A TWO-STAGE SIMULATION-BASED ON-LINE OPTIMIZATION SCHEME FOR HVAC DEMAND RESPONSE

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ABSTRACT

The on-line control optimization for building heating, ventilation and air conditioning (HVAC) systems is crucial for automatic demand response. Simulation-based optimization techniques usually require intensive computation, even with advanced optimization algorithms, and therefore are not feasible for on-line decision making. This article presents a two-stage scheme in which an "optimal strategy pool" is generated by off-line optimization on the identified weather patterns. And only a small number of strategies are subject to on-line simulation evaluation. This two-stage approach shows superior capability of identifying optimal DR strategies and reducing on-line computation load, simultaneously. A case study with EnergyPlus simulation of a large education facility at Berkeley, CA is included.

INTRODUCTION

The demand response (DR) control strategies of HVAC systems in buildings, especially commercial buildings with medium to large spaces, have been studied by many groups using analytic, simulation and field approaches (Rabl and Norford 1991; Morris, Braun et al. 1994; Keeney and Braun 1997; Xu and Yin 2009; Yin, Xu et al. 2010). Advanced controls of thermostat setpoints and HVAC equipment operations have been developed to reduce the building peak load. For example, Xu and Yin (Xu and Yin 2009) tested the potential of "pre-cooling" thermostat setpoint strategy in reducing the peak HVAC load in large commercial buildings in California hot climate zone. The authors observed 20-30% peak load reduction being achieved on hot days, with night pre-cooling and raising the cooling setpoint in critical time period. Field survey results showed that the thermal comfort had not been compromised during the test. Yin, et. al. (Yin, Xu et al. 2010) presented their studies on optimization of pre-cooling strategies using calibrated simulation model. They developed a Demand Response Quick Assessment Tool (DRQAT), which was built based on DOE's whole building energy simulation engine, EnergyPlus. Optimal DR strategies were identified by simulations, and were implemented to a test building. The measured consumption agreed well with the simulation result, and the power consumption during the peak period was reduced by 15%-30%. The application of building automation systems, such as APOGEE from Siemens Building Technology USA, enables the real-time access of HVAC performance data, load status, weather condition/forecast and DR signals. It also allows immediate or scheduled execution of control directives. As a result, on-line control optimization that responds to the building dynamics and weather changes becomes possible.

There are two approaches in developing the optimal control strategy for building HVAC system – one is based on simulation and the other is trying to directly solve optimization problems. The first approach relies on whole building simulation engines, such as EnergyPlus. With inputs of building geometry, building envelope, internal loads, HVAC systems and weather data, simulation engines are able to compute the energy consumption using physical or approximate equations. Various optimizers can be involved to identify the optimal strategies among many. This simulation-based approach can provide acceptable accuracy, but require large amount of engineering effort to develop and calibrate the simulation model for each specific building, and computation load is considerably heavy.

The second approach is trying to model building energy consumption in such manner that, given certain objective functions and constraints, the optimal solution can be solved directly – simulation is usually not involved. The advantages of this approach include: (1) relatively low computation load, and therefore, is capable of quick responding; (2) one generic model applies to different buildings; and (3) the prediction accuracy might improve over time, if machine learning is employed. But this approach is considered challenging in both modeling phase (because of complexity nature of the system) and optimization phase (due to high nonlinearity and continuous-discrete nature).

In this article, a simulation-based HVAC control optimization scheme is proposed. This optimization scheme includes two stages: off-line optimization and on-line optimization. On the off-line stage, exhaustive search or other algorithms can be applied with detailed energy simulation, and the optimal and several near-optimal strategies will be identified for each typical daily weather pattern. A mechanism is designed to select the "top choices" for all weather patterns and generate an "optimal strategy pool". On the on-line stage, upon availability of weather forecast, all the candidates in the "optimal strategy pool" will be evaluated, and the optimal strategy can be identified within a relatively short time. This optimization scheme will be detailed in the next section. The strength of this two-stage scheme is that the computationally intensive optimization is conducted off-line, which significantly reduces the computation load for on-line generation of optimal DR strategy, while (near-) optimality can be achieved.

The healthy and productive indoor environment should also be considered when DR control strategies are studied. To quantitatively evaluate the indoor thermal comfort, Fanger's Predicted Mean Vote (PMV) model and its derivation, Predicted Percent Dissatisfied (PPD) model is adopted in this study. PMV/PPD model was developed in 1970's based on a series of laboratory experiments (Fanger 1970). The model relates deviation from the optimal thermal condition to whole body metabolic effector phenomena, such as sweating and vessel dilation, and with occupants' comfort vote, in the end. Besides temperature, PMV/PPD model takes ventilation rate, mean radiant temperature and relative humidity, as well as clothing insulation and activity level, into consideration. PMV is scaled to predict occupant sensation vote on a seven-point scale: from hot to neutral, and then to cold. PPD is actually determined by PMV, and has range of values from 5% (PMV=neutral) to 100% (PMV=hot or cold). This model is included in standards such as ASHRAE Standard 55 and ISO Standard 7730 (ISO 2005; ASHRAE 2010). Although PMV/PPD model has received critiques from many researchers about its validity, reviewed by (De Dear and Brager 1998; Brager and De Dear 2001; Charles 2003), it is still the most widely used model that gives reasonable prediction of the occupant thermal comfort level, especially for the air-conditioned building environments (Fanger 1970; De Dear and Brager 1998).

METHODS

Simulation platform

Detailed EnergyPlus simulation model has been developed for the Sutardja Dai Hall on University of California, at Berkeley campus, which is a large education facility with 7 floors and total of 141,000 square feet conditioned area, hosting research labs, offices, auditoriums, etc. There are 135 zones, 6 Air Handling Units (AHUs), 110 Variable Air Volume (VAV) terminals, 1 centrifugal chiller, 1 absorption chiller, 2 cooling towers and other HVAC components in the simulation model. All HVAC equipments are operating with 24×7 schedules. The internal gains, equipment operations and controls are modeled. And system component-based calibration methodology is employed. The occupancy schedules are based on field survey; office rooms are occupied from 8:00 to 21:00 each day. The lighting and plug loads are calibrated using the data of dedicated sub-meters on each floor. And the HVAC component performance curves are derived based on the trending data, which is obtained from the building automation system. If simulation time step is 15 minutes, the difference between simulated and measured monthly energy of the building is within 10%. And the hourly energy has less than 20% error.

According to the real operation schedule, the absorption chiller is working only in summers and the centrifugal chiller only in winters. As this study is focusing on DR in summer time, the absorption chiller electric power is the only chiller consumption counted in optimization (i.e. centrifugal chiller electric power and absorption chiller steam consumption are not considered). It is also necessary to mention that only two AHUs are supplying air to office spaces in the building. The other four AHUs are dedicated for other missions, such as nano-fabrication laboratory. In this study, only the HVAC systems for office part are controllable, but the energy consumption calculation is done for all HVAC systems in the building, because all AHUs share the same plant equipment, it is difficult to separate the plant loop energy consumption for offices from that for non-office part.

MLE+, a Matlab/EnergyPlus co-simulation platform, is employed in the study. This platform uses the external interface functionality of EnergyPlus, and establishes bidirectional communication between EnergyPlus and Matlab/Simulink (Nghiem). Energy simulation and Matlab/Simulink script execution are synchronized so that at each simulation time step, Matlab can collect the performance data (e.g. meter readings) from EnergyPlus, generate control actions and "inject" back to the simulation. This co-simulation platform simplifies the simulation-based optimization. Matlab Global Optimization Toolbox is also used to design optimization algorithms.

Weather pattern identification

The historical August weather data of Berkeley, CA for the years between 2002 and 2010 has been collected. For each August day, the hourly dry bulb temperature and its simulated baseline peak load are included in the feature space, and subject to dimension reduction by principal component analysis (PCA). And then Kmeans clustering algorithm is applied. In this study, at least 19 clusters are required to ensure the variance in each cluster is lower than a pre-determined threshold. The centroid weather profile of each cluster is then obtained by taking average over all member profiles. All 19 centroid August weather profiles are depicted in Figure 1. Pattern 2, 4 and 19 are selected as the typical hot, mild and cool August weather pattern, respectively, for result presentation.

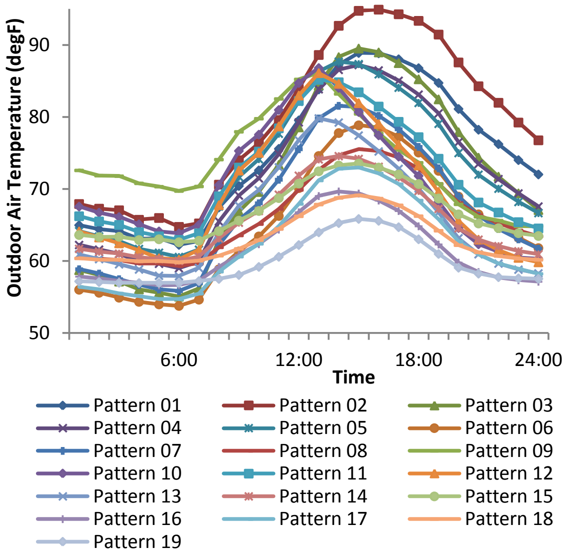

Figure 1: August daily weather patterns

DR control strategy design

In this article, global temperature setpoint adjustment (GTA), supply air temperature setpoint (SAT), supply fan pressure setting (SFP) and minimum ventilation (MinVent) are considered in DR control. The controls are detailed as the following.

GTA: The cooling setpoints of all zones are subject to change throughout the day. Pre-cooling and exponential set-up strategy is applied (Xu and Zagreus 2006; Xu and Yin 2009). As depicted in Figure 2, between 0:00 and T1, the cooling setpoint is set at the current baseline value, which is 72 ºF; between T1 and T2, the cooling setpoint is set at 70 ºF (pre-cooling); between T2 and T3, the cooling setpoint is set up exponentially to 78 ºF (exponential set-up); and between T3 and 24:00, the cooling setpoint is set back to 72 ºF. All zones are using the same GTA strategy. To reduce the size of solution space, only the three time points (i.e., T1, T2 and T3) are considered as decision variables. The setpoint values at T1, T2 and T3 are fixed at 72 ºF, 70 ºF and 78 ºF, respectively. Furthermore, time points can only be integer hours within the following ranges: $5 \leq T1 \leq 9$, $T1 < T2 \leq 14$, and $17 \leq T3 \leq 19$.

SAT: There are two AHUs dedicated for office spaces. They are controlled by the same SAT setpoint, whose current value is 56 ºF; and they share the same supply air duct. SAT setpoint values between 51 and 60 ºF are explored, with interval of 1 ºF. We assume that SAT setpoint only changes at the beginning of the DR day, to simplify the problem formulation.

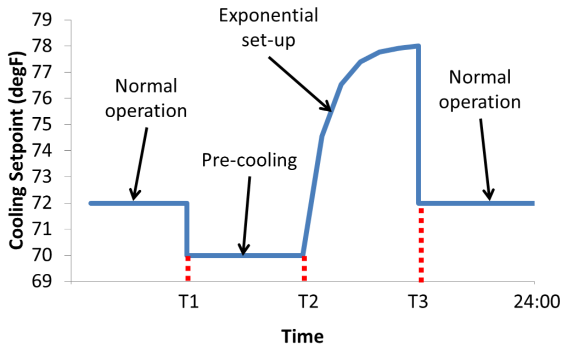

Figure 2: GTA strategy diagram

SFP: The two supply fans (SF-2A and SF-2B) in the building are variable volume fans. The operation speed is controlled by a proportional-integral-derivative controller (PID controller) to maintain the fan pressure at a fixed setpoint, which is currently 1350 Pa. SFP setpoint values between 1150 Pa and 1350 Pa are explored, with interval of 50 Pa. Again, to reduce the complexity of the problem, we assume that SFP setpoint only changes at the beginning of the DR day.

MinVent: The current minimum air flow rate settings for most of zones are found to be higher than the required levels defined by the standard (ASHRAE 62.1-2010), as illustrated in Figure 3. New minimum air flow requirements for all zones are calculated based on the area, occupancy density and functionality (ASHRAE 62.1-2010), and are implemented in a retrofitting model. The retrofitting model is the same as the base model, except for the adjusted minimum air flow requirements. The total minimum supply air volume is reduced by 28%, in the retrofitting model (Figure 4).

A DR strategy is defined by five decision variables, which are GTA(T1), GTA(T2), GTA(T3), SAT and SFP. The total number of strategies is 5250. All strategies are tested on the retrofitting model, rather than on the base model. Therefore, MinVent applies to all tested strategies, by default, even though it is not mentioned in the strategy description.

Two-stage optimization

Stage I: For any weather pattern i (i=1, 2, 3, …, 19), DR strategy j (j =1, 2, 3, …, 5250) will be evaluated by EnergyPlus simulation. The hourly HVAC energy and hourly PPDs of all zones are calculated by the simulation. A simplified peak day price model (PDP, see Figure 5) is applied to calculate the energy cost (C).

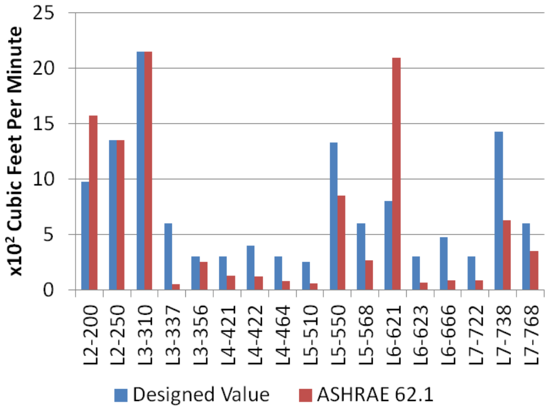

Figure 3: Minimum ventilation rates of sample zones

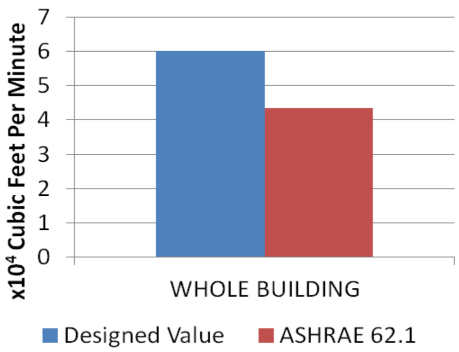

Figure 4: Minimum ventilation rate of the building

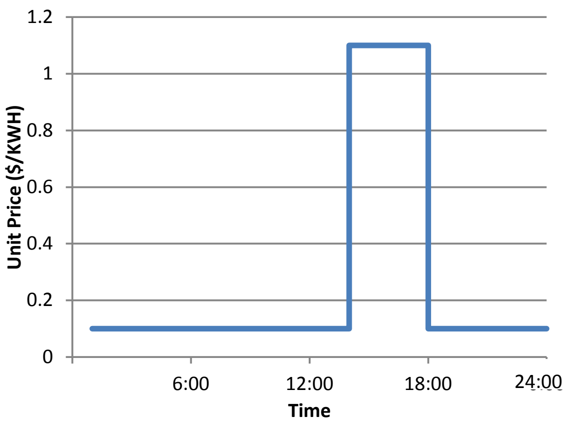

Figure 5: Simplified peak day price model

The 24-hour PPD values of the occupied zones are summed up to generate the "thermal comfort loss" (U). After min-max normalization, normalized energy cost ($\bar{C}$) and thermal comfort loss ($\bar{U}$) will time their corresponding weights (w_c *and* w_u, respectively), and add together to provide the objective value $F_{i,j}$ (Equation (1)). Exhaustive Search (ES) and other optimization algorithms can be applied on this stage, to obtain the optimal objective value $F_i^* = \min_j F_{i,j}$.

$$F_{i,j} = w_c \frac{C_{i,j} - C_{min}}{C_{max} - C_{min}} + w_u \frac{U_{i,j} - U_{min}}{U_{max} - U_{min}} \qquad (1)$$

Stage II: On Stage I, the evaluations of all 5250 DR strategies are done for each of 19 centroid weather profiles, using ES (the cases of using other optimization algorithms will be discussed later). On Stage II, for each weather pattern i, strategy j will be selected if it saitisfies Equation (2).

$$F_{i,j} \leq \alpha F_i^* \qquad (2)$$

where α is the pre-determined threshold, and α =1.1 is used in this study. Denote the total number of selected strategies by N_i. The selected strategies are sorted by ascending objective values. And let j^k be the k-th strategy in this rank (k = 1, 2, 3, …, N_i). Each of the selected strategies will be assigned with a "likelihood" score (L). The likelihood scores are determined by Equation (3) and (4).

$$\sum_{k=1}^{N_i} L_{i,j^k} = 1 \qquad (3)$$

$$\frac{L_{i,j^{k+1}}}{L_{i,j^k}} = \beta, k = 1, 2, 3, \dots, N_i - 1 \qquad (4)$$

where β is the pre-determined ratio, and β = 0.5 is used in this study. The overall likelihood score of strategy j for all weather patterns is given by Equation (5):

$$L_j = \sum_{i=1}^{I} p_i L_{i,j} \qquad (5)$$

where, I is the total number of weather patterns, and p_i is the probability that the weather of the planning day is of pattern i. p_i can be estimated by dividing the number of pattern i days in the record with the total number of recorded days.

An "optimal strategy pool" can be created by selecting candidate strategies with large overall likelihood score. As this pool will contain a smaller number of candidate strategies, exhaustive search within the pool can provide the best solution for a given weather condition; and this search can be conducted on-line.

RESULTS

Exhaustive search optimization

The simulation evaluations of all DR strategies have been done for each of 19 centroid weather profiles. The result is summarized in Table 1.

ES optimization shows that the optimal DR strategies are able to reduce the peak load by as much as 18% – about 109 kW – on typical hot day (weather pattern 2), 38 kW on typical mild day (weather pattern 4) and 22 kW on typical cool day (weather pattern 19). Figure 6 shows the total HVAC power profile of optimal strategies, in comparison with that of baseline controls, for the three typical weather patterns.

Table 1: Optimization by Exhaustive Search

Weather Pattern #	Optimal DR Strategy						Baseline Peak Load (kW)	Optimal Peak Load (kW)	Peak Load Reduction (kW)
	ID*	GTA(T1)*	GTA(T2)*	GTA(T3)*	SAT*	SFP*			
1	4817	9	10	18	60	1150	531	480	51
2	4823	9	12	18	60	1150	603	495	109
3	4818	9	10	19	60	1150	520	476	43
4	4818	9	10	19	60	1150	512	473	38
5	4818	9	10	19	60	1150	512	474	38
6	4755	6	7	19	60	1150	482	457	24
7	4818	9	10	19	60	1150	487	462	25
8	4800	8	9	19	60	1150	478	454	25
9	4818	9	10	19	60	1150	502	469	32
10	4818	9	10	19	60	1150	497	469	29
11	4818	9	10	19	60	1150	500	469	31
12	4818	9	10	19	60	1150	495	468	27
13	4818	9	10	19	60	1150	481	458	23
14	4818	9	10	19	60	1150	475	452	24
15	4818	9	10	19	60	1150	476	452	24
16	4755	6	7	19	60	1150	467	444	23
17	4755	6	7	19	60	1150	472	449	23
18	4755	6	7	19	60	1150	468	445	23
19	4755	6	7	19	60	1150	463	441	22

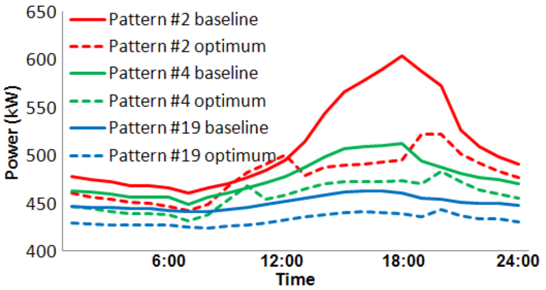

Figure 6: HVAC power profile of optimal DR strategies

As mentioned in the introduction of simulation model, the absorption chiller is the only chiller running in the studied period. The electric power of absorption chiller is consumed by the refrigerant pump in the chiller. This consumption is considered constant and small – compared with those of other HVAC components. Calculation and operation records also suggest that the chiller in Sutardja Dai Hall is significantly oversized, and as a result the chiller is running at minimum load most of the time. The simulation model replicates such phenomenon (data not shown). Therefore, the chilled water pumps and condenser water pumps in the model are running at constant speed, even though they are modeled as variable speed drives. The pump power is not changing with different DR strategies and weather patterns. Consequently, almost all peak load reductions are contributed by reduced supply fan power and return fan power.

Table 2: GA parameters

Population size	50
Creation function	Uniform
Scaling function	Rank
Selection function	Stochastic Uniform
Elite count	2
Crossover fraction	0.8
Crossover function	Scattered
Mutation function	Uniform with rate=0.3
Maximum generation	20
Function tolerance	1.00E-06

The result also confirms that the temperatures in all occupied zones are maintained between 70 and 78 °F, and the PPDs are lower than 20% at all time (data not shown).

Genetic algorithm optimization

Genetic Algorithm (GA) is applied as an alternative method for off-line optimization. The Global Optimization Toolbox provided in Matlab is employed. The GA parameters are summarized in Table 2.

Table 3: GA result for weather pattern 2

Trials	GTA (T1)*	GTA (T2)*	GTA (T3)*	SAT*	SFP*	# of evaluations
1	9	12	18	60	1150	357
2	9	12	18	60	1150	470
3	9	12	18	60	1150	319
4	9	12	18	60	1150	400
5	8	9	18	60	1150	310
6	9	12	18	60	1150	361
7	9	12	18	60	1150	342
8	9	12	18	60	1150	390
9	9	12	18	60	1150	322
10	9	12	18	60	1150	334
11	9	12	18	60	1150	432
12	9	12	18	60	1150	386
13	9	12	18	60	1150	360
14	9	12	18	60	1150	366
15	9	12	18	60	1150	369
16	9	12	18	60	1150	378
17	9	12	18	60	1150	422
18	9	12	18	60	1150	395
19	9	12	18	60	1150	376
20	9	12	18	60	1150	347
ES	9	12	18	60	1150	5250

For each weather pattern, GA is tested with 20 repeats. The optimal strategy for weather pattern 2 obtained in all 20 tests are summarized in Table 3. According to this result, in 19 out of 20 (95%) GA trials, the optimal DR strategy can be obtained [9, 12, 18, 60, 1150]. And the average number of simulation evaluations is 372. Similar results can be obtained for all 19 weather patterns (Table 4). Generally, by applying GA, the optimum is not guaranteed, but the probability of obtaining the top 3 DR strategies is high. Meanwhile, the calculation load is reduced by nearly 93%.

Table 4: GA success rates and efficiency

Weather Pattern	p(1)	p(2)	p(3)	Ave. # of evaluations
1	95%	95%	95%	346
2	95%	95%	95%	372
3	50%	50%	95%	365
4	35%	35%	100%	359
5	75%	75%	75%	379
6	95%	95%	100%	337
7	30%	70%	85%	365
8	35%	100%	100%	356
9	95%	95%	95%	392
10	60%	60%	95%	388
11	80%	80%	80%	381
12	40%	85%	85%	378
13	20%	70%	90%	354
14	10%	50%	70%	352
15	30%	75%	100%	359
16	90%	100%	100%	327
17	100%	100%	100%	337
18	90%	100%	100%	315
19	85%	100%	100%	337

p(1): probability of obtaining the optimum
p(2): probability of obtaining the optimum or the 2nd best
p(3): probability of obtaining the optimum, the 2nd or the 3rd best

Stage II – Optimal strategy pool

After the evaluation of all 5250 DR strategies for all 19 centroids, the top strategies are selected using the mechanism described above. Table 5 shows the selected strategies and their corresponding likelihood scores for weather pattern 2, 4 and 19. The overall likelihood scores are calculated, and only 13 strategies have non-zero scores. These 13 strategies constitute the optimal strategy pool (Table 6).

Validation of the Optimal Strategy Pool algorithm

To validate the optimal strategy pool algorithm (OSP), 13 historical August days of Berkeley, CA are randomly sampled for testing. The result of OSP is compared with the ES optimization and other two on-line optimization algorithms – GA and pattern based strategy selection (PBS). The optimal DR strategies obtained by each algorithm as well as total number of evaluations are shown in Table 7.

By applying PBS, the optimal strategy for a sample weather is assumed to be the same for the weather pattern it belongs to. PBS does not require on-line simulation evaluation of DR strategies, therefore, it seems to be a perfect on-line optimization algorithm. However, according to our result, PBS algorithm fails to identify the optimal strategy for Sample Day 1, 4, 6, 9 and 12. GA performs slightly better, as it fails for Sample Day 4, 5, 8 and 12. As a contrast, OSP successfully identifies the optimal DR strategy for all sample days. And furthermore, OSP only requires 13 on-line simulation evaluations, which is 3.5% of evaluations by GA, and 0.2% of evaluations by ES. It takes about 2 minutes to finish one simulation execution (on a personal PC laptop). This infers that ES needs 7.3 days, GA needs 12 hours, but OSP only needs less than 30 minutes to obtain the optimal DR strategy for a given weather profile.

Table 6: The optimal strategy pool

DR strategy ID	Overall likelihood score	GTA (T1)*	GTA (T2)*	GTA (T3)*	SAT*	SFP*
4818	8.2381	9	10	19	60	1150
4755	4.2000	6	7	19	60	1150
4817	2.3963	9	10	18	60	1150
4800	1.8857	8	9	19	60	1150
4728	0.6667	5	6	19	60	1150
4779	0.6095	7	8	19	60	1150
4823	0.5039	9	12	18	60	1150
4820	0.252	9	11	18	60	1150
4826	0.126	9	13	18	60	1150
4754	0.0667	6	7	18	60	1150
4829	0.0315	9	14	18	60	1150
4827	0.0157	9	13	19	60	1150
4824	0.0079	9	12	19	60	1150

DISCUSSION

In HVAC systems, ventilation equipment consumes large portion of energy. An optimal DR strategy should be able to reduce ventilation power during critical period. To achieve this goal, the volume flow rate of supply air and/or fan pressure setting should be reduced. Raising zone temperature setpoint in critical period is able to reduce the demands for cooled air. Our results suggest that by applying GTA only, the ventilation rates of most of zones are kept at minimum level during critical period (data not shown). This implies that zone minimum air flow requirement might be the bottleneck for further reduction of supply air volume flow rate. Therefore, MinVent strategy would be necessary to couple with GTA strategy, so that the ventilation rate of the building during the critical time can be reduced to as low as the standard allows. MinVent strategy is not effective in the non-critical period, as, with lower cooling setpoints, the supply air demand becomes higher than the minimum level. So, more rigorously, MinVent strategy is a retrofitting strategy that maximizes the building DR capability, rather than a DR strategy.

Table 5: Optimal and near-optimal DR strategy selection

Weather Pattern 2			Weather Pattern 4			Weather Pattern 19		
DR Strategy ID	F	Likelihood Score	DR Strategy ID	F	Likelihood Score	DR Strategy ID	F	Likelihood Score
4823	0.4242	0.5039	4818	0.3391	0.6667	4755	0.2926	0.6667
4820	0.4246	0.2520	4817	0.3399	0.3333	4728	0.2938	0.3333
4826	0.4247	0.1260						
4817	0.4248	0.0630						
4829	0.4279	0.0315						
4827	0.4284	0.0157						
4824	0.4284	0.0079						

Table 7: Validation of the Optimal Strategy Pool

Sample Day (Pattern)	Algorithm				
	ES	PBS	GA	OSP	
1 (pattern 19)	4728	4755	4728	4728	Opt. DR strategy ID
	5250	0	288	13	# of on-line evaluations
2 (pattern 3)	4818	4818	4818	4818	Opt. DR strategy ID
	5250	0	349	13	# of on-line evaluations
3 (pattern 9)	4818	4818	4818	4818	Opt. DR strategy ID
	5250	0	358	13	# of on-line evaluations
4 (pattern 8)	4779	4800	4755	4779	Opt. DR strategy ID
	5250	0	362	13	# of on-line evaluations
5 (pattern 14)	4818	4818	4779	4818	Opt. DR strategy ID
	5250	0	380	13	# of on-line evaluations
6 (pattern 13)	4800	4818	4800	4800	Opt. DR strategy ID
	5250	0	383	13	# of on-line evaluations
7 (pattern 16)	4755	4755	4755	4755	Opt. DR strategy ID
	5250	0	308	13	# of on-line evaluations
8 (pattern 8)	4800	4800	4755	4800	Opt. DR strategy ID
	5250	0	311	13	# of on-line evaluations
9 (pattern 18)	4755	4818	4755	4755	Opt. DR strategy ID
	5250	0	326	13	# of on-line evaluations
10 (pattern 18)	4755	4755	4755	4755	Opt. DR strategy ID
	5250	0	311	13	# of on-line evaluations
11 (pattern 17)	4755	4755	4755	4755	Opt. DR strategy ID
	5250	0	339	13	# of on-line evaluations
12 (pattern 14)	4800	4818	4779	4800	Opt. DR strategy ID
	5250	0	361	13	# of on-line evaluations
13 (pattern 16)	4755	4755	4755	4755	Opt. DR strategy ID
	5250	0	323	13	# of on-line evaluations

Another way of reducing ventilation power consumption is to set the fan differential pressure (or static pressure) at lower level. In reality, this can be achieved by step-wisely reducing the pressure setting while monitoring the valve position at each VAV terminal. In simulation, zone temperatures need to be monitored to ensure that low fan pressure is still able to deliver enough cooled air to all zones. The simulated zone temperatures in our study confirm the cooled air delivery is adequate. Note that, according to the simulation result, the optimal strategies for all weather patterns have SFP setpoint value at its lower bound (1150 Pa). It implies the fan pressure setting can be further reduced. However, field tests would be needed to determine the real lower bound of SFP setpoint.

According to the GTA parameters in the optimal DR strategies, it is obvious that, only when the weather is relatively hot (weather pattern 2), longer pre-cooling period is needed (3 hours). For the remaining weather patterns, only one hour pre-cooling is needed (Table 1). Consider that pattern 2 is rare for August of Berkeley, CA (only a few cases in 9 years), pre-cooling might not be necessary for DR most of time.

The solution space in this study contains 5250 DR strategies. Although the size of this solution space has been reduced intentionally, as only a few controllable points are involved, and only discrete values are considered for each point, simulation-based ES optimization still requires several days to obtain an optimum. In real cases, an on-line DR control optimization should deal with more controllable points, and higher resolution would be expected. Thus, ES optimization is not feasible for on-line response.

This article is proposing an alternative method for on-line HVAC control optimization. The key of this method is to move the computationally intensive optimization to off-line. A knowledge base, which is the "optimal strategy pool" in this study, can be generated based on off-line results. This optimal strategy pool is supposed to contain much smaller number of candidate strategies, and, therefore, turns on-line simulation-based optimization feasible. The PBS strategy is heuristically qualified for this type of two-stage scheme, and is seemingly more favorable, as no on-line optimization would be needed. However, our results (Table 7) suggest that optimal strategy for the centroid profile of a weather pattern is not necessarily the optimal for the individual weather of this pattern. But, it is likely that the optimal strategy for any individual weather is among the top choices for the pattern's centroid weather. Then, ideally, if all top choices for all centroid weathers are selected to generate a "pool", such pool should be able to cover the optimal strategy of most individual weathers.

Although, due to the time constraint, only 13 sample days are tested to validate the OSP approach, the results show that this approach is able to reduce the on-line optimization time by 99.8%, while the optimal DR strategies are still obtained. It is also recognized that, as more points are subject to control optimization, even off-line ES will be impossible or computationally expensive. Then, other sophisticate optimization techniques have to be involved on off-line stage. There is one criterion for choosing off-line optimization technique – it should be able to identify not only the optimal solution, but also the second, the third, and, perhaps, more best solutions in the rank.

To aggregate the selected "top choices" for all weather patterns, a mechanism based on likelihood score is adopted. This mechanism is simple and heuristic. More advanced aggregation mechanism might be necessary to ensure enough coverage of the generated "optimal strategy pool". An ideal aggregation mechanism needs to capture the following information: (1) the possibility of appearance for each weather pattern; (2) the characteristics of each weather pattern (e.g., the temperature range); and (3) the distance between weather patterns.

It is recognized by the authors that many other factors may have impacts on HVAC consumption, such as humidity control, economizer setting, heat recovery, etc. They are not involved in this study, either because they are not implemented in the studied system (humidity control and heat recovery), or simply to limit the scope of the study. Since the two-stage on-line optimization scheme demonstrated in this article is a generic approach for HVAC DR strategy optimization, it would apply to systems with different specifications, although further study will be needed to examine its efficiency and accuracy.

CONCLUSIONS

In this article, we presented a two-stage scheme to perform on-line simulation-based HVAC DR control optimization. On the off-line stage, computationally intensive optimizations are conducted for weather patterns identified from the historical weather data. Based on the results from the first stage, a knowledge base, or an "optimal strategy pool" can be generated, which is expected to contain the optimal DR strategies for any daily weather profiles with high probability. And this knowledge base will be used on the on-line simulation-based optimization. On the second stage, simulation evaluation on each candidate strategy in the knowledge base will identify the best strategy. Our results show that this best strategy is likely to be the optimal HVAC control strategy for the planning day. In the case study of Sutardja Dai Hall, our approach successfully identifies the optimal strategy for all 13 sample days, with significantly less simulation evaluations. And the optimal strategy is able to reduce the HVAC peak load by 18% for a typical hot August day of Berkeley, CA.

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