A HIERARCHICAL DESIGN OPTIMIZATION FRAMEWORK FOR BUILDING PERFORMANCE ANALYSIS

Ruchi Choudhary[1], Ali Malkawi[2], and Panos Y. Papalambros[3]
[1]Doctoral Program in Architecture, University of Michigan, Ann Arbor, MI-48109, USA
[2]Department of Architecture, University of Pennsylvania, Philadelphia, PA-19104, USA
[3]Mechanical Engineering Department, University of Michigan, Ann Arbor, MI-48109, USA

ABSTRACT

This article presents a mathematical model that provides explicit support for preserving the consistency between decisions made at various points during building performance analysis. Analytical Target Cascading, a multilevel engineering design optimization framework, is applied to the energy analysis process. Within this framework, the energy analysis problem is decomposed into hierarchical levels based on individual performance goals. Interactions among all levels in the hierarchy are accounted for by linking them mathematically. A top-down and bottom-up iterative process is applied to determine the optimal values of performance goals compatible with one another. Application to the energy analysis of a three zone example is presented and results are discussed.

INTRODUCTION

Informed decision-making has been an important goal of building simulation research in many forms. The plethora of performance analysis tools in the building industry is meant to provide the decision-makers with information that facilitates and supports their task. However, this information by itself has proven to be of limited use and so various simulation packages come with post-processing abilities that include statistical analysis, AI-based evaluations, and facilities to optimize design parameters towards some performance goals. Still, the decision-maker has to cope with the challenge of delegating multiple analysis tasks, each of which require both overlapping and distinct decision parameters, and then of aggregating their results into a single compatible set of design decisions. Decision support for any single design goal is therefore not very helpful when those decisions are likely to contradict responses from other design analyses.

Past work on computational decision models have used multi-criteria formulations with preference or non-preference based strategies for accounting multiple performance goals (Caldas et.al., 2002; Jedrzejuk et.al., 2002; Klemm et.al., 2000; Wright and Loosemore, 2001). These applications typically provide the decision maker with those values of decision variables which best accommodate a weighted set of performance criteria. The difficulty in elaborating these efforts to include more than a few analysis tasks and decision variables is that the problem quickly becomes too large and complex to be implemented altogether. Furthermore, different performance goals often require a unique analysis of design in varying degrees of complexity and with varying extent of design information. Likewise, design decisions for achieving these goals are made under varying degrees of freedom since the constraints on the decision parameters become more specific and numerous at detailed levels.

Recognizing the multi-criteria and complex nature of building performance analysis, and highlighting the importance of unique decision models for different performance goals, we propose a multilevel optimization process referred to as Analytical Target Cascading (ATC). Hitherto applied to automotive designs (Kim et.al., 2001 and 2002), ATC provides a systematic process propagating the desired top-down performance targets to appropriate specifications for a product’s subsystems and components (Papalambros, 2001).

In applying ATC to building performance we view performance based decision-making as analogous to any complex problem. Related assumptions include:

- A complex problem can be decomposed or partitioned into sub-problems that can be further decomposed.
- It is possible to identify a hierarchical structure in the decomposition.
- Performance targets are behavioral specifications that we want to achieve by our design decisions. These specifications can be represented numerically as functions of the decision parameters.

Once a problem is decomposed in a hierarchical multilevel structure, the subproblems can be solved independently. An ATC problem is formulated when mathematical links are identified between the subproblem solutions. An overall solution is obtained by optimizing "solution-matching" between subproblems through a coordination strategy.

In the following section we describe the ATC process at a general level (the description is condensed, and for further details we refer the reader to the original literature in Kim, 2001). Then, through a fictional pilot application we demonstrate the strengths of this framework for (a) coordinating multiple decision-making tasks in compatibility with one another, (b) providing explicit decision support including tradeoffs between performance goals, and (c) purposeful use of simulation tools in decision-making.

THE ATC PROCESS

The ATC framework is based on posing a problem using two types of models: the *decision model* and the *analysis model*. As shown in figure 1, a decision model is the representation of performance targets (**T**), actual system performance (**R**), decision variables (**x**) and, all relevant constraints on decision variables (**g**, **h**). The analysis model comprises of the analysis tool and a post-processor: The analysis tool, (typically a simulation), is used to compute some responses (**r**), as functions of decision parameters, and a post-processor is invoked to amass those responses into performance values **R**.

The first step in setting up an ATC problem is to decompose the problem hierarchically. Typically four types of decomposition strategies are commonly found in systems design literature (Wagner, 2001): *Object decomposition* divides a system into physical components such as building, zones, rooms and components. *Aspect decomposition* divides the system according to different specialties involved in its modeling and would be a relevant consideration when multiple performance considerations feature for a physical entity. *Sequential decomposition* is applied to problems involving flow of elements or information. It is a difficult option for architectural design analysis because it presumes uni-directionality of design information. *Model decomposition* is based on decomposing the problem on the basis of the mathematical model of the design problem and functional dependencies of the design relations.

Once the decision model is decomposed, appropriate analysis models are associated with each element in the hierarchy. An analysis model is appropriate if it can compute performance values as functions of its decision variables. Every analysis

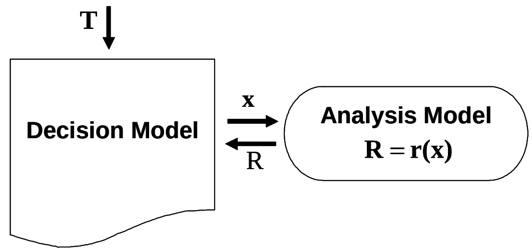

Figure 1: Models in the ATC framwork

model evaluates design decisions by taking variables and parameters as input and returning performance values as output.

The clear separation between the decision and the analysis model is an important feature in this hierarchical decomposition approach. It implies that the decision models can be freely modified as per the problem, by adding or changing performance goals or decision variables. New functional relations can be included as additional constraints depending on the peculiarities of the problem under consideration. Furthermore, analysis tools can be used efficiently without information overload of irrelevant decision variables. The independence of the decision model from the analysis model also provides the flexibility to use any relevant analysis tool that is available. Finally, for any particular subproblem in the hierarchy multiple analysis models can be also used if required.

The second step is to formulate the ATC problem by identifying horizontal and vertical links between the hierarchically decomposed problems. Horizontal links are called *linking variables* (**y**). Linking variables represent decisions shared among two or more decision models at the same level (Kim, 2001). Their value is determined individually by the decision models that share them and coordinated by the upper level parent problem. This implies that subproblems that share linking variables must also have a common decision model at the upper level.

The vertical relationships between decomposed levels are embodied through building performance targets. As shown in figure 2, at hierarchical level *B*, the decision model receives the value of lower level performance values ($\mathbf{R}^L_{B.1}, \mathbf{R}^L_{B.2}$) and linking variables ($\mathbf{y}^L_{B.1}, \mathbf{y}^L_{B.2}$). It also receives target values for performances $\mathbf{R}^U_B$ from the decision model located at the level above. Based on these sets of information from the upper and lower levels, the problem at level *B* constitutes finding those values of $\tilde{\mathbf{x}}$, $\mathbf{y}_\mathbf{B}$, $\mathbf{R}_{B.1}$, and $\mathbf{R}_{B.2}$ which yield performance values $\mathbf{R}_B$ with minimum deviation from $\mathbf{R}^U_B$ passed down from the upper level and also match

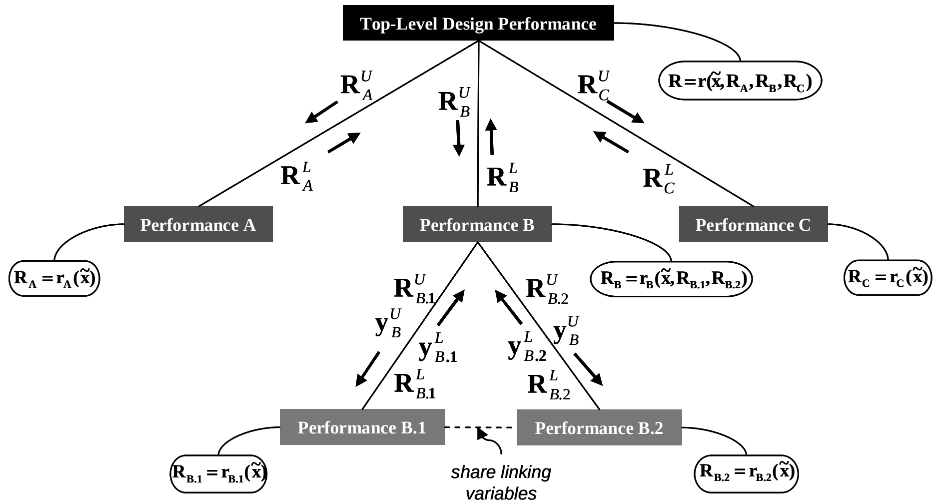

Figure 2: Interactions between Hierarchical Levels in ATC Formulation

$\mathbf{R}_{B.1}^L, \mathbf{R}_{B.2}^L$ and $\mathbf{y}_{B.1}^L, \mathbf{y}_{B.2}^L$ from the lower levels. Note that in these interactions the performance values $\mathbf{R}_{B.1}$ and $\mathbf{R}_{B.2}$ are decision variables at the level above so that their value is determined in compatibility with upper level performances.

For target matching a problem S_{ij} for *j*-th design model at the *i*-th level, the general formalization of this optimization process is given in Eq. (1). The following symbols are used to define it:

T	performance targets
R	performance returned by analysis model
r	responses computed by analysis tools
$\mathbf{R}^U$	target values of **R** from an upper level
$\mathbf{R}^L$	target values of **R** from a lower level
y	linking variables
$\mathbf{y}^U$	target values of **y** from an upper level
$\mathbf{y}^L$	target values of **y** from a lower level
$\boldsymbol{\varepsilon}_R$	deviation tolerance for performances
$\boldsymbol{\varepsilon}_y$	deviation tolerance for linking variables
g	inequality constraints in a design problem
h	equality constraints in a design problem
x	vector of all design variables
$\tilde{\mathbf{x}}$	local design variables
$\tilde{\mathbf{x}}^{\min}$	lower bound of $\tilde{x}$
$\tilde{\mathbf{x}}^{\max}$	upper bound of $\tilde{x}$

S_{ij} : Minimize $\left\|\mathbf{R}_{ij}-\mathbf{R}_{ij}^U\right\|+\left\|\mathbf{y}_{ij}-\mathbf{y}_{ij}^U\right\|+\boldsymbol{\varepsilon}_{\mathbf{R}_{ij}}+\boldsymbol{\varepsilon}_{\mathbf{y}_{ij}}$

with respect to: $\tilde{\mathbf{x}}_{ij}, \mathbf{y}_{ij}, \mathbf{y}_{(i+1)j}, \mathbf{R}_{(i+1)j}, \boldsymbol{\varepsilon}_{\mathbf{R}}, \boldsymbol{\varepsilon}_{\mathbf{y}}$ (1)

where: $\mathbf{R}_{ij}=\mathbf{r}_{ij}\left(\mathbf{R}_{(i+1)j}, \tilde{\mathbf{x}}_{ij}, \mathbf{y}_{ij}\right)$

subject to:

$$\left\|\mathbf{R}_{(i+1)}-\mathbf{R}_{(i+1)}^L\right\| \le \boldsymbol{\varepsilon}_{\mathbf{R}}$$

$$\left\|\mathbf{y}_{(i+1)}-\mathbf{y}_{(i+1)}^L\right\| \le \boldsymbol{\varepsilon}_{\mathbf{y}}$$

$$\mathbf{g}_{ij}(\mathbf{R}_{ij}, \tilde{\mathbf{x}}_{ij}, \mathbf{y}_{ij}) \le 0$$

$$\mathbf{h}_{ij}(\mathbf{R}_{ij}, \tilde{\mathbf{x}}_{ij}, \mathbf{y}_{ij}) = 0$$

$$\tilde{\mathbf{x}}_{ij}^{min} \le \tilde{\mathbf{x}}_{ij} \le \tilde{\mathbf{x}}_{ij}^{max} \qquad \mathbf{y}_{ij}^{\min} \le \mathbf{y}_{ij} \le \mathbf{y}_{ij}^{\max}$$

Once the ATC problem is set up for all elements in a hierarchy in the form shown in Eq. 1, a coordination strategy can be applied to iterate through the multi-level structure. The formulation is both top-down and bottom-up, implying that once some overall performance targets are specified at the top most level, they are disseminated down to determine the value of lower level performances. Likewise, if performance targets are initially specified for lower level problems, then the upper level performances can be determined based on the information propagated up from the lower levels. In this manner, the decisions made at any particular level in the hierarchy are ensured to be consistent with all other components of the decomposed problem. The iterative process of cascading targets is repeated until specified termination criteria are met.

PILOT APPLICATION

We now demonstrate the applicability of the ATC process to building performance optimization through a fictional case. Thermal design of a three zone building is being considered: one office and two workshops (figure 3).

This problem is defined for making decisions on the size of the building parts: wall and window areas, and control settings for velocity and temperature, such that the building is thermally efficient. Depending on the function and schedules of use, the following targets are specified for the building: *(a) Overall floor area:* In seeking values of external wall length the given overall area of the building should be maintained, *(b) Thermal performance of*

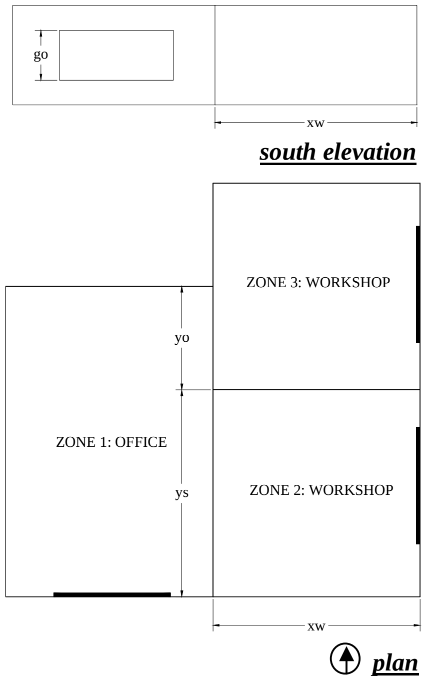

Figure 3: The Three Zone Example Case

room 1, 2 and 3: 100% thermal efficiency is targeted for the building. This implies that at the best case, the summation of the thermal performance of all three zones should yield 100% performance.

The two workshops are assumed to be identical in terms of use, environmental conditions, and occupancy. For these two zones the thermal performance goal is formulated for minimizing the annual heating and cooling energy. For the office, thermal efficiency means maximizing the number of occupied hours for which a suitable occupant comfort index is maintained. In addition to these targets, zone performances must be within defined feasible limits of average room temperatures and thermal comfort at all occupied hours, and total annual energy cost. The performance criteria and constraints assumed throughout this example are formulated for the purpose of demonstrating the applicability of ATC to multi-criteria assessments.

ATC FORMULATION

The analysis problem as posed constitutes three sets of performance goals distinguishable by their scope in the overall analysis problem as well as the variables they depend on: the first set of performance targets (overall area T_A and 100% thermal efficiency T_P) represent the total analysis problem, and are in fact a function of the other two set of performance goals. The second (area of the workshops A_w and energy use P_w) and third (area of the office A_o and its thermal comfort P_o) sets of targets belong to separate functional zones, and hence are functions of different variables except for the common wall y_s between the office and the workshops.

The three-zone building is therefore “object decomposed” in a bi-level structure. The building analysis problem is represented at the top level (Z) where target values T_A and T_P are specified for overall building area A and thermal efficiency P. This problem is decomposed into two subproblems at the second level: Subproblem 1 (Z_{s1}) represents the office and subproblem 2 (Z_{s2}) represents the workshops. Since the two workshops are assumed identical, thermal performance value and area are computed only for one and then doubled to include the second workshop in the overall analysis. The common wall between the workshop and office (y_s) is represented as a linking variable, which means that it is coordinated by the top level problem Z.

The following mathematical formulations are used to setup the ATC process for this problem. Figure 4 shows the performance values, variables included at each level as well as the information flow up and down the levels. In addition to the ATC nomenclature, symbols used throughout this example are:

Z overall building performance model
Zs1 office decision model
Zs2 workshop decision model
T_A target area of the three zone building
T_P target performance of the three zone building
A total area of the three zone building
P total performance of the building
A_o area of the office
P_o thermal comfort of the office
A_w area of the workshop
P_w total annual energy used by the workshops
y_s wall between the office and workshop [m]
x_w length of workshop wall [m]
y_o length of office wall [m]
g_o window height of office [m]
g_w window wall percentage of workshop
$_o$ as subscript defines attributes of office
$_w$ as subscript defines attributes of workshop
v mean zone velocity [m/s]
h heating setpoint temperature [°C]
c cooling setpoint temperature [°C]
E total annual heating and cooling energy [J]
E_{ref} limits on total annual energy use [J]
H heating energy [J]
C cooling energy [J]
T average mean temperature [°C]
Φ hourly value of comfort index [PMV]
V % hours in which Φ is maintained within a specified range
V_{ref} limits on V
k scaling factor

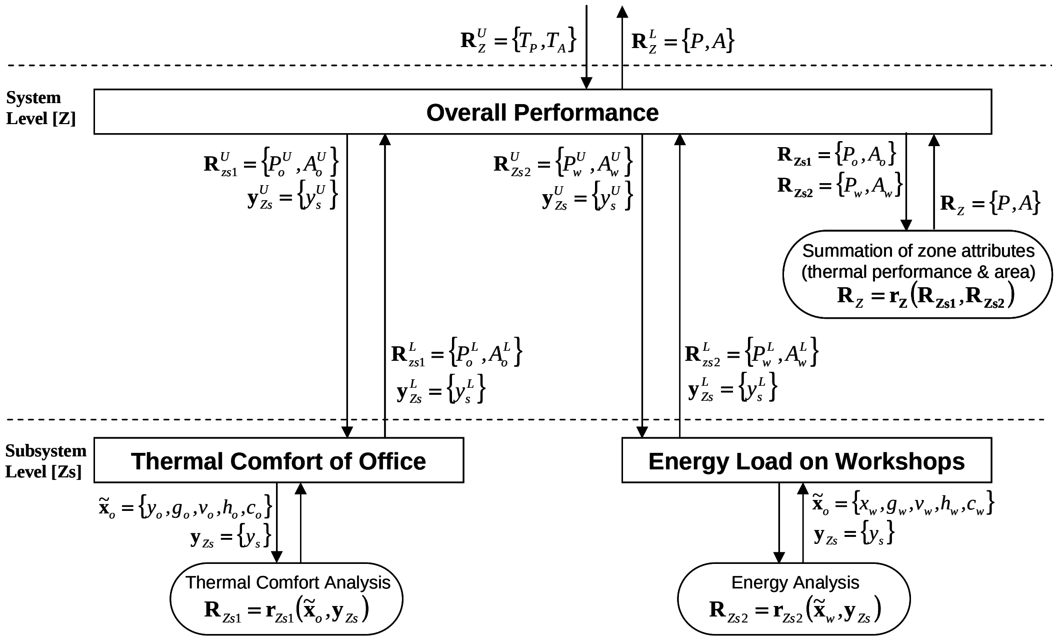

Figure 4: Information Exchange between Decomposed Levels of the Three Zone Case

<u>Top Level Decision Model</u>

Z: Minimize $(P-T_P)^2+(A-T_A)^2+\boldsymbol{\varepsilon}_\mathbf{R}+\boldsymbol{\varepsilon}_\mathbf{y}$

with respect to:

$$P_o,A_o,P_w,A_w \qquad (2)$$

$$\boldsymbol{\varepsilon}_\mathbf{R},\boldsymbol{\varepsilon}_\mathbf{y}=(\varepsilon_{P_o},\varepsilon_{P_w},\varepsilon_{A_o},\varepsilon_{A_w},\varepsilon_y)$$

where:

$$\mathbf{R}_Z[P,A]=\mathbf{r}_Z(P_o,A_o,P_w,A_w)$$

subject to:

$$(P_o-P_o^L)^2\le\varepsilon_{P_o}\quad (A_o-A_o^L)^2\le\varepsilon_{A_o}$$
$$(P_w-P_w^L)^2\le\varepsilon_{P_w}\quad (A_w-A_w^L)^2\le\varepsilon_{A_w}$$
$$(y_s-y_{s1}^L)^2+(y_s-y_{s2}^L)^2\le\varepsilon_y$$
$$P_o^{\min}\le P_o\le P_o^{\max}\quad A_o^{\min}\le A_o\le A_o^{\max}$$
$$P_w^{\min}\le P_w\le P_w^{\max}\quad A_w^{\min}\le A_w\le A_w^{\max}$$
$$y_s^{\min}\le y_s\le y_s^{\max}$$

The top level analysis model sums the zone attributes and returns the total area *A* and thermal performance *P* values of the building (as shown in Eq. 3):

$$P=(P_o+2P_w)\quad A=(A_o+2A_w) \qquad (3)$$

In addition to minimizing difference between targets and performances, the deviation tolerances (ε_R and ε_y) used to coordinate lower level information, are also minimized (see Eq. 2). At an ideal case the deviation tolerences are expected to be zero implying that values of the building level variables match the performance values determined at the level below, and the value of the shared variable y_s is set same at both sub-problems. In this particular example there are no local variables at the top level. Therefore, the only constraints are those formulated for coordinating the lower level information.

<u>Subproblem Decision Models</u>

$\mathbf{Z_{s1}}$: Minimize $(P_o-P_o^U)^2+(A_o-A_o^U)^2+(y_s-y_s^U)^2$

with respect to:

$$\tilde{\mathbf{x}}_o=(y_o,g_o,v_o,h_o,c_o) \qquad (4)$$
$$\mathbf{y}_{Zs}=(y_s)$$

where:

$$\mathbf{R}_{Zs1}[P_o,A_o]=\mathbf{r}_{Zs1}(\tilde{\mathbf{x}}_o,\mathbf{y}_{Zs})$$

subject to:

$$E_o-E_{refo}\le 0 \qquad V_o-V_{refo}\le 0$$
$$T_o^{\mathbf{min}}\le T_o\le T_o^{\mathbf{max}} \qquad \tilde{\mathbf{x}}_o^{\mathbf{min}}\le\tilde{\mathbf{x}}_o\le\tilde{\mathbf{x}}_o^{\mathbf{max}}$$

$\mathbf{Z_{s2}}$: Minimize $(P_w-P_w^U)^2+(A_w-A_w^U)^2+(y_s-y_s^U)^2$

with respect to:

$$\tilde{\mathbf{x}}_w=(x_w,g_w,v_w,h_w,c_w) \qquad (5)$$
$$\mathbf{y}_{Zs}=(y_s)$$

where:

$$\mathbf{R}_{Zs2}[P_w,A_w]=\mathbf{r}_{Zs2}(\tilde{\mathbf{x}}_w,\mathbf{y}_{Zs})$$

subject to:

$$E_w-E_{refw}\le 0 \qquad V_w-V_{refw}\le 0$$
$$T_w^{\mathbf{min}}\le T_w\le T_w^{\mathbf{max}} \qquad \tilde{\mathbf{x}}_w^{\mathbf{min}}\le\tilde{\mathbf{x}}_w\le\tilde{\mathbf{x}}_w^{\mathbf{max}}$$

In sub-problem 1 (Eq. 4) Thermal performance P_o is defined by the PMV comfort index and 100%

	Target Values	Optimal Values
Top-Level problem		
Thermal comfort in office	0.0	0.00
Area of office	0.0	0.07
Total heating and cooling energy of the workshops	0.0	0.11
Area of workshop	0.0	0.03
Subproblem 1: Office Performance		
Thermal comfort in office	0.00	0.02
Area of office	0.07	0.05
Subproblem 1: Workshop Performance		
Total heating and cooling energy of the workshops	0.11	0.06
Area of workshop	0.03	0.00

Figure 5. Scaled Target and Optimal Performance Values of the Three Zone Case from the ATC Process

comfort index is returned when the absolute value of average comfort index at all occupied hours *n* during a year is zero:

$$P_o = \left(\sum_{i=1}^{n} |\Phi_i| \right) \Big/ n \qquad (6)$$

P_w in Eq. 5 is the total heating and cooling energy used during the year (for *m* number of hours) scaled by the maximum feasible value E_{refw} specified as a constraint.

$$P_w = \left(\sum_{i=1}^{m} H_{w_i} + \sum_{i=1}^{m} C_{w_i} \right) \Big/ E_{refw} \qquad (7)$$

A_o and A_w are computed as functions of their geometry variables, scaled between 0 and 1, and subtracted by one so that the maximization of area is posed as a minimization function.

$$A_o = \left|1 - k_o\left(x_o(y_s + y_o)\right)\right|$$
$$A_w = \left|1 - k_w\left(x_w y_s\right)\right| \qquad (8)$$

Constraints on both zone problems include maximum feasible limits on total annual energy used for heating and cooling, minimum and maximum average zone temperature, and limits on the comfort index at all occupied hours. Additionally, upper and lower bounds are specified on all local variables.

The analysis models of both subproblems use Energy Plus (Crawley et.al., 2001) for computing zone performances. All evaluations are run hourly, for one year.

All decision variables, constraints and functions used in this formulation are scaled between 0 and 1. These functional relationships complete the mathematical formulation of the three zone case and the hierarchical optimization process can now begin.

HIERARCHICAL OPTIMIZATION

Starting from the top level, deviations between specified targets (T_A, T_P) and performance values (A, P) are minimized with respect to A_o, P_o, A_w, and, P_w. Once determined, optimal values of these zone attributes are cascaded down to subproblems 1 and 2 as target values $([A_o^U, P_o^U],[A_w^U, P_w^U])$. At this point, an estimated initial value of the linking variable y_s is also passed down to both zone level problems as target (y_s^U).

At the zone level the local and linking variables of subproblem 1 are optimized such that the resulting values of A_o, P_o, and y_s best match the upper level values passes down as targets, while satisfying all feasibility constraints. Similarly, variables of subproblem 2 are sought such that deviations between A_w, P_w, and y_s and their corresponding target values determined at the upper level are minimized.

Once the decision variables are optimized for zone level problems, their performance values and linking variables are passed back to the building level problem as lower level targets $\left(\left[A_o^L, P_o^L, y_s^L\right], \left[A_w^L, P_w^L, y_s^L\right]\right)$ and the building level problem is re-solved so that not only deviations between overall building targets and performances are minimized, but also the deviation tolerances between the zone performance and linking variables determined at the building level and its values passed back from the zone level.

One target cascading iteration is complete when zone information is fed back to the top level decision model. For this top-down case the iterations were terminated when the deviation values became smaller than a specified tolerance and also when the variables of all the decision models in the hierarchy stopped changing between subsequent iterations. At the end of the cascading process all performance targets (T_A, T_P, A_o, A_w, P_o, P_w) and linking variables (y_s) are determined in compatibility with one another. "Compatibility" here means meeting the targets as closely as possible, while satisfying constraints throughout the hierarchy.

We used Sequential Quadratic Programming (SQP) to optimize of the top level performance targets. SQP is a gradient based optimization algorithm, which means that it uses function gradients to make decisions about which designs to explore. The algorithm is fast for small problems and produces locally optimal design.

Since SQP requires all decision variables and design relations to be smooth, superEGO (Sasena, 2002) was used to optimize zone level problems where some design relations are non-smooth (the functions have discontinous jumps). An approximation based global optimization algorithm, superEGO is also efficient for problems where the analysis models may include calls to expensive simulation tools: The algorithm takes an initial data sample of the objective function and fits a surrogate model to that data. It uses the surrogate model to search for optimal solutions and therefore reduces the number of calls to the analysis model. Although not highly critical in our example case, this feature is an important consideration for any future applications where expensive simulations could make the ATC process extremely time-consuming.

RESULTS

For the three zone case, the ATC process terminated in 12 iterations. Figure 5 shows the tradeoffs between building and zone level targets. These tradeoffs represent the best compromise between performance targets while meeting all feasibility constraints. This optimization is therefore assisting queries such as: What are the implications of the specified performance goals on all other performances considered in a problem?

Since this example case is small, these results are also compared to results obtained when the same problem when posed as one optimization problem, and solved "all at once", namely, without the ATC decomposition (this comparison is a validation of ATC given by Kim, 2001). The "all at once" problem was optimized using superEGO. Table 1 shows both the ATC and "all at once" solution: $\boldsymbol{f}$ is the total deviation between all targets and performance goals as represented by the top-level objective function in the ATC formulation, and [A_o, P_o, A_w, P_w] are the performance values determined for the two zones.

Ideally, the solution to the "all at once" problem should be the same or better than the ATC results for the same problem. However, we obtained better results when the problem was solved by the ATC process (see value of f in Table 1): The use of SQP at the top level of the ATC formulation allowed better convergence towards the true optimum. Additionally, partitioning of the problem results in lower dimensionality of optimization problem (5 variables per subproblem as against 11 variables when the problem is solved "all at once") which increases the performance of superEGO and also improves convergence.

In general, computational expense of the analysis and non-smooth functional dependencies are common features of the energy analysis problem. Therefore, it is difficult to solve the whole problem using gradient based optimization algorithms such as SQP. On the other hand, solving the whole problem using superEGO compromises the solution. As it turns out, by allowing the use of different optimization strategies suitable at specific levels of the system decomposition, the ATC process results in a better solution.

	Solution from Target Cascading	"All-at-Once" Solution
P_o	0.00	0.19
A_o	0.07	0.19
P_w	0.11	0.17
A_w	0.03	0.004
y_s	0.95	0.76
y_o [m]	4.31	4.38
g_o [m]	0.84	1.01
v_o [m/s]	0.14	0.10
h_o [°C]	21.21	21.75
c_o [°C]	21.34	21.67
x_w [m]	10.10	10.8
g_w [%]	0.67	0.83
v_w [m/s]	0.18	0.20
h_w [°C]	20.34	21.56
c_w [°C]	23.93	21.88
$\boldsymbol{f}$	**0.0117**	**0.0359**
ε_{p1}	0.0005	
ε_{p2}	0.0023	
ε_{a1}	0.0002	
ε_{a2}	0.0009	
ε_{y}	0.0013	

Table 1: ATC and "all-at-once" Solutions for the Three Zone Case

CONCLUSIONS & CURRENT WORK

Results from the pilot study are encouraging and demonstrate the potential of the ATC process for lending clarity and tractability to the typically complex decision-making problems in building performance analysis. In performance based decision-making, it is particularly beneficial to be able to determine compatible performance targets at all decision nodes on the basis of some overall specifications. Furthermore, at the end of the target cascading process, it is possible to systematically revisit the problem if some targets are not met, or if trade-offs between different performance goals do not appeal to the decision maker.

In addition, the decomposition approach allows the individuality of a local analysis task to be preserved and so: (a) analysis tools can be invoked at particular levels and for specific needs avoiding information overload, (b) the decision-making space for a local problem is clearer since it only includes locally relevant variables and functional relationships, and (c) appropriate optimization algorithms can be invoked depending specifically on the formulation of the local analysis problem. As a further step, we are also developing a general framework for decomposing building performance problems.

Some general issues raised through the pilot study are identifying the typical decision-variables that are considered during the analysis process. For example, external wall and roof assemblies are important decision variables in an exterior load dominated zone. However, they are difficult to include as decision variables due to non-sooth functional dependencies. Another challenge is identifying analysis tools that are relatively fast and also sensitive to changes in the values of decision-variables. Finally, the solution obtained from the target cascading process depends on how the performance targets are weighted at the top level and this poses problems typical of multi-criteria formulations. Work in progress addresses these issues. Although we present its applicability through a pilot study, this strategy is valid for a broad class of complex building performance problems where the multiplicity of functions and performance specifications make it particularly difficult to retain the integrity of design decisions. Such applications also constitute work in progress.

REFERENCES

Caldas L.G., and L.K. Norford, “A Design Optimization Tool Based on a Genetic Algorithm”, *Automation in Construction*, 11(2002) 173-18.

Crawley Drury B., Lawrie L.K., Winkelmann F.C., Buhl W.F., Huang Y.J., Pedersen C.O., Strand R.K., Liesen R.J., Fisher D.E., Witte M.J. and Jason Glazer, “EnergyPlus: Creating a New-Generation Building Energy Simulation Program”, *Energy and Buildings*, 33 (2001) 319-331.

Jedrzejuk H. and W. Marks, “Optimization of shape and functional structure of buildings as well as heat source utilisation example”, *Building and Environment*, 37 (2002) 1249-1253.

Kim, H.M., “Target Cascading in Optimal System Design”, Ph.D. Thesis, Department of Mechanical Engineering, University of Michigan, Ann Arbor, Michigan, USA, 2001

Kim, H.M., Rideout, D.G., Papalambros, P.Y., and J.L. Stein, “Analytical Target Cascading in Automotive Vehicle Design”, *Proceedings of the 2001 ASME Design Automation Conference*, Pittsburgh, Pennsylvania, USA, September 9-12, 2001.

Kim, H. M., Kokkolaras, M., Louca, L., Delagrammatikas, G., Michelena, N., Filipi, Z., Papalambros, P., and D. Assanis, “Target Cascading in Vehicle Redesign: A Class VI Truck Study”, *International Journal of Vehicle Design*, 29(2002) 199-225.

Klemm, K., Marks, W., and A.J. Klemm, “Multi-criteria Optimization of the Building Arrangement with Application of Numerical Simulation”, *Building and Environment*, 35 (2000) 537-544.

Papalambros, P.Y., “Analytical Target Cascading in Product Development”, *Proceedings of the 3rd ASMO UK / ISSMO Conference on Engineering Design Optimization*, Harrogate, North Yorkshire, England, July 9-10, 2001.

Sasena M., “Efficiency and Flexibility Enhancements for Constrained Global Design Optimization with Kriging Approximations”, Doctoral Dissertation, Department of Mechanical Engineering, University of Michigan, Ann Arbor, MI, USA, 2002.

Wagner T., “A General Decomposition Methodology for Optimal System Design”, Doctoral Dissertation, Department of Mechanical Engineering, University of Michigan, Ann Arbor, Michigan, USA, 2001

Wright J. and H. Loosemore, “The Multi-Criteria Optimization of Building Thermal Design and Control”, In *Proceedings of the Seventh International IBPSA conference*, Brazil, 2001.