framework, contributes to raising the quality of the results, especially for planning energy generation, distribution and delivery.

While carrying out a simple survey on building properties reduces uncertainty in the results, a large

Table 4 Result of FSM and category of parameters on treatment of uncertainty†1

Systems	Index	Description	System COP			Peak Electricity			Primary energy			Kind	Diffi-culty	Cate-gory	Case†2				
			DAC	C	DHC	DAC	C	DHC	DAC	C	DHC				1	2	3	4†3	5†4
Building properties	1	thickness of concrete layer in outside wall										P		D					
	2	thickness of insulation in outside wall	---	+++	++	++	+		+	--	-	P		A			O	O	O
	3	height of floor	+									P		A				O	O
	4	thickness of concrete layer in floor slab		+		+	+		+	+	+	P		A				O	O
	5	area of window on façade	++/--	+	+	++			++	+	+	P		A				O	O
	6	kind of window	--	++		-			-			P		A			O	O	O
	7	length of overhang				-	-					P		A				O	O
	8	radiation emissivity of outside wall										P		D					
	9	solar absorptance of outside wall	+	+								P		A				O	O
	10	thermal conductivity of insulation										P	*	D					
	11	air change ratio due to infiltration	+/-	--		++	++		+	+		P	*	C					O
	12	sensible heat capacity of rooms	+	+		++	+	+	+			P	*	C					O
	13	schedule of occupants	--	--	-	--	-		--	--	-	O	*	B					O
	14	light wattage	+/-	--	--	--	--	-	-	-	-	P		A				O	O
	15	number of occupants	+/-	-	--	--	-	-	--	--	-	O	*	B					O
	16	internal heat gain (HG) from office equipment	---	++	++	+++	+++	++	+++	++	++	O	*	B			O	O	O
	17	convection/radiation split ratio of HG fr. office equipment										O	*	D					
	18	set point temperature of conditioned rooms	---	++		---	--	-	---	--	-	O		B					O
	19	air supply temperature for cooling	--	++	+	+++			++	+		O		B					O
	20	efficiency of total heat exchanger	+			++			+	+		O	*	B					O
	21	quantity of outdoor air intake	--	--		+/-	+		++	++		P		A				O	O
	22	adoption of natural ventilation	---	-		-	-	-	---	---	--	P		A				O	O
	23	operation hours of HVAC systems	---	---	---	---	--	-	+++	+++	++	O	*	B					O
	24	interruption of direct solar radiation by neighboring buildings	+++	+	++	--/+	-		-			P		A				O	O
	25	size of building	***	***	***	**	**	**	**	**	**	P		A			O	O	O
	26	zoning of conditioned and un-conditioned area	***	***	***	**	**	**	**	**	**	P		A			O	O	O
Distributed AC system	30	grade of rated COP	+++			---			---			P		A		O	O	O	O
	31	heat loss from refrigerant pipeline	---			++			+			O	*	B					O
	32	air short circuit arround the outside unit				+						O	*	C					O
	33	deterioration of rated COP	---			++			++			O	*	B					O
Central	34	grade of rated COP for cooling		+++			-			-		P		A		O	O	O	O
	35	deterioration of rated COP for cooling		--								O	*	B					O
Both in Central and DHC	36	heat loss from duct		---	-		-			--		O	*	B					O
	37	heat loss from pipe in building		--	-					+		O	*	B					O
	38	temperature fluctuation of returned chilled water			-							O	*	B					O
DHC	39	grade of rated COP for cooling			+++			-			-	P		A		O	O	O	O
	40	heat loss from district heat delivery pipeline			---						+	O	*	B					O
	41	pressure loss of heat delivery pipeline			-							O	*	B					O
	42	deterioration of rated COP for cooling			--			+			+	O	*	B					O

†1The number of '+' and '-' is decided as follows: System COP(for DA-C, 1:$R_{n,i} > 5\%$, 2:$R_{n,i} > 7.5\%$, 3:$R_{n,i} > 10\%$ & for C and DHC, 1:$R_{n,i} > 2.5\%$, 2:$R_{n,i} > 5\%$, 3:$R_{n,i} > 10\%$); Peak electricity load and annual primary energy consumption(1:$R_{n,i} > 5\%$, 2:$R_{n,i} > 10\%$, 3:$R_{n,i} > 20\%$)

†2 Parameters fixed in each case for the analysis in the section "Adressing the source of uncertinty" (O indicates parameters fixed in each case)

†3 Parameters labeled as 'P' in 'Kind' without '*' mark in 'Difficulity' and which elementary effects rated more than one '+' or '-' on any performance indicator

†4 Parameters labeled by '*' mark in 'Difficulity' and which elementary effects rated more than one '+' or '-' on any performance indicator

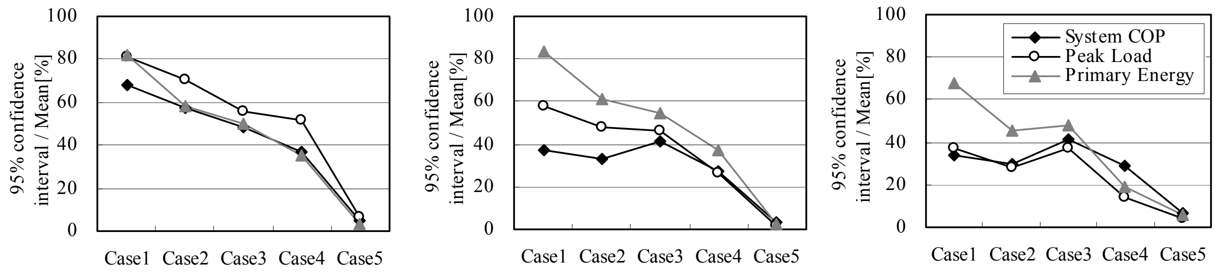

Figure 5 95% confidence interval of the performance indicators with different fixed parameters' set (Results were divided by the mean value shown in Figure 4: D-AC, Central and DHC from left)

uncertainty still remains in the outputs as shown in the results for Case 4. Especially on the system COP, uncertainty in factors that require difficult field survey and measurements accounts for more than 50% of the variance in the outputs. Thus, the required survey and measurements have to be carried out during the implementation of DEM, in order to model the energy use in buildings with a sufficient resolution to evaluate energy saving measures.

Framework for DEM

According to the simulation results in Table 4, we established a method to deal with uncertainty in building properties and operational conditions as shown in the last column of Table 4 by following the procedure shown in Figure 2. The final design for the energy management framework is schematically shown in Figure 6. The framework comprises 3 databases, as well as a field survey and measurement scheme in addition to the simulation model. The building properties database contains building properties categorized as 'A' in Table 4. The uncertainty database contains the 'ON' and 'OFF' values as reference data of parameters categorized as 'C' to assume proper conditions for performing simulations. The field survey and measurement scheme is designed to investigate factors categorized as 'B'. The priority of the survey and measurements is given by the value of $R_{n,i}$ shown in Table 4. If the uncertainty in these factors can be prepared as reference data in a database, it will be helpful to reduce the work to carry out the detailed field survey and measurements.

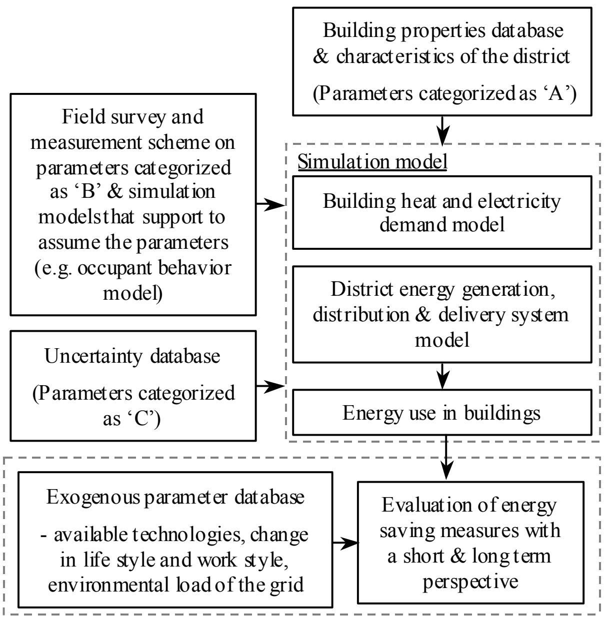

Figure 6 Framework for DEM

Based on these databases and the scheme, the energy use in buildings can be modeled with an appropriate resolution in order to evaluate energy saving measures. Most importantly for a task of DEM, the exogenous parameter database is taken into account in the evaluation process, in order to adjust the short and long term plans on DEM according to the long term trends of the exogenous parameters, such as change in climatic conditions and life style and work style of occupants, and future prospects of available technologies and energy sources.

DEMONSTRATION OF THE MANAGEMENT FRAMEWORK

In order to demonstrate whether the developed energy management framework does indeed provide useful information when we assumed specific buildings, a Monte Carlo study was performed with two building configurations (A and B) in Figure 7 as a case study of the local energy generation, distribution and delivery planning. For each system alternative, the overall COP was observed in more than 300 simulation runs assuming the current and future situations as explained in Figure 7. Figure 8 shows the 95% confidence interval of the overall COP for each system alternative due to uncertainty of parameters categorized as 'C' and 'D' (results for the Distributed air-conditioning system and Central HVAC system are shown on each building configuration A and B respectively). The 95% confident intervals are sufficiently narrow to compare performance of these alternatives. Thus, the designed energy management framework is capable of providing reliable information for local energy generation, distribution, and delivery planning on DEM.

CONCLUSION

This paper proposes a method to develop a framework for district scale energy management that encompasses site design, local energy generation, distribution and delivery planning. A parameter

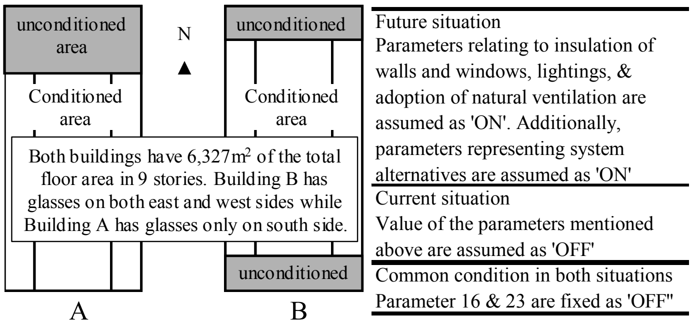

Figure 7 Building configuration A and B & the description of the current and future situations (the future situation assumes adoption of various energy saving measures in these buildings)

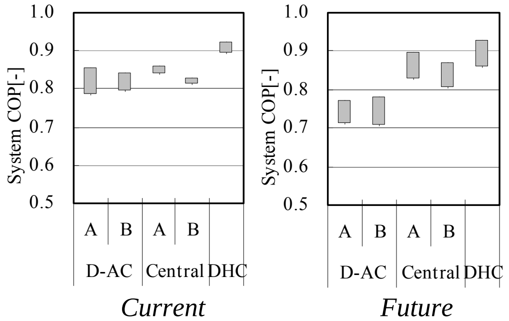

Figure 8 95% confidence interval of System COP (Mean$_n$ ±2·S$_n$ where S$_n$ is the total standard deviation observed in the validation study)

screening technique is used to determine which building properties and operational conditions have to be addressed in particular. Based on the parameter screenings results, we designed a method to deal with the uncertainty in these factors, in order to predict operational energy use with a sufficient resolution for evaluating various energy saving measures. The designed framework consists of a simulation model, as the fundamental part, a building properties database, an uncertainty database and a field survey and measurement scheme. These databases and the scheme are introduced to reduce the gap between simulation results and reality. Although the method is discussed for cooling and heating energy generation, distribution and delivery planning, the proposed method could be applicable to other problems, such as planning of a micro-grid.

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